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2025

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Impact of renewable energy sources on greenhouse gas emissions reduction in Germany, Sweden and Poland

**Ignas Mikalauskas¹, Zenona Ona Atkociuniene²,
Asta Mikalauskiene³**

¹ Vilnius University, Kaunas Faculty, Institute of Social Sciences and Applied Informatics, Lithuania, ORCID: 0000-0003-0879-0900, ignas.mikalauskas@knf.vu.lt (corresponding author);

² Vilnius Gediminas Technical University, Faculty of Creative Industries, Department of Creative Communication, Lithuania, ORCID: 0000-0001-9887-1530, zenona-ona.atkociuniene@vilniustech.lt;

³ Vilnius University, Kaunas Faculty, Institute of Social Sciences and Applied Informatics, Lithuania, ORCID: 0000-0002-4301-2058, asta.mikalauskiene@knf.vu.lt.

Abstract: Transitioning to renewable energy sources is highly important to reduce greenhouse gas emissions. In this study, we look at Germany, Sweden and Poland. These three countries have different energy policies and commitments. While there has been significant progress in adopting renewable energy across Europe, the effectiveness of these policies and their impact on reducing emissions is very different. Therefore, this research aims to assess how renewable energy affects GHG emissions in these countries and to provide insights into what strategies work best. Using a compiled dataset from 2003 to 2023, the study employs correlation, regression and time-series analysis. It is done to understand the relationship between renewable energy use and GHG emissions. In Germany and Sweden, there are strong negative correlations (-0.92 and -0.90), which indicate that increased renewable energy use significantly reduces emissions. However, in Poland, the correlation was much weaker (-0.23) and it suggested that the impact of renewables has been less effective. Digging deeper, our regression analysis highlighted that wind energy is particularly effective in reducing emissions, especially in Sweden. In Poland, while other renewable sources show promise, their impact is not yet statistically significant. Time-series forecasts suggested that Germany and Sweden will continue to see reductions in emissions, Poland will make gradual progress. These results show the need for continued policy support and best practice innovations in renewable energy.

Keywords: Renewable energy sources, emissions reduction, energy transition, climate change, energy consumption.

JEL Classification: Q01, Q42, P18.

APA Style Citation: Mikalauskas, I., Atkociuniene, Z. O., & Mikalauskiene, A. (2025). Impact of renewable energy sources on greenhouse gas emissions reduction in Germany, Sweden and Poland. *E&M Economics and Management*, 28(4), 1–13. <https://doi.org/10.15240/tul/001/2025-4-001>

Introduction

The world is grappling with serious environmental issues based on climate change – especially high emissions of greenhouse gases (GHG)

in the atmosphere. Therefore, the transition to renewable energy sources (RES) has been recognized as a key strategy by many countries. This paper aims to analyze the impact of RES

on GHG emissions reduction in 3 European countries – Germany, Sweden and Poland. These countries represent distinctive cases because they have diverse energy policies, they are at different levels of RES adoption and different possible environmental outcomes.

Renewable energy's relevance is shown by the potential that it can drastically reduce GHG emissions, and it has been documented in scientific literature. For example, Cumming and von Cramon-Taubadel (2018) and Foxon (2017) share what are the implications of sustainable energy transitions to achieve economic growth and ecological sustainability.

The choice to pick Germany, Sweden and Poland for this study has a strategic viewpoint. Germany shows a comprehensive and very ambitious plans for energy transition because of their *Energiewende* policy (Fischer et al., 2016; Von Hirschhausen 2014). Sweden already has a very long-standing sustainability commitments and had already planned to achieve 100% renewable electricity by 2040 mainly through their hydro and bio energy sectors (Amiandamhen et al., 2020; Gustavsson et al., 2011). And Poland remains reliant on fossil fuel – coal especially and therefore they are facing high levels of economic and social barriers for their transition to renewable energy (Brauers & Oei 2020; Krzywda et al., 2021; Nyga-Łukaszewska et al., 2020).

This research addresses a gap in the scientific literature because it provides a comparative analysis of the impact of RES on emissions reductions in 3 countries from a large 20-year dataset with the combination of 3 different methods applied, while previous studies often focus on singular aspects or single-country analysis. The novelty of this study lies in the methodological diversity and the depth of the insights it provides. This data can provide valuable information to policy and strategic decision makers in countries that are trying to achieve a sustainable energy transition.

The study uses a combination of correlation, regression and time-series analysis to research the relationship between RES and GHG emissions. The total dataset includes data from 2003 to 2023, including primary energy consumption, electricity generation and GHG emissions. Correlation analysis uses Pearson correlation coefficients to show the linear relationships, regression analysis uses linear regression models to determine the causal effects of different

RES on GHG emissions while also adjusting for influencing factors. Time-series analysis uses the ARIMA models to forecast the future trends for energy consumption and emissions, which shows insights into the long-term impacts of different renewable energy policies.

The paper is structured as follows. In the introduction part, we outline the context of this research. The literature review summarizes the latest and current research on the impact of renewables on GHG emissions while identifying the gaps addressed by this study. Methods and data part of the work presents a sample of data sources, a description of analytical methods used, and the rationale for selecting Germany, Sweden and Poland. The results section presents the findings from the analytical research and highlights the key trends and differences between the countries. Afterwards, a discussion is carried out that interprets the results, compares them with previous studies and discusses the implications for possible policies and for future research. In the conclusions section, we summarize all the main findings, emphasize the study's contributions to the field, and suggest directions for future research.

This paper, unlike other studies that do not provide comprehensive assessments of RES impacts on environment, aims to overcome this gap and provides thorough comparative analysis of emissions reduction. This would help to get the best practices, common challenges and policy implications for other countries aiming to perform better in sustainability. It is within this perspective that an understanding of the environmental, economic and social dimensions of adopting renewable energy has relevance for informed debate on sustainable energy transitions.

1 Theoretical background

The implementation of RES across Europe has brought remarkable environmental benefits regarding the reduction of GHG emissions. European Environment Agency (2021) and CAN Europe (2024) argue that the growth in electricity produced from renewables since 2005 is helping to decrease environmental pressures worldwide and lower economic costs linked with climate change. Moreover, the European Environment Agency (2024) reports that with higher levels of renewable energy resources, there are expected societal benefits that support and sustain different goals in Europe.

While Marsland and Staples (2024) and Fujii and Lee (2024) emphasize the urgency in adopting RES more quickly to reduce such slow policy impacts on negative health, that will eventually hinder the concept of sustainable development.

The International Energy Agency (IEA, 2023) points to a tectonic influence of the energy crisis on the deployment of renewable energies in the EU, whereas according to Ember Climate (2024), recent drops in coal and gas use and CO₂ emissions have been equally attributed to renewable sources. According to the Heinrich Böll Foundation (2024), domestic supply from renewable sources doubled between 2005 and 2022, enhancing energy security with fewer emissions. More details about such benefits are available through further studies. Risks and environmental effects linked to renewable energy use and production are also discussed in Girgibo et al. (2024) and Osman et al. (2023), as Ivanova and Datta (2023) point out that the public should be enlightened about how renewable energy impacts the environment positively.

Saidi and Omri (2020) further analyzed the impact of renewable energy on carbon emissions and economic growth in Europe, thus testifying that renewable energy adoption leads to sustainability.

Andreas et al. (2017) also identify that wealth disparities shape the adoption of renewable energy, with the argument that renewable energy may be considered a luxury for wealthier countries. In contrast, Jerez et al. (2015) and Hertwich et al. (2015) study the relevance of alternative climate scenarios in each case and conduct life-cycle assessments of different electricity-supply scenarios for the same case to underscore the environmental benefits of various renewable energy technologies that highlight the need for ambitious climate change mitigation schemes.

Owusu and Sarkodie (2016) and Arioğlu Akan et al. (2015) further explain the contribution of renewable energy to ensuring sustainability and preventing climate change by going through policies and outcomes in European countries and observing sharp cuts in GHG emissions and high levels of energy security have been noticed because of the shift toward the usage of renewable sources of energy.

Indeed, several studies have been conducted on the progressive achievements and the regressions in the use of renewable energy

in chosen nations such as Germany, Sweden and Poland. Kim et al. (2015) observed a positive change in Germany since the implementation of the Energiewende policy: high rates for Sweden, with the two primary sources being hydroelectric power and bioenergy and a gradual improvement for Poland, though it is still based on coal for energy. Komarnicka and Murawska (2021) and Bórawski et al. (2022) compare and conclude that vast emission reductions have been realized in Germany and Sweden, while Poland is moving slowly.

Rybak et al. (2022) and Lapinskienė and Peleckis (2017) both look at the relationship between environmental taxes and economic growth but in a manner concerning their impact on emissions and posit that such policy, besides a policy over RES, worked well for Sweden and may also apply successfully in the case of Poland. Bohdanowicz (2021) and Ślusarczyk et al. (2022) describe public support and economic effects with an emphasis that in Germany, people have high awareness and support, whereas it is progressing very slowly in Poland.

Stec and Grzebyk (2022) and Dominiak and Oleszczyk (2019) indicate the high-scale renewable energy penetration in Germany and Sweden, along with their emissions reduction. In contrast, they also underline Poland's transition process, and the issues encountered. Brodny and Tutak (2020) and Miškinis et al. (2021) have been able to use cluster and dynamic analysis for comparison of the adoption of RES, where they find Sweden and Germany remain on the front line of efforts in mitigation, with Poland gradually improving.

Gołasa et al. (2021) and Ślusarczyk et al. (2022) also work on renewable energy in agriculture and economic growth, while Poland is already gaining many of such benefits. Effective emissions cuts and strengthening economic resilience are studied in Sweden and Germany. In overall meaning, the integration of renewable energies in Europe highly contributes to the decrease of GHG emissions and fosters energy security, demonstrating basic societally and economically essential effects. Policies and their accompanying educational frameworks should be adequate for sustainable development and climate goals achievement.

2 Research methodology

This study used a three-pronged statistical approach – correlation analysis, regression

analysis, and time-series forecasting, applied to annual panel data from Germany, Sweden, and Poland between 2003 and 2023. The aim was to investigate the extent to which renewable energy sources influence GHG emissions across different policy and economic environments.

Correlation analysis. Pearson correlation coefficients were calculated to assess the linear relationship between the share of renewable energy in total energy consumption and annual GHG emissions. This was done for each country individually using 20 years of data. A secondary correlation was also performed between renewable energy share and time (years) to evaluate long-term trends.

Regression analysis. We developed country-specific multiple linear regression models, where the dependent variable was total annual GHG emissions (in CO₂ equivalents). Independent variables included the consumption of different energy types (solar, wind, hydro, nuclear, other renewables), total primary energy use, and energy intensity (measured in kWh/\$GDP).

Multicollinearity was assessed using variance inflation factors (VIF), and high-VIF predictors were iteratively removed. This allowed for robust estimation of the marginal impact of each energy type on emissions while controlling for other factors. The general form of a regression equation is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon \quad (1)$$

where: Y – the dependent variable; X_1, X_2, \dots, X_n – the independent variables; β_0 – the intercept; $\beta_1, \beta_2, \dots, \beta_n$ – the regression coefficients; ϵ – the error term. The regression coefficients, along with their test results (p -values), will be derived from the statistical software in question. This would make it possible to determine the extent and direction of the impact of renewable energy on the chosen emissions-related metrics while other influencing variables are held constant.

Time-series analysis. Autoregressive integrated moving average (ARIMA) models were

Tab. 1: Energy dataset sample of 2003, 2013 and 2023

Year	Germany	Sweden	Poland
Primary energy consumption (TWh)			
2003	4,010.47	609.24	1,034.21
2013	3,868.52	603.54	1,131.32
2023	3,169.55	597.50	1,143.45
Electricity generation (TWh)			
2003	602.03	135.39	150.01
2013	629.69	153.03	163.78
2023	504.79	166.36	168.75
Renewables (% equivalent primary energy)			
2003	3.64	28.30	0.68
2013	12.06	39.28	5.22
2023	24.39	53.89	12.15
Energy intensity level of primary energy (MJ/\$2017 PPP GDP)			
2003	3.98	5.57	5.71
2013	3.34	4.48	4.17
2023	2.74	3.54	3.47

Note: TWh – terawatt-hour; MJ – megajoule; PPP – purchasing power parity; GDP – gross domestic product.

Source: own based on Hannah et al. (2023a, 2023b)

applied to forecast primary energy consumption, energy intensity, and per capita GHG emissions for the period 2024–2028. Prior to modeling, each series was tested for stationarity using the augmented dickey-fuller (ADF) test. Non-stationary series were log-transformed and differenced. Forecasts were then back-transformed to the original scale and reported with 95% confidence intervals. These projections offer a forward-looking assessment of whether current renewable energy trajectories are likely to meet emissions reduction targets. The general ARIMA model is given by:

$$ARIMA(p,d,q) \quad (2)$$

where: p – the number of lags in the model (this is the autoregressive part); d – the degree of differencing (i.e., the number of times the data have had past values subtracted); q – the size of the moving average window.

A good and adequate understanding of the relationship between these various RES will be provided concerning the environmental and economic outcomes by applying such analytical methods within the study. The findings would, therefore, inform multiple policy decisions and further the cause of sustainable energy in Germany, Sweden and Poland.

Data. A robust analysis was made from the data compiled in this study from 2003 to 2023. Tab. 1 presents the sample of the energy dataset, while the sample of the GHG emissions dataset is shown in Tab. 2. The presented samples are cut short to 2003, 2013 and 2023, while the data used to receive study results contain the entire dataset of all years between 2003 and 2023.

Tab. 2 shows the GHG emissions dataset, which reveals details about GHG and CO₂ annual emissions from different countries. This dataset is detailed and covers a 20-year period from 2003 to the most recent available data in 2023 that provides an ample foundation for analyzing how energy consumption and GHG emissions have changed over this time.

3 Results and discussion

3.1 Results

Correlation analysis. The correlation between renewable energy consumption and CO₂ emissions reveals that Germany has a correlation coefficient of -0.92 , indicating a strong negative correlation. Sweden's correlation coefficient is -0.90 and it is also showing a strong negative correlation. But Poland's correlation coefficient is -0.23 , which is essentially reflecting a weak negative correlation.

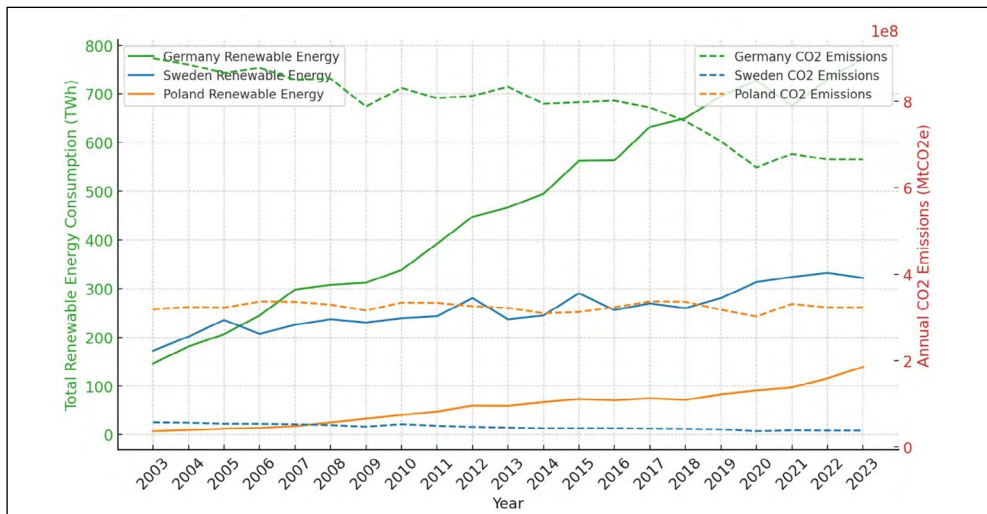


Fig. 1: Impact of renewable energy consumption on CO₂ emissions

Source: own

Fig. 1 shows that Germany has a steady increase in renewable energy consumption as well as a general downward trend in CO₂ emissions. In this case, Sweden exhibits a very significant growth in renewable energy consumption (with CO₂ emissions fluctuating) but generally trending downwards. Poland shows a semi-gradual increase in renewable energy consumption while its CO₂ emissions

seem to present a mixed trend – both increases and decreases over the years.

Fig. 2 presents the correlation analysis between the year and the renewable energy share in total primary energy consumption for each of the three countries – Germany, Sweden and Poland (from 2003 to 2023). Each scatter plot illustrated are the data points for the renewable energy share for each year.

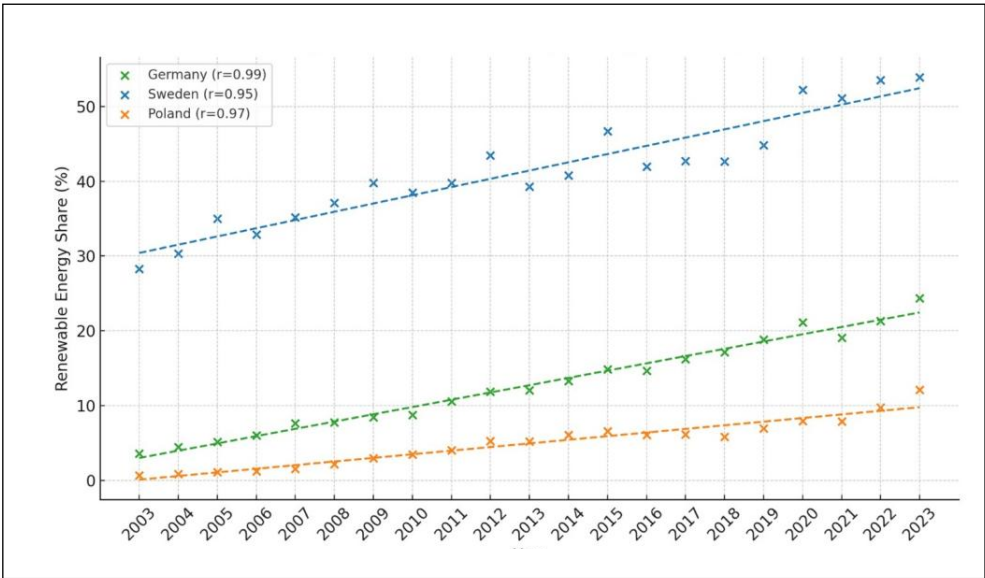


Fig. 2: Renewable energy share in total primary energy consumption

Note: The dashed lines represent the linear regression fits.

Source: own

The correlation coefficients do reveal a very strong positive correlation between the renewable energy share and the year for Germany ($r = 0.99$). It is therefore indicating a consistent increase over time. Sweden ($r = 0.95$) is reflecting substantial growth while Poland's ($r = 0.97$) increase is more gradual over the years in comparison to Germany and Sweden.

Regression analysis. For Germany, Sweden and Poland, three datasets used with variables containing information for regression analysis on energy consumption and GHG emissions of regions. Target variable was annual GHG emissions (in CO₂ equivalents).

Predicting variables were entirely composed regarding energy consumption (e.g., solar, wind, hydro, nuclear), intensity about energy use, primary power usage and renewables.

For each country, a linear regression model was developed including a set of predictor variables. This showed high multicollinearity of predictors, demonstrating large coefficients but non-significant results. Produced VIF for each predictor variable to detect multicollinearity. Observed high VIF values are severe multicollinearity issues. Removed predictors with the highest VIF values iteratively until all remaining predictors had a VIF < 10. Retrained

the regression models with reduced predictors using VIF values having no multicollinearity. More stable coefficient estimates and *p*-values were received.

As viewed in Tab. 2, we can define the following connections for each of the countries:

- i) Germany: solar and nuclear both had an independent, no-statistical-uncertainty connection to GHG emissions;
- ii) Sweden: solar consumption (TWh) – positive and significant, increasing solar energy use associated with increased GHG emissions, which

is counterintuitive and might indicate underlying factors not captured by the model; wind use (TWh) – negative and highly significant, suggesting that more wind energy consumption reduces GHG emissions; nuclear consumption (TWh) – insignificant;

iii) Poland: other renewables (including geothermal and biomass) (TWh) – close to a significant negative change in GHGs, indicating potential for reducing emissions, although at a low level; all other variables were not statistically significant.

Tab. 2: Reduced regression model results

Variable	Coefficient	<i>p</i> -value
Germany		
Solar consumption (TWh)	–503,162.8	0.515
Nuclear consumption (TWh)	401,219.6	0.234
Sweden		
Solar consumption (TWh)	1,353,581.0	0.009
Wind consumption (TWh)	–344,777.2	<0.001
Nuclear consumption (TWh)	27,842.9	0.394
Poland		
Solar consumption (TWh)	263,171.0	0.593
Wind consumption (TWh)	–167,301.3	0.698
Other renewables (including geothermal and biomass; TWh)	–1,267,146.0	0.064
Primary energy consumption per GDP (kWh/\$)	–16,741,370.0	0.663

Note: TWh – terawatt-hour; kWh – kilowatt-hour; GDP – gross domestic product.

Source: own

Once multicollinearity has been dealt with by fitting the reduced models, it gives more stable coefficient estimates and tests of significance. This will further show a better understanding of the effects that RES have on GHG emissions in Germany, Sweden and Poland, which could bring about a coherent policy for sustainable energy investments.

Time-series analysis. Three different datasets for time-series analysis were used for Germany, Sweden and Poland, each holding various energy and environmental metrics from 2003 to 2024. The key variables of interest in each country were: i) primary energy consumption (TWh); ii) primary energy

consumption per GDP (kWh/\$); and iii) per capita GHG emissions, CO₂ equivalent.

For each country, we checked the data for all relevant variables and consistency between the datasets. We tested for stationarity using the augmented dickey-fuller (ADF) test. The results indicated that the data for all three variables in each country was non-stationary. To address this, we applied a log transformation to stabilize its variance and make it more suitable for ARIMA modeling. We then differenced the log-transformed data to make it stationary.

We used ARIMA models with the log-transformed and differenced data. Using the fitted ARIMA models, we forecasted each variable

over the next five years. The forecasted values were then exponentiated back to the original scale (reversed the log transformation) to interpret the results. We also calculated confidence intervals to provide an estimate of the range within which the predictions are expected to fall.

The forecasts for Germany, Sweden and Poland were aggregated into single plots for each variable, identified in Figs. 3–5. These plots include: i) historical data for each country, displayed as lines with markers; ii) forecasted data for the next five years, displayed as lines with markers in different colors; and iii) confidence intervals around the forecasted values (shaded areas).

As viewed in Figs. 3–5, the combined charts paint a full picture of what is expected in all three countries. Key variables include:

i) primary energy consumption (TWh): forecasts indicate the overall path for primary energy consumption over the next five years.

Confidence intervals give a sense of how confident we are that future values would fall within this range, providing an estimate for variability in energy consumption;

ii) primary energy consumption per GDP (kWh/\$): this variable measures the efficiency of using primary energy in relation to economic output. These forecasts are important for evaluating possible future increases and decreases in energy efficiency, which can then be integrated into economic or environmental planning;

iii) per capita GHG emissions in CO₂ equivalents: this metric is illustrative of future emission trends, a key factor for monitoring progress against climate targets and designing policies to lower overall emissions.

It gives important information regarding future trends in Germany, Sweden and Poland. These insights can inform policymakers, researchers and stakeholders to make energy and environmental decisions that are evidence-based.

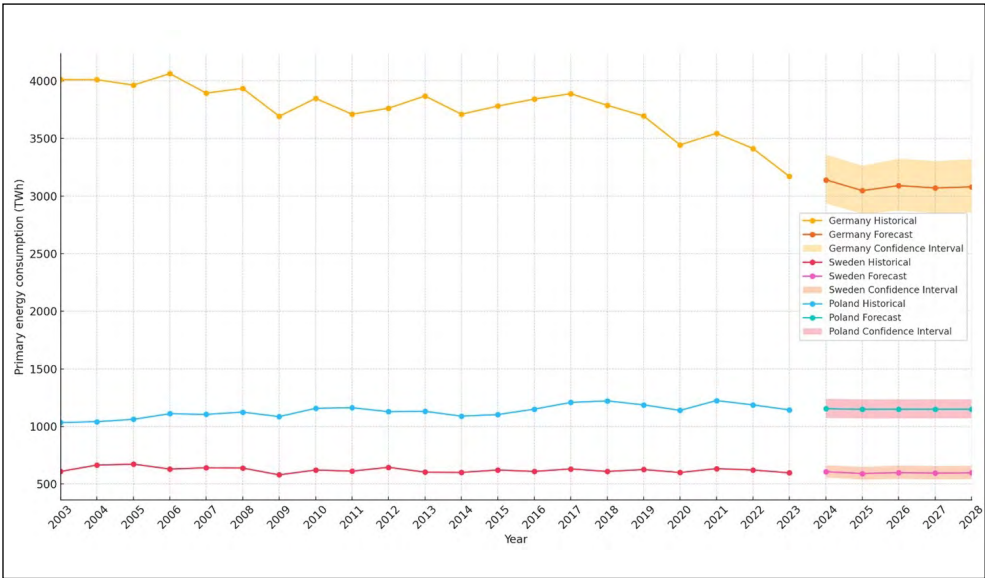


Fig. 3: Forecast for primary energy consumption (TWh)

Source: own

3.2 Discussion

This study includes unique strengths – a very large and ongoing dataset that comprises 20 years (2003–2023) translating into

high-powered longitudinal insights. Given that it incorporates various metrics, such as primary energy consumption, energy intensity and per capita emissions, the resolution is more

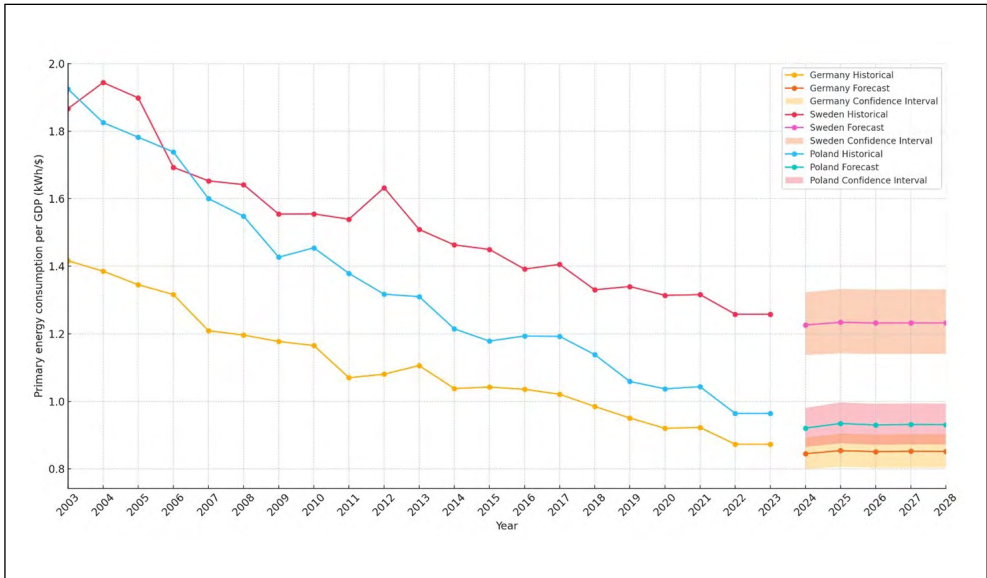


Fig. 4: Forecast for primary energy consumption per GDP (kWh/\$)

Source: own

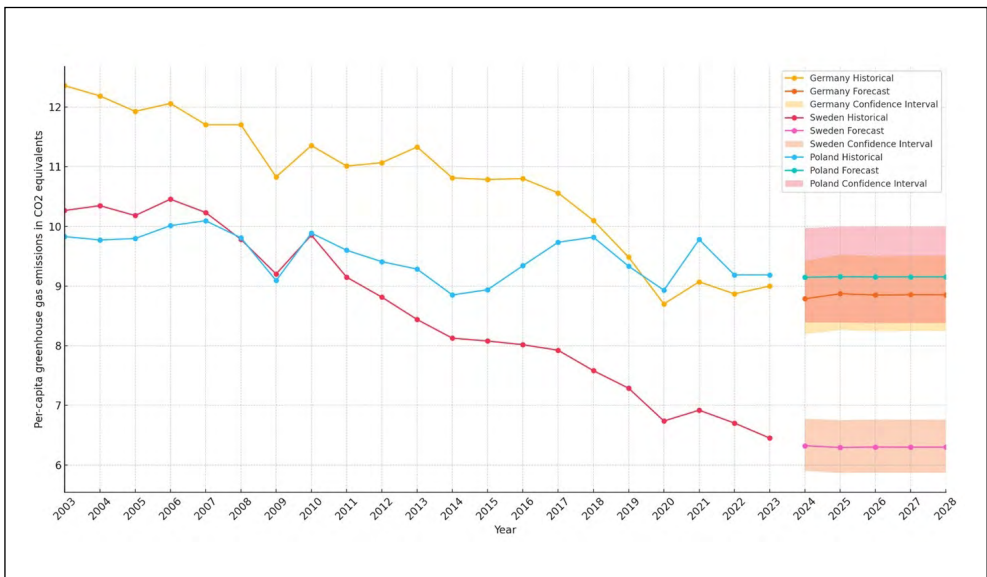


Fig. 5: Forecast for per capita GHG emissions in CO₂ equivalents

Source: own

detailed than what datasets used by Kim et al. (2015), Komarnicka and Murawska (2021) and Brodny and Tutak (2020). We have used correlation, regression and time-series approaches to examine the effects of renewable energy integration. Therefore, we argue that this methodological diversity goes above and beyond the standard single analytical approaches in many works such as Dominiak and Oleszczyk (2019), Ślusarczyk et al. (2022) as well as Bohdanowicz (2021).

Tab. 3 offers a concise synthesis of our findings vis-à-vis previous research. It highlights both convergences and new insights. For example, while literature points to Germany and Sweden's successes, our regression models reveal nuanced sectoral effects, such as the lack of significant solar impact in Germany and a counterintuitive positive solar-emissions relationship in Sweden. These could reflect lag effects, measurement inconsistencies, or auxiliary emissions from solar panel production. Poland's stagnation, despite EU alignment efforts, reinforces the limitations of top-down policy without localized implementation capacity. Overall, Tab. 3 aids in juxtaposing expected and observed outcomes, adding robustness to our comparative approach.

The cross-country differences observed in this study can be partially attributed to divergent policy frameworks and institutional capacities. Germany's strong performance aligns with long-term policy commitments under the Energiewende initiative, which integrates substantial subsidies, public ownership of renewables, and progressive regulation (Fischer et al., 2016). Sweden benefits from longstanding institutional support for hydropower and bioenergy, facilitated by early liberalization and coordinated governance (Amiandamhen et al., 2020). Conversely, Poland's limited impact stems from its institutional inertia, regulatory uncertainty, and socio-political dependency on coal-based employment structures (Brauers & Oei, 2020). These differences underscore how institutional design, regulatory coherence, and financial incentives significantly mediate the outcomes of RES adoption and GHG reduction.

The ARIMA models help to predict the future primary energy consumption, energy intensity and per capita emissions for the next 5 years. This is a massive improvement over the predictive power of Rybak et al. (2022) and Stec and Grzebyk (2022), with the latter two predominantly having retrospective

Tab. 3: Summary of literature findings, empirical results and regression insights on RES and GHG emissions in Germany, Sweden and Poland

Aspect	Germany	Sweden	Poland
Literature review findings	Significant GHG reductions from Energiewende policy (Brodny & Tutak, 2020; Kim et al., 2015); potential hidden costs (Hertwich et al., 2015)	Leading role in hydropower and bioenergy, ambitious 2040 target (Komarnicka & Murawska, 2021); potential risks of hydropower (Girgibo et al., 2024)	Slow transition, high coal reliance, EU-driven progress (Dominiak & Oleszczyk, 2019; Ślusarczyk et al., 2022); policy change impacts (Rybak et al., 2022)
Study results	Strong negative correlation (−0.92) between renewable energy and CO ₂ emissions; emissions reduced from 1,005 to 739 million tons CO ₂ equivalents	Strong negative correlation (−0.90) between renewable energy and CO ₂ emissions; emissions reduced from 92 to 70 million tons CO ₂ equivalents	Modest negative correlation (−0.23) between renewable energy and CO ₂ emissions; emissions stable around 366 million tons CO ₂ equivalents
Regression analysis	No significant impact of solar and nuclear energy on emissions	Significant negative impact of wind energy on emissions; unexpected solar energy impact	Negative but not significant impact of other renewables on emissions
New achievements	Extensive dataset (2003–2023), multiple indicators; diverse analytical methods, including correlation, regression and time-series analyses; ARIMA models for future forecasts, policy recommendations		

Source: own

studies. As a result, the results highlight that policy support and innovation must be ongoing. The comparative study showcases best practices and pitfalls across economic contexts, revealing the specific insights that policymakers in other jurisdictions can derive when working to improve renewable energy adoption and emissions reductions policies.

Despite the strengths of this study, certain limitations should be noted. First, causality can only be inferred cautiously, as observational data may contain residual confounding. Although multicollinearity was addressed, omitted variable bias (e.g., economic shocks, technological spillovers) may persist. Second, ARIMA models rely on historical patterns; sudden exogenous shocks (e.g., geopolitical crises, climate-related disasters) could render forecasts inaccurate. Lastly, the dataset lacks subnational disaggregation, which may obscure regional policy effects. These caveats point to important areas for future refinement.

Conclusions

The aim of this study was to analyze the impact of RES on GHG emission reduction in Germany, Sweden and Poland due to their typical differences in the character of their energy policies and commitments. Therefore, the study used analytical correlation, regression and time-series analyses from a 2003–2023 indicator dataset with various renewables, emissions and other metrics. A common goal was achieved – the best practices and common challenges were identified, as well as policy implications for countries, that are aiming to improve their sustainable energy adoption through renewables.

In the literature review, highlights were showcased over studies that have examined the environmental benefits of renewable energy and the role RES plays in the reduction of GHG. It was also supported by studies from institutions like the European Environment Agency and the International Energy Agency. The review showed a diverse range of impacts from different European countries, but the particular emphasis was put on Germany, Sweden and Poland.

The study employed statistical approaches (correlation, regression, time-lapse) that were performed to understand the relationships between renewable energy consumption, GHG emissions and other indicator variables.

A sample dataset (from the full 2003–2023 dataset) was presented.

Correlation analysis revealed that there is a strong negative relationship between renewable energy consumption and CO₂ emissions in Germany and Sweden (coefficients of -0.92 and -0.90), but Poland showed a weaker negative correlation (coefficient of -0.23). Regression analysis showed that in Germany the solar and nuclear energy had no significant impact on emissions, in Sweden – wind energy consumption had a significant negative effect on emissions, in Poland – other renewables, including geothermal and biomass, had a potential but it was not statistically significant to have a negative impact on emissions.

The time-series analysis forecasted primary energy consumption, as well as energy intensity and per capita GHG emissions for the next five years. Germany is expected to continue having a downward trend in emissions and primary energy consumption, Sweden is projected to improve on its energy efficiency metrics and Poland is expected to have a gradual improvement in energy consumption and GHG emissions, but the heavy reliance on coal could hinder significant progress.

Within the discussion section, we have identified the unique strengths and the scope of the study – the 2003–2023 dataset, comparing it more favorably to prior research. We have seen that the diversity of methods applied provided a better understanding of the whole impact of RES on mitigating GHG emissions.

In general, this study has confirmed that renewable energy adoption does indeed reduce GHG emissions. The findings from this cross-country research may be used to further develop better policies to accelerate renewable energy adoption, reduce emissions and achieve international climate targets.

Nevertheless, the institutional dimension should not be overlooked. Future comparative studies may benefit from integrating political economy variables, regulatory indices, and implementation capacities into causal models to deepen understanding of the policy-outcome nexus.

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Sustainability in the digital era: Exploring the role of public websites

Antanas Usas¹, Dalia Streimikiene²

¹ Lithuanian Sports University, Department of Sports and Tourism, Lithuania, ORCID: 0000-0001-9717-9112, antanas.usas@lsu.lt;

² Lithuanian Sports University, Institute of Sports Science and Innovation, Lithuania, ORCID: 0000-0002-3247-9912, dalia.streimikiene@lsu.lt (corresponding author).

Abstract: In the digital era, public sector websites serve as critical platforms for delivering services, engaging citizens, and promoting sustainability. This study investigates the relationship between consumer sustainability expectations and the perceived quality of public sector websites, focusing on how these digital platforms influence trust and user satisfaction. Employing a mixed-methods approach, the research integrates an extensive literature review with a quantitative survey based on the SERVQUAL model. Data were collected from 381 respondents through an online questionnaire measuring five key dimensions: reliability, responsiveness, tangibility, assurance, and empathy. The statistical analysis revealed significant disparities between user expectations and actual experiences. Public websites exceeded expectations in reliability, competence, and empathy, particularly in accessibility, inclusivity, and the provision of sustainability-related training. However, responsiveness and transparency in institutional sustainability metrics were identified as areas requiring improvement. Despite growing demands for environmentally conscious digital services, many government websites lack sufficient mechanisms to communicate sustainability efforts effectively. These findings highlight the necessity for public institutions to integrate sustainable design principles, improve digital responsiveness, and enhance transparency to foster greater public trust and engagement. By addressing these gaps, policymakers and digital strategists can create more effective and inclusive e-government services that align with global sustainability objectives. This study aligns with the journal's focus on sustainability by examining how digital governance can contribute to environmental, social, and economic well-being. The research underscores the importance of user-centered design and sustainable digital strategies in enhancing the perceived quality of public services, ultimately supporting long-term sustainability goals and citizen engagement in digital governance.

Keywords: E-government services, user experience, digital sustainability, service quality assessment, public sector innovation.

JEL Classification: I00, I31, O00, Q01.

APA Style Citation: Usas, A., & Streimikiene, D. (2025). Sustainability in the digital era: Exploring the role of public websites. *E&M Economics and Management*, 28(4), 14–28. <https://doi.org/10.15240/tul/001/2025-4-002>

Introduction

The digitalization of public sector services is a key of modern governance, aimed at enhancing efficiency, transparency, and citizen engagement (Ahmad et al., 2021). As digital interfaces increasingly mediate interactions

between citizens and public institutions, the design and content of public sector websites play a crucial role in shaping consumer perceptions of service quality and institutional accountability (Ingaldi & Tatar, 2024). Public sector websites are not only portals for information dissemination

but also tools to reflect organizational values, including sustainability, a growing priority for governments worldwide (Tuebou, 2024).

Sustainability, environmental, and social dimensions, have emerged as a dominant expectation among citizens, driven by global initiatives such as the United Nations Sustainable Development Goals (SDGs) (United Nations, 2015). Broccardo et al. (2023a) mention that public sector websites are important in promoting these values, serving as platforms to communicate sustainable practices, reduce administrative inefficiencies, and facilitate citizen participation. However, the challenge lies in aligning these sustainability objectives with the public's perceived quality of digital interactions, which directly influences their trust, satisfaction, and continued engagement with these services (Aksin-Sivrikaya & Bhattacharya, 2017).

Recent studies Broccardo et al. (2023b) and Ortina et al. (2021) suggest that the integration of sustainability features into public sector websites can significantly affect consumer satisfaction and behavioral intentions. According to Kwilinski et al. (2023) incorporating green IT practices, accessible design, and user-centric content can enhance both perceived quality and the perceived sustainability of online public services. Nevertheless, consumer expectations for sustainability are dynamic and influenced by factors such as technological advancements, demographic trends, and societal values (Kwilinski et al., 2023). The perceived quality of these websites often depends on tangible elements such as usability, design aesthetics, content accuracy, and responsiveness, as well as intangible aspects like trustworthiness and alignment with societal goals (Aksin-Sivrikaya & Bhattacharya, 2017; Pérez-Martínez et al., 2023). Despite the growing body of research on e-government services, limited attention has been given to the intersection of sustainability expectations and perceived website quality in the public sector. This study seeks to focus on this area by examining the factors that influence consumer perceptions of sustainability and quality in public sector websites.

The aim of this research is to explore the intersection of consumer sustainability expectations and the perceived quality of public sector websites, examining how these digital platforms can promote sustainability and enhance citizen engagement.

By examining these interrelations, the research offers actionable insights for policy-makers

and digital strategists to design online platforms that not only meet functional and aesthetic standards but also reflect sustainability commitments. The findings aim to support public institutions in building trust and engagement, promoting a digital environment that aligns with citizen values and advances sustainability objectives.

1 Theoretical background

1.1 Sustainability in public sector websites

Broccardo et al. (2023b) suggest that sustainability in the context of public sector digital interfaces refers to the alignment of digital service delivery mechanisms with principles that promote long-term environmental, social, and economic well-being. This encompasses not only the operational efficiency of these platforms but also their capacity to facilitate eco-friendly practices, equitable access, and transparent communication with citizens. Focusing on the transformative role of e-government services as interface, sustainability integrates both technical and societal dimensions to ensure these digital platforms serve diverse stakeholder needs while minimizing negative impacts on future resources (Santarius et al., 2023).

From an environmental perspective, sustainability focuses on reducing the carbon footprint associated with public sector operations. Public websites achieve this by digitizing traditionally paper-intensive processes, such as tax filings or permit applications, thereby reducing the need for physical documents and in-person visits (Kwilinski et al., 2023). Additionally, energy-efficient website hosting, the use of renewable energy sources for data centers, and adherence to green IT practices contribute to reducing environmental impacts (Santarius & Wagner, 2023). These transitions support cleaner energy use and minimize physical resource inputs, exemplifying the intersection of technology and sustainability.

In terms of social sustainability, public sector digital interfaces must prioritize inclusivity and accessibility, ensuring that no demographic is excluded from accessing government services. This includes features like multilingual support, responsive designs for mobile devices, and compliance with accessibility standards such as WCAG (Web Content Accessibility Guidelines). Multiple studies (Bonsignore, 2024; Marjerison & Gatto, 2024) emphasize the importance of inclusive institutions and highlight

how digital public services can meet the needs of vulnerable groups, such as individuals with disabilities, immigrants, and the elderly. These practices align with the broader goal of promoting equitable access and social cohesion through e-government platforms.

Government efforts to incorporate sustainability into online platforms have become a big scientific discussion, reflecting global priorities for environmental stewardship, social inclusivity, and resource efficiency (Adanma & Ogunbiyi, 2024). These efforts align closely with the broader goals of e-government, which aim to modernize public administration through digital innovation. The integration of sustainability into digital governance is not just a technical enhancement but a strategic approach to achieving long-term societal and ecological goals. Studies have shown that governments worldwide are prioritizing energy-efficient data centers, low-impact web hosting, and digital document management systems as means to reduce the carbon footprint of administrative operations (Khosravi et al., 2024). European Union's Green Deal emphasizes digitalization as a pathway to achieving net-zero emissions by leveraging technologies that minimize resource consumption while maintaining high service quality. These practices parallel the transformative potential of e-government highlighted in multiple studies (Kibria & Hong, 2024; Taoufik & Azmani, 2025), where digital systems reduce the need for physical infrastructure and paper-based processes.

Governments have also focused on designing inclusive and equitable platforms, which are essential for achieving social sustainability. Research indicates that many public websites now join international accessibility standards, such

as the Web Content Accessibility Guidelines (WCAG), to ensure services are usable by all citizens, including those with disabilities (Paul, 2023). A lot of studies (e.g., Bonsignore, 2024; Kwilinski et al., 2023) mention efforts to promote transparency and accountability through sustainable online platforms, that is one of the focal points of government initiatives. Open data portals allow citizens to access environmental, financial, and administrative information, fostering trust and enabling informed decision-making (Kwilinski et al., 2023). Platforms such as Denmark's "OpenGov" and India's "Digital India" program serve as examples of how governments leverage digital tools to align with global sustainability goals, such as the United Nations Sustainable Development Goals (SDGs). These initiatives resonate with the Adanma and Ogunbiyi, (2024) and Chopra et al. (2024) studies discussion of e-government's capacity to enhance citizen-government interactions and create transparent, customer-centric ecosystems. The integration of sustainability and digital governance is further reflected in crossborder collaborations, such as the European Union's Digital Decade program. This initiative seeks to ensure that all public services in the EU are accessible online by 2030 while meeting stringent environmental and accessibility standards (European Court of Auditors, 2022).

These efforts mirror the focus on crossborder interoperability and cooperation discussed in the Bernyte (2018) article, emphasizing the need for unified frameworks that promote sustainability at scale (Tab. 1).

Despite the studies mentioned in Tab. 1, and good examples, challenges persist in operationalizing sustainability within public sector

Tab. 1: Global consumer values and principles in public websites related to sustainability

Take care of yourself	Take care of the community	Take care of the environment
Consumption of local foods	Transparency, openness and trust	Sustainable materials
Plant based diets	Localization	Climate change
Work and life balance	Recycling	Eco-friendly practices
Efficiency and cost effectiveness	High expectations from businesses	Carbon footprint reduction
Health and safety	Empathy for family, friends and community	Durability of products

Source: own based on Bernyte (2018), Adanma and Ogunbiyi (2024), Chopra et al. (2024), and Bonsignore (2024)

websites. Multiple research highlights issues such as uneven technological infrastructure, limited funding, and varying levels of stakeholder engagement as barriers to achieving sustainability goals (Chopra et al., 2024). These challenges show the need for these types of studies about continuous refinement and alignment of public sector digital services with evolving societal needs and technological capabilities.

In summary, sustainability in public sector digital interfaces extends beyond technical efficiency to encompass a holistic approach to environmental, social, and economic well-being. Public websites are not just tools for administrative convenience, they are strategic assets that embody sustainable values while enhancing citizen interactions and trust in public governance. The integration of sustainability into these interfaces reflects a commitment to leveraging technology for long-term societal progress, aligning with the transformative potential of e-government services.

1.2 The impact of sustainability on consumer perceived quality of public websites

Sustainability and perceived quality in public sector websites are interconnected dimensions that collectively shape user experiences and influence behavioral outcomes. A sustainable digital platform is one that not only minimizes its environmental footprint but also delivers high-quality, user-centric services that meet societal values such as accessibility, transparency, and trustworthiness (Shih et al., 2024). This synergy reflects the broader objectives of e-government initiatives, where technological efficiency and inclusivity are emphasized as drivers of user satisfaction and engagement. Consumers increasingly associate sustainability with quality, expecting public services to reflect their values regarding conscious consumption (Bothe et al., 2016).

Sustainable practices directly influence the technical infrastructure supporting public sector websites. According to Sh. Ahmad et al. (2022) utilizing green hosting services powered by renewable energy and optimizing server load management reduces environmental impact while ensuring reliable and efficient website performance. Websites can also highlight these efforts through dedicated pages or icons, signaling eco-consciousness

to users, which enhances trust and satisfaction. A study by Ott et al. (2016) demonstrated that nearly all universities and over half of the corporations in the study had a designated sustainability landing page on their websites, but fewer than 40% quantified their sustainability claims on any topic.

Accessibility is a core element of sustainability when applied to websites, ensuring that all users, including those with disabilities, have equitable access to digital services. Adhering to standards like the Web Content Accessibility Guidelines (WCAG) and offering features such as screen-reader compatibility or adjustable text sizes not only demonstrate a commitment to social sustainability but also elevate the perceived quality of the platform. Mason et al. (2022) found that 95.3% of popular environmental communication websites have potential critical accessibility errors, highlighting the need for accessibility improvements to bridge the digital divide and increase environmental literacy. Public sector websites serve as key tools for promoting transparency by publishing sustainability reports, performance metrics, and environmental initiatives. Open data portals embedded within these websites allow users to track government commitments to sustainability, such as carbon neutrality goals or resource conservation measures.

These interfaces significantly influence behavioral outcomes, such as trust, satisfaction, and continued engagement through environmental efficiency, accessibility and inclusivity transparency and accountability. Several researches indicate that users are more likely to advocate for and repeatedly use websites that visibly prioritize sustainability while delivering exceptional service quality (Alcaraz-Quiles et al., 2014; Sh. Ahmad et al., 2022). Conversely, a lack of alignment between these dimensions can lead to distrust, reduced engagement, and a negative perception of public institutions. Sustainability and perceived quality are deeply intertwined within public sector websites, with each dimension reinforcing the other to create a holistic and impactful user experience. Public websites that effectively integrate these elements can meet user expectations, enhance trust, and contribute to broader societal goals.

Perceived quality in public sector websites is a multidimensional construct which includes usability, content accuracy, and visual appeal. These dimensions are critical for understanding user satisfaction and trust, directly influencing

public engagement and the perceived legitimacy of online government services. Multiple scientific studies are analyzing these dimensions from different perspectives. Content accuracy is the most important for trust and reliability in public sector websites. Accurate, up-to-date, and comprehensive information fosters confidence in government services and supports informed decision-making by users (Zhang et al., 2021). Chen et al. (2021) have shown that inconsistencies or outdated content can erode trust, discouraging users from relying on online platforms for critical tasks. According to Raza et al. (2020), content quality in public sector websites must address the dual objectives of transparency and user satisfaction. Hussain et al. (2021), based on their research results, conclude that presenting clear tax policies or social benefits information aligns with the goal of fostering accountability and trust in government operations. De Las Heras et al. (2020) added that machine learning tools, such as automated content validation, can further enhance content accuracy, and overall satisfaction.

Visual appeal is the aesthetic aspect of website design, including layout, color schemes, typography, and overall branding. While visual appeal may seem secondary to functionality, research indicates that it significantly influences users' first impressions and overall satisfaction with digital services (Momenipour et al., 2021). Multiple researchers show the influence of visual appeal on user engagement. Hogarth et al. (2025) results indicated that the extent of sustainability posts on social media represented less than 20% of total social media posts. Rietveld et al. (2020) revealed that visual emotional appeals in Instagram posts drive customer engagement, with positive high and negative low arousal images being most effective, while informative appeals, except for brand-related ones, do not. Similarly, work by Thwairan (2024) showed that visual design elements in website design significantly impact user experience and interaction, influencing aesthetic appeal and interaction. Another study by Pengnate and Sarathy (2017) emphasized visual appeal has a greater impact on customer trust in unfamiliar vendors than ease of use, with female customers valuing visual appeal more than males. These findings reinforce the idea that visual design is not aesthetic but a functional component that directly impacts user perceptions of quality and trust.

A thorough analysis of the existing literature on service quality reveals that several variables linked to service quality have been proposed. Consumer expectations for public sector websites have evolved, shaped by experiences with private-sector platforms. Research indicates that unmet expectations in these areas can erode trust and reduce engagement, making it critical for public institutions to design websites that meet functional and aesthetic standards while embodying sustainability values.

The SERVQUAL methodology provides an ideal framework for evaluating and enhancing these dimensions within public sector websites (Raza et al., 2020). By assessing service quality across its five dimensions (tangibles, reliability, responsiveness, assurance, and empathy) SERVQUAL enables a systematic evaluation of how well these platforms align with consumer expectations and societal goals. This approach can specifically support: i) tangibles: measuring usability, visual appeal, and accessibility of websites to ensure alignment with user needs; ii) reliability and responsiveness: evaluating the accuracy and timeliness of information, along with the ability to adapt to changing user demands; iii) assurance: understanding trust-building components like transparency in sustainability practices and content reliability; and iv) empathy: addressing inclusivity by ensuring the websites cater effectively to diverse demographics, including vulnerable groups.

Incorporating SERVQUAL into the research framework will provide actionable insights for public sector institutions to enhance digital service quality while reinforcing sustainability commitments.

H1: There is a significant difference between expected and perceived usability, visual appeal, and accessibility of public sector websites.

Multiple of research emphasizes that usability, visual appeal, and accessibility are critical dimensions influencing user engagement and perceived quality. Public sector websites often fail to match consumer expectations, as usability standards like responsive design (Lun et al., 2024). Well-designed interfaces significantly enhance user experience, but poor usability and outdated designs are common barriers to meeting expectations.

H2: There is a significant difference between expected and perceived reliability of public sector websites.

Reliability is foundational to trust in government websites, as highlighted by the importance of accurate and up-to-date content. Pérez-Martínez et al. (2023) demonstrate that accurate, timely, and relevant information significantly affects user perceptions. However, public sector websites often struggle to maintain the expected level of content accuracy due to bureaucratic delays and resource constraints.

H3: There is a significant difference between expected and perceived responsiveness of public sector websites.

Responsiveness, including timeliness in delivering services and adapting to user needs, is highlighted as a critical factor in user satisfaction. Chopra et al. (2024) discuss how public websites often lag in providing timely updates or adapting their interfaces to accommodate new user demands.

H4: There is a significant difference between expected and perceived assurance of public sector websites.

Assurance, especially in the form of transparency and sustainability commitments, is increasingly important as consumers associate these qualities with organizational credibility. Kwilinski et al. (2023) highlight that users value visible sustainability practices, such as eco-conscious website hosting or carbon footprint tracking.

H5: There is a significant difference between expected and perceived empathy of public sector websites.

Inclusivity and user-centric design are emphasized as critical for achieving social sustainability. The article discusses the importance of features like multilingual support and accessibility for individuals with disabilities (Marjerison & Gatto, 2024). Despite efforts to align with standards, the implementation is inconsistent, particularly for vulnerable populations (Santarius & Wagner, 2023). Users often find these websites less inclusive than they expect, resulting in a big difference in perceived empathy.

2 Research methodology

The methodology for this study was designed to explore how consumer sustainability expectations and perceived quality influence user engagement on public sector websites. The research employed a mixed-methods

approach, combining scientific literature analysis and quantitative data collection and analysis to provide a comprehensive understanding of the topic.

The study utilized a cross-sectional survey method, conducted in two phases. First, a structured online questionnaire was distributed to measure user expectations of public sector website sustainability aspects. Second, the same questionnaire was distributed after users visit public sector websites and specially look for sustainability aspects. Participants were selected using stratified random sampling to ensure representation across different user groups, including age, gender. The required sample size was calculated using the Paniotto formula with a 95% confidence level and a 5% margin of error.

2.1 Data collection instruments

A survey instrument based on the SERVQUAL framework was adapted to measure perceived quality and sustainability expectations in the context of public sector websites. The instrument included 21 items rated on a 5-point Likert scale, ranging from “strongly disagree” to “strongly agree” and two demographic questions: i) reliability: consistency and accuracy of website functionality; ii) responsiveness: promptness in addressing user inquiries and technical issues; iii) tangibles: the visual appeal, ease of navigation, and eco-friendly design of the website; iv) assurance: trustworthiness and credibility of the website’s content; and v) empathy: perceived efforts to personalize and cater to user needs, including sustainability concerns.

The questionnaire also included demographic questions to understand user diversity and its potential impact on perceptions. The survey was conducted entirely online. Links to the questionnaire were distributed via email and social media platforms targeting users of public sector websites. Participants completed the survey voluntarily. A total of 381 respondents participated in the survey. Quantitative data were analyzed using SPSS program for statistical calculation, assessing the relationship between sustainability expectations and perceived quality.

The SERVQUAL-based survey was pre-tested with a pilot group of 50 respondents to ensure clarity and reliability. Cronbach’s alpha was calculated for each dimension,

achieving an overall reliability score of 0.93, indicating high internal consistency.

Reliability analysis. First reliability analysis was conducted to evaluate the internal consistency of the questionnaire used in this research which assessed consumer expectations regarding sustainability and perceived quality on public sector websites. The reliability of the instrument was tested using Cronbach's alpha. The reliability analysis was performed using SPSS, and the results are summarized (Tab. 2).

In Tab. 2, Cronbach's alpha for all dimensions exceeded the acceptable threshold of 0.70, indicating good internal consistency. The highest reliability was observed for empathy ($\alpha = 0.86$), reflecting strong coherence among the items related to the visual and functional design of the websites. The responsiveness dimension had the lowest reliability score ($\alpha = 0.80$), which is still within an acceptable range but suggests room for improvement in questionnaire items measuring this domain.

Tab. 2: Reliability analysis		
Dimension	Number of items	Cronbach's alpha
Reliability	5	0.82
Responsiveness	4	0.78
Tangibles	4	0.80
Assurance	4	0.83
Empathy	4	0.86
Total	21	0.87

Source: own

The combined Cronbach's alpha of 0.87 for the entire questionnaire indicates excellent reliability, signifying that the questionnaire items consistently measure the intended constructs.

3 Results and discussion
3.1 Results

To evaluate how users generally rate the five dimensions shaping their impressions of the quality of public sector websites, we analyzed data as summarized in Tabs. 3–8. This analysis highlights significant variations in the ratings of expectations versus perceived quality across dimensions such as reliability, responsiveness, competence, empathy, and tangibility. Using independent *t*-tests, we assessed whether the differences between the two sample expectations and perceived quality were statistically significant.

Tab. 3 shows an analysis of user expectations versus perceived quality for the reliability dimension of public sector websites. Tab. 3 shows the mean and standard deviation (SD) values for both expectations and perceived quality across several aspects, including the accuracy and clarity of information, transparency

in institutional sustainability metrics, the functionality of e-services, and the availability of digital services. Significant differences between expectations and perceived quality are observed in most items, with *p*-values ≤ 0.05 , indicating that users' perceptions of quality exceed their expectations, particularly regarding the accuracy of information, uninterrupted e-services, and the digital availability of public services. However, no significant difference is found in the transparency of sustainability metrics, with one aspect ($p > 0.05$) showing no notable discrepancy between expectations and perceived quality.

Tab. 4 compares users' expectations and perceived quality regarding the responsiveness dimension of public sector websites. It evaluates aspects such as the website's ability to provide quick and clear responses, allow user feedback, inform users about service updates, and offer technical assistance. Tab. 4 shows that most items have *p*-values greater than 0.05, indicating no significant difference between users' expectations and perceived quality, particularly for the response speed, feedback options, and availability of technical assistance.

Tab. 3: Reliability expectations and perceived quality analysis

Questions	Expectation, mean \pm SD	Perceived quality, mean \pm SD	<i>p</i> -value
The website provides accurate, updated, and clearly presented information	4.2 \pm 0.7	4.5 \pm 0.5	0.000*
Website provides transparent information on institutional sustainability metrics	3.0 \pm 0.8	3.5 \pm 0.6	0.000*
The website includes transparent information on institutional sustainability metrics (e.g., CO ₂ emissions, waste management)	3.0 \pm 0.7	3.1 \pm 0.4	>0.050
E-services of the website function without interruptions and allow for remote service use	4.1 \pm 0.4	4.7 \pm 0.2	0.000*
Major public services are available in digital format, reducing paper and energy consumption	3.5 \pm 0.5	4.2 \pm 0.6	0.000*

Note: * *p*-value is significant at the $p < 0.05$.

Source: own

Tab. 4: Responsiveness expectations and perceived quality analysis

Questions	Expectation, mean \pm SD	Perceived quality, mean \pm SD	<i>p</i> -value
The website delivers quick and clear responses to user queries	4.6 \pm 0.3	4.5 \pm 0.5	>0.050
The website enables users to provide feedback and participate in sustainability-related surveys	2.3 \pm 1.2	2.5 \pm 0.8	>0.050
Users are informed promptly about significant changes and updates in service delivery	4.0 \pm 0.8	4.5 \pm 0.4	0.000*
Technical assistance is available if issues arise while using the website's services	3.8 \pm 1.0	3.6 \pm 0.5	>0.050

Note: * *p*-value is significant at the $p < 0.05$.

Source: own

Tab. 5: Competence expectations and perceived quality analysis

Questions	Expectation, mean \pm SD	Perceived quality, mean \pm SD	<i>p</i> -value
The website instills confidence in the institution's adherence to sustainability commitments	3.2 \pm 1.3	3.3 \pm 0.8	>0.050
Information about the expertise of the institution's specialists in sustainability is available	3.6 \pm 0.8	3.5 \pm 0.7	>0.050
The website offers training and guidance on sustainable practices and energy saving	3.0 \pm 0.9	4.1 \pm 0.5	0.000*
The website adheres to data protection and privacy standards	4.2 \pm 0.6	4.0 \pm 0.7	>0.050

Note: * *p*-value is significant at $p < 0.05$.

Source: own

However, a significant difference is observed for the prompt communication of service updates ($p = 0.000$), where perceived quality exceeds expectations. This suggests that users feel the website is more responsive in keeping them informed about service changes than they initially expected.

Tab. 5 compares users' expectations and perceived quality in relation to the competence dimension of public sector websites. It examines several factors, including confidence in the institution's sustainability commitments, availability of information on expert knowledge in sustainability, provision of training on sustainable practices, and adherence to data protection standards. Most items show no significant differences between expectations and perceived quality, as indicated by p -values greater

than 0.05, including confidence in sustainability, expertise information, and data protection adherence. However, a significant difference is observed regarding the availability of training and guidance on sustainable practices, where perceived quality (mean = 4.1) significantly exceeds expectations (mean = 3.0), with a p -value of 0.000. This suggests that users feel the website provides more comprehensive guidance on sustainability than they anticipated.

Tab. 6 compares the users' expectations and perceived quality regarding the empathy dimension of public sector websites. It evaluates several factors, including the accessibility of the website's content for diverse user needs, the availability of services in multiple languages, the provision of information about local environmental events, and the ease of communication

Tab. 6: Empathy expectations and perceived quality analysis

Questions	Expectation, mean \pm SD	Perceived quality, mean \pm SD	p -value
The website's content is accessible to diverse user needs (e.g., people with disabilities, older adults)	4.1 \pm 0.5	4.8 \pm 0.1	0.000*
The website offers services and information in multiple languages	4.0 \pm 0.6	4.7 \pm 0.2	0.000*
Information about local environmental events and projects is available on the website	3.8 \pm 0.7	4.4 \pm 0.4	0.000*
Contact forms allow users to communicate with the institution and provide feedback	4.6 \pm 0.3	4.9 \pm 0.1	0.000*

Note: * p -value is significant at $p < 0.05$.

Source: own

Tab. 7: Tangibility expectations and perceived quality analysis

Questions	Expectation, mean \pm SD	Perceived quality, mean \pm SD	p -value
The website design is modern, tidy, and visually appealing	4.2 \pm 0.6	4.3 \pm 0.5	>0.050
The website adapts easily to different devices (e.g., mobile phones, tablets)	4.4 \pm 0.4	4.6 \pm 0.3	>0.050
The website is easy to navigate, with information readily accessible	4.0 \pm 0.6	4.2 \pm 0.4	>0.050
The website's content and design reflect the institution's commitment to sustainability	3.1 \pm 0.7	3.2 \pm 0.6	>0.050

Source: own

via contact forms. All items in Tab. 6 show significant differences between expectations and perceived quality, with p -values of 0.000, indicating that users' perceptions of the website exceed their expectations. Notably, users perceive the website as significantly more accessible, inclusive, and responsive in offering multilingual services, environmental information, and communication opportunities than they had initially expected.

Tab. 7 compares users' expectations and perceived quality concerning the tangibility dimension of public sector websites. It assesses factors such as the modernity and visual appeal

of the website design, adaptability to different devices, ease of navigation, and the reflection of the institution's commitment to sustainability in the website's content and design. Tab. 7 reveals that there are no significant differences between expectations and perceived quality for any of the items, as indicated by p -values greater than 0.05. This suggests that users' expectations and perceptions align closely regarding the visual appeal, adaptability, usability, and sustainability focus of the websites, with no substantial discrepancies between the two. Despite that we can see that all statements were evaluated higher in perceived quality.

Tab. 8: SERVQUAL model dimension analysis

Dimensions	Expectation, mean \pm SD	Perceived quality, mean \pm SD	p -value
Reliability	3.6 \pm 0.6	4.0 \pm 0.5	0.000
Responsiveness	3.7 \pm 0.9	3.8 \pm 0.6	>0.050
Competence	3.5 \pm 0.9	3.7 \pm 0.7	0.030
Empathy	4.1 \pm 0.6	4.7 \pm 0.2	0.000
Tangibility	3.9 \pm 0.6	4.1 \pm 0.5	>0.050

Source: own

Tab. 8 shows a comparison of the five SERVQUAL dimensions between consumer expectations and the perceived quality of public sector websites. Reliability dimension shows a significant difference between the expectations and the perceived quality of the public sector websites, with users' perceptions of the websites' reliability surpassing their expectations ($p = 0.000$). The expectation of reliability, which encompasses accurate and up-to-date information, as well as the transparency of institutional sustainability metrics, was met or exceeded by users' experiences with these websites. In contrast, the responsiveness dimension did not reveal a significant difference between expectations and perceived quality for most items, except for the prompt communication of service updates ($p = 0.000$). This suggests that, while users generally expect timely and clear responses, their experience with the responsiveness of public sector websites was not significantly different

from their expectations in most areas, except when it came to service updates. Similar to responsiveness, the competence dimension also showed no significant difference between users' expectations and their perceptions, except for the provision of training and guidance on sustainable practices ($p = 0.000$). Users rated the websites' competence in terms of providing sustainability-related guidance and training higher than their initial expectations, suggesting that these features were a pleasant surprise for users. The empathy dimension revealed significant differences in all items, with users' perceptions of the websites' empathy far exceeding their expectations ($p = 0.000$). Users perceived public sector websites as more accessible, inclusive, and responsive to diverse user needs, especially in terms of multilingual support and accessibility for people with disabilities. The tangibility dimension showed no significant differences between expectations and perceived quality ($p > 0.05$), indicating that

users' expectations were closely aligned with their experiences regarding the website's visual appeal, adaptability, and ease of navigation.

The hypothesis ($H1$) that there is a significant difference between expected and perceived reliability of public sector websites is supported. The t -statistic of 6.67 and the p -value of $p < 0.000$ indicate a highly significant difference, suggesting that users' perceptions of the reliability of public sector websites exceed their expectations. This shows that users generally find the websites more reliable than they anticipated, particularly in terms of accurate and timely information.

The hypothesis for responsiveness ($H2$), which proposes a significant difference between expected and perceived responsiveness, is not supported. The t -statistic of 1.11 and p -value of 0.27 suggest that there is no significant difference between what users expect and what they perceive regarding the responsiveness of public sector websites. This indicates that users' experiences with the website's responsiveness were largely in line with their expectations.

The hypothesis for competence ($H3$), which posits a significant difference between expected and perceived competence, is supported. With a t -statistic of 2.25 and a p -value of 0.03, a significant difference was found, indicating that users perceive public sector websites as more competent in delivering sustainability-related training and information than they expected. This suggests that users are pleasantly surprised by the extent to which these websites provide useful resources on sustainability.

The hypothesis for empathy ($H4$) is also supported. A t -statistic of 10.00 and $p < 0.000$ demonstrate a significant difference, indicating that users perceive public sector websites as far more empathetic in terms of accessibility, inclusivity, and responsiveness to diverse user needs than they initially expected. The websites exceeded expectations by offering better support for vulnerable groups, multilingual services, and personalized content.

The hypothesis for tangibility ($H5$) is supported. With a t -statistic of 3.33 and a p -value of 0.001, there is a significant difference, indicating that users perceive public sector websites to be more visually appealing, navigable, and aligned with sustainability goals than they anticipated. This suggests that users found the website design and content to be more user-friendly and environmentally conscious than expected.

The research results suggest that there are substantial positive perceptions of the quality of these websites in terms of their overall functionality, sustainability practices, and inclusivity. Despite some sustainability aspects having very low expectations, the results indicate that there are several factors to consider regarding user expectations and perceived quality. This highlights the need for public sector websites to better align their sustainability features with users' evolving expectations to improve overall satisfaction and engagement.

3.2 Discussion

Research examined the relationship between consumer sustainability expectations and the perceived quality of public sector websites. By analyzing the differences between expected and perceived dimensions of quality, including reliability, responsiveness, competence, empathy, and tangibility, this research shows insights into how well public sector websites meet the growing consumer demand for sustainability features and high-quality user experiences. The findings suggest that public sector websites generally exceed user expectations in several dimensions, but there remain areas for improvement, particularly in responsiveness. In some areas user expectations are very low.

The results indicate that public sector websites are perceived as more reliable than users expected. The significant difference in the reliability dimension ($p < 0.001$) indicates that users perceive the websites as accurate, timely, and transparent in delivering information. The high ratings in reliability suggest that public sector websites are successfully meeting these expectations, which is crucial for fostering trust and encouraging ongoing engagement. This finding is consistent with previous research, which highlights the centrality of trust in enhancing user satisfaction with digital government services (Ahmad et al., 2021).

Despite the generally positive findings in other areas, responsiveness emerged as a dimension where user expectations closely align with their perceptions. The lack of significant difference (p -value = 0.27) suggests that users find the response times and the accessibility of information on public sector websites to be adequate but not exceeding their expectations. Public sector websites were perceived as more competent than users

expected, especially in relation to the provision of sustainability-related content and guidance. The significant difference (p -value = 0.03) in the competence dimension highlights those users appreciated the resources provided on sustainable practices, energy-saving initiatives, and the government's commitment to sustainability. Research results suggest that public sector websites are increasingly seen as reliable sources of information on sustainability, meeting the growing demand for environmentally conscious and responsible digital services.

Empathy, particularly in terms of accessibility and inclusivity, was another area where public sector websites exceeded user expectations. As the findings suggest, ensuring that websites are user-centric and accessible is not only crucial for meeting the needs of all citizens but also for building trust and engagement with government services (Bonsignore, 2024; Marjerson & Gatto, 2024). This research results indicate that users felt the websites were more empathetic than they anticipated. This includes providing multilingual support, ensuring accessibility for individuals with disabilities, and offering content that caters to diverse demographic groups. The websites' efforts in inclusivity align with the broader goal of promoting social sustainability through equitable access to public services.

Tangibility, which encompasses the visual appeal, design, and usability of public sector websites, was another dimension in which public sector websites exceeded user expectations. The significant difference (p -value = 0.001) between expected and perceived tangibility indicates that users found public sector websites to be more visually appealing, easier to navigate, and more aligned with sustainability goals than they initially expected. A well-designed, intuitive website enhances usability, reduces cognitive load, and improves the user experience, all of which are critical for fostering positive perceptions and increasing engagement with public services (Momenipour et al., 2021).

One of the key findings from this study is the evolving nature of consumer expectations in relation to sustainability. While some sustainability aspects of public sector websites were rated with low expectations, the results reveal that users still perceive significant improvements in how these websites incorporate sustainability features. The difference in expectations and perceived quality highlights

that, while public sector websites have made progress, there is still room for growth, particularly in making sustainability more visible and integrated into the overall user experience.

Conclusions

This research highlights that public sector websites successfully surpass user expectations across key dimensions, including reliability, competence, empathy, and tangibility. Users particularly appreciated the accurate, transparent, and current information provided, which reinforced their trust in digital governance. Competence was clearly evident through the provision of comprehensive sustainability resources, detailed guidance on sustainable practices, and visible institutional commitments to sustainability goals. Additionally, the empathetic design features, such as inclusivity, multilingual support, and accessibility tailored specifically for diverse user groups, significantly enhanced overall user experiences. Furthermore, the visual appeal and intuitive design of these websites contributed positively to usability and user satisfaction.

Responsiveness emerged as a critical area requiring focused improvement, particularly concerning timely communication of updates and effective mechanisms for gathering and addressing user feedback. This aspect is vital, as prompt and clear responses can substantially impact user perceptions of service quality and institutional credibility. Improving responsiveness will thus be essential for enhancing overall user satisfaction, strengthening public trust, and fostering continuous engagement with digital public services. By addressing these areas, public institutions can ensure their websites not only meet but consistently exceed evolving user expectations and effectively align with broader sustainability commitments.

The study's limitations include a relatively limited sample size and the cross-sectional nature of the survey, restricting generalizability and insights into longitudinal trends. Future research could benefit from larger, more diverse samples and longitudinal methodologies to track changes in user expectations and perceptions over time. Additionally, further studies could explore in greater detail how specific sustainability features influence user engagement and satisfaction, providing more targeted insights for public sector digital strategists.

Acknowledgments: This research was funded by the Research Council of Lithuania (LMTLT), Agreement No [S-PD-24-112].

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Similarity of EU countries in macroeconomic, innovation, and institutional performance – The case of FDI determinants

Ludmila Bartokova¹, Simona Circova²

¹ Technical University of Kosice, Faculty of Economics, Department of Economics, Slovakia, ORCID: 0000-0001-8662-660X, ludmila.bartokova@tuke.sk (corresponding author);

² Technical University of Kosice, Faculty of Economics, Department of Economics, Slovakia, ORCID: 0009-0008-7710-7558, simona.circova@tuke.sk.

Abstract: Most countries nowadays are linked closely by trade flows, financial transactions, or mutual migration flows. As a result, their overall performances tend to converge. This paper compares 27 European countries with the aim of finding their similarities or differences based on their performance over the last decade. For consistency reasons, we included the United Kingdom and Croatia in the sample, despite not being EU members for the entire period, while Luxembourg was excluded due to data irregularities. The variables used in the analysis were chosen based on the previous literature research as well as their links to foreign direct investment (FDI) flows. The observed period of 2010–2021 was determined according to the data availability. The applied method of cluster analysis is a standard procedure when comparing countries and looking for their mutual similarities in various areas. Our three-part cluster analysis confirmed that in macroeconomic performance, the EU countries tend to follow the same trajectory, and their evolution still follows the same patterns that are closely linked to their EU entry and initial starting position. The overall results confirm that in most cases, the innovation/institutional performance reflects that of the economy's health. Countries with weaker macroeconomic performance or those still undergoing some forms of catching-up process are also characterised by significantly lower levels of R&D expenditure or weaker institutional performance, resulting in the underperformance of this sector. This creates certain innovation and institutional gaps between “older” and “newer” members of the EU. The comparison by FDI inflows indicates the existence of the linkages not only between FDI inflows and a country's macroeconomic performance but also between FDI and countries' institutional and innovation characteristics.

Keywords: Cluster analysis, European countries, macroeconomic, innovation and institutional indicators, FDI.

JEL Classification: F21, F15, O11, O30.

APA Style Citation: Bartokova, L., & Circova, S. (2025). Similarity of EU countries in macroeconomic, innovation, and institutional performance – The case of FDI determinants. *E&M Economics and Management*, 28(4), 29–43. <https://doi.org/10.15240/tul/001/2025-4-003>

Introduction

In the last 15 years, there have been many changes in the overall economic environment that EU countries needed to deal with. Firstly, the financial and debt crises, later followed by

the pandemic and, more recently, the inflation episode. Each of these required some form of political response and adoption of various fiscal or monetary measures. It is a widely known fact that neither the Eurozone nor the European

Union as a whole can be considered a homogeneous group of countries. However, there are certain areas where the EU members could be considered similar. The macroeconomic performance in the EU usually tends to follow the same trends, which can be explained as the closeness created by respecting the Maastricht criteria or brought about by the very close trade and investment flows among the countries. EU trade or investment flows are mostly intra-EU.

When comparing EU countries and their macroeconomic performance, a common approach is to divide countries into several groups based on their entry date to the EU or their current level of convergence to the EU average values. Generally, these groups of countries tend to perform similarly on the macroeconomic level. When looking deeper and comparing other domains of their performance, we might find these similarities reduced.

In this paper, we have decided to verify to what extent these countries are similar, both in their macroeconomic profiles, inflows of foreign capital, innovation, and institutional domain. The main objective is to verify to what extent country-level differences in the three domains (macroeconomic, innovation, and institutional datasets) would consequently impact the overall classification of countries. The variables were chosen with regard to their links to foreign direct investment. It is widely accepted that inflows of long-term capital in the form of foreign direct investment (FDI) can improve the country's overall performance. That is why our focus was on the variables that could be considered important FDI determinants. This, of course, required extensive research of the literature. The analysis was carried out with the aim that the obtained results could be used as a starting point for further, much more detailed analyses.

The paper is divided into sections as follows: theoretical background, research methodology, results and discussion, and conclusions.

1 Theoretical background

The indicators that could be used to evaluate the country's overall performance are numerous, but the choice of specific ones would mostly depend on the area of analysis. As mentioned above, we have decided to focus on those that are also considered key determinants of FDI inflows. FDI flows have been the subject of many analyses for some time, with economists

studying either their main determinants or their impacts. In general, the drivers of capital flows vary from the most obvious one, i.e., higher profits, to less prominent ones, such as various country-specific characteristics.

Various indicators, often cited as significant determinants of FDI, are generally categorised into groups, such as economic, institutional, geographic, and, more recently, innovation indicators (Nguyen, 2023). Economic factors refer to, e.g., trade openness, labour costs, available and skilled workforce, market size, economic stability and growth, fiscal stance and tax rates, exchange rate, and quality of infrastructure (Baharumshah et al., 2019; Carstensen & Toubal, 2004; Dellis et al., 2022; Hunady & Orviska, 2014; Jáč & Vondráčková, 2017; Mateev & Tsekov, 2014). Institutional factors refer to institutional quality and institutional environment, such as the degree of political risk, the degree of corruption, intellectual property protection, and institutional distance (Shah et al., 2015). Sabir et al. (2019) or D'Ingiullo and Evangelista (2020) use the set of institutional variables from the World Governance database, notably the control of corruption, government effectiveness, political stability and absence of violence or terrorism, regulatory quality, rule of law, and voice and accountability. Jones et al. (2020) also point out that determinants may differ based on a country's development level, as suggested by their findings of for the EU25.

It is widely accepted that inward FDI plays an important role in economic development, as it is usually linked to the transfer of new technologies from more advanced economies. As a result, productivity is expected to grow, both within industries and along the supply chains (Bruno et al., 2021). This is particularly true in less developed countries, where incoming FDI is expected to generate positive spillover effects for the host country (Hunady & Orviska, 2014). It is not surprising that economists are still highly interested in studying various FDI determinants, attempting to ascertain their respective significances.

For economic factors, such as tax rates and their impacts, the literature presents mixed results. Razin and Sadka (2007) found that higher tax rates reduce the likelihood of FDI in a sample of OECD countries. Later analyses (e.g., Hunady & Orviska, 2014), however, showed that, in the case of EU26 panel datasets for the period of 2004–2011, the impact of corporate tax

rates on FDI was not statistically significant. On the other hand, trade openness and labour costs were proven to be particularly significant.

The study by Dellis et al. (2022) focused on the role of structural and institutional characteristics. They assumed that well-functioning institutions and markets in the host country can attract more inward capital flows, as they imply fewer investment risks. These analyses were carried out for both EU and EMU countries, and in both cases, well-functioning economic structures were identified as a relevant determinant of FDI inflows in advanced economies. Chen and Jiang (2023) also analysed the role of institutional quality in attracting FDI inflows using panel data of G20 countries from 2005 to 2020. They confirmed that better institutional quality attracts FDI inflows indirectly by increasing trade openness, accelerating industrial structure optimisation, and encouraging technological innovations. According to Ullah and Khan (2017), a higher institutional quality facilitates more efficient use of investments. In contrast, poor institutions could impede FDI and act like a tax (Buchanan et al., 2012). The research of Kaufmann et al. (2010) suggests that strong institutions foster investor confidence, while weak institutions hinder investment efficiency and technological progress. What is more, regional disparities, even within a single country, play a crucial role, as some areas can leverage institutional quality as a competitive advantage to attract higher FDI inflows.

Mateev and Tsekov (2014) analysed FDI flows into Western and Eastern European countries over the period 1994–2012, trying to identify key determinants of these flows. Comparisons across two groups of EU countries showed that FDI flows tended to be more attracted by the macroeconomic stability and high level of institutional development in Western European countries. In contrast, Eastern European countries, characterised by higher credit risk and lower institutional quality, recorded lower levels of FDI inflows. The analysis by Sabir et al. (2019), based on data from 90 countries over the period 1996–2016, confirmed a generally positive impact of institutional quality on FDI, which was stronger in developed than in developing countries.

Another perspective is to analyse the FDI flows through the lens of economic integration. If countries are as deeply integrated as those in the EU, could this impact their FDI inflows? The usual argument for

deep integration stems from the fact that the elimination of customs duties and obstacles to capital movement should shift these flows from the outside to the inside of the integration group. The research by Bruno et al. (2021) estimated that EU membership increased FDI flows by 60%–85% (extra-EU inflows) and by 50% (intra-EU inflows). The positive impacts for the EU were even more significant when compared to shallower forms of integration (e.g., EFTA, NAFTA, and Mercosur).

A similar study of Bevan and Estrin (2004) on European transition countries, namely the CEEC group (Central and Eastern European countries), revealed that even before their full integration into the EU, these countries were already attracting FDI. However, there were significant differences in this group: Central European countries with more favourable initial conditions were able to attract higher volumes of FDI compared to those with poorer performance and a riskier economic environment, i.e., South-Eastern European countries.

The attractiveness of the newer EU members (2004 enlargement) as FDI host countries remains an interesting topic for analysis. Jáč and Vondráčková (2017) examined the case of the Czech Republic and its appeal for FDI inflows through a questionnaire survey. The companies cited tax legislation, investment incentives, and the availability of skilled labour as important factors in their investment decisions.

Jude and Silaghi (2016) focused on the FDI impacts, particularly the job creation, in a panel of 20 Central and Eastern European countries during the period from 1995 to 2012. Their empirical findings revealed that despite an initial negative effect, the overall long-term impact is positive. Similar findings were presented by Crescenzi and Ganau (2024). A study by Sapienza (2010) for 25 European transition economies in the period 1990–2005 also suggests that FDI, together with exports, has significant positive effects in terms of know-how or technology on a country's economic growth.

It has been proven that the determinants of an economy's dynamics can vary depending on its specific characteristics and level of development and would, to some extent, differ between advanced and less advanced countries. According to some authors (Loukil, 2016; Nguyen, 2023), traditional FDI determinants are gradually receding into the background, giving

way to other variables, particularly those closely linked to innovation. FDI inflows often bring new production technologies and know-how. In addition, FDIs contribute to the production of high-quality or high-tech export products in the host country (Erdal & Göçer, 2015). This is why FDI flows are frequently linked to a country's innovation capability and competitiveness and, together with R&D expenditures, are considered significant factors in maintaining the country's growth (Can et al., 2017; Singh, 2019).

Beyond the inflows of new capital, technology, and new skills (technological, marketing, or other), FDI is also assumed to affect the recipient's economy by bringing in secondary spillovers. Such spillovers can occur due to the leakage of the companies' proprietary knowledge or as a response of domestic firms to the arrival of foreign firms. Findings by Loukil (2016) suggest that FDIs are more likely to stimulate innovation if the country has a sufficient level of technological development or the infrastructure with innovation absorption capacity. Similarly, Chen et al. (2022) confirm that domestic firms were more likely to react to the FDI inflows by copying foreign innovations rather than investing in their own R&D (a sample of developing countries at the turn of the 1990s and 2000s). The CEE countries (Szarowská, 2018) over a similar period (1995–2016) showed comparable results, with foreign business R&D being less beneficial to domestic economies due to the underdeveloped innovation infrastructure.

The G7 countries were studied by Can et al. (2017). Their findings confirm that FDI and R&D expenditures are strongly correlated with economic growth. Erdal and Göçer (2015) investigated the effects of FDI on R&D expenditures and innovation in 10 developing countries in Asia. The results suggest that FDI inflows contribute to speeding up R&D and innovation activities that subsequently lead to the production of high-tech products with higher value-added and increase the export revenues. Similarly, Sandu and Ciocanel (2014) confirmed that FDIs increase the production capacity of high-tech products or the number of patent applications. With new innovations arising continuously from, e.g., advancements in technology, innovation-related determinants are likely to impact FDI inflows significantly more than they did in the past.

For our analysis, we have decided to study the similarity of EU countries based on the above-mentioned determinants. Our aim is to examine the diversity of the groups resulting from cluster analysis within the context of the FDI inflows.

2 Research methodology

The presented analysis is based on previous research and the above-mentioned studies. The sample of analysed countries comprises EU countries and covers the period of 2010–2021. Both the choice of countries and the period were determined by the availability of the data.

This study uses cluster analysis (CA) to assess country-to-country resemblance. CA is a powerful tool for finding patterns and structure in data, but it is also linked to certain challenges and limitations that need to be considered. This approach is usually adopted with the aim of sorting the selected data into several relatively homogenous subsets (clusters), such that units (objects) within individual clusters are as similar as possible, while units (objects) belonging to different clusters are the least similar possible (Lund & Ma, 2021). In other words, the objects are grouped based on similarities within one cluster and their differences compared to another. The smaller the variance of individual variables, the more homogeneous the group of objects in the same cluster.

In our analysis, we tested the similarity and distance of EU countries, which represent “*n*” objects. Each country (object) can be described by certain characteristics, “*k*” = determinants (macroeconomic, innovation, and institutional). The aim was to verify the differences and similarities of the countries grouped into individual clusters using various sets of data. Each category comprised variables selected from the previous research (Tab. 1). The set of macroeconomic variables consisted of fundamental macroeconomic indicators used for describing a country's overall macroeconomic situation (GDP per capita, inflation, unemployment), competitiveness and growth conditions (corporate tax rate), and fiscal stance (government debt, long-term interest rate). The institutional dataset from the World Bank's WGI database consisted of six indicators that represent general perceptions of the quality of governance across countries. The innovation dataset consisted of variables that reflect

a country's potential for innovations and growth (R&D expenditures, employment in the ICT sector), the transformation of the potential into tangible innovations (patents, value-added in ICT), and the ability to commercialise this potential (hi-tech exports). The ICT sector was selected, as ICT and innovation are traditionally viewed as deeply interconnected. This sector is an important source of technological innovation, but it also drives and enables innovation across all industries. What is more, it also provides the technological infrastructure that promotes new discoveries in almost every other sector.

To observe the similarity of objects in the analysis, various measures can be used, e.g., the correlation coefficient, association coefficient, distance measure, or probability measure of similarity. The distance measure, particularly Euclidean distance, is one of the most widely used metrics for this purpose and can be calculated as follows:

$$d_{ij} = \sqrt{\sum_{k=1}^n (X_{ik} - X_{jk})^2} \quad (1)$$

where: X_{jk} – the value of the k^{th} variable for the j^{th} object; X_{ik} – the value of the k^{th} variable for the i^{th} object.

Before performing CA, certain assumptions must be met, i.e., the absence of missing values or outliers and the lack of data discrepancies; otherwise, data transformation is necessary to ensure the reliability of the results. Furthermore, the absence of multicollinearity among variables is crucial. If high correlation is detected, factor analysis should be applied to address the issue (Strielkowski et al., 2024).

The CA was conducted in R Studio using annual data (2010–2021) from three various datasets of macroeconomic, innovation and institutional variables. Firstly, the samples were tested to verify whether the basic CA assumptions were met. If assumptions were violated, the corrective measures, such as factor analysis, were applied. Due to significant values of correlation (institutional dataset), the factor analysis was performed. The Kaiser-Meyer-Olkin test (KMO) was used to determine whether principal component analysis (PCA) would be necessary. The KMO value indicated that

Tab. 1: List of macroeconomic, innovation, and institutional variables

Source	Variables
EPO	Patents (<i>PAT</i>), million per capita
Eurostat	10-year bonds interest rate (<i>10YB</i>)*, % Government debt (<i>GDEBT</i>), % GDP Employment in ICT (<i>EMP</i>), % total Hi-tech exports (<i>HTECHe</i>), % total ICT sector value added (<i>GVA</i>), % total
IMF	GDP per capita (<i>GDP pc</i>), USD Foreign direct investment inflows (<i>FDI</i>), % GDP
OECD	Corporate tax (<i>TAX</i>), %
World Bank	Inflation rate (<i>INFL</i>), % Unemployment rate (<i>UNEMP</i>), % R&D expenditures (<i>RD</i>), % GDP Control of corruption (<i>CC</i>), index Government effectiveness (<i>GE</i>), index Political stability and absence of violence/terrorism (<i>PV</i>), index Regulatory quality (<i>RQ</i>), index Rule of law (<i>RL</i>), index Voice and accountability (<i>VA</i>), index

Note: * data for Estonia were estimated based on the similarities with other Baltic countries.

Source: own

PCA should be applied to prevent data distortion and to avoid misclassification of countries into clusters.

To perform PCA, Bartlett's test was used to assess whether the data was suitable for factor analysis. The Elbow method was used to determine the optimal number of principal components. In our case, it was primarily two components. The same testing approach was applied to all three datasets.

To obtain the resulting clusters, Ward's method was applied, which is one of the most widely used hierarchical clustering methods. It aims to create clusters of similar size by minimising the variance within each cluster. The homogeneity of clusters is measured by the within-cluster sum of squares, which deviates from the error sums of squares mean (Strielkowski et al., 2024):

$$ESS = \sum_{i=1}^{n_h} \sum_{h=1}^q (x_{hi} - \bar{x}_{ch})^2 \quad (2)$$

where: n_h – the number of objects in the cluster; x_{hi} – the value of the i^{th} object in the h^{th} cluster; \bar{x}_{ch} – the mean of the values in the cluster.

For the study, we used a hierarchical agglomerative clustering procedure, where objects are gradually merged based on their similarities and differences. This approach provides a more complex structure compared to non-hierarchical methods. It is also suitable for revealing deeper patterns in data (Higuchi & Maehara, 2021).

3 Results and discussion

Cluster analysis was performed on the sample of 27 EU countries using annual data from the period 2010–2021. The time range was decided based on the data availability. Due to some data irregularities, Luxembourg was excluded from all datasets. However, for consistency reasons, we decided to include both the United Kingdom and Croatia in the sample, even though neither country was a member for the whole period. The aim was to examine the year-on-year changes in the sorting of the countries into clusters. We assumed that the countries grouped together in one cluster will continue to follow the same trajectory in the subsequent years and thus will still belong to the same cluster. Nevertheless, should a country be hit by,

e.g., a negative shock or encounter some significant economic changes, it would surely be manifested in its cluster placement or by a shift to another one.

The analysis was carried out using three separate datasets described in Tab. 1, which cover the macroeconomic situation as well as the innovation and institutional characteristics of the countries. Since we opted for a hierarchical arrangement of clusters, the optimal number of clusters was determined based on the similarity of values in each year and represented by the D-index. The final dendrograms were generated for each year and all sets of variables. However, due to the limited scope of this paper, we present only a representative sample of our results. More detailed results can be obtained from the authors upon request.

Firstly, we applied CA methods on the macroeconomic dataset. A detailed study of dendrograms based on annual data revealed that, except for some minor shifts between the clusters, the cores of each group were relatively stable. The same steps were then repeated with the sets of innovation and institutional variables. Here again, the cluster analysis indicated very similar results. Based on the comparison of annual results, four representative clusters were created to reflect general groupings of European countries (Tab. 2). In some cases, a country's assignment to a particular cluster was based upon its occurrence in these clusters, i.e., the frequency with which it was placed in clusters C1–C4 using the CA methods. These results are also presented in the dendrograms (appendix, Fig. A1) and boxplots for each variable (Figs. 1–3).

When comparing the obtained results, certain patterns emerge. As expected, there is a certain divide between the original "older" EU members and the "newer" ones (Jones et al., 2020). For each dataset, the Northern countries (Finland, Sweden, and Denmark) were mostly grouped with the Netherlands and Austria (C1). The other Western countries, such as France, Germany, Belgium, Great Britain, and Ireland, were typically grouped in the second cluster (C2). The countries that joined the EU either in the 2004 enlargement or later were mostly grouped together in the last two clusters (C3 or C4). In many cases, the Southern countries (Italy, Portugal, Spain, and sometimes Greece) were evaluated as being closer to this group than to the first two clusters. On the other

Tab. 2: Results of CA – clusters by groups of variables (2010–2021)

Clusters	Macroeconomic	Institutional	Innovation
C1	FIN, SWE, DNK, NLD, AUT, IRL, DEU, GBR, SVN	FIN, SWE, DNK, NLD, AUT, IRL	FIN, SWE, DNK, NLD, AUT, BEL, DEU
C2	FRA, BEL, ESP, ITA, PRT, MLT, CYP	DEU, FRA, BEL, GBR, ESP, EST	IRL, MLT
C3	GRC	BGR, ROU, HRV, LVA, CYP, ITA, GRC	CZE, HUN, EST, GBR, FRA
C4	SVK, CZE, HUN, POL, LVA, LTU, EST, HRV, BGR, ROU	CZE, SVK, HUN, POL, MLT, SVN, LTU, PRT	SVK, POL, HRV, SVN, BGR, ROU, LTU, LVA, CYP, ESP, PRT, ITA, GRC

Source: own

hand, some of the new members (Slovenia, Cyprus, or Malta) were often considered more similar to C1 or C2 due to their favourable results in certain areas. However, in terms of macroeconomic performance, Greece was mostly placed in a separate, one-country cluster reflecting its ongoing struggles linked to the debt crisis from the early 2010s. As these issues persisted in the following years, the country was excluded from all previous clusters.

The similarity of the countries grouped together in four clusters can also be demonstrated by the distribution of values for the analysed variables. For each variable, summary statistics were calculated for the entire sample of 27 countries and compared to those of the selected clusters. This approach highlighted the most significant differences among clusters (appendix, Tab. A1).

In the case of the macroeconomic dataset, C1 can be characterised as the group consisting of the wealthiest countries (average value of 50,000 USD pc), with stable and low inflation and unemployment rates (averaging 1.4% and 6.7%, respectively), government debt relatively close to the Maastricht reference value (66% of GDP), relatively low long-term interest rates (1.5%), and slightly higher corporate tax rates (21%). For example, Slovenia was part of C1 in most years, thanks to its stable macroeconomic performance and despite its GDP pc being below the C1's average. When compared to C1, the C2 group could be characterised as consisting of less wealthy (32,000 USD pc) but more indebted EU members (99.5% GDP) with stable inflation (1.2%), slightly higher and more diverse unemployment rates (ranging

from 3.4% to 26%, with an average of 10.5%), and higher tax rates (ranging from 10% to 44%). Here again, the inclusion of Cyprus, may not seem obvious, but the country is linked to this group through its high government debt nearing 100% of GDP but generally stable macroeconomic performance. The notable difference is its corporate tax rate of 12.5%, which is significantly lower than the C2's average of 28%. The lowest corporate tax rates are typical for the C4 (17% on average). However, this group is also characterised by relatively low GDP pc (15,5000 USD pc), stable inflation with its average value of 2% being at the ECB's target level, and a slightly higher but significantly more variable unemployment rate (ranging from 2% in Czechia to 19% in Latvia, with an average around 8.4%). The group's average government debt (43.6%) stayed below the Maastricht's 60% reference value, but the values were more dispersed, ranging from less than 10% in Baltic countries to 86% in Croatia.

The comparison of the same group of countries using the institutional dataset resulted in somewhat similar results (Fig. 2). Here again, the three Northern countries were grouped together with the Netherlands, Austria, and Ireland. This group performed the best across all six indicators (average index values around 1.58), reflecting the group's characteristics such as strong democratic and credible institutions, a high level of political freedom and effective governments, transparent and independent legal systems and low levels of corruption. The C2 cluster consisted of the Western European countries and Estonia. Its performance was slightly less successful than that

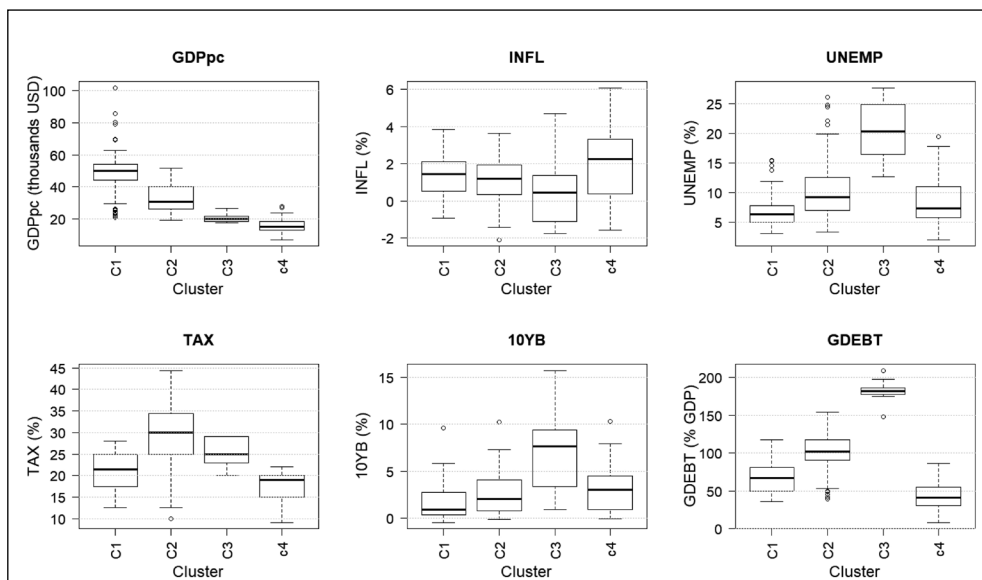


Fig. 1: Distribution of values for macroeconomic dataset (clusters 1–4)

Source: own based on Eurostat (2024), IMF (2024), OECD (2024), World Bank (2024)

of the C1 group (average index value of 1.2). The Southern countries (Italy, Spain, Portugal, and Greece) were considered similar in terms of their institutional characteristics. Although performance across countries may vary slightly, overall results indicate the weakest results in governance among the EU sample (average index value of 0.46). The newer EU members were once again grouped together. Based on the WGI indicators, the C4 group has a more diverse governance profile. These countries generally perform well in terms of political stability and security, regulatory quality and government effectiveness. However, their performance is more variable in the domain of corruption. Overall, the distribution of values for C1–C4 shows a certain downward trend, with the best performance attributed to C1, followed by C2, and then C3. These findings are, to some extent, consistent with the results of Bruno et al. (2021), who emphasise the impact of EU membership on FDI. There is also some similarity to the findings by Bevan and Estrin (2004) or Kaufmann et al. (2010), who highlighted the institutional gap between old and new EU members.

The results of the C4 group exceeded those of the C3 group. This can be seen in the boxplots for all variables. It is evident that the variability of values at the country level, especially for C1 and C2, is less pronounced than in macroeconomic performance. However, the most significant range can be observed within the C3 group for almost every variable. The only domain in which new members would attain a superior evaluation is political stability and the absence of violence and terrorism. In particular, the PV's average values for the C1 and C4 groups were 0.98 and 0.89, respectively, while the C2 group (mostly western EU) and C3 (mostly southern EU) averaged around 0.49 or 0.36, respectively. These values also showed significant variability, reflecting a decade marked with several terrorist attacks in, e.g., France, Belgium, or Spain (Gilli & Tedeschi, 2022).

The next step was the classification of countries based on the innovation dataset. The obtained results pointed to very similar groups as before. Findings, presented in the boxplots (Fig. 3) confirm that, again, the results tend to deteriorate when we move from the North and

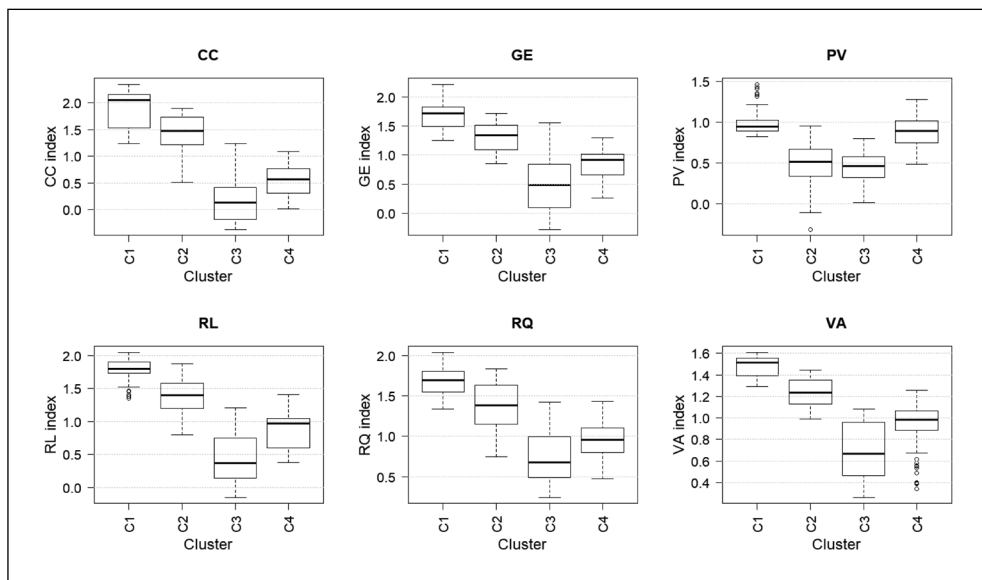


Fig. 2: Distribution of values for institutional dataset (clusters 1–4)

Source: own based on World Bank (2024)

West to the South and East. The three Nordic countries were consistently grouped together with Austria, the Netherlands, Belgium, and Germany (C1). These countries are frequently cited as important leaders in both innovation potential and performance (Brodny et al., 2023; Dutta et al., 2023; WIPO, 2024), a status attributed to their high levels of R&D expenditure and orientation towards knowledge-based economies (average values around 3% of GDP). This group also performed well in the areas of patents per million inhabitants, employment in the ICT sector, and ICT value-added (averages of 317, 5.1%, and 4.9%, respectively). The average share of R&D expenditure was significantly lower for other groups, ranging from C4's 1% to C3's 1.85% of GDP. This was also reflected in the average number of patents per million inhabitants (ranging from 22 in C4 to 59 for C3) and the values of hi-tech exports (from C4's 10% to C3's 21% of exports). The shares of ICT employment appear to be relatively balanced for C1–C3, ranging from 4.2% to 4.96%. Our results, which point to an innovation gap between old and new EU members, partially align with the study by Erdal and Gocer (2015), conducted on a sample of advanced economies.

The C2's highest values for hi-tech exports and ICT value-added could be linked to the strong presence of multinational corporations and trade conditions. The weakest performance and a relatively higher dispersion of values were observed in the C4 group. This was evident both in terms of innovation potential (R&D expenditures, ICT employment) and innovation performance (ICT value-added, patents and hi-tech exports). These results suggest a potential link between the volume of financial resources allocated to R&D to develop a country's innovation potential and the tangible outcomes of these efforts. Similar findings can also be found in Can et al. (2017) or Singh (2019). That is why, national governments in C4 countries should allocate more funds to R&D domain to enhance their innovation potential.

The final step of the analysis consisted of the comparison of FDI inflows as % of GDP over the period of 2010–2021. Firstly, we analysed basic summary statistics of countries with the aim of identifying similarities at the country level (Tab. 3, Fig. 4). Based on the variability of FDI inflows, the sample was divided into three groups, denoted FDI1-3.

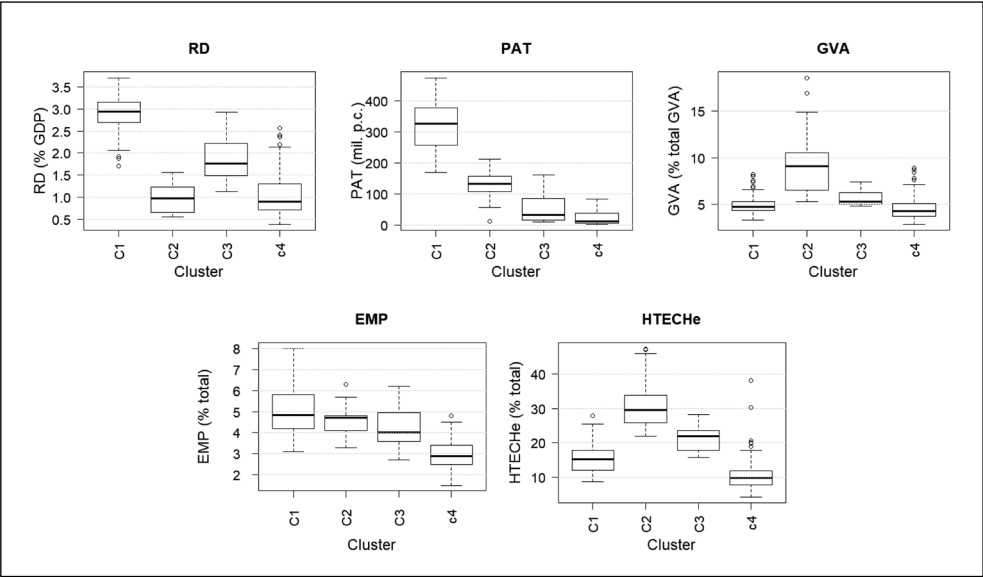


Fig. 3: Distribution of values for innovation dataset (clusters 1–4)

Source: own based on EPO (2024), Eurostat (2024), World Bank (2024)

Tab. 3: Groups of countries by FDI inflows as % GDP (2010–2021)

FDI group 1	FDI group 2	FDI group 3
FIN, SWE, DNK, AUT, DEU, GBR, FRA, ITA, PRT, ESP, GRC	LVA, LTU, SVK, CZE, POL, SVN, HRV, BGR, ROU	BEL, NLD, IRL, MLT, CYP, HUN, EST

Source: own

As shown in Tab. 3 and Fig. 4, these groups are only partially aligned with those created through clustering, although some similarities remain. The Northern and Western countries (old members) appeared to have comparable values of FDI inflows. With the exception of certain countries, the FDI inflows could be considered relatively stable, with the standard deviation ranging from 0.79% (France) to 3.99% (Finland). The average inflow for the entire group was 1.74%. The FDI2 group (new members) could be characterised by slightly lower variability (from 0.78% – Romania to 3.2% – Latvia) and a higher average inflow of the group (2.95%). The FDI3 group comprised countries with the most variable FDI inflows, with its average (30.4%) significantly exceeding those of FDI1

and FDI2. The last FDI3 group can also be characterised by the lowest corporate tax rates, e.g., Hungary – 9%, Ireland – 12.5%, or Malta – 5%, which represent the effective tax rate for foreign companies (OECD, 2024).

When compared with the result of the CA (Tab. 1), it is evident that, with the exception of the countries with the most favourable tax conditions, the groups based on FDI inflows generally align with the patterns observed in the macroeconomic and institutional datasets. The FDI1 members are mostly consistent with the C1 and C2 countries (Fig. 1) from the macroeconomic dataset, where corporate taxes were the highest. While Razin and Sadka (2007) or Jáč and Vondráčková (2017) also emphasised the importance of corporate

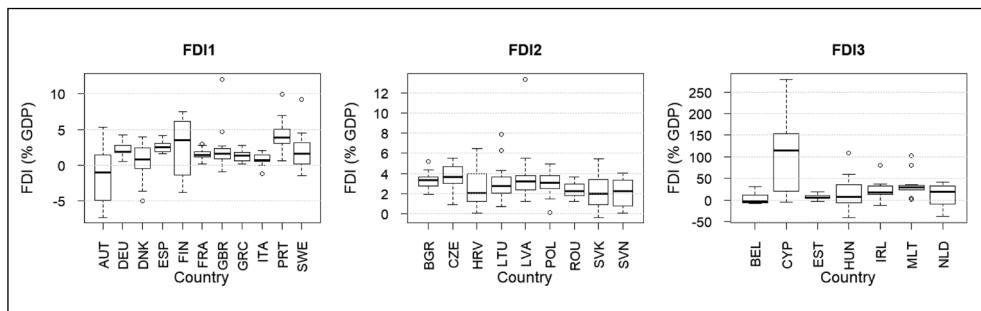


Fig. 4: Distribution of values for FDI inflows (% GDP)

Source: own based on IMF (2024)

tax rate levels in terms of attracting FDI inflows, Hunady and Orviska (2014) point to its less significant impact. The institutional environment of these countries was also evaluated as more favourable, similarly to the findings of Dellis et al. (2022), Bevan and Estrin (2004). Studies by Kaufmann et al. (2010), Mateev and Tsekov (2014), or Dellis et al. (2022) also highlight significant regional differences in FDI inflows within the EU, with higher FDI inflows in more advanced EU countries with stronger institutions. Our results could also be considered consistent with these observations. It is obvious that the C3 and C4 countries should put more effort into improving their institutional environments, with a particular focus on addressing corruption.

Based on the simple comparison of both parts of the analysis, we can conclude that these findings largely align with the macroeconomic and institutional dataset. However, some similarity can also be found with the results obtained from the innovations dataset.

Conclusions

The main goal of this paper was to examine the differences and similarities in overall performance of EU economies. The analysis was conducted using standard statistical methods, as well as cluster analysis (hierarchical approach), on a sample of 27 countries over the period 2010–2021. The three sets of variables (macroeconomic, institutional, innovation) were selected based on our previous research and their link to FDI, with the aim of using these results as a starting point for further, more detailed analyses.

In general, the macroeconomic performance within the EU tends to follow similar trends. Nevertheless, a closer look reveals that countries can be grouped based on their characteristics. For the institutional or innovation environment, country-level results are often more variable. Our analysis confirmed that, aside from minor shifts among groups caused by external factors or crises, the classification of countries into four separate groups remained relatively stable throughout the years for all three studied areas. In very general terms, we can claim that the countries' performance aligns with their EU entry date. To some extent, there is a downward-sloping trend in overall performance as we move from the North and West towards the East and South of Europe.

For all three datasets used in CA, C1 mostly consists of strong economies with stable institutions and high innovation performance. An efficient institutional environment, lower corruption, and political risks promote economic performance, stability, and a positive business climate. This, in turn, fosters higher investments in innovation, science, and research, thereby enhancing the competitiveness of these countries. The C1 countries can be described as some of the most economically advanced countries.

Economically strong but institutionally less efficient countries were grouped into the cluster C2. Although characterised by relatively high GDP and GDP pc, they are not innovation leaders like Scandinavian countries. However, they still invest more than 1.5% of their GDP in R&D, strengthening their innovation potential, which is also reflected in a significant number of patents

per million inhabitants (e.g., Germany). These countries remain attractive to foreign investors, but certain regulatory or administrative barriers may limit their competitiveness. Investors are primarily drawn to them due to factors such as market size (France, Germany), strategic location (United Kingdom), or favourable tax conditions (Ireland).

Later EU members were often grouped together (mostly C3 and C4). Despite some exceptions (e.g., Slovenia or Estonia), it was uncommon for these countries to form a cluster with more developed EU members. The primary difference between older members (more developed countries, C1–C2) and newer members is the lower institutional quality and higher levels of corruption, which may influence investor decision-making and, subsequently, FDI inflows. This disadvantage is sometimes offset by lower corporate tax rates (e.g., Hungary, Cyprus). In general, new members can be characterised mostly as the smaller, more open economies, dependent on other countries, with weaker institutional support and, in some cases, higher investment risks. Their competitiveness often stems from lower labour costs rather than the high-tech sector, which is typically underfunded, as reflected by relatively low R&D expenditures (around 1% GDP). Therefore, allocating more funds to R&D, alongside the gradual improvement of the institutional environment, should be the primary focus of national policies of these countries.

In our analysis, we sought to examine the differences and similarities in the macroeconomic, innovation, and institutional performance of EU economies. Based on the comparisons of both parts of the analysis, we can conclude that the similarities in FDI levels largely align with the results of the CA for the macroeconomic and institutional datasets. Some similarities can also be found with the results obtained from innovation datasets. These results also raise new questions. Are corporate tax rates and the macroeconomic stability the only determinants of the FDI inflows and their variability? What are the roles of the institutional environment and good governance? What is the link between FDI inflows and a country's innovation characteristics? Traditionally, FDI inflows were often linked to macroeconomic variables as their most significant determinants. However, rapid changes across all domains have increased the importance

of more comprehensive research, with new determinants now being analysed.

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Appendix

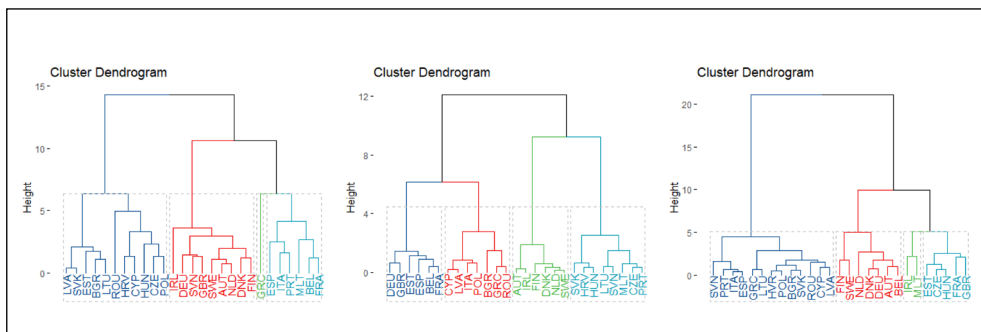


Fig. A1: Representative dendrograms – macroeconomic (left), institutional (middle), and innovation (right) datasets

Source: own based on EPO (2024), Eurostat (2024), IMF (2024), OECD (2024), World Bank (2024)

Tab. A1: Summary statistics – FDI inflows as % GDP (2010–2021)

Country	Min	Max	Mean	Median	Std. dev.
DNK	-4.99	3.94	0.58	0.85	2.73
FIN	-3.83	7.46	2.67	3.51	3.99
SWE	-1.48	9.17	2.14	1.62	2.81
AUT	-7.31	5.32	-1.38	-0.99	3.99
DEU	0.50	4.19	2.28	1.86	0.98
GBR	-0.87	12.03	2.38	1.64	3.33
FRA	0.20	2.99	1.53	1.43	0.79
ITA	-1.16	2.12	0.79	0.76	0.84
PRT	0.64	9.89	4.23	3.88	2.41
ESP	1.57	4.12	2.57	2.48	0.79
GRC	0.18	2.79	1.36	1.32	0.80
LVA	1.19	13.33	3.86	3.22	3.20
LTU	0.74	7.88	3.23	2.78	2.03
EST	-3.13	19.21	7.37	6.57	5.62
SVK	-0.36	5.44	2.21	1.99	1.94
CZE	0.90	5.53	3.66	3.67	1.36
POL	0.15	4.96	2.97	3.07	1.25
SVN	0.07	4.01	2.13	2.25	1.42
HRV	0.09	6.49	2.74	2.08	2.15

Source: own

Premature stalling of the catching-up process in CEECs: The case of Slovakia

Karol Morvay¹

¹ Bratislava University of Economics and Business, Faculty of Economics and Finance, Department of Economic Policy, Slovakia, ORCID: 0000-0001-5790-9694, karol.morvay@euba.sk (corresponding author).

Abstract: The slowdown in the catching-up process has attracted considerable attention, as it is a phenomenon observed in a real context. It has affected almost all CEE countries after the global financial crisis, but to an unequal extent. The article deals with the problem of stalling catching up with advanced economies from the Slovak perspective. It is a problem with broad links to all sectors of the economy as it affects business activity, public administration and households. The analysis is constructed as an explanatory case study (trying to present and explain the different trajectory of one economy compared to a set of similar ones), which relies on the insights of growth accounting. Its aim is to prove that (i) Slovakia experienced a more pronounced break in the convergence trend than the other CEE5 countries; and that (ii) the slowing factors were spread across all growth drivers used in growth accounting (capital, labor, total factor productivity). In the case of capital, there was a fall in the investment rate and a halt in the overcoming of the gap in capital deepening. In the case of labor inputs, there has been a shift from a labor force excess to a shortage. There has been a significant backwardness in the forces supporting total factor productivity (R&D, accumulation of intellectual property products, quality of regulation). The decline in the total factor productivity (TFP) dynamics has been identified in several studies as a causal factor in the convergence slowdown. And it is precisely in the forces supporting TFP that the most significant weaknesses are identified in the case of Slovakia.

Keywords: Convergence, investment rate, labor force shortage, productivity, Slovak economy.

JEL Classification: O47, O11, E22, E24.

APA Style Citation: Morvay, K. (2025). Premature stalling of the catching-up process in CEECs: The case of Slovakia. *E&M Economics and Management*, 28(4), 44–63. <https://doi.org/10.15240/tul/001/2025-4-004>

Introduction

For about a decade, there have been analyses of a slowdown in the catching-up of Central and Eastern European (CEE) countries with the most advanced economies. This is related to the fact that such a tendency has been emerging in the real economy in this very decade. After the financial crisis and the global recession (i.e., after 2009), the process of catching up with the level of the more advanced European economies stalled. There have been worried comments about the failure of CEE countries to meet their strategic

objective, but also academic articles quantifying the contributions of various factors to growth (or to its slowdown). With hindsight, the picture has changed somewhat: there are signs of a renewed catching-up process in several CEE economies. But not in all. The motivation for this article is thus given by an observed problem in a real context.

This article examines the problems of the slowdown in CEE real convergence, using Slovakia as a case study. The aim is to demonstrate and explain two occurrences (working hypotheses 1 and 2):

H1: The problem of slowing convergence is more severe in Slovakia than in the other CEE5 countries (V4 + Slovenia).

H2: The weakness has affected all categories of growth and convergence drivers across the board – capital, labor, and factor productivity. It has affected them more severely than in the other countries of the group.

This paper is not about quantitative modelling; it would not be an appropriate procedure for the object of study. It is not intended to generalize about the behavior of this group of economies, and the paper does not deal with a large number of observations (from which it would be desirable to construct a simplifying model). Rather, it is focused on identifying the specifics of one economy (when compared with the rest of a small set of similar economies) and attempting to interpret them. In this way, the methodology is based on the creation of explanatory case studies. The analysis relies primarily on data from national accounts and other databases from Eurostat and the World Bank. For international comparisons, the data for the Slovak Republic as an individual case study are primarily compared with the smaller group of CEE5. In some places, comparison with the wider CEE group (11 former transition economies, now EU members) is used.

The Slovak scenario is an attractive object of study, but also a warning for policy makers across the broad set of former CEE transition economies.

1 Theoretical background

The significant differentiation of the process of real convergence already during the early phase of the transition of the CEE economies (looking at whole economies as well as regions and sectors) was investigated by Landesmann and Stehrer (2002). They interpreted different patterns in the course of real convergence. While they confirmed the existence of a starting advantage for economies with a more pronounced initial gap (a more pronounced initial lag in productivity and product quality), they showed that the existence of such a "laggard advantage" does not automatically imply its exploitation. During and shortly after the global financial crisis, differentiation in the catching-up process became more pronounced and patterns of progression changed (Smirnykh & Wörgöter, 2021). New manifestations of differentiation

in both convergence dynamics and in models of growth and convergence have emerged, as shown by Gyorffy (2022) and Vukov (2023).

Žuk et al. (2018) provided an analysis of the reasons for the different dynamics of real convergence and demonstrated the changing role of growth factors in the development phases of CEE economies. They also presented the slowdown of the catching-up process after the global financial crisis and the roots of this phenomenon in individual production factors. In doing so, they relied on the principles of growth accounting, in which the performance of an economy depends on capital inputs, labor inputs and total factor productivity (TFP). The authors showed, that the dynamics of real convergence were (before its slowdown in the last decade) driven primarily by changes in total factor productivity; yet inputs supporting further TFP growth are scarce. Common features of the more successful convergence countries have been identified, e.g., improving quality of institutions, external competitiveness and innovation, high levels of trade openness, high levels of human capital and relatively high investment rates. Accelerating and sustaining convergence in the region is expected to require further efforts to improve institutional quality and innovation, boost investment and counterbalance the effects of an ageing population. However, there is no complete agreement in the literature on the relative role of performance drivers (capital, labor, TFP) in determining the growth and convergence of CEE countries. The results of analyses using growth accounting vary according to the period or set of CEE countries chosen. Between 2000 and 2008 (this was a period of relatively strong growth of economies, ending with the global financial crisis), the contribution of TFP and capital inputs was highly valued (Labaj, 2007; Pokrivčák & Záhorský, 2016; Žuk et al., 2018). Labor accumulation also supported growth; its contribution remained small. The conclusions of Pokrivčák and Záhorský (2016) are somewhat different in that they attributed the largest growth contribution to capital accumulation (especially non-ICT capital). In the case of Slovakia, they put TFP in second place, but still with a significant positive contribution to growth. The post-crisis economic slowdown was across analyses mainly associated with slower TFP change. Kónya (2023) takes a different approach but reaches similar conclusions.

Analyzing a sample of 11 CEE countries, the author demonstrated the critical role of productivity factors in determining which countries continue to converge and which are stuck. Therefore, economic policy should primarily focus on productivity growth factors and a well-functioning capital market. Chiacchio et al. (2018) explained the background of the decline in the role of TFP on the basis of a two-stage process of technology diffusion. In the first stage, firms in the host economy benefit from their direct exposure to new technologies created in their parent firms as a result of their participation in global value chains (GVCs). In the second stage, technologies are transferred to the remaining firms in the host economy through domestic production networks. Moreover, imports of intermediate products (backward linkages) are a channel of technology diffusion within GVCs. Because of their deep integration in GVCs, CEE countries have been exposed to two phenomena highly correlated with their TFP performance over the last 15 years: (i) a slowdown in TFP growth of parent firms located outside CEE; and (ii) a slowdown in the growth of participation in GVCs, which is also evident for CEE countries. In addition, the authors show that the capacity of firms in CEE countries to absorb new knowledge has declined since the crisis. This is related to the low level of R&D investment in CEE countries during the post-crisis period.

The slowdown in TFP growth in a large part of European economies is also demonstrated by Čekmeová (2016) and Radicic et al. (2023). The authors conclude a significant slowdown in TFP growth across the European Union in the second decade of the 21st century. This also hinders the transmission of TFP growth across GVCs to CEE countries.

Papers examining the principle of so-called “dependent growth” have contributed to the understanding of the slowdown in real convergence. Myant (2018) argued that the more than two-decade-long phase of rapid convergence and strong growth in CEE (the author worked with a sample of V4 countries) was made possible by the principle of dependent development and growth. External investment entered the economy along with multinational corporations. These allowed the expansion of export-oriented production activities, engaging CEE countries in global markets. Such developments brought temporary rapid growth,

still leaving a substantial lag relative to the more advanced economies of Western Europe. After examining the strategies of multinationals operating in CEE and data on their product mix, he argued that the low labor cost factor gives them good reason not to transfer their most advanced products and processes to CEE, and the transfer of less advanced activities in return helps them to keep labor cost levels below those in Western Europe. The implication is that these countries cannot catch up with Western Europe without a change in growth model. In a similar line, Soreg (2018) argued that there is doubt about the ability of some CEE countries to continue real convergence following the reduction in external sources of financing after the global financial crisis. The previous strong growth and convergence can also be described, according to this author, as manifestations of dependent growth, with the inability of these economies to continue on their own (with the limitation of previously massive external financing). Related to this, Galgóczi and Drahokoupil (2017) argued that the old growth model is not entirely lifeless. After several years of convergence stalling after the global financial crisis, it was again largely external forces (in the form of FDI or EU funds) that played a significant role in reviving growth and real convergence in some of the CEE economies (in the period since around 2015). According to these authors, there is little evidence that the region is in a position to embark on a qualitative change in its growth model. R&D activities are among the lowest in the EU, the propensity to innovate is low, and the high degree of internationalization in production networks is not matched with internationalization of R&D and innovation. Labor shortages and the scarcity of suitably skilled labor limit economic development prospects and the region does not appear to be ready for the digital era. A crucial barrier is the lack of innovation capacity.

Since the stagnation of the catching-up process is a serious empirically observed phenomenon in economic reality, it has become the subject of analyses, evaluations and recommendations by international organizations. IMF (2016) has raised the question of how CESEE countries can get back on the fast convergence path and, in answering it, emphasized promoting capital deepening, improving labor supply and enhancing institutional quality (CESEE – Central Europe and South-East

Europe). The OECD (2022) analysis was concerned with sustaining productivity gains that have historically been based on integration into global value chains. It considers this essential for reviving economic convergence and supporting living standards in a society with an ageing population. It notes that the strong productivity gains of some firms in the competitive manufacturing sectors have not successfully spread to small and domestic firms, reflecting the duality of the Slovak economy.

Some authors have reacted to the unfavorable data on the evolution of real convergence by showing distortions in purchasing power parity (or purchasing power standard). Dujava and Zudel (2023) quantified the impact of distortionary factors, identifying a change in the approach to imputed rents as the most significant. After adjusting the time series of GDP per capita at purchasing power parity for the parity distortions, the trend was more favorable. They recommended working with data in euros until the parity distortions are clarified and removed. However, a significant slowdown in real convergence was still present (albeit in a milder form), even after the correction of the distortions identified by them. Hlaváč (2023) also confirmed the quantification of imputed rents as the most significant source of distortions. In the Slovak Republic this is a significant item in the GDP structure, given the extremely widespread use of owner-occupied housing. Without going into detail, the problems associated with the estimation of imputed rents have led to inaccuracies in parity and thus to an underestimation of GDP per capita levels at parity. This created a picture of a reversal in real convergence after 2015. Importantly, however, even after removing the distortion, catching up to the levels of more advanced economies has slowed down very significantly, the essence of the problem of a stalled catch-up process is still present. It is precisely because of the questioning of the correctness of the parity data that we pay attention in the following to the dynamics of catch-up when expressed in different units of measurement.

2 Research methodology

The article uses previously published findings from growth accounting as its starting point. These have quantified the role of capital accumulation, labor accumulation and the role of total factor productivity in the growth and real convergence of CEE economies – at different

stages of development (as shown in the literature review). Building on this knowledge, the analysis proceeds to examine the status and dynamics of those drivers that determine the shape of growth factors (capital, labor, TFP).

The analysis proceeds in two steps: (i) in the first step, it shows that the slowdown in the process of catching up to the level of more advanced European economies is a more pronounced and longer-lasting phenomenon in the Slovak economy than in similar CEE economies. To do this, it uses comparisons of the dynamics of the catching-up process in different periods. The research question: *RQ1: Is the slowdown in the catch-up process for the Slovak Republic demonstrably more pronounced and longer lasting compared to similar, former CEE transition economies?* The assumption (H1) is that this is indeed the case and the Slovak economy is more affected by the catch-up slowdown than similar CEE countries; and (ii) the second step attempts to examine the shape of the factors of growth and real convergence. It examines the evolution of capital inputs, labor inputs and TFP-enhancing inputs. The research question: *RQ2: Is the slowing catching-up process reflected in any of the growth and convergence factors (capital, labor, TFP)?* The assumption (H2) is that the slowdown in catch-up has its roots in problematic tendencies in all three categories of production factors.

The article has the nature of an explanatory case study (and thus a qualitative research strategy). Such an approach is appropriate for the chosen research questions. The aim is not to generalize or modelling phenomena, but to analyze the specific development trajectory of one chosen economy, when confronted with a set of similar economies. The use of a case study, in order to examine phenomena in their real context, draws on the work of Chrasťina (2019). It can be assumed that the object of study (the Slovak economy) has deviated from similar economies in the area of real convergence at some point in time. Thus, it is a suitable object for investigation by a case study (CEE countries that are members of the EU are included in the aforementioned sample, mainly due to the quality and availability of data). However, the insights gained in this way should not be generalized - they are related to the specific case of the Slovak economy in a given period. It can also be assumed that it is possible

to identify weaknesses in the growth and convergence factors that explain the specific trajectory of the Slovak economy.

3 Results and discussion

3.1 A view of the slowing convergence process

The assumption is that the Slovak economy is affected by the catch-up problem differently and more severely than other CEE5 economies.

First, the basic storyline: in the period after 2000 until the global financial crisis and recession of 2008–2009, the Slovak economy was successful in catching up with more advanced European economies. It was even one of the leaders in the catching-up process. For the sake of simplicity, this stage will be referred to as the “earlier period.” After the global crisis, with a little distance, comes the turning point. First, a halt in catching-up (or a temporary reversal of the process) is seen across the whole group of CEE5 countries. Then, after such a turning point, comes the problem from the Slovak perspective: the slowdown in catching-up is stretched out over time, although there are signs of a recovery in catching-up in the other countries of the group. This problematic stage is simplistically referred to in the following text as the “later period.” The turning point occurred around 2012–2013, when convergence slowed down considerably.

In most CEE countries, a break in the catching-up process is emerging during or after the global recession (2009). In some cases, this is a short-term phenomenon (in the Baltic economies). In the case of Slovakia (or, e.g., in Croatia), it is a longer-term phenomenon. In Fig. 1, it is clearly visible that Slovakia was very successful in the catching-up process during the period 2001–2008 (showing the steepest curve in Fig. 1a). However, a break then occurs, and the catching-up curve for Slovakia becomes almost horizontal thereafter. Meanwhile, the other countries in the group show signs of overcoming the problem from around 2015–2016 onwards. In other CEE countries outside the CEE5, the catch-up break is less explicit or more short-lived (Fig. 1b). The Baltic countries have substantially improved their position and, in some cases, have overtaken the CEE5 countries in the process of catching up to the level of the front-runners. The case of Estonia acts as an inspiration for the CEE5 countries in this regard as well.

When price level differences are eliminated (using a purchasing power standard, as shown in Fig. 1c), measured levels move higher and catch-up curves flatten. The development in the case of the SR (Slovak Republic) here looks like a serious setback. After 2015, there is a decline in relative levels, and convergence seems to have been replaced by divergence. The criticisms of the measurement of this indicator in the SR, mentioned in the literature review, should be taken into account.

The deterioration of the relative level of the SR vis-à-vis the others in the CEE5 group is well visible in Fig. 1d. Over the period 2013–2023, the relative level of the SR to all in the group has worsened.

Scale matters, but it does not change the nature of the problem. Fig. 2 shows the break in the catch-up trend from the Slovak perspective. Three measures are used: in euros, in purchasing power standards and in constant prices obtained by chaining volumes. This representation in three units of measurement is intended to avoid doubts associated with the measure (each of them has its own weakness in terms of its explanatory power). A strip separating the two stages is inserted in the graph to signal a break. In any expression, an adverse change after the breakpoint period is present. It can be seen when assessing the relative level of the Slovak Republic against both the EU and the CEE5 countries. Only the degree of deterioration is questionable (for some measurements, there is a significant slowdown, for others, there is a significant decline in the relative level to the given grouping of countries).

Slovakia is also an outlier when extending the coverage to the whole set of CEE countries (Fig. 3). When GDP per capita growth rates are combined over two equally long periods (earlier period and later period defined above), it has a distinctly extreme position; this implies a particularly pronounced difference in GDP per capita dynamics between the two periods. In the other countries, the dynamics were much more balanced.

The extreme position of Slovakia shows an extraordinary slowdown between the two periods. The very strong GDP per capita growth in Slovakia in the earlier period is combined with the weakest growth in CEE in the later period. This also demonstrates a specific feature of the SR (note the distance from other CEE5 countries). In the SR, the adverse break

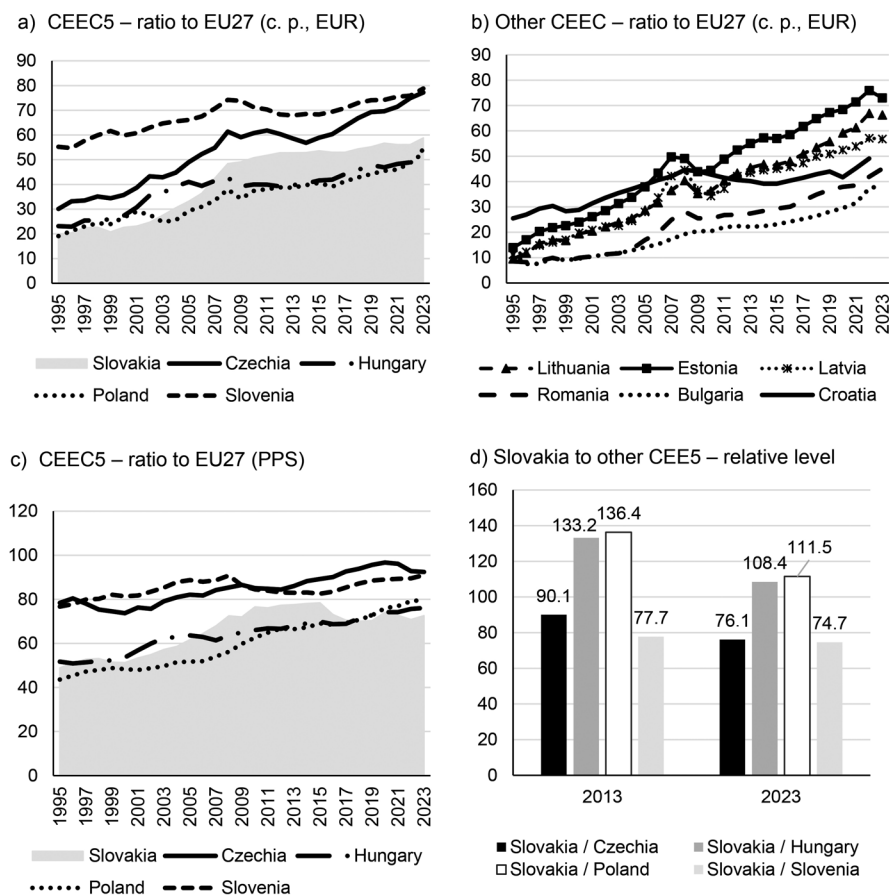


Fig. 1: Insights on convergence of GDP per capita levels

Note: C. p. – Current prices; relative level in Fig. 1d is calculated from data in current prices.

Source: own based on Eurostat data

is more explicit, which is consistent with the formulation of *H1*.

In order to avoid being affected by significant shocks, Tab. 1 compares not only two decades of development, but two equally long growth phases (periods unaffected by significant global recessions). In the earlier growth phase, real GDP per capita growth was strongest in the CEE group, but weakest after the break.

Both when comparing two decades separated by a break and when observing two growth periods, the conclusions are similar. Slovakia moved from the leading position in the earlier period to the lagging position in the later period. Thus, Slovakia was more affected by the catching-up break than most CEE economies. After such a preliminary and partial conclusion, the analysis goes on to explore the drivers of growth in an attempt

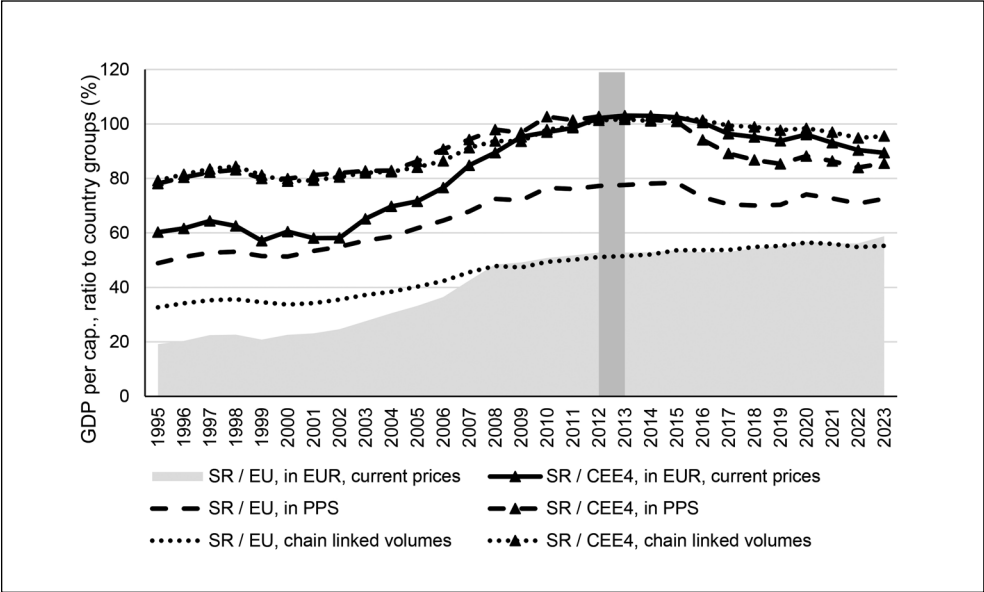


Fig. 2: Alternative views on convergence slowdown of the Slovak economy

Note: CCE4 = CEE5 except of Slovakia (average values for Czechia, Hungary, Poland and Slovenia); the inset vertical grey band represents the boundary between two qualitatively different periods.

Source: own based on Eurostat data

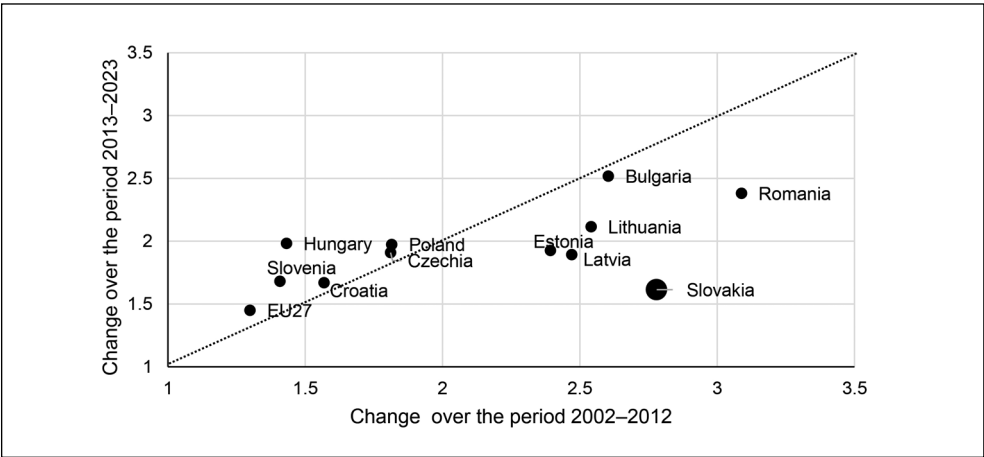


Fig. 3: Slovakia as an outlier (the combination of GDP per capita dynamics in the two ten-year periods)

Note: The value is the total change in GDP per capita in current prices (EUR), over the ten-year periods shown (index, start of period = 1).

Source: own calculations based on Eurostat data

Tab. 1: Confronting GDP per capita growth in decades and growth phases (total changes over the periods; %)

	Long-term periods		Growth phases	
	2002–2012	2013–2023	2002–2008	2013–2019
From data in current prices				
Slovakia	178.0	61.4	149.6	25.9
Czechia	81.1	91.0	80.3	42.3
Hungary	43.2	98.3	52.8	45.2
Poland	81.5	97.4	74.2	37.5
Slovenia	40.8	68.1	49.8	31.4
From data in constant prices				
Slovakia	57.0	24.0	49.5	19.9
Czechia	27.4	20.5	29.9	22.7
Hungary	16.7	39.1	21.5	28.8
Poland	49.1	47.0	33.6	30.2
Slovenia	16.5	28.7	28.9	21.1

Source: own based on Eurostat data

to examine which and to what extent they have weakened.

3.2 Examining the shape of the real convergence drivers – In which are the weaknesses?

Having sketched the picture of stalled catch-up in the previous section, the next section is devoted to the identification of weaknesses in each category of drivers (in production factors and in total factor productivity). The working hypothesis *H2* is that these weaknesses cut across all three driver categories.

The following approach is inspired by the work of Žuk et al. (2018), which examined the status of growth factors used by growth accounting (and the influences determining the status of these growth factors). The dynamics of capital formation (or its quantity per worker), the dynamics of labor inputs, and several influences that affect factor productivity will be considered.

Capital – A decelerated and strongly fluctuating accumulation

The extent of capital formation in relation to the size of the economy can be expressed in terms of the investment rate. The investment rate (expressed as a share of gross fixed

capital formation in GDP) in the Slovak Republic has been declining for a long time and is highly volatile.

It can be assumed that, in the interest of real convergence, the investment rate in Slovakia should be higher than in more advanced economies. However, this is no longer the reality. Since around 2012, the investment rate in the SR has not exceeded that of the EU27 (Fig. 4). The sharp increase in the investment rate in 2015 and 2023 reflects the uneven absorption of capital transfers from EU funds – it is a last-minute absorption after the end of the budget period. Such uneven absorption of EU funds, with massive last-minute rushed absorption, creates sharp fluctuations in investment parameters with peaks after the end of the corresponding budget period. Apart from these peaks, the rate of investment declines and lags behind. There is a significant difference with the trends in household's consumption: while household's consumption is converging towards the EU average, the level of gross fixed capital formation has stopped converging (Fig. 5).

When comparing within the CEE5, there is one specific feature of the Slovak economy: it is the only one where there has been no convergence in the level of gross fixed capital formation after 2012. And only in Slovakia

have the relative levels of consumption and capital formation reversed their positions over time (Tab. 2). In the earlier stages, the relative level (relative to the EU27) of capital formation was higher than the level of household's

consumption. In the last decade, they have reversed their positions. Household's consumption has converged towards the EU27 level, but capital formation has not. This may be problematic in relation to long-term growth.

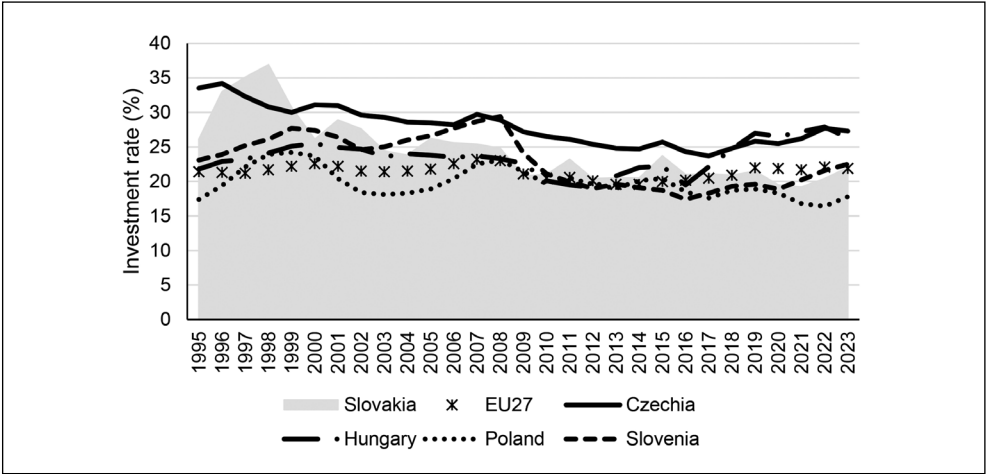


Fig. 4: Investment rate (share of gross fixed capital formation in GDP)

Note: Calculated from data in current prices.

Source: own based on Eurostat data

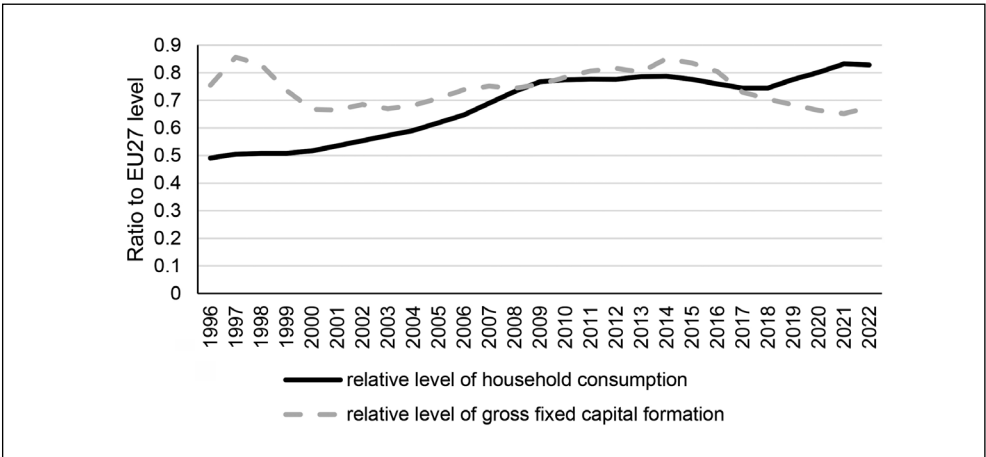


Fig. 5: Convergence of fixed capital formation level and household's consumption level

Note: Ratio Slovakia/EU27, smoothed by a moving average over three years, calculated from data in purchasing power standards (PPS); due to the significant volatility of gross fixed capital formation, the series are smoothed by a three-year moving average.

Source: own based on Eurostat data

Another indication of weakening capital accumulation dynamics is the unfavorable position of the Slovak Republic in the comparison of fixed assets stock dynamics. The relatively weak (second weakest in the whole CEE group) growth dynamics of the stock of fixed assets in the post-2012 period have limited the growth effects of capital accumulation. Thus, there is evidence of a weakening of capital inputs as measured through the flow variable (as an annual flow

relative to GDP), in relative levels of capital formation relative to EU27 levels, and in the value of the accumulated stock of fixed assets.

Labor – From labor force abundance to its shortage

The input “labor” has undergone a breakthrough development in three decades. The history of the labor market in the Slovak Republic offers an almost textbook example of the reversal

Tab. 2: Relative levels of household's consumption and fixed capital formation (share to EU27 level; %)

	1995	2002	2012	2023
Czechia				
Relative level of household's consumption	69.4	68.6	76.8	83.5
Relative level of fixed capital formation	122.8	104.4	106.2	115.2
Hungary				
Relative level of household's consumption	50.2	58.8	63.9	70.4
Relative level of fixed capital formation	52.6	69.0	63.3	91.5
Poland				
Relative level of household's consumption	46.7	59.2	74.5	87.5
Relative level of fixed capital formation	35.4	41.8	64.8	64.7
Slovenia				
Relative level of household's consumption	81.2	83.2	86.5	92.2
Relative level of fixed capital formation	82.9	95.6	78.5	93.5
Slovakia				
Relative level of household's consumption	47.2	56.0	78.3	82.2
Relative level of fixed capital formation	59.6	70.7	78.1	72.8

Note: Calculated from data in purchasing power standards (PPS).

Source: own based on Eurostat data

of two periods. In the first, the problem was insufficient job creation and mass unemployment; in the second, the problem was insufficient labor supply and the increasing scarcity of this production factor. Such a transformation from scarcity of job opportunities to scarcity of work-force implies initially an “employer's market” (with unlimited supplies of unused labor input). Subsequently (and rather abruptly, more sharply than in the other V4 countries), the situation explicitly changes to an employee market, with an increase in both the scarcity and the price of exploitable labor input.

Fig. 6 characterizes this transformation from several perspectives. Both the economic activity rate and the employment rate have been rising significantly over the last decade (2013–2023). And yet the difference between them has been shrinking. It has been easy to draw labor resources from widespread unemployment. Bringing the employment rate closer to the participation rate (or activity rate) implies that the employment rate has risen more through the removal of unemployment and less through the pulling in of the economically inactive segments of the population.

Further increases in these parameters face obstacles.

Both the employment rate and the economic activity rate have risen to record highs in the history of the Slovak Republic. In international comparison, these are normal levels, with a small margin existing (e.g., the employment rate in the Slovak Republic in 2023 was still the lowest in the V4 or CEE5).

The relationship between supply and demand in the labor market has changed fundamentally since around 2011–2013. The base for the formation of labor supply (the number of working-age people) has started to decline continuously. As of 2017, the population in this age cohort was declining by about 1% per year.

With a relatively strong growth in the number of employed (which is an imperfect proxy for labor market demand), this has inevitably meant increasing labor market tensions. The pandemic period has temporarily interrupted this trend, but due to unfavorable demographic trends, this is a long-term problem.

The balance of increases on the supply and demand side of the labor market (expressed relative to the number of employed, for comparability) has been in negative numbers over the last decade. The change in demand was a larger number than the change in supply. It is a state of deepening labor scarcity (Fig. 6d).

Moreover, the depletion of the available labor force has been associated with a decline

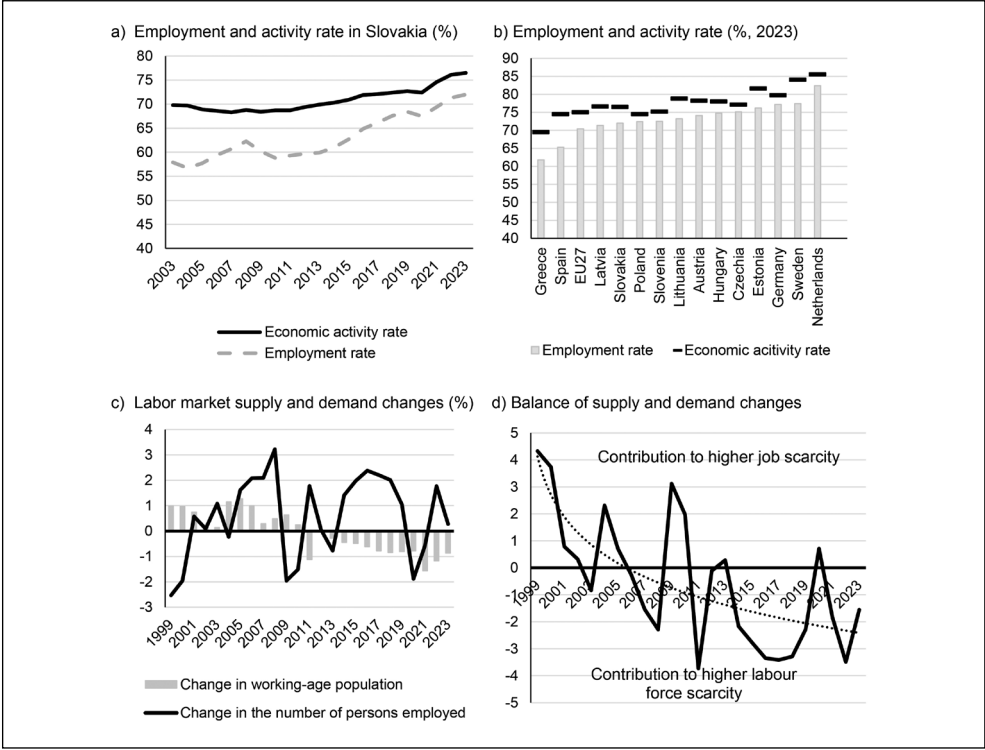


Fig. 6: Manifestations of rising labor market tensions

Note: Economic activity rates and employment rates are expressed for the 16–64 age cohort; labor market supply is represented by the number of working-age persons, while demand is represented by the number of employed persons, in both cases, this is an imperfect representation; balance of supply and demand changes – year-on-year change in the working-age population minus year-on-year change in the number of employed; Fig. 1d – this balance is expressed as a proportion of total employment (%).

Source: own based on Eurostat data

in the average number of hours worked per worker. This has intensified the problem: the volume of labor inputs is limited both by the scarcity of suitable labor force and by the decline in the number of hours worked per person employed. The decline in the number of hours worked per worker has been much more pronounced in Slovakia than in the other countries in the group (Fig. 7). This was facilitated by the policy of reducing hours during the pandemic, but it is also a longer-term trend. As a result of this trend, hourly labor

productivity is developing more favorably than per capita productivity. However, by reducing the number of hours worked, Slovakia loses the opportunity to compensate for its low hourly productivity (less productive economies partly compensate for lower productivity by working more hours).

The changed role of labor inputs has also brought about a change in the functional structure of income (Fig. 8). The share of wages in value added has changed fundamentally. In the earlier period (up to 2012 in this case),

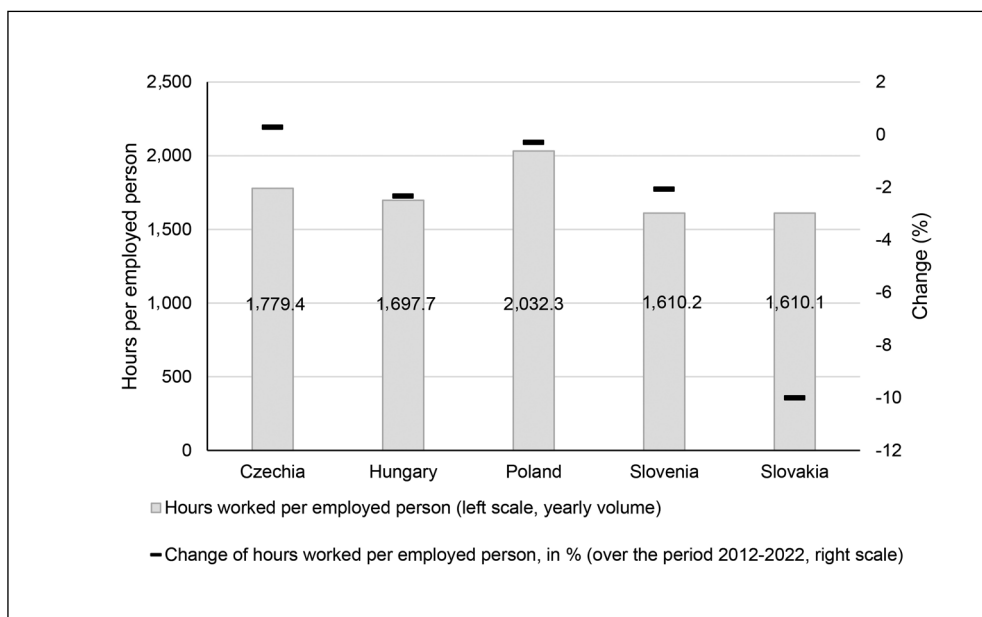


Fig. 7: Constrained labor inputs in Slovakia

Source: own based on Eurostat data

the share of wages in value added was lowest in CEE5, while in the later period it was the highest (Fig. 8a). Thus, the ratio between additional profits and additional wages changed markedly (Fig. 8b) – to the detriment of profits and in favor of wages. The sharp rise in the wage share of GDP may represent one possible manifestation of the “wage-driven growth” described by Stockhammer and Onaran (2013).

Such a structural change in incomes, driven by the increasing scarcity of labor, has a range of impacts. It shifts income in favor

of households and to the disadvantage of corporations. In fact, the Slovak economy has undergone significant income restructuring in this direction. This encourages consumption at the expense of corporate investment. It is a link by which labor shortages also contribute to weakening capital accumulation. Such a structural shift in incomes was also a supporting factor for consumption growth outpacing investment (it has already been shown above that household’s consumption converged much faster than capital formation).

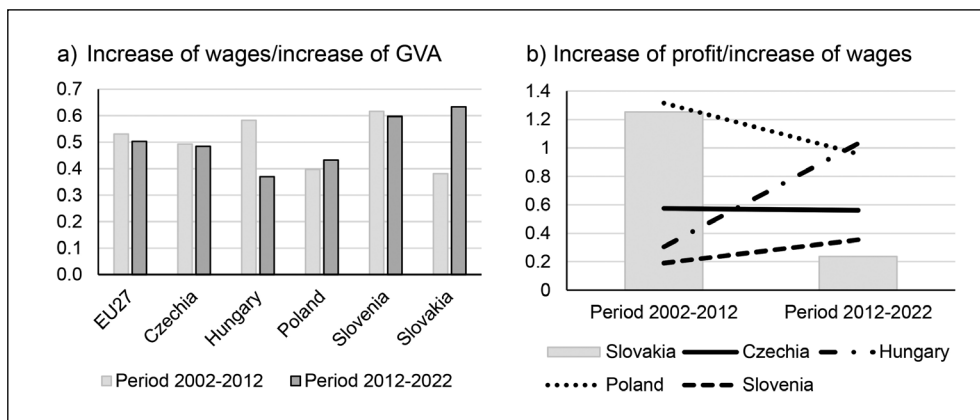


Fig. 8: Changes in the composition of the additional income

Note: National accounts categories are used; wages – compensation of employees, these are wages and salaries plus social contributions paid by the employer (this category also corresponds to labor costs); GVA – gross value added; profits – represented by the net operating surplus.

Source: own based on Eurostat data

Total factor productivity (TFP) – Neglected pillars

It is difficult to determine exactly what drives TFP. It is a mix of factors, not all of which are clearly quantifiable. One can approach them by looking at the mix of inputs that could increase TFP. Some represent research and development, others the quality of institutions or the capacities to undertake more intellectually demanding economic activities.

In the previous sections, the amount of capital entering the economy has already been considered. However, for productivity, it is also necessary to look at the structure or nature of this capital. The structure of assets acquired is indicative of changes in the structure of economic activities. In advanced economies, the dynamics of intellectual property products in the structure of fixed assets has increased significantly (these are research and development outcomes, databases, software and similar products). Slovakia is not only lagging behind in the acquisition of such highly prospective types of assets, but there is also no tendency to catch up with the parameters of advanced economies or other CEE countries in this category (Fig. 9; Morvay & Hudcovský, 2018). Commonly, capital deepening is calculated as the capital/worker ratio. However, in expressing specific capital

deepening, when, instead of total fixed capital, only the segment of capital needed for intellectually demanding activities is included in the calculation, the weakness of the SR stands out. Its weakness lies precisely in the capital component, which is essential for the new model of productivity and competitiveness. Slovakia thus has an unfavorable combination of a relatively weak change in total fixed assets and a very weak change in intellectual property products (Fig. 10). If the problem of weakened dynamics of total capital formation (weakening of the “capital” factor) was noted earlier, here it is possible to add to it a structural problem in fixed capital accumulation (which weakens TFP).

The quality of the institutional framework of the economy has an indirect impact on TFP. The impact of institutional quality tends to be underestimated; the quality of the institutions themselves is difficult to measure. Components of the WGI (Worldwide Governance Indicators) can be used, especially the regulatory quality and government effectiveness indicators. These factors are representative of the diverse mix of factors that can influence the manner and extent to which capital and labor are used.

The WGI data show that the quality of institutions in the Slovak Republic improved significantly during the culmination of the efforts

to join the EU (2004) and the euro area (2009). Subsequently, the quality of governance did not improve; rather, the relative position of the Slovak Republic deteriorated. The values showing the quality of institutions also include the values for Estonia, as a country with a successful on-going real convergence (Fig. 11).

Research and development is a prerequisite for strengthening TFP. Slovakia has been lagging behind in corporate R&D for a long

time, with no tendency to improve (Fig. 12). This is the factor that Chiacchio et al. (2018) used to explain the poor uptake of new knowledge by domestic firms in CEE.

In summary, the weakened TFP drivers are represented by three indicator groups. First, very weak accumulation of such assets that serve more intellectually demanding economic activities. Those activities should be at the core of prospective structural changes.

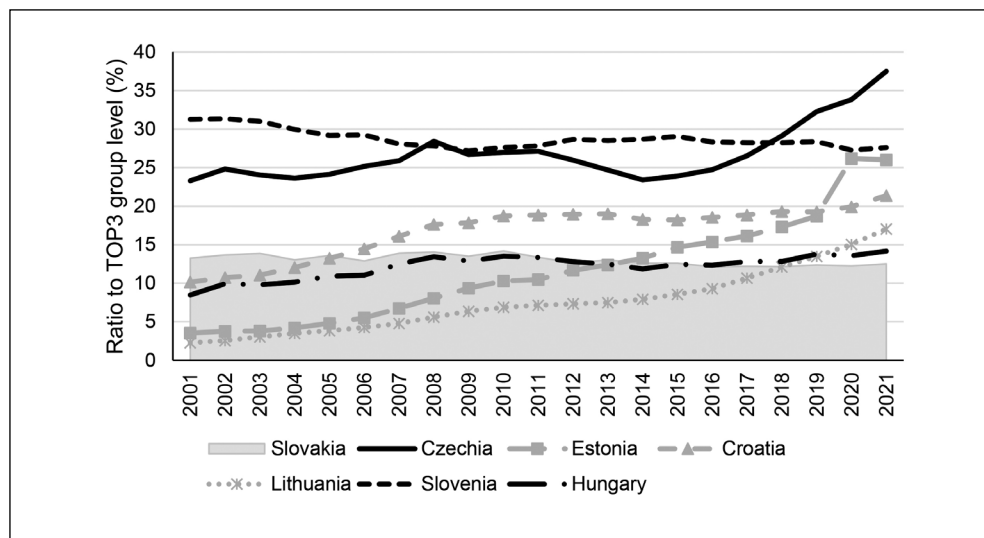


Fig. 9: Intellectual property products per worker (a specific capital deepening indicator)

Note: TOP3 is the average value in three EU countries with the highest value of capital per worker ratio (Denmark, Austria and Finland).

Source: own based on Eurostat data

The Slovak case of the structure of accumulated fixed assets does not correspond to the requirements of the new growth model and the creation of new factors of competitiveness. Second, significant lagging behind in the parameters of business R&D. This state of affairs is a blocker to the absorption of new knowledge in enterprises. And third, lagging behind in the quality of the institutional framework, specifically in indicators of regulatory quality or government effectiveness. Institutional quality has been improving under the pressure of economic integration. Subsequently, it has slowly eroded.

The identified gaps in the individual drivers of growth and convergence also imply scope for economic policy. Not all drivers of convergence in a small, extremely open economy can be easily influenced by economic policy.

In the context of weakening capital accumulation dynamics, the state can act directly through public investment and indirectly through stimulating private investment by improving the investment environment. When labor accumulation limits are encountered, it can act by improving conditions for labor immigration and for the compatibility of work and family caring (drawing parents with young children into

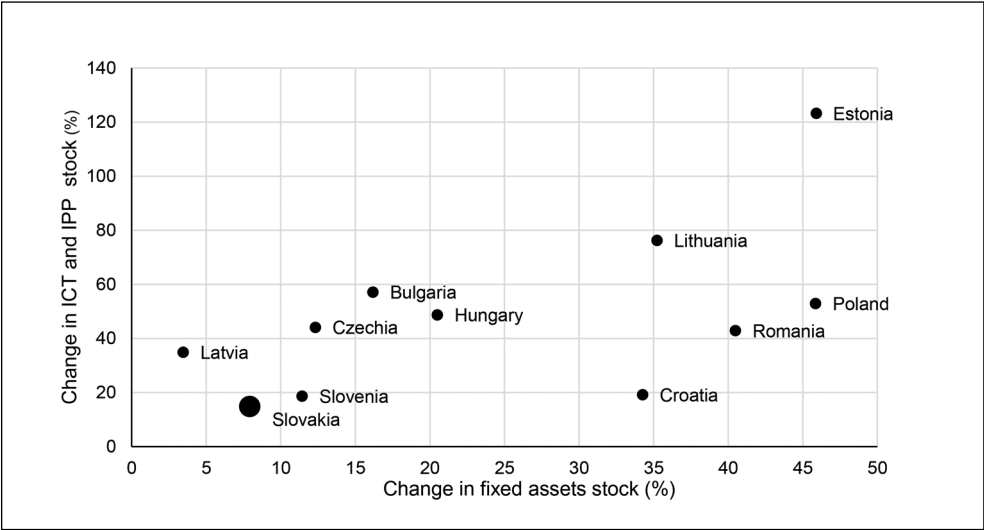


Fig. 10: Total fixed assets stock increase vs. ICT + intellectual property products stock increase (total change over the period 2012–2021)

Note: Calculated from data in fixed prices; ICT – information and communication technologies; IPP – intellectual property products.

Source: own based on Eurostat data

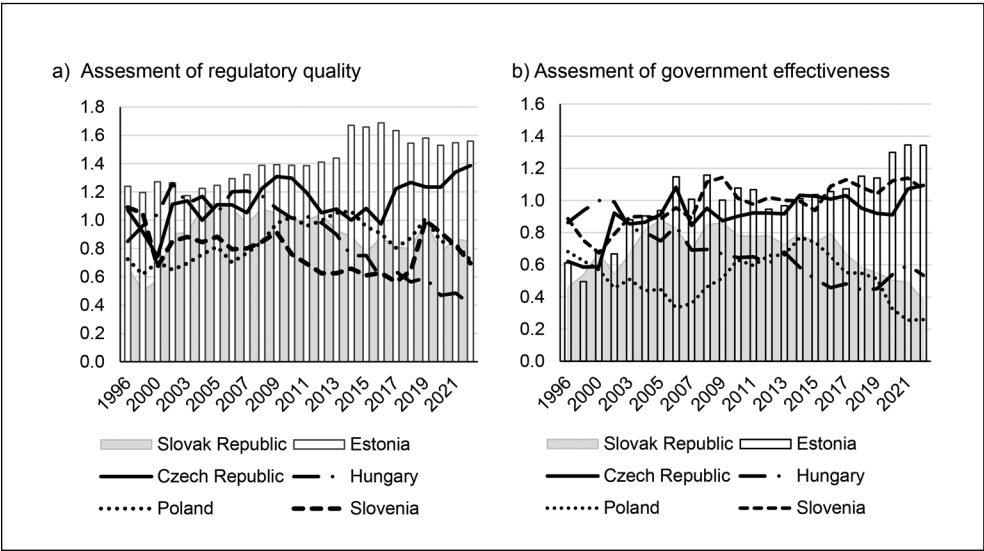


Fig. 11: Evaluation of institutional quality using WGI

Note: Extracted from Worldwide Governance Indicators.

Source: The World Bank

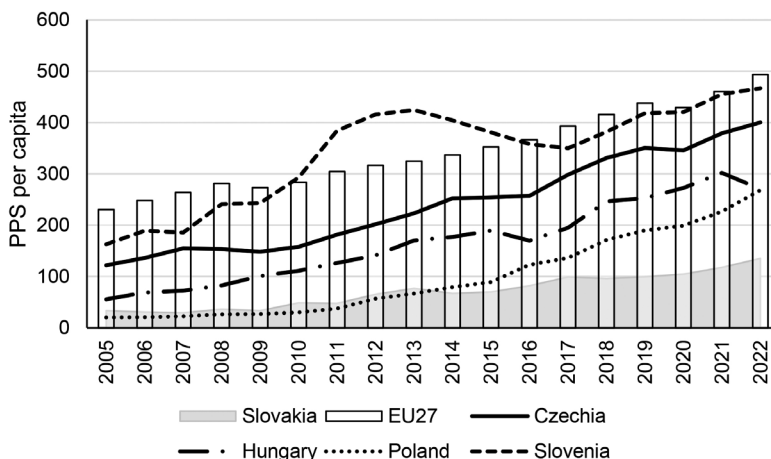


Fig. 12:

Business enterprise expenditure on research and development per capita (purchasing power standards per inhabitant)

Source: own based on Eurostat data

work). For factors promoting TFP, there are many instruments (because TFP is a strongly multidimensional problem). Thus, for factors affecting TFP, the state has more instruments (quality of education, industrial policy, support for innovation, a more attractive business environment, support for R&D), but cannot guarantee the transfer of these measures to TFP. In fact, each of the measures has a rather "loose" relationship with TFP, the state can only increase the possibilities for positive spillovers. However, as the weakened TFP supporting factors have been identified as the "weakest link in the chain," this is where policy action is required as a priority.

A complicating factor is the ongoing consolidation of public finances (from 2024 onwards), which has a restrictive effect on the dynamics of the economy. There are also several uncontrollable (or little controllable) risk factors, such as the rise of protectionism in foreign trade (Slovakia is extremely dependent on growth incentives from foreign trade), the demographic crisis or geopolitical tensions (thus reducing the investor attractiveness of the broad region).

3.3 Discussion

The analysis in this article contributes to the debate on issues of real convergence in Central

and Eastern Europe, and in Slovakia in particular, in two areas. First, the analysis concludes that the Slovak economy is demonstrably more affected by the problem of slowing down the catching-up process (confirmation of *H1*). The slowdown in catch-up, present since around the beginning of the 2010s, has in some periods gone through to its complete absence, which is a unique case in the CEE area. This confirms the arguments made in Vukov (2023), Gyorffy (2022), Slacik (2024) that the group of Central European economies is experiencing new manifestations of differentiation in the aftermath of the global financial crisis. Gyorffy (2022) found that CEE countries grouped themselves into two clusters during this period according to the direction of their growth model (Czech Republic, Slovenia and Estonia on a path towards knowledge-intensive, high quality growth, the others pursuing a growth model based on cost-competitiveness). Slovakia is in a unique position within these two groups, due to the lack of convergence with the more advanced ones. This paper has confirmed this and added to the argument: Slovakia represents a case of a more fundamental reversal in the dynamics of convergence and is significantly out of line with the trajectory

of the economies in the group. The previously fairly uniform growth pattern of the V4 economies, as used by Vukov (2023), has been disrupted; Slovakia has deviated significantly from this pattern.

Second, more importantly, the paper demonstrates that there are significant limits in all three types of production factors that block the catching-up process (confirmation of *H2*). The confirmed cross-cutting nature of the problem, stretching across production factors (with the most prominent role of TFP changes) is consistent with papers based on variants of growth accounting or development accounting, while complementing their arguments. Papers in this area commonly work with the problem of low capital accumulation and low capital deepening level as one of the barriers. In this context, Konya (2023) has demonstrated the substantial but significantly differentiated role of capital accumulation and capital deepening in real CEE convergence. To such considerations can be added the findings of our article on significant differences in the structure or quality of accumulated fixed capital. While capital accumulation and capital deepening are also interesting to analyze when looking at total capital, differentiating capital accumulation by certain categories of capital may be useful (given that there are specific types of capital in which Slovakia's economy lags behind, in particular, especially intellectual property assets). Similarly, Slacik (2024), in relation to the persistent capital stock gap, pointed out that there might be an even more important gap concerning the quality of capital.

The article notes Slovakia is exceptionally significantly lagging behind in those driving forces that should influence the growth and positive contribution of total factor productivity. These drivers are highly heterogeneous, TFP is not a directly measurable variable (it is residual) and is affected by a wide range of factors. It is frequently associated in the literature with a lack of R&D spending and a lack of innovation. It is frequently associated in the literature with a lack of R&D spending and a lack of innovation. But as the paper shows, the well-known problem of low R&D spending is accompanied by a deteriorating quality of the institutional environment. Such linkages compound the problem and, as the literature has shown, the dynamics of TFP have, over time, moved from being a driver of Slovak growth and convergence

to being a drag on these processes. In this respect, the findings of the paper are in line with those of Radicic et al. (2023), who argue that even closing the R&D spending gap may not have the desired effect on innovation. This may be due to an inappropriate, unmotivating institutional environment, deterioration in the quality of governance. Research and development cannot fulfil its role in fostering innovation and absorbing technological spillovers. The well-known fact from the literature that TFP is slowing down in both advanced economies and CEE, and that TFP growth in CEE is no longer as strongly pulled by external factors, should lead to a strong emphasis on its domestic support. The article proved that this has not been happening in the Slovak economy for a long time. There are some policy implications from the fact. If productivity is the critical link in the chain, then public policy activity should be related to it. This is despite the fact that this is a cross-cutting issue concerning all three factors of growth and convergence. Labor accumulation will only be able to play a very small role in promoting growth and convergence because of demographic factors (in earlier papers labor accumulation still had its positive, though not decisive contribution). Enhanced capital accumulation and enhanced capital deepening can play a positive role, it requires creating a more attractive environment for both foreign and domestic investment. But the most significant policy space opens up in identifying and promoting sources of productivity, similar to Konya (2023).

The neglect of productivity drivers can be particularly damaging to categories of smaller businesses. In this regard, Baksay and Nagy (2022) have shown a negative impact precisely in the SME category and thus on the deepening of duality in the corporate sector. Supporting productivity drivers can thus simultaneously support this segment and mitigate duality (which is particularly pronounced in the Slovak Republic). The interruption of the catch-up process has a variety of sub-causes, and this article could not and did not want to cover the whole complex problem. There remained a number of "white points" and challenges for further research.

A decline in the dynamics of investment activity was detected (e.g., expressed by a decrease in the investment rate). This is one of the likely causes of the slowdown in real

convergence, as the investment rate has fallen below the level in the target economies. But this is an oversimplification and there is an open question associated with it. It is not examined here what level of the investment rate is actually needed for real convergence to continue in the conditions of Slovakia. It can be assumed that there may be differences between CEE countries in this, depending on the structure and quality of investment (with different contributions to efficiency and productivity). There may also be differences depending on the position of economies on their catch-up trajectory (or depending on the distance from the so-called steady state in the convergence process).

The analysis works under the assumption that the quality of governance (as measured by the components of the Worldwide Governance Indicator) has an impact on productivity improvement opportunities. However, this is couched in vague terms. It would be desirable to examine this relationship in more detail and identify which elements of governance have the most significant relationship with productivity enhancement.

Preliminary findings (beyond the scope of this paper) suggest that the problem of convergence stagnation has an interesting regional picture and is associated with a narrowing of the traditionally very pronounced regional economic disparities. The challenge would thus be to explore the regional dimension of this problem.

An unaddressed topic in this article (and also a possible partial cause of the problem presented) is the impact of the introduction of the euro. If, for example, the euro was introduced with an overvalued domestic currency, some of the longer-term manifestations might be consistent with the pattern depicted here. It would also be consistent with the observed halt in the growth of Slovakia's share of global export markets (at levels around 0.38% according to Eurostat). This suggests the need to examine such a potential impact. Earlier analyses focusing on Slovakia's growth and convergence did not show any negative impact of the euro in this respect. However, this issue has resurfaced after a prolonged break in convergence.

It is questionable to what extent the case of Slovakia is a relevant threat to other CEE economies. Although the article is conceived as a study of the different trajectory

of the Slovak economy, it is worth noting this trajectory in the whole group of CEE countries. This is despite the fact that the results of the case studies should not automatically be generalized. All these countries have so far only partially achieved their strategic goal of catching up with the performance of more advanced European economies. There is therefore room to "replicate" the Slovak case of stagnation on this trajectory.

Conclusions

The article confirmed two assumptions: (i) the slowdown in the catching-up process in the second decade of this century could initially be seen as a phenomenon present across CEE countries, but subsequently differentiated. The case of the Slovak Republic is specific. The stalling of the catching-up process is longer-term and the break between the earlier period of successful convergence and the later period of its slowdown has been much more pronounced; and (ii) it has been shown that the stagnation of the catching-up process in Slovakia is related to weaknesses that stretch across the growth factors: the production factors labor and capital, as well as TFP. This is not a failure of one particular identifiable growth factor, but rather an across-the-board problem cutting across all three growth factors used in growth accounting. All three "engine valves" of the growth and convergence sources have reduced flow. Neither of these growth sources has escaped dampening effects. And, as the article has shown, these dampening influences have been more pronounced in Slovakia than in the other CEE5 countries.

Weaknesses of individual growth factors take different forms. In the case of capital and labor, it is possible to measure directly the weakening of the flow (in the case of capital) or the supply constraint (in the case of labor). But in the case of TFP, one can only demonstrate a lack of the forces that are supposed to strengthen TFP. The literature points to the weakening of the role of TFP as a crucial element in the slowdown in growth and convergence. And it is in the drivers affecting TFP where the very weak performance of Slovakia (when compared in CEE5) is present. These drivers do not face such a physical limit as, e.g., the labor factor (limited by demographics). As TFP-enhancing factors are the weak

link in the chain, this is where there is room for significant improvement.

It is unlikely that the problem presented here will be eliminated in the short or medium term; substantial measures would have to have been implemented in the recent past. There are no signs of a trend reversal in the drivers of convergence. Therefore, this phenomenon will continue to be an agenda for both research and policy discourse.

Acknowledgments: Supported by grant No. 1/0567/25 "Technological change and specific labour demand in the Slovak Republic" of the "VEGA Scientific Grant Agency."

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Role of investments in profit formation in the era of Industry 4.0: Case study of the Czech manufacturing industry

Martin Kral¹, Martina Hedvicakova²

¹ University of Hradec Králové, Faculty of Informatics and Management, Department of Economics, Czech Republic, ORCID: 0000-0003-2237-3564, martin.kral.2@uhk.cz;

² University of Hradec Králové, Faculty of Informatics and Management, Department of Economics, Czech Republic, ORCID: 0000-0001-9751-8292, martina.hedvicakova@uhk.cz (corresponding author).

Abstract: This study investigates the role of investments in shaping profitability within the Czech manufacturing industry between 2008 and 2022. Drawing on comprehensive industry-level data, we analyze the relationship between investment volume, efficiency, and profitability, particularly within the evolving framework of Industry 4.0. Our findings show that larger sectors with higher investment volumes generally achieve greater profitability. However, this relationship is non-linear: excessive investments can reduce efficiency, as reflected in declining added value per unit of investment. Regression analyses reveal that added value is the primary driver of profitability across manufacturing industrial sectors. Other factors, such as workforce size and the lagged effects of investments, exhibit only limited explanatory power. Furthermore, the study identifies inefficiencies arising from overinvestment, which may be attributed to market saturation, failure to fully realize economies of scale, and the unintended effects of government subsidy schemes. These results emphasize the importance of strategic investment planning that prioritizes long-term efficiency rather than short-term quantitative expansion. In the rapidly evolving context of Industry 4.0, firms must align their investment strategies with sector-specific conditions and technological demands to maintain sustainable competitiveness. This study illuminates the complex dynamics between investment behavior and profitability, offering valuable insights for managerial decision-making and economic policy formulation. It contributes to a broader understanding of how targeted investment strategies can enhance the performance of manufacturing sectors undergoing technological transformation.

Keywords: Industry, performance, key performance indicators, profit, investment.

JEL Classification: L60, G31.

APA Style Citation: Kral, M., Hedvicakova, M. (2025). Role of investments in profit formation in the era of Industry 4.0: Case study of the Czech manufacturing industry. *E&M Economics and Management*, 28(4), 64–78. <https://doi.org/10.15240/tul/001/2025-4-005>

Introduction

Performance evaluation of companies is extremely important for strategic decision-making and optimizing business processes. In the context of the rapid technological developments of recent years and the continuing tendency of companies to replace costly human labour

with technology, the evaluation of company performance and efficiency is becoming even more important. Many studies provide an overview of how investments in capital and technology affect the productivity of firms and industries (e.g., Acemoglu & Restrepo, 2018; Syverson, 2011). Meanwhile, the optimization

of capital structure is crucial to ensure the efficient and sustainable functioning of a company. Therefore, every firm must strive to maximize the efficiency and long-term sustainability of its financial resources (Vrbka et al., 2022).

In the modern industrial environment, evaluating the performance of companies is essential to assess their success and competitiveness in the market. Many different financial ratios are used to assess performance. However, the choice of appropriate indicators depends on the specific objectives and strategies of each firm. Investment and technological innovation play an important role in this process, especially in the context of Industry 4.0 and Industry 5.0, which transform traditional industrial processes through digital technologies and automation (Xu et al., 2021).

This article focuses on the analysis of the impact of investment on firm performance in the context of the technological transformation of Industry 4.0, with a specific focus on the manufacturing industry. Building on previous work (Hedvičáková & Král, 2021), we not only examine the interrelationship of the main economic indicators of different industries but also critically analyse the relationship between investment, value-added and profits. In doing so, we use both the absolute values of these indicators and their relative values (i.e., performance indicators), which are essential for efficiency assessment.

Industry 4.0 brings new technological innovations that have the potential to positively affect the efficiency of companies and the performance of entire industrial sectors. Increasing investment and technological innovation is expected to lead to automation, cost reduction and increased profitability. However, this assumption needs to be tested and analysed to see whether the expected changes are taking place. The key question is whether investment generally leads to more efficient operations or only to the expansion of industrial sectors, regardless of their efficiency. This question is important to assess whether there is a real industrial revolution or only a formal growth of industries.

In the analysis beyond the absolute values of economic indicators, we also use ratio indicators and their interrelationships. This approach allows us to identify the direct impact of investment and minimise the distortions caused by the different size of industries.

It is key to understanding how investment affects the economic performance of firms and the overall development of the industrial sector in the context of Industry 4.0. Theoretically, there may be excessive growth in investment due to various interventions (e.g., by the government), but without impacting profitability.

The study also looks at possible negative consequences. In the extreme case, the high profits of the past years could lead to further growth in current investment regardless of profitability and uncertainty in the output market (Liu & Jiang, 2012; Pinheiro, 2008). Moreover, if there are problems in production or sales (e.g., due to the economic crisis), there could be significant problems not only for firms but also for entire industries.

1 Theoretical background

A growing number of studies on Industry 4.0 highlight the importance of context in the transition to new technologies and their impact on industrial growth. Digitisation, automation and technological innovation are fundamentally transforming business ecosystems and influencing the strategic development of companies. In this context, companies are increasingly addressing the question of to what extent investments are a key factor influencing profitability in the context of Industry 4.0 (Audretsch & Belitski, 2021).

Profitability assessments are typically based on ratio indicators that allow for the analysis of overall business efficiency and productivity at the industry level. These metrics provide information on how efficiently the invested capital is used and its ability to generate returns (Abdo & Aboubakr, 2019). These indicators typically compare net profit to a certain baseline, which may be the total volume of investment or the scale of corporate activities. Other authors (i.e., Abdo & Aboubakr, 2019) state that the specific method of calculating the profitability indicator depends on the methodology used and the chosen base variable. In order to obtain relevant conclusions, it is necessary not only to perform the actual calculations of profitability indicators but above all to correctly interpret their values and identify the key factors that influence their development (Abdo & Aboubakr, 2019; Stejskal et al., 2016). Businesses typically reach the most accurate conclusions when they compare their results with previous periods or with industry averages (Abdo & Aboubakr,

2019; Knápková et al., 2017). Such an analysis allows not only to track long-term performance trends, but also to compare competitive positions and identify the factors that have the greatest impact on profitability.

Key performance indicators (KPIs) are measurable values that allow organisations to monitor and evaluate the effectiveness of their activities concerning set strategic objectives. KPIs allow us to identify whether activities are being carried out efficiently and help to optimize any resources involved (Meier et al., 2013). KPIs can be financial or non-financial and their proper selection is essential to optimize business processes and improve overall performance (Parmenter, 2020). Some of the most commonly used KPIs in the field of business performance include profitability, return on investment (ROI), labour productivity and customer satisfaction (Kaplan & Norton, 1996). Performance management research shows that the effective use of KPIs contributes to better resource allocation and the achievement of long-term competitive advantage (Verhaelen et al., 2021).

Building on this, the literature stresses the importance of selecting appropriate KPIs in effectively measuring and managing business performance, which can be challenging given the wide range of options available. To achieve maximum benefit, it is essential to select the optimal number of KPIs that are aligned with the organisation's strategic objectives. Studies highlight that too many KPIs can lead to information overload, while too few can result in inadequate coverage of key performance areas (Bititci et al., 1997; Bourne et al., 2000). Most studies recommend 10–20 KPIs for a comprehensive performance evaluation (Bititci et al., 1997). For small and medium-sized enterprises (SMEs), a lower number (8–12 KPIs) is often recommended (Garengo et al., 2005; Taticchi et al., 2010). Studies agree on key areas such as financial performance, process performance, customer satisfaction and innovation. Therefore, it is important to clearly define the main concepts of the decision-making process, such as strategic priorities, key processes and expected outcomes, and select the most appropriate KPIs based on these.

In industrial applications, a key consideration is the impact of the new production technology on the company's financial results, especially on EBIT figures. Capacity planning

determines the extent of investment when implementing a new technology. The literature offers different approaches to evaluate the efforts to migrate a production system to a new machine or technology. In addition to these costs, it is also necessary to consider operating costs such as salaries, materials costs and support function costs (Peters, 2015).

Some researchers developed a multi-criteria approach to assess the value of a new technology to a manufacturing system using an extended net present value calculation approach (Schuh et al., 2012). This valuation model allows for quantifying, measuring, and assessing the consequences of applying a specific technology and its value contribution to the manufacturing system. This provides a comprehensive assessment of the new technology in terms of its impact on production processes, efficiency and overall value to the production system. This approach provides an important framework for strategic decision-making in the area of investment in new technologies and contributes to optimising production processes and increasing competitiveness.

Industrial enterprises invest heavily with the goal of increasing profitability, which serves as a key indicator of efficiency and the optimal use of resources. The long-term sustainability of profits depends on the continuous channeling of resources into profitable investments. With increasing profitability, firms can redirect more capital into lucrative opportunities, thereby enhancing their financial stability and future profitability (Radjab, 2024).

In general, a company's profits are influenced by three main factors: physical capital, human capital (HC), and structural capital (SC). Profitability and productivity are further affected by these factors, combined with relational capital. Among these, physical capital has the greatest impact on overall firm performance (Xu & Li, 2022).

Studies suggest that costs are predominantly concentrated in physical assets, which negatively impacts profits (Reis et al., 2021). However, a higher proportion of intangible activities, compared to tangible ones, has a positive effect on profits across most manufacturing sectors, regardless of their technological intensity. Research conducted in the Czech Republic (Dvouletý & Blažková, 2022) confirms that firm performance is significantly influenced by total factor productivity.

It also highlights that large companies achieve considerably higher sales and EBIT compared to small and medium-sized enterprises (SMEs). Another analysis from the Czech Republic (Chandrapala & Knápková, 2013), which used return on assets (ROA) as the primary variable, revealed that firm size, sales growth, and capital turnover positively influence financial performance. Conversely, debt and inventory are associated with a significant negative impact on financial performance.

The findings of Valaskova et al. (2018) indicate that the most significant predictors for determining a company's potential failure are net return on equity, cash ratio, current ratio, net working capital, RE/TA ratio, financial debt ratio, and current asset turnover. These factors play a critical role in managing financial risks and influencing a company's profitability and long-term prosperity.

2 Research methodology

In this article, we build on previous research (Li & Chen, 2022) that examined the relationship between investment and profitability at the firm level, extending this approach to entire industries. We explore whether the positive relationship between investment and profit is influenced more by the size of these industries rather than by investment itself.

The research is conducted as a case study, utilizing comprehensive data from the manufacturing industry in the Czech Republic. The choice of the Czech Republic is based on the following reasons: (i) the Czech Republic is a mature, medium-sized democratic country, whose legislation and regulations align with the uniform policies of the European Union; (ii) the development of the Czech Republic's open and export-oriented economy is closely interconnected with global economic trends. This interconnection minimizes the influence of local determinants (e.g., political measures, national regulations, demographic factors), which play only a marginal role; and (iii) the Czech Republic is notable among EU countries for its strong reliance on the industrial sector. Manufacturing accounts for the largest share of total industry output (approximately 84%) and employs 92% of all workers in the industrial sector.

Given the importance of manufacturing, data from all manufacturing sectors are systematically collected at the national level. This extensive database enables comprehensive

analyses and the identification of significant relationships, minimizing the risks associated with partial data collection or potential inaccuracies, such as those arising from questionnaire-based surveys.

2.1 Data

This article is based on unique aggregate data on the Czech manufacturing industry for the years 2008–2022, obtained from the Ministry of Industry and Trade of the Czech Republic. For the purpose of this study, we primarily utilize data related to investment and Industry 4.0 for each section of the manufacturing industry, as listed below. This approach builds on previous research findings (Hedvičáková & Král, 2021; Pavelkova et al., 2021; Valaskova et al., 2018).

The dataset includes the following indicators: (1) revenues, (2) costs, (3) earnings before interest and taxes (EBIT), (4) investments, (5) value added, (6) number of employees, and (7) average wage. Together, these indicators provide insights into the economic efficiency and profitability of investment projects, supporting more effective decision-making processes.

There is no universal rule in the literature for selecting financial ratios to evaluate firm performance, as firms may rely on different sets of ratios depending on their unique circumstances. Additionally, scholars often differ in the ratios and methodologies they use to assess firm performance (Yousaf & Dey, 2022).

Data are available for each of the 21 main divisions and 84 subdivisions of manufacturing according to the CZ-NACE classification. The main divisions of the manufacturing industry are: (1) Manufacture of food products; (2) Manufacture of beverages; (3) Manufacture of textiles; (4) Manufacture of wearing apparel; (5) Manufacture of leather and related products; (6) Manufacture of wood, cork, wickerwork and straw products, except furniture; (7) Manufacture of paper and paper products; (8) Printing and reproduction of recorded media; (9) Manufacture of chemicals and chemical preparations; (10) Manufacture of basic pharmaceutical products and pharmaceutical preparations; (11) Manufacture of rubber and plastic products; (12) Manufacture of other non-metallic mineral products; (13) Manufacture of basic metals, metal smelting, foundry; (14) Manufacture of fabricated metal structures and fabricated metal products, except machinery and equipment;

(15) Manufacture of computers, electronic and optical instruments and equipment; (16) Manufacture of electrical equipment; (17) Manufacture of machinery and equipment n.e.c.; (18) Manufacture of motor vehicles (except motorcycles), trailers and semi-trailers; (19) Manufacture of other transport equipment; (20) Manufacture of furniture; (21) Other manufacturing.

In view of the current dynamic times, which have been marked by unexpected events in recent years (notably the COVID-19 pandemic), and the consequent rise in inflation, the nominal financial data are adjusted for inflation as measured by the consumer price index for each respective year. The base year (CPI = 100) was 2008, and consumer price indices published by the Czech Statistical Office were used to calculate the adjusted value.

2.2 Methods

The aim of this article is not only to determine whether the positive relationship between investment and EBIT can be approximated to whole industries but also to identify whether a higher share of investment also leads to higher profitability (efficiency), regardless of the size and type of industry.

We set out two basic research questions.

RQ1: Is investment a statistically significant factor affecting the level of profits of industries?

The purpose of this research question is to confirm the positive association between investment and profit levels. In this regard, we build on the findings of previous studies (Li & Chen, 2022; Ninh et al., 2018) and generalize the results of individual firms to manufacturing sub-industries using comprehensive data.

Several studies have examined the relationship between investment and profit levels in different industrial sectors. Research on the Brazilian industrial sector (Almeida et al., 2021) shows that the profit rate, which includes components such as output-to-capital ratio and capacity utilization, has both short-run and long-run positive effects on industrial investment, suggesting a significant effect on profit levels. In the context of the Indian manufacturing sector, the profit rate and its components also show positive impacts on investment, further supporting the idea that investment significantly affects profit levels (Basu & Das, 2017).

The verification of this assumption is based on several statistical methods. The basic

initial method is correlation analysis, based on which Pearson correlation coefficients and their statistical significance are determined. Since some investments take time to produce observable effects, this analysis includes a 1–5 year lag to account for the delayed impact. The selected time frame captures both short-term (1–2 years) and medium-term (3–5 years) outcomes, which aligns with existing empirical findings suggesting that investment benefits (such as increased productivity or institutional improvements) often emerge gradually (Sarkar & Zhang, 2013). Including this lag structure allows for a more comprehensive assessment of investment effectiveness over time. Following the correlation analysis, causal relationships between the sub-variables are identified. The amount of profit is estimated through multivariate regression. In this way, we determine the strength and predictive ability of the independent variables – value-added, active number of entities, average number of employees, average wage, current investment (Y-0), and investment realized in the last 1–5 years (Y-1, Y-2, Y-3, Y-4, Y-5). The regression coefficients were calculated using the stepwise method, which allows for each additional regressor to be added based on a significance test of the regression parameters, excluding those that are not statistically significant. In this analysis, however, only the first model in each step (containing a single explanatory variable) was selected for further interpretation. The selection was based not only on statistical significance, but also on the explanatory power of the variable, as reflected by the improvement in the coefficient of determination. This conservative modeling approach reduced the risk of multicollinearity and overfitting, as the contribution of each variable was explicitly assessed before advancing to the next step.

RQ2: Is there a statistically significant relationship between profitability and investments?

The purpose of this question is to see if it is possible to generalise a possible positive relationship between investment and profit (EBIT). There may be two reasons for a positive relationship. The first reason is the positive effect of investment per se, the investment will make production more efficient, reduce operating costs and increase profits (Dvouletý & Blažková, 2022; Ponduri et al., 2023; Reis

et al., 2021). The second reason may be the indirect effect of the size and type of firms and hence entire industries. Larger industries may take advantage of their position, invest more and make higher profits than smaller industries simply because they are larger or operate in a more profitable area.

To answer this research question (RQ2), it is, therefore, necessary to first eliminate the size factor. For this purpose, we have used ratio indicators (called performance indicators), separately for all sub-sectors of the manufacturing industry and all years under study in the period 2008–2022 (Hedvičáková & Král, 2021; Stejskal et al., 2016; Valaskova et al., 2018). Using the indicators calculated in this way, we then performed a correlation analysis and obtained the values of Pearson correlation coefficients, including their significance. To find and evaluate causal relationships, as in the case of absolute values of the selected indicators, we proceed to build a regression model.

All calculations were performed using statistical software (SPSS Statistics).

3 Results

The Czech manufacturing industry employs approximately one-fifth of the Czech economically active population. In 2022, a total of 1,095,138 employees will work in the Czech industrial sector, which represents 20.70% of the economically active population. The largest share in manufacturing (15.94%) was accounted for by the manufacture of motor vehicles, trailers, and semi-trailers. This sector also offered the highest average wage to employees in the given year, amounting to 1,269 EUR per month (in 2022, the average exchange rate was 24.565 CZK per EUR). Given its size, this sector also had the highest sales, costs, investment and value-added. In addition to the manufacture of motor vehicles, the manufacture of metal structures and fabricated metal products, the manufacture of machinery and equipment, the manufacture of electronic equipment and the manufacture of food products are also important for the Czech Republic, employing a total of approximately 612,000 people (58.18% of those working in industry). These five sectors also recorded the highest absolute real investment values in 2022 (approximately 4.27 billion EUR), corresponding to 4.49% of the total investment costs in the manufacturing industry.

3.1 Relationships of selected indicators and determinants of EBIT

Overall, the average share of investment in total costs in manufacturing has been between 4% and 6% over the long term, with the largest shares in the lower-employed industries – manufacture of basic pharmaceutical products and pharmaceutical preparations (7.70%), printing and reproduction of recorded media (7.23%) and manufacture of beverages (7.00%).

Based on correlation analysis, the basic relationships between the reported values of the different industries can be identified. The values of the Pearson correlation coefficients are shown (Tab. 1).

There is a strong positive linear relationship between all reported values. Larger industries (those with more employees, higher investment, and greater value added) tend to achieve higher profits. Based on correlation analysis, we could argue that if firms hire more employees, increase investment, raise wages, etc., they will also experience higher profits. However, this simplistic concept presents logical issues. For example, there is a strong and statistically significant correlation (0.803) between EBIT and costs. It would be illogical to claim that higher profits can be achieved with higher costs, on the contrary, costs reduce profits. Therefore, to address the research objective and questions, we proceeded with regression analyses to assess not only the strength of the explanatory variables but also to resolve potential logical inconsistencies.

The first step is to predict profit using the following variables:

- (i) Number of active business entities. We expect that a larger number of active businesses will contribute to higher profits for the entire industry;
- (ii) Average number of employees. We assume rational behavior of companies, meaning that employing a larger workforce will help achieve higher profits;
- (iii) Average wage. We assume that a higher average wage is associated with a higher level of qualification, which in turn contributes to profit generation;
- (iv) Added value. We expect that the production of goods with higher added value is linked to higher market prices, leading to increased profits;
- (v) Investments of various ages. Investments are associated with improved efficiency in the production process, which should result

Tab. 1:

Correlation analysis (inflation-adjusted values for manufacturing industry subgroups; 2013–2022)

	EBIT	Costs	Investments						Average wage	Average number of employees	Added value	Revenue
			Y-0	Y-1	Y-2	Y-3	Y-4	Y-5				
EBIT	1	0.803**	0.831**	0.810**	0.795**	0.792**	0.783**	0.754**	0.308**	0.620**	0.881**	0.823**
Costs	0.803**	1	0.937**	0.936**	0.933**	0.927**	0.926**	0.905**	0.290**	0.820**	0.940**	0.999**
Investments Y-0	0.831**	0.937**	1	0.966**	0.935**	0.914**	0.917**	0.905**	0.297**	0.827**	0.953**	0.941**
Investments Y-1	0.810**	0.936**	0.966**	1	0.963**	0.930**	0.929**	0.915**	0.308**	0.818**	0.948**	0.939**
Investments Y-2	0.795**	0.933**	0.935**	0.963**	1	0.963**	0.942**	0.914**	0.308**	0.817**	0.944**	0.935**
Investments Y-3	0.792**	0.927**	0.914**	0.930**	0.963**	1	0.964**	0.913**	0.306**	0.816**	0.937**	0.928**
Investments Y-4	0.783**	0.926**	0.917**	0.929**	0.942**	0.964**	1	0.951**	0.301**	0.818**	0.936**	0.927**
Investments Y-5	0.754**	0.905**	0.905**	0.915**	0.914**	0.913**	0.951**	1	0.285**	0.800**	0.911**	0.906**
Average wage	0.308**	0.290**	0.297**	0.308**	0.308**	0.306**	0.301**	0.285**	1	0.090*	0.283**	0.288**
Average number of employees	0.620**	0.820**	0.827**	0.818**	0.817**	0.816**	0.818**	0.800**	0.090*	1	0.888**	0.817**
Added value	0.881**	0.940**	0.953**	0.948**	0.944**	0.937**	0.936**	0.911**	0.283**	0.888**	1	0.947**
Revenues	0.823**	0.999**	0.941**	0.939**	0.935**	0.928**	0.927**	0.906**	0.288**	0.817**	0.947**	1

Notes: * $p < 0.05$, ** $p < 0.01$ (statistical significance levels); investments Y-0 indicate current investments, while investments Y-1 to Y-5 refer to investments made 1 to 5 years ago, respectively.

Source: own based on Ministry of Industry and Trade (2024)

in higher profits. However, their effects may manifest with a delay, so we consider investments of different ages (0–5 years);
(vi) Revenues. We assume that higher sales are linked to companies realizing economies of scale, where relatively cheaper production leads to higher profits.

The results of the regression analysis are presented in Tab. 2.

Based on the data analysis from individual industrial sectors within the manufacturing industry, we can conclude that 77.7% of the variance in profit values can be explained by a single variable – added

Tab. 2:

Regression analysis (explanation of EBIT, manufacturing industrial sectors; 2013–2022) – Part 1

Model		Unstandardized coefficients		Standardized coefficients	<i>t</i>	Sig.	<i>R</i> ²
		B	Std. error	Beta			
1	Constant	-76,996.427	100,752.439		-0.764	0.445	0.777
	Added value	0.303	0.006	0.881	52.123	<0.001	
2	Constant	429,996.263	68,637.887		6.265	<0.001	0.902
	Added value	0.538	0.008	1.566	64.237	<0.001	
	Average number of employees	-226.829	7.173	-0.771	-31.622	<0.001	
3	Constant	327,717.342	58,962.587		5.558	<0.001	0.929
	Added value	0.715	0.013	2.080	56.635	<0.001	
	Average number of employees	-241.866	6.193	-0.822	-39.052	<0.001	
	Investments Y-2	-0.652	0.038	-0.497	-17.003	<0.001	

Tab. 2: Regression analysis (explanation of EBIT, manufacturing industrial sectors; 2013–2022) – Part 2

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	R ²
		B	Std. error	Beta			
4	Constant	242,483.091	56,832.121		4.267	<0.001	0.936
	Added value	0.701	0.012	2.039	57.915	<0.001	
	Average number of employees	-252.805	6.009	-0.859	-42.071	<0.001	
	Investments Y-2	-0.576	0.037	-0.439	-15.401	<0.001	
	Number of active business entities	103.363	11.300	0.090	9.147	<0.001	
5	Constant	254,888.392	54,440.288		4.682	<0.001	0.941
	Added value	0.731	0.012	2.128	60.270	<0.001	
	Average number of employees	-251.849	5.755	-0.856	-43.761	<0.001	
	Investments Y-2	-0.454	0.039	-0.346	-11.747	<0.001	
	Number of active business entities	96.792	10.849	0.084	8.922	<0.001	
	Investments Y-5	-0.292	0.035	-0.195	-8.455	<0.001	

Note: Investments Y-0 indicate current investments, while investments Y-1 to Y-5 refer to investments made 1 to 5 years ago, respectively.

Source: own based on Ministry of Industry and Trade (2024)

value. The second most important variable explaining profit is the number of employees. In contrast to the correlation analysis, the number of employees has a negative effect on profit. Therefore, one of the assumptions – that larger industrial sectors (measured by the number of employees) achieve higher profits – was not confirmed. The third variable, which slightly increases the determination index, is investments with a two-year delay. However, the paradox lies in the fact that this effect on total profit in the current period is also negative. This could be explained by factors such as technological obsolescence, where past investments lose their effectiveness over time as technology evolves. Another possible explanation is market saturation, where additional investments yield diminishing returns once the market has reached its optimal capacity. Additionally, if past investments were misallocated or excessive, they might not have generated the expected benefits, leading to a negative effect. On the other hand, the number of active business entities, as the fourth predictor, shows a positive relationship with the total profit of the respective industrial sector. Nevertheless,

the determination index increases only marginally with each additional variable, indicating that the effect of the additional variables on the overall model quality is negligible.

Given that added value is the strongest determinant of profit, we applied the same regression analysis procedure to the value-added indicator. The statistically significant variables explaining the amount of value added are presented in Tab. 3.

Although all other variables in each of the models are statistically significant, the added value is predominantly determined by current investments (Y-0), with the determination index of model 1 being 0.888. The additional regressors are no longer necessary for the model, as they only slightly improve its quality (e.g., the number of employees increases the model quality by just 1.9%).

Based on the above analyses, we can confirm that the relationship between investments and profits can be applied to entire industrial sectors. Therefore, there is a clear causal connection: a higher volume of investments is crucial for the growth of added value, and added value, in turn, is an indispensable factor for the growth of profits.

Tab. 3: Regression analysis (explanation of added value, manufacturing industrial sectors; 2013–2022)

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	R ²
		B	Std. error	Beta			
1	Constant	1,745,736.301	197,499.333		8.839	<0.001	0.888
	Investments Y-0	3.717	0.045	0.942	83.056	<0.001	
2	Constant	1,400,905.208	165,661.608		8.456	<0.001	0.922
	Investments Y-0	2.150	0.089	0.545	24.267	<0.001	
	Investments Y-4	1.903	0.097	0.438	19.516	<0.001	
3	Constant	561,428.311	153,503.681		3.657	<0.001	0.941
	Investments Y-0	1.679	0.083	0.426	20.345	<0.001	
	Investments Y-4	1.502	0.089	0.346	16.952	<0.001	
	Average number of employees	220.958	13.454	0.247	16.423	<0.001	
4	Constant	589,211.697	150,247.988		3.922	<0.001	0.943
	Investments Y-0	1.495	0.086	0.379	17.416	<0.001	
	Investments Y-4	0.874	0.132	0.201	6.613	<0.001	
	Average number of employees	212.251	13.236	0.238	16.036	<0.001	
	Investments Y-3	0.834	0.132	0.203	6.302	<0.001	
5	Constant	428,127.861	149,697.937		2.860	<0.001	0.946
	Investments Y-0	1.526	0.084	0.387	18.094	<0.001	
	Investments Y-4	0.888	0.130	0.205	6.856	<0.001	
	Average number of employees	184.719	13.758	0.207	13.426	<0.001	
	Investments Y-3	0.868	0.130	0.211	6.689	<0.001	
	Number of active business entities	178.368	29.655	0.051	6.015	<0.001	

Note: Investments Y-0 indicate current investments, while investments Y-1 to Y-5 refer to investments made 1 to 5 years ago, respectively.

Source: own based on Ministry of Industry and Trade (2024)

3.2 Performance indicators relations

We then used a set of performance indicators to assess the effectiveness of investments and the performance of industries. With the help of appropriately set performance indicators, we were able to eliminate potential problems caused, for example, by the size of individual industries (e.g., the possibility that larger companies and industries realize greater profits due to their size). However, the effectiveness of investments in such a case may or may not be high. Here, we can refer to the principles of profit maximization and the long-term development of costs for larger companies.

The growth of companies, and the expansion of industries are associated with higher management costs and usually also an increase in bureaucracy.

The specific performance indicators are based on the findings mentioned above and describe the link between investments, costs, added value, profit and the number of employees. Since a direct causal relationship between older investments and current profit has not been proven, we only consider current investments Y-0 in the following sections: (i) share of investments in total costs (%); (ii) investments per employee (thousands CZK); (iii) EBIT per investment (%);

- (iv) EBIT per employee (thousands CZK);
- (v) EBIT in proportion to total costs (%);
- (vi) added value in proportion to investments (%);
- (vii) added value in proportion to costs (%); and
- (viii) added value per employee (thousands CZK).

Despite the positive relationship between investments, added value and profit as separate indicators, this relationship cannot be confirmed for ratio indicators based on the correlation analysis performed (Tab. 4).

Tab. 4:

Correlation analysis (inflation-adjusted indicators, manufacturing industrial sectors; 2013–2022)

	Investments Y-0/total costs	Investments Y-0/employee	EBIT/ Investments Y-0	EBIT/ employee	EBIT/ costs	Added value/ investments Y-0	Added value/ costs	Added value/ employee
Investments Y-0/total costs	1	0.619**	-0.273**	0.086*	0.260**	-0.476**	0.350**	0.089*
Investments Y-0/ employee	0.619**	1	-0.157**	0.518**	0.165**	-0.499**	-0.168**	0.629**
EBIT/investments Y-0	-0.273**	-0.157**	1	0.495**	0.612**	0.606**	0.165**	0.281**
EBIT/employee	0.086*	0.518**	0.495**	1	0.636**	-0.025	0.038	0.893**
EBIT/costs	0.260**	0.165**	0.612**	0.636**	1	0.134**	0.600**	0.430**
Added value/ investments Y-0	-0.476**	-0.499**	0.606**	-0.025	0.134**	1	0.272**	-0.104**
Added value/costs	0.350**	-0.168**	0.165**	0.038	0.600**	0.272**	1	-0.039
Added value/employee	0.089*	0.629**	0.281**	0.893**	0.430**	-0.104**	-0.039	1

Notes: * $p < 0.05$, ** $p < 0.01$ (statistical significance levels); investments Y-0 indicate current investments.

Source: own based on Ministry of Industry and Trade (2024)

Higher and statistically significant positive values of correlation coefficients mainly occur for indicators weighted by the number of employees (investment, added value, profit). From this perspective, we can state that higher investment values lead to higher added value and profit across industrial sectors of different sizes, as measured by the number of employees. However, when evaluating these sectors based on the amount of costs, this mutual connection weakens by about half (e.g., the correlation between the share of investment in total costs and profitability is only 0.260).

Moreover, if we consider the above values comprehensively, we can draw some interesting conclusions. For example, industrial sectors with a higher share of investment in total costs paradoxically achieve lower added value in relation to investment (-0.476) and also lower profit per investment (-0.273). This suggests that a high level of investment can lead to inefficiencies, which in turn result in lower profitability. This partial conclusion is also supported by the negative relationship between investment and the number of employees: the higher

the investment per employee, the lower the added value per investment (-0.499), and the lower the profit per investment (-0.157).

These relationships can also be observed in the partial graphs (Fig. 1). While it is practically impossible to confirm any relationship trend between some indicators (e.g., the share of investment in total costs and profitability), for others, the trend is quite clear (e.g., added value per investment and profit per investment), as shown in Fig. 1.

For the sake of completeness, following the correlation analysis, we have further built upon the findings above and created a multivariate regression model. The objective of this model is to estimate the added value per investment (since added value determines profit) by using the volume of investments, specifically, the share of investments in total costs and the amount of investment per employee. This enables us to test whether a higher volume of investments is associated with at least a comparable level of efficiency, or whether the added value per investment decreases as the share of investments increases (thus,



Fig. 1: Performance indicators relations (QQ-RR graph)

Source: own based on Ministry of Industry and Trade (2024)

the efficiency of each additional investment cost diminishes). The results of the regression analysis are shown in Tab. 5.

The results of the compiled models provide relatively weak informative value. The determination index reaches only 0.294 when considering both explanatory variables. More than 70% of the variance in the added value per investment indicator is thus explained by other phenomena. Despite this limiting factor, the original

assumption cannot be supported, namely that the more companies invest, the higher the profit they will achieve. On the contrary, it turns out that higher shares of investments in total costs paradoxically reduce the efficiency of investments, as the added value per investment decreases. If we take into account the positive relationship between added value and profit, we can argue that an “unnatural” increase in investments would result in lower profit per

Tab. 5:

Regression analysis (explanation of added value per investment, manufacturing industrial sectors; 2013–2022)

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	R ²
		B	Std. error	Beta			
1	Constant	7.093	0.128		55.355	<0.001	0.249
	Investments Y-0/employee	-0.009	0.001	-0.499	-16.102	<0.001	
2	Constant	7.719	0.153		50.523	<0.001	0.294
	Investments Y-0/employee	-0.006	0.001	-0.332	-8.673	<0.001	
	Investments Y-0/costs	-19.474	2.764	-0.270	-7.046	<0.001	

Note: Investments Y-0 indicate current investments.

Source: own based on Ministry of Industry and Trade (2024)

investment, as well as lower added value. In such a scenario, both companies and entire industries could face unexpected challenges, which might be exacerbated by economic fluctuations and demand-side problems.

4 Discussion

The results of the analysis suggest that the amount of investment alone is not a sufficient indicator of its efficiency. While larger companies and industrial sectors show higher absolute profits, the correlation between investment and profitability indicates that their investment strategies may not always be efficient. The key question, therefore, remains: what causes this phenomenon? One possible explanation is the monopoly or oligopoly position of large companies. Companies that control a significant portion of the market can achieve high profits due to their market power rather than investment efficiency. Monopolistic or dominant companies often have the opportunity to set higher prices than in a competitive environment, which allows them to maintain profitability without having to maximize the use of invested capital. A different perspective is offered by study of Bonanno et al. (2023), where the authors concluded that firms engaged in productive innovation show a higher motivation to improve their efficiency and, above all, profitability. The profit persistence coefficient is positive and modest. The findings of Alshehadeh et al. (2024) confirm that investment opportunities have a robust, positive impact on profit sustainability. Results of Yadav et al. (2022) show a negative link between firm size and

profitability, and a positive link between growth and profitability, suggesting that while growth boosts profits at first, increasing size eventually leads to declining efficiency.

Another factor that can affect investment efficiency is government subsidies and incentives. While public funding is intended to stimulate growth, it can sometimes lead to inefficient investments if firms prioritize political goals over market-driven decisions. This distortion occurs when firms invest in areas that align with government priorities, rather than focusing on those that would maximize long-term profitability. The political implications of this are significant. Government interventions can distort the normal investment decision-making process by prioritizing industries or sectors that are politically favored, irrespective of their economic viability. This political interference may divert resources away from more productive uses, leading to suboptimal investments that could reduce overall economic efficiency. For example, when firms are reliant on government funding, they may prioritize short-term projects to meet political goals or secure further subsidies, rather than focusing on long-term sustainable innovation or efficiency improvements. Additionally, the allocation of subsidies can create competition for funding, where firms with better lobbying capabilities may gain access to more financial resources, despite potentially weaker investment strategies. Other research (Dai & Cheng, 2015) highlights that there is a certain threshold beyond which further increases in public subsidies will no longer increase a firm's investment in R&D. A minimum

level of public subsidies is needed to stimulate a firm's private spending on R&D. Once public subsidies exceed a certain threshold, they can begin to partially or completely replace private investment. This suggests that there is an optimal level of subsidies that could improve efficiency, making it crucial for policymakers to carefully calibrate their support.

Large firms often benefit from economies of scale, which allow them to reduce costs per unit of output. However, as a firm grows, there are often increasing costs of management, administration, and bureaucracy, which can reduce investment efficiency. If lower administrative and procedural costs are achieved, growth is supported by increasing investment, reducing unemployment, stimulating labor supply, and improving total factor productivity (Spruk & Kovac, 2019). In specific sectors such as heavy industry or technology-intensive manufacturing, investment is a key prerequisite for maintaining long-term competitiveness. Although these expenditures often require significant financial resources, their future benefits and returns are often difficult to estimate due to high levels of uncertainty and rapidly changing market conditions.

For these reasons, it is important to assess not only the volume of investments but also their actual return and efficiency. This suggests that future research should focus on a deeper analysis of the conditions under which investments actually lead to higher profitability and on identifying factors that may disrupt this relationship.

Conclusions

A more detailed assessment of industrial sectors using ratio indicators (such as the share of investment in total costs, value added per employee, and profit per investment) revealed that the relationships between these indicators are not always straightforward. Strong positive correlations mainly appear for indicators weighted by the number of employees, suggesting that increased investment can boost profit and added value. However, the link between investment share in total costs and investment efficiency is weaker, with some cases showing a negative correlation (e.g., -0.476 for added value relative to investment).

The analysis found that a higher share of investment in total costs does not necessarily lead to higher efficiency or greater added value per investment. Excessive investment can even reduce added value and profitability. This

emphasizes the importance of carefully considering investment strategies in light of long-term returns and economic fluctuations. The optimal investment level is crucial for balancing growth and efficiency in industrial sectors.

Our findings are consistent with other studies, such as Basu and Das (2017), which show that profitability influences investment decisions both in the short and long term. Companies with higher profitability tend to invest more, driven by both current economic conditions and long-term strategies. Basu and Das (2017) also highlight that profit share and the capacity-to-capital ratio positively impact investment. In contrast, the capacity utilization rate has a more complex effect, potentially signaling the need for expansion, but also leading to reduced investment due to risks like congestion or restructuring.

Žáková Kroupová et al. (2022) further support these findings by demonstrating that in the Czech food processing industry, profitability is more closely linked to efficiency than to market power. Their analysis suggests that firms with greater market power tend to achieve lower profitability, whereas smaller firms are generally more efficient and profitable (Žáková Kroupová et al., 2022). Similar conclusions were drawn by Mendes et al. (2012), who found that maintaining profitability in the Brazilian manufacturing industry depends on the efficient use of resources to meet or exceed international technological standards.

These results suggest that while investment is vital for growth, its effectiveness depends on factors such as cost structure and firms and industry size. An unconsidered increase in investment can lead to decreased value added and profitability, posing risks for companies and whole industries. Thus, it is crucial to choose investment strategies based on real returns to avoid potential issues during economic downturns or declining demand.

Acknowledgments: *The research was supported by the internal project SPEV – Economic Challenges and Opportunities within Industry 4.0 and the Societal Concepts of 5.0 and 6.0, 2025, University of Hradec Králové, Faculty of Informatics and Management, Czech Republic.*

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Promoting reverse logistics decisions using a new hybrid model based on deep learning and failure mode and effects analysis approaches

Kamelia Ahmadkhan¹, Abdolreza Yazdani-Chamzini², Alireza Bakhshizadeh³, Jonas Šaparauskas⁴, Zenonas Turskis⁵, Niousha Zeidyahyae⁶

¹ Niederrhein University of Applied Sciences, Faculty of Industrial Engineering, Germany, ORCID: 0009-0002-4448-7618, kamelia.ahmadkhan@hs-niederrhein.de;

² Islamic Azad University, South Tehran Branch, Young Researchers and Elite Club, Iran, ORCID: 0000-0001-5594-7726, abdalrezaych@gmail.com;

³ Islamic Azad University, South Tehran Branch, Iran, ORCID: 0000-0002-0190-8374, abakhshizadeh@ymail.com;

⁴ Vilnius Gediminas Technical University, Faculty of Civil Engineering, Department of Construction Management and Real Estate, Lithuania, ORCID: 0000-0003-3685-7754, jonas.saparauskas@vilniustech.lt (corresponding author);

⁵ Vilnius Gediminas Technical University, Faculty of Civil Engineering, Institute of Sustainable Construction, Lithuania, ORCID: 0000-0002-5835-9388, zenonas.turskis@vilniustech.lt;

⁶ Shahid Beheshti University, Faculty of Management and Accounting, Department of Industrial and Information Management, Iran, ORCID: 0000-0002-8396-2218, nioushayahyae@yahoo.com.

Abstract. The problem of reusing and recycling the returned products plays a crucial role in mitigating waste. Therefore, authorities must make the best decision in such situations. However, this problem is a paradoxical decision because different components often conflict with each other, which can impact the decision-making process. The proposed framework uses sentiment analysis algorithms to help decision-makers adopt the best reverse logistics decision strategy based on customer feedback. The framework provides a procedure for extracting, categorizing, and analyzing customer opinions. It strategically decides in reverse logistics to increase profit, efficiency, and customer satisfaction while reducing the returned products, costs, and waste. The framework has a high potential for utilization in a wide range of industries, so the probability of a biased opinion resulting from the limitation of taking into account a specific location or time is significantly diminished. This paper employs a big data mining approach to optimize the decision procedure in reverse logistics by using social media data based on customer satisfaction. To demonstrate the capability and effectiveness of the proposed framework, a real case study based on the Apple Notebook, a branch of the electronics industry, is illustrated. Consequently, a separate sentiment analysis based on a recurrent neural network (RNN), a deep learning approach, is fulfilled for notebook features and models. The framework can determine the most appropriate disposition decision in reverse logistics. Furthermore, a failure mode and effects analysis (FMEA) procedure was employed to make some suggestions about Apple.

Keywords: Reverse logistics, social media, recurrent neural network (RNN), failure mode and effects analysis (FMEA), sentiment analysis.

JEL Classification: M11, M21, C45, D81.

APA Style Citation: Ahmadkhan, K., Yazdani-Chamzini, A., Bakhshizadeh, A., Šaparauskas, J., Turskis, Z., & Zeidyahyae, N. (2025). Promoting reverse logistics decisions using a new hybrid model based on deep learning and failure mode and effects analysis approaches. *E&M Economics and Management*, 28(4), 79–98. <https://doi.org/10.15240/tul/001/2025-4-006>

Introduction

Electrical and electronic equipment (EEE) has revolutionized daily life in communication, entertainment, and personal productivity. This industry uses devices such as laptop computers, notebooks, and smartphones to make information flow active for more people. However, these devices consume a tremendous amount of energy and resources. This problem is a potential disaster for the economy (Delavar et al., 2022), geopolitical, geochemical (Yousefi et al., 2020), and social sectors (Fitzpatrick et al., 2014). In addition, the ICT industry is recognized as rapidly progressing in high-tech; computational memory and power capacity are ever-changing processes. A drawback of rapid high-tech progress is the risk of underutilized lifetimes and premature obsolescence (Proske et al., 2016).

Consequently, many EEE products may pollute the environment (Jayaraman et al., 2019). Different environmental impacts connected to the EEE products can be observed from the enormous embodied energy related to manufacturing. In addition, the risk of human and ecological health effects that may result from releasing toxic materials during end-of-life management should be considered (Meyer & Katz, 2016). Therefore, some strategies should be made to extend the productive life of resources through recycling, remanufacturing, repair, reuse, and long-life design (André et al., 2019).

Such measures are valuable ways of diminishing the environmental impact of EEE products (Eygen et al., 2016). One of the most appropriate strategies is to extend the lifetimes of EEE by using a reusing or recycling process (Kasulaitis et al., 2015). However, employing consumers' opinions can make a practical decision to improve the competitive advantage. On the other hand, consumers' opinions can lead to diminishing the returned products. Manufacturers usually use a reverse logistic (RL) decision to increase profits and efficiency and decrease risk and losses simultaneously. RL, an approach for economic and social development, proposes a set of actions, procedures, and resources to enable the collection and restitution of solid wastes to the business sector for reuse in either its cycle or any other production cycles or for environmentally appropriate final disposal (Ghisolfi et al., 2017; Lindqvist, 2015).

The literature review shows a substantial gap in making a proper decision on the returned products. Therefore, it is necessary to develop a systematic procedure to analyze consumers' opinions and make an RL decision based on the output of users' reviews. Likewise, this procedure can identify the root cause of the returned products and make some suggestions about returning products. However, producers make different ways to meet the consumers' needs in order to adapt their products to market requirements. To achieve this aim, several techniques are employed, including consumer feedback in retail stores, direct/indirect interviews, market research, market and competitor monitoring, and CRM methods (Stefanou et al., 2003). In addition, sellers cannot provide an appropriate atmosphere to obtain consumers' complaints/praise. Consequently, they cannot receive comprehensive feedback for future analyses.

On the other hand, social media and interconnecting platforms play a significant role in decision-making. Based on the statistics, 30% of the data generated is constituted by social media platforms (Raghavendra & Mohan, 2019). Different social media platforms with massive amounts of data, such as Twitter, can reflect users' reviews in a reliable environment. Because of the characteristics of Twitter that can always be accessed without any temporal or spatial restriction and can be connected easily and quickly if only the Internet has been connected, users unceasingly create small and large content ranging from their mere trifles to social issues and disasters (Yoo et al., 2018). This platform uses an application programming interface (API) to provide affordable access to data. The primary purpose of this research is to investigate how users' reviews can affect RL decisions and how these decisions change customers' opinions from purchasing a new product to one that is reused. This paper uses a data analysis approach based on social media to connect the notebook supply chain with a customer-based process. An approach based on customers is more effective, significantly increasing customer satisfaction (Agrawal et al., 2016). Proper decisions on returned products in RL can lead to a decrease in waste, an increase in long-term profits, and a focus on customer-centric RL. The limitations of location and language are ignored in the paper. The proposed model uses the Twitter streaming API to extract data from Twitter.

A pre-processing approach is conducted to separate several sections of the tweet. Likewise, a sentiment analysis (SA) (Bu et al., 2024) based on the recurrent neural network (RNN), a deep learning approach (Mienye et al., 2024), is implemented in positive, negative, and neutral tweets. RNNs are among deep learning techniques that process data from initial input to final output. RNNs employ feedback loops to loop information back into the network during the computational process. This differs from a feed-forward neural network, which can connect inputs and enable an RNN to process historical data. After implementing the sentiment analysis, a procedure for determining the optimization rate in RL disposition decisions is conducted. In the final step, recommendations based on the FMEA procedure are proposed for better decisions in facing customer-centric RL. This paper has different advantages and benefits: (i) developing a model based on the SM data analysis that automatically connects consumers' opinions with RL disposition decisions. This model not only diminishes returned products and hazardous waste but also increases profit and customer satisfaction; (ii) the enhancement of classification accuracy by using classification algorithms; (iii) the development of experimental analyses for making better decisions in coping with customer-centric RL; and (iv) the introduction of the proposed framework for future

research directions to extend for different kinds of industries.

The rest of the paper is organized as follows. The following section surveys the literature review, including consumer satisfaction, social media, and customer behavior. A description of the proposed model is illustrated in the third section. An illustration is presented and described in the fourth section. Customer satisfaction parameters are identified in the fifth section, and RL optimization is analyzed. The following section expresses the model's potential capabilities. Lastly, the results are concluded, and future directions are outlined.

1 Theoretical background

The literature focuses on various topics, including social media (SM), reverse supply chain/ reverse logistic (RSC/RL), customer satisfaction, and SA. In addition to increasing profit and customer satisfaction and simultaneously decreasing waste and returned products, material and money streams are more investigated in the RL process (Kurilova-Palaisaitiene et al., 2018; Shaharudin et al., 2015). For better understanding, the information streams relating to reuse/recycle strategies are ignored in the RL decision-making processes. Although consumer opinion has recently been considered, this process makes it uncomfortable for consumers to give their views on retail stores.

Tab. 1: Categorization of the reverse and forward SC studies – Part 1

Topics	Papers	Methods
Inventory forecast and control	(Raut et al., 2021)	Big data analytics
	(Ma et al., 2021)	Game theory and Bellman's continuous dynamic planning theory
	(Dai & Liu, 2020)	Qualitative analysis and fuzzy evaluation
	(Yu et al., 2021)	Organizational information processing theory
	(Kappelman & Sinha, 2021)	Stochastic optimization methods
Product feedback (design/redesign)	(Gbadamosi et al., 2020)	Big data design options repository
	(Cuomo et al., 2021)	Big social data
	(Li, 2021)	Field-programmable gate array
	(Sfafi & Aissa, 2020)	DECIDE
	(Vialeto & Noro, 2020)	Cluster analysis
	(Liu et al., 2020)	Big data analytics
	(Dong et al., 2020)	Fuzzy techniques

Tab. 1: Categorization of the reverse and forward SC studies – Part 2

Topics	Papers	Methods
Transportation and shipment	(Lian et al., 2020)	Big data
	(Kaffash et al., 2021)	Big data algorithms and applications
	(Tzika-Kostopoulou et al., 2024)	Big data algorithms
	(Neilson et al., 2019)	Big data and analytics
	(Balbin et al., 2020)	Data mining
	(Gohar et al., 2018)	Big data analytics
Reverse logistics	(Campos et al., 2020)	Structural equation modeling
	(Afra & Behnamian, 2021)	Mixed-integer linear programming

Source: own

Therefore, most researchers have found a suitable SM alternative. Some data mining techniques, including deep and machine learning and dictionary-based approaches, can extract the anticipated information from SM (Ma et al., 2019). In this paper, an approach based on machine learning is selected. The SM analysis in SC management has been prevalent, although rarely used in RL (Mishra & Singh, 2018). Since this research investigates reverse logistics, the most common studies from the literature point of view are categorized and described in Tab. 1. The main forward and reverse supply chain studies are listed in Tab. 1. Tab. 1 categorizes studies into four key topics. Likewise, the techniques applied

by researchers and insights from the papers are described.

2 Research methodology
2.1 Recurrent neural network (RNN)

A recurrent neural network (RNN), a branch of artificial neural networks (ANN), is widely applied for deep learning, natural language processing, and pattern recognition (Apaydin et al., 2020; Hewamalage et al., 2021).

An RNN has a high potential to recognize the patterns involved in the dataset and employ these patterns to predict the following situation. An RNN is a powerful tool for developing complex models by simulating neuron activity in the human brain (Wang et al., 2019). This

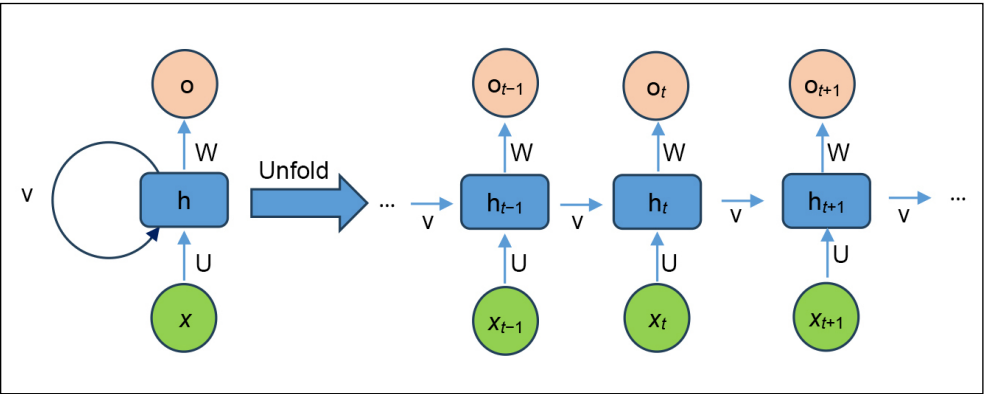


Fig. 1: An RNN diagram

Source: own

network can significantly formulate situations where context is critical to estimating a result. Since RNNs employ a feedback loop to process a set of information, resulting in a final output, they are different from other kinds of ANNs. This feedback loop is known as memory (Moghar & Hamiche, 2020).

An RNN, ideally suited for machine learning problems, can remember its input with the help of an internal memory. This network has been known as a robust algorithm in deep learning. Fig. 1 depicts an RNN network and its components. The figure (unfold state) shows that the input state is in the bottom, the hidden state in the middle, and the output state in the top. The network weights are indicated as U, V, and W. RNNs can be used in language

models to predict the next word in a sentence. RNNs have different advantages, including the capability of handling sequence data, handling inputs of varying lengths, and storing or memorizing historical information (Pang et al., 2020; Zhang et al., 2021).

With varying architectures, different types of RNNs have been developed (Hewamalage et al., 2021; Lin et al., 2021). Many-to-one is a famous type of structure. In this case, many inputs from different time steps produce a single output. Fig. 2 shows how an input vector (X_t , X_{t+1} , X_{t+2}) produces a single output (y_t). These networks are applied for emotion detection and sentiment analysis, in which the class labels depend on the sequence of words.

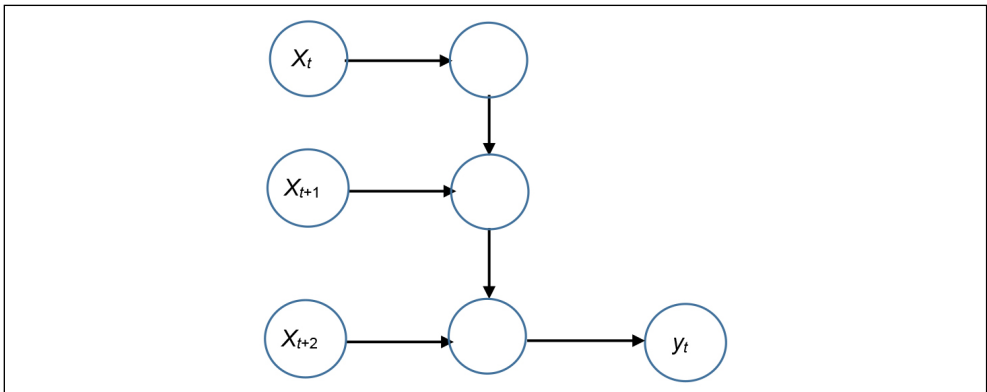


Fig. 2: Many-to-one structures

Source: ownes

2.2 Failure modes and effects analysis (FMEA)

FMEA, developed in the 1940s, is a systematic procedure for identifying the possible failures in a design, manufacturing, and assembling process (Ceylan et al., 2023; Hatefi & Balilehvand, 2023; Sumrit & Keeratibhubordee, 2025; Xue et al., 2024). This technique is known as a standard process analysis tool. This method identifies any failure or error that affects the consumer and studies the consequences of any failure. Failures are ranked by a combination process based on their consequences, frequency, and easy detection. The FMEA process proposes some preventive measures

to eliminate or reduce the failures with the highest priority. The FMEA procedure can be used from the beginning of the earliest conceptual design stages to the end of the product's life. A correctly implemented FMEA effort has some significant benefits as follows (Ahmadi et al., 2023; Ceylan, 2023):

- (i) this method provides a systematic approach to conducting a successful design;
- (ii) this method analyzes potential failure mechanisms and their impact on system operations;
- (iii) the technique can provide a procedure for early identification of a failure, which may be critical to mission success;

- (iv) the method evaluates the effect of the proposed changes on mission success;
- (v) this method can be a base of fault-detection devices;
- (vi) this method can be an essential evaluation for early testing planning.

2.3 The content analysis

Based on the basic concepts of the systems, the confidence is between zero and one, and the polarity indicates a value between zero and one. Polarity indicates opinion positivity, and confidence indicates certainty of polarity (Dashtipour et al., 2016). $Confidence_{Total}$ and $Polarity_{Total}$ can be defined as follows:

$$Confidence_{Total} = \frac{\sum Confidence}{n} \quad (1)$$

$$Polarity_{Total} = \frac{\sum Polarity}{n} \quad (2)$$

where: $n = 3$ indicates the number of approaches. When trained with emoticons, NB, SVM, and MaxEnt techniques have at least an accuracy rate of 80%. The $Confidence_{Total}$ and $Polarity_{Total}$ thresholds would not change from being at least 0.8 since the equal-weighted voting mechanism is employed in this research. Therefore, when the value of $Polarity_{Total}$ is more than 0.8, it receives a positive rate; when the value is less than 0.8, it receives a negative rate; otherwise, it receives a neutral rate. Likewise, it is only analyzed when the value of $Confidence_{Total}$ is greater than 0.8.

2.4 The Twitter data survey

Several problems, including information extraction, data gathering, and database analysis, must be taken into account while the SM dataset is analyzed. These three issues are expressed on Twitter. Data extraction from Twitter is accomplished by using a keyword list. The list uses tweeter API to gather the information from tweets. Twitter streaming API collects 1% of Twitter's existing dataset. In this paper, a specific set of keywords accomplishes the data extraction process from tweeter (for 91 days).

Each tweet, containing several main objects, can be known as a single code. After posting, each tweet has two situations, including retweeting and quoting. The first reflects a retweet object with similar characteristics that can be added to the tweet object. The second

demonstrates a quote object with similar characteristics that can be added to the tweet object. All these objects have identical characteristics, whereas the values are entirely different. To prevent redundant data, these tweet objects are merged. This is the first step in defining alpha parameters. The alpha is obtained for every tweet to reflect the user's interest. The tweets with the most negligible value will be removed under the merging process. The alpha value can be defined as follows:

$$\alpha = N_r + N_q + N_{rp} + N_u \quad (3)$$

where: N_r – the number of times a tweet has been retweeted; N_q – the number of times a tweet has been quoted; N_{rp} – the number of times a tweet has been replied to; and N_u – the number of times Twitter users have liked a tweet.

2.5 Proposed framework

The proposed framework based on SM data analytics is used to obtain knowledge about the notebook's problems. Analyzing end-users' positive/negative sentiments helps managers gain a competitive advantage, optimize the decision process, and add value. A text preprocessing step can be considered to eliminate the invaluable data imposed by SM data (Zhang et al., 2018).

The limitation of language is ignored in this study to maximize accuracy by translating all non-English texts into English. The proposed framework uses a general text preprocessing step to simplify knowledge extraction. The model uses an RNN to identify the satisfaction or dissatisfaction statement. Then, an FMEA analysis is accomplished to recognize the most critical risks and their relative weights for making the best decision strategy for future improvement. Fig. 3 illustrates the proposed framework with two key features. The first indicates the keyword identification, and the next indicates the content analysis and the SM data analysis. For a better understanding, Fig. 4 illustrates how the proposed approach is fulfilled.

As depicted in Fig. 3, a model-feature matrix (keywords matrix) is constructed by placing features in columns and models in rows (Tab. 2). After constructing the keywords matrix, a consumer opinion matrix is generated based on the translated tweets. Then, the SA approach determines consumer opinion and makes

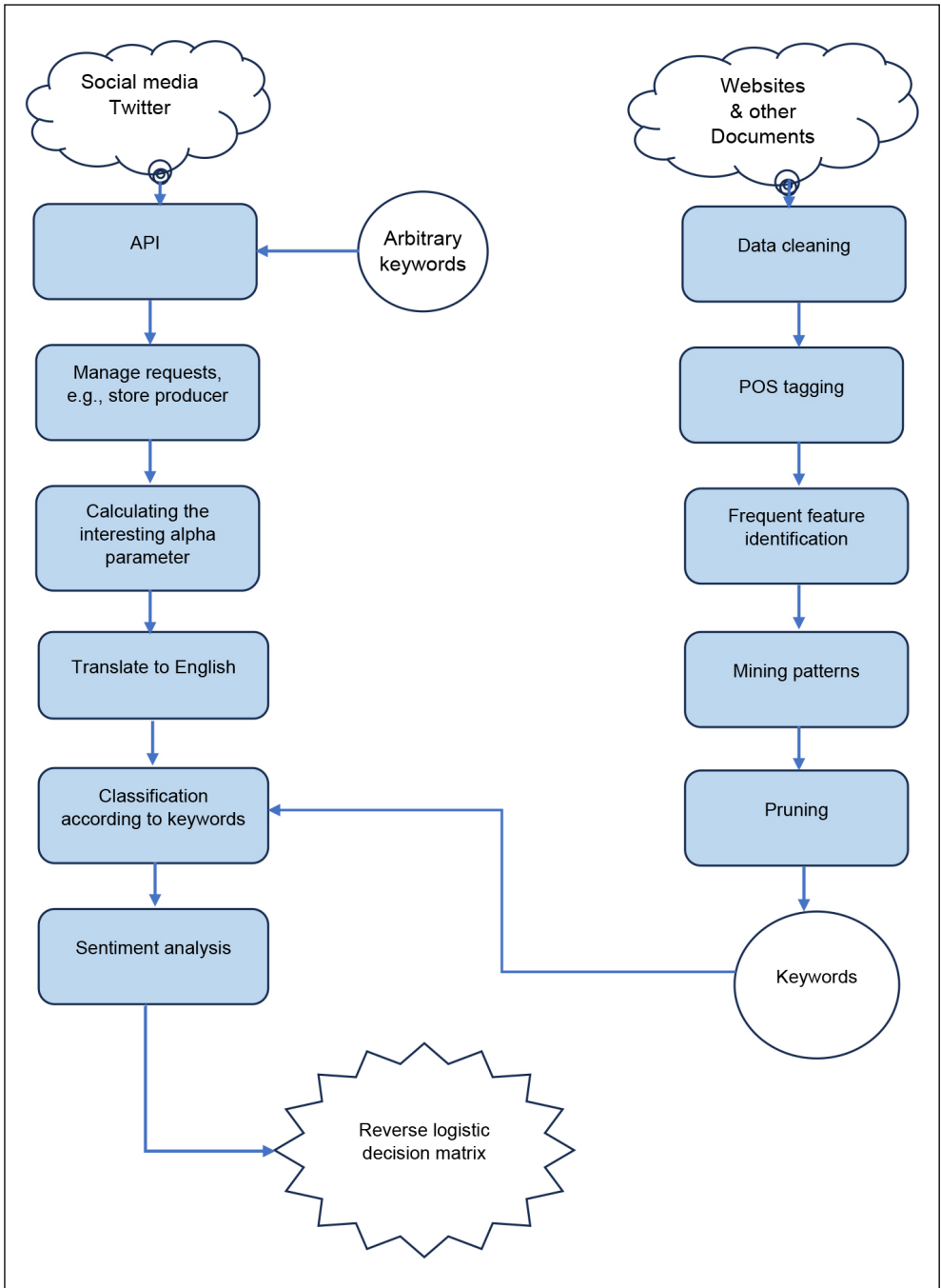


Fig. 3: Proposed framework

Source: own

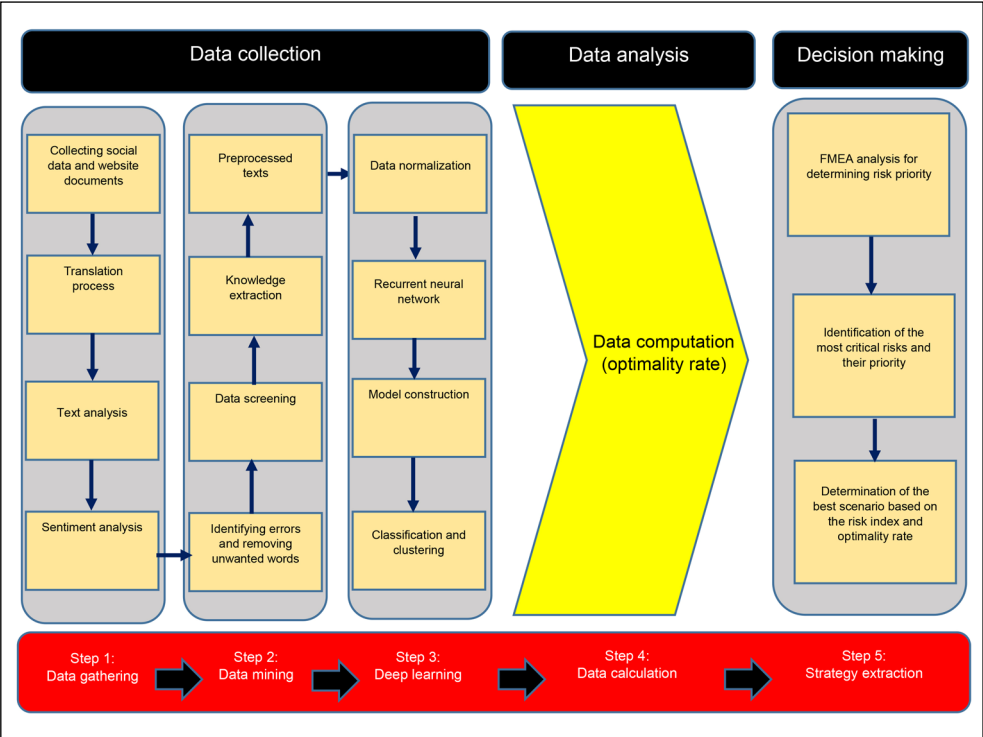


Fig. 4: The proposed process

Source: own

an SA matrix. Finally, recommendations for transferring the standard RL into a customer-based RL are presented based on the SA matrix. Also, an FMEA analysis is conducted to identify the most critical risks for remedying the destinations.

3 Implementation of the proposed framework

A considerable amount of data is widely available on Twitter, so more than 500 million tweets are added daily. Therefore, the analysis of all Twitter data is practically impossible. To overcome such a problem, many studies have used the data gathered during a limited period. As seen in Fig. 3, a systematic process should be conducted to receive a logical response from the model. The optimality gained in various notebook models is calculated for every notebook's direct feature. For every MacBookPro model, the optimality

gained in various MacBookPro features is computed.

3.1 Collecting data

Firstly, the keywords about the notebook industry are gathered and stored in a database. The keywords are MacBookPro. These terms and their corresponding translated words are case-insensitive. API communication protocol uses the JSON format to send the data to the requester. As described above, each received tweet can be divided into four tweet objects and stored in a specific database. Based on the results, 38,178,278 tweets were established, of which 9,770,412 were retweets (26%). In the notebook industry, the number of retweets reflects ordinary occasions. 71% of the tweets (26,981,744) are obtained as the quoted tweets. When a consumer releases a new opinion, the users show their sentiment through quoted tweets.

Tab. 3 presents the notebook as the only keyword extracted from the database; 38,178,278 tweets are analyzed. English, Japanese, and Portuguese are the most popular languages, while English is at the first level. The raw dataset needs to be prepared for SA. The invaluable tweets, including HTML links and handles, are removed.

Afterward, tweets are categorized. Finally, SA is carried out, and polarity and confidence rates are obtained. Some conditions are implemented to increase the accuracy of the method. Firstly, a tweet with fewer than 25 characters is deleted after removing links and handles. Secondly, tweets with fewer than five texts are also deleted. Thirdly, the tweets with $\alpha \leq \alpha_0$, $\alpha_0 = 10$ are not analyzed, as the most frequent opinions are only investigated. By eliminating

the tweets with $\alpha \leq \alpha_0$, the unpopular tweets are not investigated, and the probably biased alpha parameter is ignored. The alpha value may be biased for the last days of data gathering. Likewise, $\alpha_0 = 10$ is a random value to show that the desired popularity level has been achieved.

In addition, different keywords filter out the tweets to only consider those related to the notebook. As depicted in Fig. 5, the character lengths of tweets vary from 0 to 280 characters (before using any exclusion criteria). The most popular character length is 65–70 characters (388,587 tweets), whereas the least standard size is 5–10 characters (9,762 tweets). Tweets concentrate on advertising and selling notebooks. Some properties, such as notebook cases and batteries, are ignored.

Tab. 2: Constructing the SA matrix

		Features				
		F_1	F_2	F_3	...	F_m
Models	M_1	x_{11}	x_{12}	x_{13}	...	x_{1m}
	M_2	x_{21}	x_{22}	x_{23}	...	x_{2m}
	M_3	x_{31}	x_{32}	x_{33}	...	x_{3m}

	M_n	x_{n1}	x_{n2}	x_{n3}	...	x_{nm}

Source: own

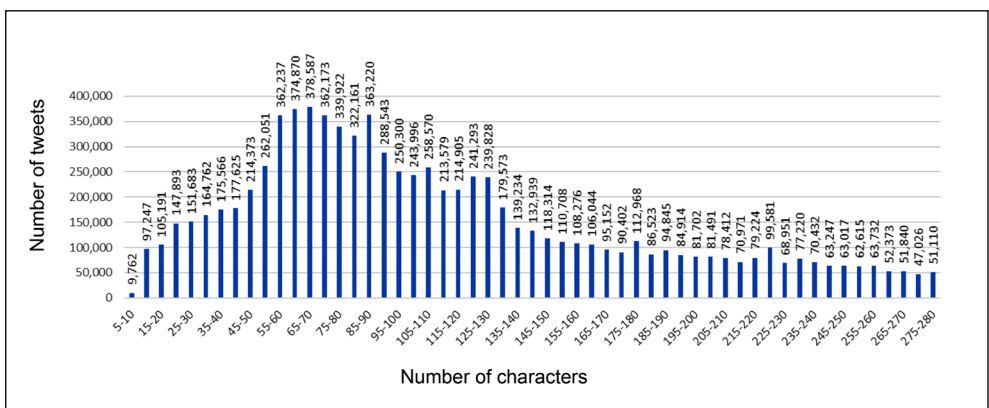


Fig. 5: Number of characters

Source: own

Tab. 3: Tweet numbers

Type	Explanation	Tweet	Ratio (%)	The tweets filtered with the "MacBookPro" keyword
TO	Original tweet	38,178,278	46.7	19,089,139
TO-RSO	Retweet	9,770,411	12.0	4,885,205
TO-QSO	Quote	26,981,744	33.0	13,490,872
TO-RSO-QSO	Quote of retweet	6,781,525	8.3	3,390,762
Total		81,711,958	100.0	40,855,979

Source: own

3.2 Keyword selection

In the form of the consumer opinions matrix, two types of keywords are adopted. The company launched its first series in 2008, and newer models have been released yearly (Inc., accessed February 11, 2020). In this study, notebooks produced by different companies are investigated. The first batch of keywords includes the notebook models. Next, the second batch is obtained using a notebook capabilities list.

In the second step, the expert team classified and merged the features based on notebook

case studies. The team determined direct or indirect relationships between the features and RL. A direct effect is a feature that directly influences the decision process. In contrast, an indirect effect is described as the impact of customer satisfaction/dissatisfaction on the return of products. The second batch contains both direct and indirect features (Tab. 4). This study selected an expert team with seven evaluators, comprising three notebooks, two laptops, and two automobile experts with experience in an international marketplace.

Tab. 4: Notebook features and their impact on RL extracted by experts

No.	1	2	3	4	5	6	7	8	9	10
Features	Price	Storage	Screen	Design	Memory	Chip	Camera	Graphic	Security	Pay
Impact on RL	Indirect	Direct	Direct	Direct	Direct	Direct	Direct	Direct	Indirect	Indirect
No.	11	12	13	14	15	16	17	18	19	20
Features	Siri	Battery	Trackpad	Sensors	Wireless	Connector	Warranty	IOS	Trade-In	Accessory
Impact on RL	Indirect	Direct	Direct	Direct	Direct	Direct	Indirect	Indirect	Indirect	Direct

Source: own

3.3 Sentiment analysis matrix

As described, after constructing the $m \times n$ matrix of consumer opinions, the consumer opinions matrix is transferred into an SA matrix, in which x_{mn} indicates the final sentiment polarity.

In the above matrix, x_{mn} is obtained by the polarity and confidence of each tweet and is indicated as happy/unhappy (H/U). First, the tweets with a confidence value between $[-0.8, 0.8]$ are eliminated. Next, the average polarity of the remaining tweets is obtained. For the average

polarity of more than 0.8, it is indicated as "happy" ($x_{mn} \equiv H$); whereas, for the average polarity less than -0.8 , it is indicated as "unhappy" ($x_{mn} \equiv U$). The keywords in Tab. 5 are employed in categorizing tweets in the consumer opinion matrix. Thirty-eight million one hundred seventy-eight thousand two hundred seventy-eight tweets use the keyword notebook. Still, this number is diminished because of the limitations in improving the productivity of the analyzed tweets and eliminating unrelated tweets.

The SA algorithm

The literature mentions that the SA algorithms are grouped into three main classes. Based on the high level of accuracy, supervised machine learning algorithms are used to make an automated system for the proposed framework. SVM, NB, and MaxEnt are among the most popular supervised machine learning algorithms. Since the accuracy rate is an ever-changing value, determining the accuracy rate is an exciting matter. Mahalakshmi and Sivasankar (2015) showed that the precision of machine learning algorithms could decrease when new datasets with different words are applied to training data. An innovative voting system is designed to overcome this problem. Tab. 5 depicts a higher precision in the dataset is achieved.

The positive and negative tweets using happy/unhappy emoticons are applied for training algorithms. Therefore, 5,218 positive and 8,966 negative tweets were identified (total tweets = 14,184).

Next, 10,000 tweets are randomly selected and tested to obtain the accuracy rate.

This study selects the most famous machine learning classifiers for classification accuracy calculation. The accuracy rate of different approaches is depicted in Tab. 6. As presented in the last row of Tab. 6, the proposed SA method has an accuracy rate of 89.9%. Since the accuracy level depends on the dataset, some researchers have used state-of-art methods in the literature. A comparison between the proposed innovative process and the other algorithms is depicted in Tab. 6.

As depicted in Tab. 6, deep learning is more complex than other algorithms. This complexity requires more financial resources to be implemented. However, the proposed voting system has the same accuracy and is simultaneously less complex than deep learning. In a practical analysis, more precision with less complexity is preferred.

Tab. 5: The accuracy rate of several algorithms

Algorithms	Precision (%)
SVM	81.3
MaxEnt	79.2
NB	79.6
Voting classifier	91.7

Source: own

Tab. 6: Accuracy rate of several techniques

Study	Technique	Precision (%)
(Greaves et al., 2012)	Machine learning and natural language processing techniques	81.0–89.0
(Basiri et al., 2020)	Naive Bayes, decision tree, random forest, and <i>k</i> -nearest neighbors, and three deep learning-based methods	82.0–88.0
(Zou et al., 2021)	Microblog	65.0–80.0
(Balahur & Turchi, 2014)	Supervised learning	68.4
Proposed	Benchmark machine learning (SVM, NB, MaxEnt)	89.9

Source: own

3.4 Optimality rate

Since manufacturers usually apply a reuse strategy for their products and features, an optimality index is proposed to calculate optimality by dividing the number of unhappy consumers

into the total number of notebook models/features as follows:

$$RLD = \frac{DC}{CD} = \frac{DRR}{RD} \quad (4)$$

where: *RLD* – the optimality of RL decision gained by implementing the proposed method; *DC* – the number of decisions changed by the proposed method; *CD* – the number of the company's default decisions; *DRR* – the number of decisions changed from "reuse" to "recycle" by the proposed method; *RD* – the number of company's reuse decisions.

Based on users' opinions, the optimality of RL decisions is calculated. As aforementioned, consumer satisfaction encourages a manufacturer to use a reuse strategy for the returned products, and user dissatisfaction encourages a manufacturer to apply a recycling strategy for the returned products.

Based on the gathered data, practitioners could make a customer-centric SC from a reverse SC. Three types of data are used

to calculate the optimality of RL. These data are used for three different levels: (i) notebook features level: by using notebook features, decides on a specific feature of any notebook models to optimize RL; (ii) notebook models level: by using notebook models, decides on a specific model that contains many features to optimize RL; and (iii) notebook models and features level (two dimensional): by using notebook models and features simultaneously decides on each feature of any notebook models to optimize RL.

In Fig. 6, the optimization level is gained by dividing the number of recycling strategies into the total number of notebook features. As an example, the optimality of the RL decision obtained for the screen and design features of all notebook models is calculated as follows:

$$\text{Screen} \Rightarrow \frac{\text{number of decisions changed by the proposed method}}{\text{number of company's default decisions}} = \frac{13}{19} = 0.6842 \quad (5)$$

$$\text{Design} \Rightarrow \frac{\text{number of decisions changed by the proposed method}}{\text{number of company's default decisions}} = \frac{7}{19} = 0.3684 \quad (6)$$

From Fig. 6, the resistance feature has the maximum optimization level, and the connector has the smallest one. This means that among all notebook models, users are the most satisfied with the connector feature and the least confident with the screen, power, and battery features. As a result, user satisfaction among all notebook models leads to reuse suggestions, and user dissatisfaction leads to recycling

suggestions. For making RL decisions, the optimality is calculated on every notebook model.

Consequently, by dividing the number of recycling strategy suggestions into the number of notebook models, the level of optimization is obtained (Fig. 7). As an example, the optimality of the RL decision gained for the direct features of MacBookPro 15.1 and MacBookPro 16.1 can be calculated as follows:

$$\text{MacBookPro 15.1} \Rightarrow \frac{\text{number of decisions changed by the proposed method}}{\text{number of company's default decisions}} = \frac{4}{13} = 0.3077 \quad (7)$$

$$\text{MacBookPro 16.1} \Rightarrow \frac{\text{number of decisions changed by the proposed method}}{\text{number of company's default decisions}} = \frac{3}{13} = 0.2308 \quad (8)$$

The most optimized notebook models are the MacBookPro 17.3 and MacBookPro 17.4, and the least optimized MacBookPro models are the MacBookPro 11.4 and MacBookPro 12.1. This means that among all notebook features, users are the most satisfied with the MacBookPro 17.3 and MacBookPro 17.4

and the least confident with the MacBookPro 11.4 and MacBookPro 12.1. Therefore, most MacBookPro 17.3 and MacBookPro 17.4 features are reused, whereas most MacBookPro 11.4 and MacBookPro 12.1 are recycled. In addition, the level of optimality is calculated on each MacBookPro model and each feature.

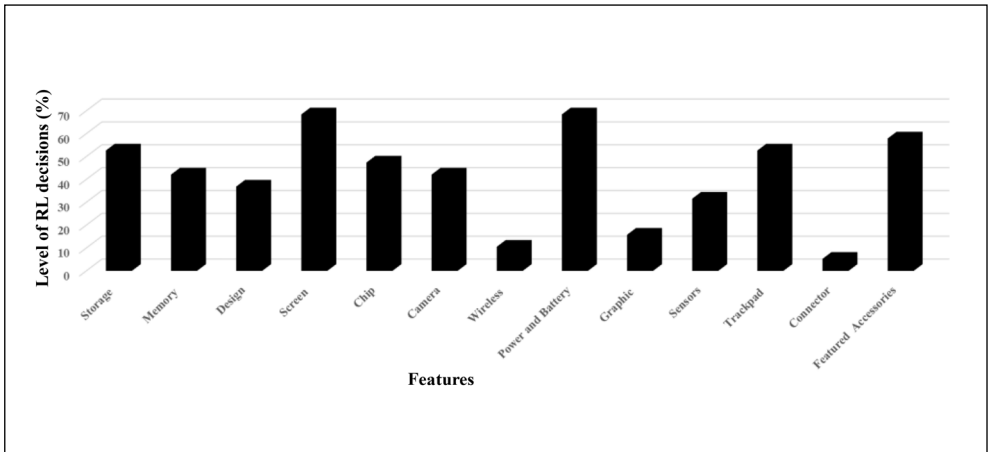


Fig. 6: Optimization level of RL decisions

Source: own

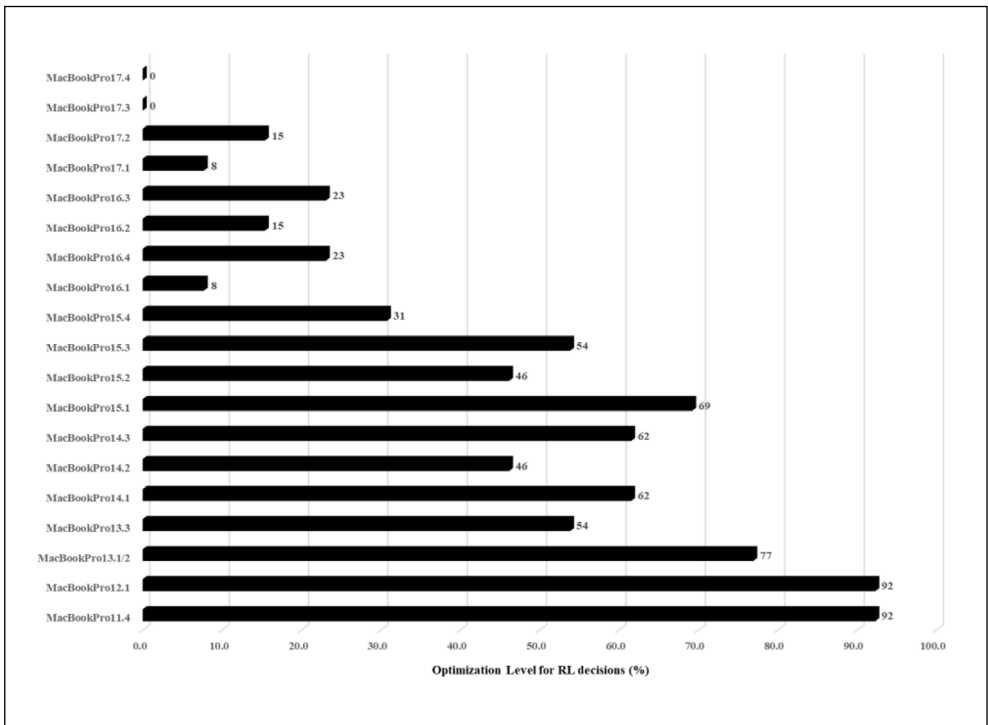


Fig. 7: Optimization level for RL decisions separated by MacBookPro models

Source: own

3.5 FMEA procedure and its discussion

An FMEA procedure is conducted to identify the riskiest component to obtain more reliable findings. The FMEA method compensates for the possible shortages of the basic proposed model. This process can break a complex problem into several simple issues to efficiently solve the problem under consideration. This can lead to a more reliable and accurate result.

The results derived from decision-makers are separately shown in Tab. 7. The results demonstrate the most essential failure factors impacting consumers' WEEE recycling engagement. To better understand, Fig. 8 graphically depicts the difference between the importance of the components. The figure shows that factors such as "power and battery" and "storage" are the most crucial failure factors. In contrast, "design" and "memory" are among the least critical factors.

Tab. 7: Risk index

Property	Probability	Severity	Detection	Risk priority index	Rank	Relative risk weight
Storage	4	3	3	36	2	0.144
Memory	2	2	2	8	6	0.032
Design	1	2	1	2	7	0.008
Screen	3	4	2	24	3	0.096
Chip	2	2	3	12	5	0.048
Camera	2	3	2	12	5	0.048
Wireless	2	3	2	12	5	0.048
Power and battery	4	4	3	48	1	0.192
Graphic	2	3	3	18	4	0.072
Sensors	2	3	4	24	3	0.096
Trackpad	3	2	3	18	4	0.072
Connector	2	3	3	18	4	0.072
Featured accessories	3	2	3	18	4	0.072

Source: own

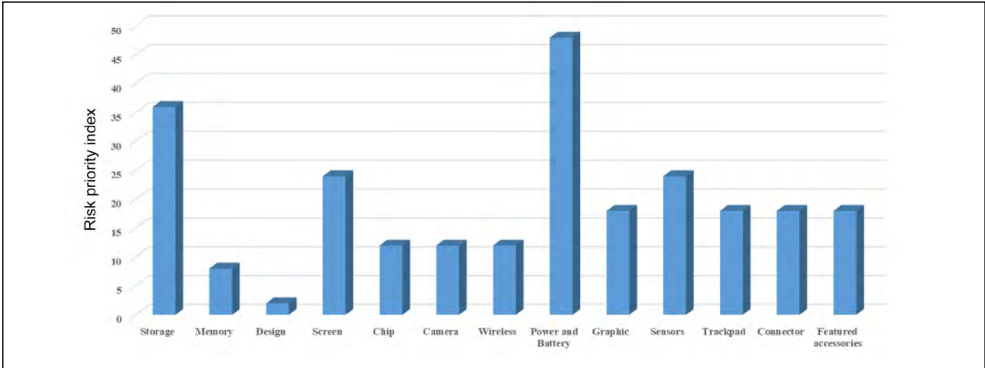


Fig. 8: Graphical risk index

Source: own

From the last column of Tab. 7, “power and battery” and “storage” are approximately one-third of the risk volume. Therefore, financial planning and supportive programs are required to reduce the massive volume of the corresponding risk, increase the life cycle, and consequently diminish environmental deterioration. This can lead to a substantial decrease in overall costs and improve efficiency.

4 Discussion

Manufacturers must investigate customer behavior and the components that influence their performance to remain sustainable in this volatile market. This can diminish waste, improve efficiency, and become more consumer-oriented. Based on the principal concepts of RL, consumer feedback is a function of the return of money, materials, and information from the user to the producer. Several reasons force consumers to provide feedback. However, there are many problems defined by end-users' tweets about notebooks (Naldi et al., 2018). Therefore, this research uses unique methods to investigate the issue under consideration. The information extracted from SM posts (complaints/praise) is used to make an RL decision on achieving the aim. End-users' opinions/attitudes toward the product are among the significant concerns of notebook manufacturers (Leonard et al., 2019). By interactively delivering valuable content, social media bridges the gap between manufacturers and consumers, empowering companies to transform their advertising strategies and extend their reach beyond geographical constraints (Ilieva et al., 2024). Social media demonstrated its role in enhancing customer insights and driving more effective marketing strategies (Theodorakopoulos & Theodoropoulou, 2024). Manufacturers can analyze the evaluation outputs to improve product positioning, devise targeted promotions, and tailor marketing strategies, thereby augmenting consumer satisfaction and facilitating revenue growth (Hoque et al., 2024). The finding of this paper is in line with the previous research that showed different after-sales services quality elements can affect customer satisfaction (Shokouhyar et al, 2020). Sharifi and Shokouhyar (2021) demonstrated that camera, screen, battery, performance, and internal storage are the most significant features that affect customer buying behavior. Ngah et al. (2024) showed a stronger

effect of design for console gamers compared to mobile gamers.

This paper describes several direct and indirect features after using three different ways to calculate the level of optimality. Therefore, the root cause of problems is explained, and detailed recommendations for improving the RL decisions are made.

The users generally neglect to mention their opinions on products, but when they are displeased with any feature (whether it is an exterior or an interior factor) the producer typically recycles the external parts but normally reuses the internal ones. An overview of users' opinions on some features connected with the RL decisions is presented in the following. Future studies can investigate the other features: (i) design: all basic notebook models have been criticized for their screen quality. Some customers have been dissatisfied with the high weight of the MacBookPro 11.4. However, the high quality of the notebook screen has satisfied the consumers. Therefore, the producer can advise a reuse strategy for higher-quality screens. In addition, the high weight and the situation of the cameras have displeased the users about the design of MacBookPro 12.1. Consequently, Apple should take the problem into account in future products; and (ii) battery: different consumers have widely criticized Apple for this feature in most notebook models. Recently released notebooks have only satisfied the users with this feature. Other models have made an unpleasant experience. Battery life and charging time are two critical problems in battery satisfaction. Likewise, battery life has been a general issue in most notebook models. The battery life problem has led users to believe that some cheaper notebooks from other brands like Lenovo and Samsung can be investigated. This problem has increased the criticism of newer notebooks like MacBookPro 14.3. Fast charging and longer battery life are two main issues for many users. However, Apple should change its battery production strategies based on customers' opinions.

Conclusions

This paper provides a robust model to show how social media analytics help manufacturers obtain knowledge from end-user information. It first presents a dictionary-based framework of Twitter data to extract the most popular customers' perceptions. Next, content and

sentiment analyses are conducted to find the relationships between consumers' perceptions and corresponding effects. This paper identifies the critical issues affecting customer satisfaction from the tweet analysis, and some recommendations are proposed. Then, a 3D plot is extracted from the optimization rate to show the satisfied level of each element graphically. In the future, a more refined list of keywords can be utilized to investigate the subject further. Keywords can be extracted from a company's website and published papers using topic modeling algorithms. Furthermore, Twitter analytics may be extended to various sectors and used for data obtained over a more extended period. In addition, analytics might be conducted utilizing a search API rather than a streaming API. More algorithms (three or more) can be used during the SA phase to improve the accuracy of the proposed strategies. Other methods, such as the multinomial NB algorithm, might also improve precision.

Finally, additional strategies than averaging (e.g., fuzzy and AHP) can be utilized at the SA stage to improve decision-making based on end-user perspectives. Finally, as an essential future task, the alpha value is a good metric for ranking and distinguishing between tweets that users highlight. It should be noted that the alpha value is a time-dependent index, and the value of a tweet might grow considerably over a while; the data collection period should be stated and taken into account.

As well as, the proposed model can be validated by applying it to different products by data and information extracted from various social networks.

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How can co-institutional investors enhance the core competitiveness of enterprises? Evidence from China

Xinyong Lu¹, Meinong Xi²

¹ Zhongkai University of Agriculture and Engineering, College of Economy and Trade, China, ORCID: 0009-0008-8568-9201, luxinyong@zhku.edu.cn;

² Lingnan University, Faculty of Business, China, ORCID: 0009-0009-5148-7537, meinongxi@126.com (corresponding author).

Abstract: As of 2023, institutional investors hold approximately 44.1% of the total market capitalization of China's outstanding stocks. By simultaneously investing in multiple firms within the same industry, common institutional investors gain access to broader information channels and proprietary market insights at lower search costs. As shareholder linkages become increasingly common in the capital market, understanding their impact on firm behavior is of considerable practical relevance. This study empirically examines the relationship between common institutional investors and corporate innovation efficiency, using a panel of A-share listed companies in Shanghai and Shenzhen from 2010 to 2019. The results show that such investors enhance innovation efficiency through both monitoring and resource effects. Moreover, the effectiveness of these mechanisms is amplified by stronger internal control systems and better information environments. The study also finds that the impact of co-institutional investors is more pronounced in firms with higher agency costs and in non-state-owned enterprises. This research contributes to the literature on institutional ownership and innovation by providing micro-level evidence of the governance role played by co-institutional investors. It also offers practical insights for promoting sustainable and high-quality development in China and other developing economies.

Keywords: Internal control, information environment, Chinese economy, corporate governance, developing countries.

JEL Classification: C01, D22, G34, M41, O16.

APA Style Citation: Lu, X., & Xi, M. (2025). How can co-institutional investors enhance the core competitiveness of enterprises? Evidence from China. *E&M Economics and Management*, 28(4), 99–113. <https://doi.org/10.15240/tul/001/2025-5-017>

Early Access Publication Date: July 10, 2025.

Introduction

Since 2006, institutional investors in China have rapidly expanded alongside the ongoing development of the securities market (Cai & Li, 2018). By 2023, their holdings accounted for approximately 44.1% of the total market value of outstanding stocks (Jiang & Yuan, 2018; Lu et al., 2024), making them

influential participants in the capital market (Ni & Jin, 2024). Due to market segmentation and information asymmetry, many institutional investors simultaneously hold shares in multiple firms within the same industry for risk diversification and return maximization, leading to the emergence of common institutional investors (He & Huang, 2017). Compared

with general institutional investors, these co-investors possess greater specialization, richer supervisory experience, and stronger managerial capacity (Cheng et al., 2022). Their cross-holdings also grant them broader access to industry-specific information and allow them to obtain proprietary data at lower search costs (Gao et al., 2019). More importantly, they aim to maximize portfolio returns rather than the performance of individual firms (Chen et al., 2021), thereby gaining both the incentive and capacity to actively monitor management and participate in corporate decision-making (Dou et al., 2018). In industries with intense competition and fixed market shares, firms often generate negative externalities that hinder rational decisions (Xu & Xuan, 2021). To mitigate this, common institutional investors not only reduce inter-firm externalities but also promote strategic alliances and information sharing across firms, facilitating the allocation of scarce resources and fostering mutual gains (He et al., 2019; Li et al., 2018). As shareholder linkages grow increasingly common, understanding their impact on corporate behavior and firm value has become a topic of both theoretical and practical relevance.

China's economy has transitioned from a phase of rapid expansion to a "new normal" characterized by medium- to high-speed growth (Chi, 2023). At the micro level, however, Chinese enterprises continue to exhibit weak independent innovation capabilities and lag behind global leaders in terms of core competitiveness (Chen et al., 2022; Chen et al., 2023). This limitation not only hinders the country's long-term economic sustainability but also raises concerns over its ability to escape the "middle-income trap" (Liu et al., 2023). In response, the 19th CPC National Congress Report emphasizes that innovation is the primary engine of development and a strategic pillar for modernizing the economic system. Enhancing firm-level innovation has thus become a critical pathway to strengthening national competitiveness. Against this backdrop, how to improve the efficiency of corporate innovation has emerged as a central research topic. Yet, despite the increasing prominence of common institutional investors as external shareholders, questions remain regarding the specific governance roles they play and their influence on firm innovation (Shahzad et al., 2022). Existing research in this area has largely relied

on qualitative analyses, with limited exploration from a corporate governance perspective (Shy & Stenbacka, 2020). To address this gap, this study investigates the impact of common institutional investors on innovation efficiency using a panel of A-share listed firms in Shanghai and Shenzhen from 2010 to 2019. It further examines how internal control quality and the information environment moderate this relationship. The findings yield several practical implications: for corporate executives, they offer guidance on optimizing governance by engaging with common institutional investors; for institutional investors, they highlight the strategic value of active involvement in innovation decisions across portfolio firms; and for policymakers and regulators, the results provide empirical support for fostering cross-shareholding governance to enhance innovation and long-term economic performance. Overall, this research contributes to the literature on institutional ownership and corporate innovation while offering actionable insights for promoting innovation-driven growth in China and other developing economies.

1 Theoretical background and research hypotheses

Existing research on the corporate governance role of common institutional investors presents two contrasting perspectives. The first posits that such investors contribute positively to governance. From a monitoring standpoint, as external shareholders holding stakes in multiple firms within the same industry, common institutional investors aim to maximize portfolio returns rather than the performance of individual firms (Li & Wan, 2021). Through long-term investments in large listed companies, they accumulate substantial supervisory experience and managerial expertise. This leads to an information scale effect that reduces monitoring costs and enhances their ability to identify managerial opportunism and shirking, thereby strengthening corporate governance. From a resource perspective, excessive competition among industry peers often generates negative externalities that distort firm decision-making (He & Huang, 2017). To safeguard portfolio returns, co-institutional investors encourage knowledge sharing and efficient resource allocation across firms in the same sector (Khan et al., 2016). This not only mitigates inter-firm externalities but also lowers the cost of acquiring proprietary information, enabling firms

to make more informed strategic decisions. Furthermore, as influential market participants, mutual institutional investors often act as information intermediaries. Their disclosures about the financial and operational conditions of investee firms help reduce information asymmetry, boost investor confidence, and ease firms' financing constraints. In contrast, the second view argues that common institutional investors may exert a negative influence on corporate governance. Given the limitations of attention and resources, these investors may concentrate their efforts on high-performing firms while neglecting others, thereby weakening overall monitoring effectiveness. In such cases, they may fail to detect or prevent managerial self-interest and agency problems in a timely manner, ultimately diminishing governance quality.

First, common institutional investors can curb managerial opportunism through external governance, thereby enhancing firms' innovation efficiency. As long-term shareholders in large listed firms, these investors accumulate substantial monitoring experience and governance capabilities (Kacperczyk et al., 2005). Their professional oversight allows them to detect self-interested managerial behavior (such as the diversion of innovation funds to other uses) and to discourage underinvestment in R&D arising from managerial risk aversion. By exerting pressure, they can prompt management to allocate internal resources more effectively toward innovation. Second, co-institutional investors benefit from lower monitoring costs due to their holdings in firms with similar operations and environments (Edmans et al., 2019; Xu & Wan, 2015). Kang et al. (2018) find a significant negative correlation between monitoring costs and the number of firms linked by institutional investors. The broader the network of commonly held firms within an industry, the more efficiently these investors can monitor managerial behavior, reducing innovation inefficiencies caused by managerial shirking or risk avoidance (He & Tian, 2013). Based on the above, this study proposes the following hypothesis *H1a*:

H1a: Co-institutional investors are able to utilize the monitoring effect to increase the innovation efficiency of firms.

Second, co-institutional investors can enhance innovation efficiency by facilitating the sharing of proprietary information among firms in the same industry, alleviating financing

constraints, and leveraging their resource effects. Specifically, co-institutional investors can foster collaboration and communication across firms by establishing strategic alliances that enable the exchange of private information (Xu & Wan, 2015). In industries characterized by intense competition, firms often impose negative externalities on each other in the struggle for market share, leading to distorted decision-making and reduced innovation efficiency (Beatty et al., 2013; He & Huang, 2017). In contrast, to maximize overall portfolio returns, co-institutional investors not only seek to mitigate these inter-firm externalities but also actively build alliances that reduce competition and facilitate the sharing of strategic information within the industry (Gao et al., 2023). When firms face innovation bottlenecks, the private information provided by co-institutional investors can help avoid redundant investment and guide firms toward more targeted R&D strategies, thereby enhancing innovation outcomes. In addition, co-institutional investors help alleviate information asymmetry and financing constraints, which are significant barriers to innovation. Information asymmetry often results in limited access to funding for innovation activities, contributing to inefficiencies. By fostering strategic alliances, common institutional investors offer firms access to exclusive information and scarce resources, which can improve operational performance and market competitiveness, ultimately expanding financing channels (Khan et al., 2016). Furthermore, as market trendsetters, common institutional investors can influence the investment decisions of individual investors. Firms held by co-institutional investors tend to maintain a more transparent information environment and are more inclined to disclose relevant information, thereby strengthening market confidence and facilitating external financing. Based on the above reasoning, this paper proposes the following hypothesis *H1b*:

H1b: Co-institutional institutional investors are able to utilize the resource effect to increase the innovation efficiency of firms.

2 Research methodology

2.1 Sample selection and data sources

To avoid the potential confounding effects of the 2008–2009 global financial crisis and the COVID-19 pandemic after 2020, this study selects all listed companies on China's Shanghai and Shenzhen A-share markets from

2010 to 2019 as the sample period. The raw data are processed as follows: (1) firms with missing values are excluded; (2) companies marked with ST or ST* status are removed; (3) firms in the financial and insurance sectors are excluded due to their distinct regulatory and financial reporting standards; and (4) continuous variables are winsorized at the 1% level on both tails to mitigate the influence of outliers. After these procedures, the final sample consists of 17,319 firm-year observations. All data used in this study are sourced from the CSMAR database.

2.2 Variable definition

Explained variables. Corporate innovation is typically measured using either R&D expenditure or the number of patent applications. However, the latter is widely regarded as a more accurate indicator of innovation outcomes, as it reflects the tangible results of R&D activities, whereas R&D expenditure only captures input efforts. Consistent with prior literature, such

as Huang et al. (2024), Lerner et al. (2011) on long-term investments in U.S. private financial firms, and Yuan et al. (2023) on A-share listed firms in China — this study adopts the number of patent applications as a proxy for corporate innovation. Two specific indicators are used: (1) total innovation output (*lnPatent*): following Shang et al. (2023) and Sun et al. (2021), the total number of patents filed (including invention, utility model, and design patents) in the year of application is used to measure overall innovation output. To address the issue of right-skewed distribution, the natural logarithm of one plus the total number of patents is taken to derive the variable *lnPatent*. (2) innovation quality (*lnPatent1*): based on the criterion of originality, the number of invention patents filed annually is used as a proxy for innovation quality. The natural logarithm of one plus the number of invention patent applications is calculated to form *lnPatent1*.

Explanatory variables. Common institutional investor presence is measured using

Tab. 1: Variable definition – Part 1

Variable type	Variable symbol	Variable name	Variable definition
Explained variable	<i>lnPatent</i>	Total amount of innovation	The total number of applications for the three patent types filed by the enterprise in the year of filing
	<i>lnPatent1</i>	Quality of innovation	Based on the originality criterion, the natural logarithm of the number of applications for invention-based patents filed by an enterprise in a filing year plus one is taken as a measure of the quality of innovation of the enterprise
Explanatory variable	<i>Coz1</i>	Common institutional investor dummy variable	At the quarterly level, if the ratio of the number of shares held by institutional investors in both the firm and other firms in the same industry to the number of shares outstanding is greater than or equal to 5%, it means that there is a common institutional investor in the firm, which takes the value of 1, and 0 otherwise
	<i>Coz2</i>	Level of common institutional investor linkages	Listed companies are simultaneously held by several common institutional investor organizations
	<i>Coz3</i>	Proportion of common institutional investors	Proportion of listed companies that are institutionally owned by all common institutional investors

Tab. 1: Variable definition – Part 2

Variable type	Variable symbol	Variable name	Variable definition
Control variable	<i>Age</i>	Age of business	Time to first IPO public listing
	<i>Lev</i>	Gearing	Corporate liabilities/total corporate assets.
	<i>Growth</i>	Corporate growth	Value added of main operating income/previous period's main operating income
	<i>Roa</i>	Return on net assets	Corporate net profit/total corporate assets
	<i>Tang</i>	Percentage of tangible assets	(Fixed assets at year-end + inventories at year-end)/total assets at year-end
	<i>OC</i>	Shareholding concentration	Shareholding ratio of the largest shareholder
	<i>Nopr</i>	Nature of property rights	State-owned enterprises take 1, otherwise 0
	<i>Dual</i>	Whether the chairperson and general manager are two positions in one	Chairperson and general manager of the two positions together take 1, otherwise 0
	<i>Indlr</i>	Board independence	Number of sole directors/number of board of directors
	<i>MH</i>	Management shareholding	Number of shares held by management/total shares

Source: own

three variables, adapted from He and Huang (2017) and Khan et al. (2016). (1) *Coz1* (dummy variable): at the quarterly level, if institutional investors hold shares in both the focal firm and other firms within the same industry, and their combined shareholding exceeds 5% of the total shares outstanding, *Coz1* is assigned a value of 1; otherwise, it is 0. (2) *Coz2* (linkage intensity): this variable captures the number of distinct institutional investors that simultaneously hold shares in the focal firm and other firms within the same industry. (3) *Coz3* (proportional ownership): this variable measures the proportion of the firm's institutional shareholders that are also invested in peer firms, reflecting the depth of common institutional ownership.

Control variables. Based on the literature (Khan et al., 2016; Ni & Jin, 2024), the model controls for firm-level characteristics, including firm age, leverage ratio, revenue growth, return

on assets, and asset tangibility. In addition, key corporate governance variables are included: ownership concentration, property rights nature (state-owned or otherwise), CEO duality (whether the board chair also serves as CEO), board independence, and management shareholding ratio.

Tab. 1 lists the main variables covered in this paper.

2.3 Model building

To verify the impact of common institutional investors on corporate innovation, this paper constructs the following model:

$$\ln Patent / \ln Patent1 = \alpha_0 + \alpha_1 Coz1 / Coz2 / Coz3 + \alpha_3 Control + year + ind + k \quad (1)$$

Where: *lnPatent* and *lnPatent1* are firm innovations; *Coz1*, *Coz2*, and *Coz3* are co-institutional

investors; and *Control* is a control variable. Additionally, this paper controls for *year* and *industry* dummy variables.

3 Results and discussion

3.1 Descriptive statistics

Tab. 2 presents the descriptive statistics of the main variables used in this study. The mean values of the explained variables (total innovation and innovation quality), are 1.440 and 0.950, respectively, suggesting that, on average, listed companies in China file approximately 1.44 patents and 0.95 invention patents per year. The standard deviation of total innovation is 1.630, with a minimum of 0 and a maximum of 6.100, while the standard deviation of innovation quality is 1.290, ranging from 0 to 5.370. These figures indicate substantial heterogeneity in firms' innovation levels. The mean value of the common institutional investor dummy variable is 0.110, indicating that about 11% of listed firms are cross-held by institutional investors. Additionally, the average values for the degree of co-institutional investor linkage and the proportion of co-institutional investors are 0.080 and 0.030, respectively, suggesting that, on average, 8% of institutional investors

cross-hold shares across firms and that these institutional investors hold an average ownership stake of 3% in the listed firms. The descriptive statistics for the control variables are generally consistent with those reported in previous studies and are therefore not elaborated upon here.

3.2 Analysis of regression results

Tab. 3 presents the regression results assessing the impact of common institutional investors on firms' innovation. Columns (1), (2), and (3) report the results using total innovation output (*lnPatent*) as the dependent variable. The coefficients of *Coz1*, *Coz2*, and *Coz3* are 0.138, 0.191, and 0.413, respectively, all of which are positive and statistically significant at the 1% level. These findings suggest that common institutional investors are associated with a higher volume of innovation, as measured by the total number of patent applications. Columns (4), (5), and (6) display the regression results when innovation quality (*lnPatent1*) is used as the dependent variable. The corresponding coefficients for *Coz1*, *Coz2*, and *Coz3* are 0.194, 0.269, and 0.553, respectively, again positive and significant at the 1% level. This

Tab. 2: Descriptive statistics for key variables

Variable	Obs.	Mean	SD	Min	P50	Max
<i>lnPatent</i>	17,296	1.440	1.630	0.000	1.100	6.100
<i>lnPatent1</i>	17,296	0.950	1.290	0.000	0.000	5.370
<i>Coz1</i>	17,296	0.110	0.310	0.000	0.000	1.000
<i>Coz2</i>	17,296	0.080	0.230	0.000	0.000	0.900
<i>Coz3</i>	17,296	0.030	0.110	0.000	0.000	0.560
<i>Age</i>	17,296	18.730	30.950	2.000	18.000	20.000
<i>Lev</i>	17,296	0.450	0.200	0.060	0.450	0.880
<i>Growth</i>	17,296	0.180	0.410	-0.510	0.110	2.730
<i>Roa</i>	17,296	0.040	0.050	-0.150	0.040	0.190
<i>Tang</i>	17,296	0.260	0.190	0.000	0.230	0.870
<i>OC</i>	17,296	36.170	14.980	9.440	34.390	75.460
<i>Nopr</i>	17,296	0.460	0.500	0.000	0.000	1.000
<i>Dual</i>	17,296	0.230	0.420	0.000	0.000	1.000
<i>Indlr</i>	17,296	0.370	0.050	0.330	0.330	0.570
<i>MH</i>	17,296	0.100	0.180	0.000	0.000	0.680

Source: own

Tab. 3: Co-institutional investors and corporate innovation

Variables	InPatent			InPatent1		
	Total amount of innovation			Quality of innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
Coz1	0.138***			0.194***		
	(3.882)			(6.618)		
Coz2		0.191***			0.269***	
		(3.833)			(6.585)	
Coz3			0.413***			0.553***
			(3.865)			(6.291)
Age	-0.001**	-0.001**	-0.001**	-0.001**	-0.001*	-0.001*
	(-2.508)	(-2.498)	(-2.466)	(-1.971)	(-1.955)	(-1.903)
Lev	0.605***	0.605***	0.605***	0.638***	0.637***	0.640***
	(9.339)	(9.333)	(9.347)	(11.971)	(11.958)	(12.003)
Growth	-0.181***	-0.181***	-0.180***	-0.114***	-0.114***	-0.114***
	(-6.733)	(-6.735)	(-6.721)	(-5.171)	(-5.174)	(-5.157)
Roa	4.531***	4.532***	4.564***	3.701***	3.702***	3.748***
	(19.118)	(19.121)	(19.285)	(18.987)	(18.989)	(19.256)
Tang	0.104	0.104	0.105	-0.087	-0.087	-0.085
	(1.438)	(1.438)	(1.450)	(-1.467)	(-1.469)	(-1.438)
OC	0.001**	0.002**	0.001*	0.000	0.000	-0.000
	(2.017)	(2.025)	(1.679)	(0.144)	(0.157)	(-0.391)
Nopr	0.092***	0.093***	0.093***	0.161***	0.161***	0.162***
	(3.486)	(3.499)	(3.510)	(7.366)	(7.382)	(7.448)
Dual	-0.065**	-0.064**	-0.064**	-0.040*	-0.040*	-0.039*
	(-2.460)	(-2.456)	(-2.431)	(-1.862)	(-1.854)	(-1.823)
Indlr	-0.271	-0.272	-0.268	-0.139	-0.140	-0.134
	(-1.345)	(-1.350)	(-1.332)	(-0.837)	(-0.846)	(-0.807)
MH	0.571***	0.571***	0.567***	0.350***	0.350***	0.345***
	(8.346)	(8.341)	(8.297)	(6.228)	(6.221)	(6.135)
Constant	-0.436**	-0.436**	-0.426**	-0.484***	-0.484***	-0.472***
	(-2.432)	(-2.430)	(-2.373)	(-3.283)	(-3.277)	(-3.196)
Observations	17,296	17,296	17,296	17,296	17,296	17,296
Adj-R²	0.312	0.312	0.312	0.256	0.256	0.256

Note: *, **, *** indicate significant at 10, 5, and 1% level of significance, respectively; *t*-value in parentheses.

Source: own

indicates that co-institutional investors also contribute to enhancing the quality of innovation, as reflected in the number of invention patent applications. Taken together, these results provide robust empirical support for the paper's hypotheses, demonstrating that common institutional investors can improve both the quantity and quality of corporate innovation through their monitoring and resource allocation effects.

3.3 Robustness check

Substitution of explanatory variables. Considering that different types of patents (namely invention patents, utility models, and design patents) contribute unequally to firm value, this study follows the approach of Bianchi et al. (2014) and assigns weights of 3:2:1 to these three categories, respectively. Based on this weighting scheme, a new innovation index is constructed by taking the natural logarithm of the weighted sum of the three patent types plus one. The regression analysis is then re-estimated using this adjusted measure.

Replacing the explanatory variables by robustness tests, we empirically analyze that: the regression coefficients of *Coz1*, *Coz2*, and *Coz3* on the adjusted innovation indicator (*lnPatent2*) are 0.156, 0.216, and 0.474, respectively, all of which are positive and statistically significant at the 1% level. These findings confirm that the main conclusions of the study remain robust when the measurement of the dependent variable is altered.

PSM test. To address potential concerns related to small sample size and sample self-selection bias that may affect the validity of the regression results, this study further conducts a propensity score matching (PSM) test. Specifically, the common institutional investor dummy variable (*Coz1*) is used to divide the sample into two groups: firms with common institutional investors form the treatment group, while those without constitute the control group. The outcome variables are total innovation (*lnPatent*) and innovation quality (*lnPatent1*), while the covariates include age (*Age*), leverage (*Lev*), growth (*Growth*), return on assets (*RoA*), tangibility (*Tang*), ownership concentration (*OC*), nature of property rights (*Nopr*), CEO duality (*Dual*), board independence (*Indlr*), and management shareholding (*MH*). The nearest-neighbor matching method with a 1:2 ratio is applied, and the matched sample is used for re-estimation after confirming the parallel trend assumption.

The same matching procedure is applied to *Coz2* (the degree of common institutional investor linkage) and *Coz3* (the proportion of common institutional investors). The PSM test of our empirical regression results remains robust through the robust-type test. After matching, the coefficients of *Coz1* on *lnPatent* and *lnPatent1* are 0.129 and 0.187, respectively, both statistically significant at the 1% level, respectively, which remain consistent with those from the baseline regression. These findings confirm the robustness of the study's main conclusions following the PSM test.

Instrumental variables test (IVT). This paper recognizes that institutional investors, as professional investors in the capital market, are more likely to select listed firms with higher levels of innovation for investment. To address potential endogeneity concerns, instrumental variable (IV) testing is employed. Following the approach of Xu and Wan (2015), the inclusion of a firm in the CSI 300 index in a given year is used as an instrumental variable. Specifically, if a listed company is part of the CSI 300 index in that year, it is assigned a value of 1; otherwise, it takes a value of 0. Additionally, two-stage least squares (2SLS) regression is used to estimate the model with the instrumental variable.

The regression results when total innovation (*lnPatent*) is used as the dependent variable. The *F*-statistic in the first stage is 11.16, which exceeds the threshold of 10, indicating that there is no issue with weak instruments. Furthermore, the coefficient of *Ln300* with *Coz1* is 0.123, and the coefficient of *Coz1* with *lnPatent* is 4.849, both of which are positive and statistically significant at the 1% level. The regression results for the innovation quality measure (*lnPatent1*), which are consistent with the findings for total innovation. These results suggest that the conclusions of this paper remain robust even after addressing potential endogeneity using instrumental variables.

3.4 Heterogeneity analysis

Heterogeneity analysis of agency costs. This paper posits that co-institutional investors can enhance corporate innovation through a monitoring effect that is, by exerting more effective oversight. Specifically, compared with general institutional investors, co-institutional investors are more incentivized to monitor because each unit of monitoring cost yields not only

firm-specific benefits but also additional gains at the portfolio level. Moreover, they exhibit stronger capabilities in both information acquisition and interpretation, allowing them to monitor managerial behavior more efficiently and at lower cost. This enhanced oversight helps alleviate agency problems between shareholders and managers, thereby reducing agency costs. Consequently, when agency problems are more severe, co-institutional investors are more likely to assume a supervisory role that constrains managerial opportunism and encourages engagement in innovation activities, ultimately improving firms' innovation efficiency. Based on this reasoning, the paper hypothesizes that co-institutional investors are more effective in promoting innovation efficiency in firms with higher agency costs than in those with lower agency costs. To empirically test this hypothesis, following the approach of Wang et al. (2023), the ratio of management expenses

to operating income is adopted as a proxy for agency cost, with higher values indicating more severe agency problems. The sample is then divided into high and low agency cost groups based on the median value, and separate regressions are conducted for each group. The regression results are reported in Tab. 4.

Tab. 4 shows that in columns (1) and (3), i.e., the high agency cost group, the regression coefficients of *Coz1* vs. *lnPatent* and *lnPatent1* are 0.238 and 0.276, respectively, which are positive and significant at the 0.01 level, whereas in columns (2) and (4), i.e., the low agency cost group, the regression coefficients of *Coz1* vs. *lnPatent* and *lnPatent1* are insignificant at the 0.016 and 0.069 levels, respectively. The above regression results indicate that when the agency cost of firms is greater, the promotion effect of common institutional investors on innovation efficiency is greater, which verifies the above conjecture of this paper.

Tab. 4: Heterogeneity test for agency costs – Part 1

Variables	lnPatent		lnPatent1	
	High agency cost group	Low agency cost group	High agency cost group	Low agency cost group
	(1)	(2)	(3)	(4)
Coz1	0.238***	−0.016	0.276***	0.069
	(4.940)	(−0.310)	(7.030)	(1.560)
Age	−0.023***	−0.001*	−0.013***	−0.000
	(−7.320)	(−1.670)	(−4.930)	(−1.400)
Lev	0.653***	0.584***	0.676***	0.671***
	(6.490)	(6.510)	(8.240)	(9.000)
Growth	−0.238***	−0.111***	−0.139***	−0.078**
	(−6.370)	(−2.840)	(−4.570)	(−2.400)
Roa	4.831***	4.070***	3.786***	3.550***
	(12.400)	(13.310)	(11.920)	(13.950)
Tang	0.082	0.044	−0.124	−0.104
	(0.770)	(0.440)	(−1.430)	(−1.250)
OC	0.001	0.001	0.000	−0.001
	(0.830)	(0.640)	(0.100)	(−0.630)
Nopr	0.159***	0.040	0.216***	0.108***
	(4.140)	(1.060)	(6.900)	(3.470)

Tab. 4: Heterogeneity test for agency costs – Part 2

Variables	InPatent		InPatent1	
	High agency cost group	Low agency cost group	High agency cost group	Low agency cost group
	(1)	(2)	(3)	(4)
<i>Dual</i>	−0.116***	−0.045	−0.081**	−0.023
	(−2.970)	(−1.270)	(−2.560)	(−0.780)
<i>Indlr</i>	0.205	−0.914***	0.264	−0.650***
	(0.730)	(−3.180)	(1.150)	(−2.720)
<i>MH</i>	0.342***	0.633***	0.264***	0.347***
	(3.260)	(6.960)	(3.090)	(4.590)
Constant	−0.357	−0.127	−0.553**	−0.243
	(−1.180)	(−0.560)	(−2.240)	(−1.290)
Observations	8,648	8,648	8,648	8,648
Adj- <i>R</i> ²	0.345	0.304	0.296	0.239

Note: *, **, *** indicate significant at 10, 5, 1% level of significance, respectively; *t*-value in parentheses.

Source: own

Heterogeneity analysis of the nature of property rights. Under China's unique market-oriented economic system, state-owned enterprises (SOEs), as key pillars of the national economy, often do not pursue profit maximization to the same extent as non-state-owned enterprises (NSOEs). Due to their broader responsibilities in maintaining social stability, employment, and other non-economic objectives, SOEs are often guided by policy mandates rather than market incentives. Additionally, because of their distinct political attributes, SOEs are more prone to "one-share dominance," and it is common for the roles of board chair, general manager, and even party secretary to be held concurrently, leading to more severe insider control issues (Feng et al., 2024). Under such conditions, it is difficult for co-institutional investors (as external shareholders), to effectively exert their monitoring and resource allocation functions to enhance innovation efficiency. In contrast, NSOEs typically have more decentralized ownership structures, giving co-institutional investors greater influence and facilitating their governance and supervisory roles, which can better support improvements in innovation performance. Therefore, this paper hypothesizes that the positive effect

of common institutional investors on innovation efficiency is more pronounced in NSOEs than in SOEs. To test this hypothesis, the sample is divided based on ownership type into SOEs and NSOEs, and separate regressions are conducted for each subsample.

The regression results, presented in Tab. 5, show that in the SOE sample (columns (1) and (3)), the coefficients of *Coz1* on *InPatent* and *InPatent1* are 0.058 and −0.039, respectively, and are statistically insignificant. In contrast, in the NSOE sample (columns (2) and (4)), the coefficients of *Coz1* on *InPatent* and *InPatent1* are 0.337 and 0.459, respectively, both significant at the 1% level. These results confirm the conjecture that common institutional investors have a more substantial impact on promoting innovation efficiency in non-state-owned enterprises compared to their state-owned counterparts.

3.5 Further analysis

The impact of common institutional investors on corporate innovation under different levels of internal control. As external shareholders, the monitoring and resource effects of co-institutional investors on corporate innovation are influenced by the quality

Tab. 5: Heterogeneity test for the nature of property rights

Variables	InPatent		InPatent1	
	Nationalized business	Non-state enterprise	Nationalized business	Non-state enterprise
	(1)	(2)	(3)	(4)
Coz1	-0.058	0.337***	-0.039	0.459***
	(-1.400)	(4.650)	(-1.120)	(7.800)
Age	-0.001**	-0.029***	-0.001*	-0.018***
	(-2.010)	(-10.430)	(-1.860)	(-8.120)
Lev	-0.336***	0.690***	-0.283***	0.737***
	(-3.210)	(7.780)	(-3.250)	(10.210)
Growth	-0.101**	-0.240***	-0.066**	-0.159***
	(-2.550)	(-6.770)	(-2.000)	(-5.510)
Roa	2.239***	4.941***	1.706***	4.030***
	(5.860)	(16.330)	(5.360)	(16.370)
Tang	0.055	0.185*	-0.062	-0.059
	(0.550)	(1.800)	(-0.740)	(-0.710)
OC	-0.004***	0.001	-0.004***	-0.001
	(-3.400)	(0.790)	(-4.320)	(-0.860)
Dual	0.003	-0.086***	0.037	-0.059**
	(0.070)	(-2.830)	(0.870)	(-2.360)
Indlr	-0.557*	-0.476*	-0.322	-0.463**
	(-1.920)	(-1.720)	(-1.330)	(-2.060)
MH	1.431***	0.473***	0.220	0.333***
	(2.590)	(6.590)	(0.480)	(5.710)
Constant	-5.265***	-0.058	-5.064***	-0.155
	(-14.910)	(-0.210)	(-17.230)	(-0.680)
Observations	7,887	9,409	7,887	9,409
Adj-R²	0.393	0.289	0.365	0.221

Note: *, **, *** indicate significant at 10, 5, 1% level of significance, respectively; t-value in parentheses.

Source: own

of a firm's internal control (Devos & Li, 2021). The quality of internal control is a critical component of corporate governance, playing a pivotal role in managerial decision-making (Xu & Xuan, 2021). When internal controls are weak, the execution of established business decisions is compromised, and managers cannot be effectively constrained. In such cases, the internal control mechanisms are insufficient to support the monitoring effect of common institutional investors, which may lead managers

to engage in self-interested behavior that impedes innovation and reduces its efficiency (Palmer & Kane, 2007). Moreover, internal controls are crucial for the successful implementation of strategic decisions. While co-institutional investors can provide valuable proprietary information and scarce resources to guide firms' innovation strategies, ineffective internal controls can prevent these decisions from being fully realized, thus hindering the ability of co-institutional investors to leverage their

resource effects. This study hypothesizes that the quality of a firm's internal control positively moderates the impact of co-institutional investors on innovation, with higher internal control quality enhancing the ability of co-institutional investors to drive innovation. To test this hypothesis, this paper adopts the Dibble internal control index (Wu & Wan, 2024) to measure internal control quality. The regression results indicate that the coefficients for *Coz1* with *LnPatent* and *LnPatent1* are 0.129 and 0.187, respectively, both of which are positive and statistically significant at the 1% level. The interaction terms with *LnPatent* and *LnPatent1* also yield positive coefficients of 0.001, significant at the 1% level, suggesting that the quality of internal control positively moderates the effect of co-institutional investors on corporate innovation, thus confirming the hypothesis.

The impact of co-institutional investors on firm innovation in different information environments. Information disclosure is a critical channel through which external stakeholders can assess the operational status and financial condition of enterprises. A robust information environment can significantly reduce information asymmetry between internal and external parties, thereby enhancing the ability of co-institutional investors to leverage both monitoring and resource effects, which in turn improves the innovation efficiency of firms. On one hand, when the information environment is well-developed, co-institutional investors are better equipped to evaluate whether the innovation decisions made by managers align with the current developmental needs of the firm. They can also intervene in a timely manner to prevent managers from avoiding innovation due to self-interest or risk aversion. On the other hand, a strong information environment reduces internal and external information asymmetry, thereby improving the efficiency with which co-institutional investors can gather and utilize information. This enables co-institutional investors to provide firms with high-quality, proprietary insights from within the industry, offering guidance for innovation strategies and thereby boosting innovation efficiency. Consequently, this study hypothesizes that the quality of a firm's information environment plays a positive moderating role in the impact of co-institutional investors on innovation. Specifically, the better the information environment, the more effectively co-institutional investors can promote innovation.

To test this hypothesis, the paper follows Aslett et al. (2024) and uses analyst tracking as a measure of the firm's information environment. The regression results, reveal that the coefficients of *Coz1* with *LnPatent* and *LnPatent1* are 0.030 and 0.094, respectively, with the former being insignificant and the latter statistically significant at the 1% level. However, the coefficients of the interaction terms with *LnPatent* and *LnPatent1* are 0.101 and 0.130, both positive and significant at the 1% level. These results confirm that the information environment positively moderates the relationship between co-institutional investors and corporate innovation, indicating that a stronger information environment enhances the ability of co-institutional investors to promote innovation.

Conclusions

This paper empirically examines the impact of common institutional investors on corporate innovation using a sample of Chinese A-share listed companies from Shanghai and Shenzhen between 2010 and 2019. The results show that common institutional investors significantly enhance firms' innovation efficiency by exerting both monitoring and resource effects, leading to improvements in both the overall level of innovation and the quality of innovation. These conclusions remain robust after a series of sensitivity tests, including alternative measures of explanatory variables, the propensity score matching (PSM) test, and instrumental variable testing. Further analysis explores the moderating role of co-institutional investors in corporate innovation across different contexts, such as the level of internal control and the information environment. The findings suggest that higher levels of internal control and a more robust information environment amplify the positive impact of co-institutional investors on innovation. Additionally, compared to firms with lower agency costs and state-owned enterprises, co-institutional investors exert a more significant effect on the innovation efficiency of firms with higher agency costs and non-state-owned enterprises.

These findings not only demonstrate that shareholder linkages in the capital market influence corporate decision-making but also offer practical insights for improving innovation and promoting sustainable economic development in China and other developing countries. Based on these findings, the following policy

recommendations are made: (1) for listed companies: in light of the positive role of common institutional investors in fostering innovation, Chinese listed companies should actively encourage institutional investors to hold shares, thereby strengthening oversight on management, directing managerial focus toward innovation, enhancing access to scarce resources, and helping to overcome innovation bottlenecks. (2) for institutional investors: common institutional investors play an indispensable role in corporate decision-making, particularly in innovation and strategic direction. These investors should continuously improve their teams' expertise in corporate governance and actively engage in governance and decision-making after acquiring shares in a firm. By doing so, they can assist companies in making optimal decisions on innovation and capital structure. (3) for market regulators: co-institutional investors can enhance corporate governance and provide valuable strategic insights. Therefore, regulators should pay attention to sectors where common institutional investors are absent or where institutional investor participation is minimal, encouraging more active engagement in such industries.

While this study provides valuable insights into the role of common institutional investors in improving the efficiency of firm innovation, it is not without limitations. First, the dataset used in this paper is based only on Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges. Although China represents a unique and highly representative context due to its rapidly developing capital markets, unique corporate governance structure, and the growing presence of institutional investors, the generalizability of the findings to other countries with different institutional environments may be limited.

Future research directions could be conducted from cross-national comparative studies that examine whether the monitoring and resource effects of common institutional investors are effective in other emerging markets or developed economies. Such comparative analyses can not only improve the external validity of the results but also help reveal the boundary conditions under which common institutional ownership has an impact on firm-level innovation.

Acknowledgements: This research was supported by the Zhong Kai College of Ag-

ricultural Engineering Graduate Student Science and Technology Innovation Fund Grant (KJCX2024031) and General Program of the National Social Science Foundation (21BSH104). We would like to express appreciation to colleagues for their constructive suggestions and comments.

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The effect of digital intensity on the financial performance of enterprises in Central and Eastern European countries

Trang Lam Quynh Tran¹, Sandor Kovacs², Miklos Herdon³

¹ University of Debrecen, Faculty of Economics and Business, Agricultural and Business Digitalization Institute, Hungary, ORCID: 0000-0003-3674-9286, lam.tran@econ.unideb.hu;

² University of Debrecen, Faculty of Economics and Business, Coordination and Research Centre for Social Sciences, Hungary, ORCID: 0000-0002-1216-346X, kovacs.sandor@econ.unideb.hu (corresponding author);

³ University of Debrecen, Faculty of Economics and Business, Agricultural and Business Digitalization Institute, Hungary, ORCID: 0009-0006-1631-6554, herdon.miklos@econ.unideb.hu.

Abstract: This study investigates the significance of information and communication technology (ICT) adoption, referred to as digital intensity (DI), and its impact on the financial performance of businesses in the manufacturing, utilities, and transportation sectors within Central and Eastern European (CEE) countries. The primary research question focuses on how DI and its components influence key financial indicators across these industries. This study uses data from the EUROSTAT, ENT2 (Comprehensive Enterprise Database), and EMIS (Emerging Markets Information Service) databases to examine financial and digital indicators for 2017–2022. The timeframe was selected to account for methodological changes in EUROSTAT and EMIS reporting. To explore these relationships, the study employs multiple factor analysis (MFA), which integrates interrelated variables from distinct blocks, including DI, profitability, indebtedness, and liquidity. Initially, separate principal component analyses (PCAs) were conducted on each variable block, followed by normalization. A global PCA was then performed on the balanced blocks to map variable relationships in a reduced-dimensional space. The MFA approach also facilitates the visualization of clusters and observations, offering insights into the diverse impacts of DI. The findings reveal that DI significantly affects financial metrics, such as profitability, indebtedness, and liquidity, with integration support systems playing a pivotal role in enhancing profitability and liquidity while mitigating debt. Furthermore, improvements in internet speed and accessibility are associated with enhanced financial performance. This empirical evidence underscores the potential of strategic investments in digital infrastructure and technology to enhance financial resilience and maintain competitive advantage in a digitalized economy. The study highlights a critical gap in the literature concerning the sector-specific effects of DI on financial performance in CEE industries and emphasizes the need for tailored digital strategies that account for the unique distribution channels and customer characteristics of each sector.

Keywords: ICT adoption, multiple factor analysis, sector-specific investment, competitive advantage, profitability.

JEL Classification: M21, M15, G30, O30.

APA Style Citation: Tran, L. Q. T., Kovacs, S., & Herdon, M. (2025). The effect of digital intensity on the financial performance of enterprises in Central and Eastern European countries. *E&M Economics and Management*, 28(4), 114–130. <https://doi.org/10.15240/tul/001/2025-5-016>

Early Access Publication Date: October 3, 2025.

Introduction

The rapid digitalization of operational procedures has become a vital element of organizational strategies across industries (Hanelt et al., 2021). This transformation has profoundly impacted economic and social domains, altering ownership structures, production methods, intermediary roles, and resource utilization (Orel & Dvouletý, 2020). ICT-driven business transformation is rooted not in the economics of ICT but in its strategic application, allowing firms to reconfigure operations fundamentally. Sader et al. (2019) and Pu and Zulkafli (2024) highlighted how technological integration fosters new capabilities, enhancing business excellence and improving innovation quality, operational efficiency, and overall effectiveness. Similarly, Lee et al. (2018) emphasized the role of ICT and technical infrastructure as drivers of rapid transformations across various sectors. Hess et al. (2020) argued that digital transformation affects all sectors, while Bánhidi (2021) underlined the importance of broadband in enabling internet-based services like e-commerce and e-learning. Saura et al. (2022) further identified 15 technological attributes significantly influencing firm performance, underscoring the multifaceted impact of digitalization.

Extensive research has examined the relationship between ICT and enterprise performance. The increasing DI driven by technological advancements presents challenges for companies transitioning to modern business models. The adoption of new technologies has enabled firms to gain competitive advantages across diverse sectors, including finance (Niemand et al., 2021), banking (Tran et al., 2022), tourism (Khurramov, 2020), and supply chains (Han et al., 2021). While these studies confirm the significance of digitalization, they often focus on specific industries or regions and overlook enterprises in CEE.

CEE countries, characterized by transition economies and dynamic business environments, are increasingly integrating digital technologies in manufacturing, utilities, and transportation, enhancing efficiency and competitiveness (Szabo et al., 2020). These sectors are vital to CEE economic growth, employment, and trade (Zoltán & Gábor, 2022). Manufacturing, while contributing significantly to GDP, faces challenges in terms of labor productivity, which remains below the EU average. Research suggests that digitalization has the potential

to enhance productivity in this sector, as firms with higher digital integration demonstrate increased output efficiency (Kulcsar, 2022). The transportation sector has benefited from substantial investments in infrastructure, improving connectivity across the region, although infrastructure bottlenecks remain in countries such as Romania and Croatia (EMIS, 2025). Meanwhile, the utilities sector is undergoing modernization, with advancements such as smart grids and digital monitoring technologies driving efficiency gains. Despite growing interest in the digitalization-finance nexus, limited research explores its impact on firms within these sectors in CEE. Previous studies primarily target developed economies, neglecting CEE's unique regulatory environments, technological infrastructure, and transitional economic contexts (Egri & Tanczos, 2018). The manufacturing, utilities, and transportation sectors remain underexplored regarding DI's effects on financial performance. Additionally, the heterogeneity of CEE economies necessitates context-specific analyses due to varying institutional, cultural, and market dynamics.

This research addresses these gaps through a comprehensive empirical investigation of digital intensity's impact on financial performance in CEE manufacturing, utilities, and transportation firms, focusing on Bulgaria, the Czech Republic, Croatia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. Using quantitative methodologies and data from EUROSTAT and EMIS, the study examines: i) the extent of digitalization within selected sectors in CEE; ii) the impact of DI on key financial indicators, including profitability, leverage, and liquidity; and iii) variations in DI across the examined sectors.

The research aims to provide practical insights and strategic recommendations for optimizing digital technology integration to enhance financial performance in CEE economies.

1 Theoretical background

1.1 Digital intensity and financial performance – Macro and industry perspectives

The rapid advancement of social innovation and technological development has compelled enterprises to accelerate digital transformation efforts to enhance competitiveness and productivity (George & Schillebeeckx, 2022). At the macro level, Dabbous et al. (2023)

analyzed panel data from 34 countries using the International Digital Economy and Society Index (I-DESI) to investigate the relationship between digitalization and sustainable competitiveness. Their study incorporated five dimensions of digitalization, including connectivity, digital literacy, and public digital services, with a focus on aggregated national data, covering numerous non-European and a limited number of CEE countries. Findings indicated that while connectivity, internet use, and digital assimilation significantly enhance sustainable competitiveness, digital literacy and public digital services have comparatively weaker effects.

At the industry level, the relationship between ICT and firm performance remains a critical area of research, revealing both challenges and opportunities. Digitalization reduces market entry barriers, alters skill requirements, and encourages the adoption of automated tools, transforming labor market dynamics (Tran et al., 2023). Empirical evidence generally suggests a positive correlation between ICT investment and financial performance. For instance, Kohtamäki et al. (2020) and Yunis et al. (2018) identified that ICT adoption leads to improvements in profitability, solvency, and growth. Al-Busaidi and Al-Muharrami (2021) emphasized the strong positive effect of ICT investment on key financial performance indicators, while Popa et al. (2018) demonstrated enhanced productivity, sales growth, and operational cost reduction in small and medium-sized enterprises (SMEs).

DI in DESI measures the extent to which businesses and economies integrate digital technologies, including cloud computing, big data, and e-commerce, to enhance productivity, sustainability, and economic growth (Criveanu, 2023; Kádárová et al., 2023). Further research has also emphasized the role of digital intensity, defined as the degree of an organization's digital transformation, in improving performance. The degree of digitalization varies across sectors in CEE countries. Brodny and Tutak (2022) found significant disparities in digitalization levels among small, medium, and large enterprises. Slovenia and Croatia exhibit high digitalization in small and medium enterprises, while Romania and Bulgaria lag behind. The study also highlights a strong correlation between a country's GDP per capita, R&D expenditure, and digitalization level. Higher digital intensity promotes operational efficiency, enhances

customer engagement, fosters innovation, and strengthens competitive positioning (Abou-Foul et al., 2021; Nwankpa et al., 2022). However, contradictory findings also exist; for instance, Jardak and Ben Hamad (2022) identified a negative short-term impact of digital maturity on financial indicators such as return on assets (ROA) and return on equity (ROE), suggesting a potential delay in realizing the benefits of ICT investments. Similarly, Grant and Yeo (2018) observed that financial factors, rather than ICT, play a more decisive role in driving performance within the financial services sector. Based on this literature, the following hypothesis is proposed:

H1: Higher DI positively impacts the financial performance of firms in selected sectors in CEE countries.

1.2 Sectoral differences in ICT's financial impact

The impact of DI on firm performance varies across industries due to differences in adoption rates, competitive dynamics, and sector-specific characteristics (Neirotti & Pesce, 2019). For instance, industries with high digital adoption, such as retail and e-commerce, experience immediate benefits, whereas traditional manufacturing sectors face slower digital integration (Chu et al., 2019). Tab. 1 summarizes key studies exploring the relationship between ICT and financial performance across diverse sectors.

Existing research highlights the sectoral differences in the impact of DI on financial performance. In manufacturing, service innovations and IT infrastructure have been shown to positively influence firm performance, with effects varying across time periods and industry segments (Chen et al., 2021; Khanna & Sharma, 2022; Rehman et al., 2020). Specifically, ICT strategies and CSR initiatives play a crucial role in the steel industry's financial outcomes (Xiliang et al., 2023).

Beyond manufacturing, digital adoption has proven beneficial in other industries, but the effects differ. In transportation and storage, IT capabilities enhance firm performance by optimizing supply chains and improving operational efficiency (Yu et al., 2021; Zeng & Lu, 2021). Meanwhile, in construction, the implementation of ICT tools like ERP and BIM systems significantly boosts company performance (Mesáros & Mandićák, 2017). These findings suggest

Tab. 1: Effect of ICT on financial performance across sectors

Authors	Data	Sector	Main findings
Chen et al. (2021)	Survey data from 121 manufacturers in China	Manufacturing	Positive relationship between service innovations and financial performance
Khanna and Sharma (2022)	Growth data from Indian manufacturing firms (1998–2016)	Manufacturing	ICT significantly impacts firm outputs, with variability across periods
Xiliang et al. (2023)	Primary data from 290 steel industry employees in China	Manufacturing (steel industry)	ICT variables positively influence financial performance; corporate social responsibility (CSR) and ICT strategies are critical for improved outcomes
Rehman et al. (2020)	Survey data from 420 manufacturing SMEs in Pakistan	Manufacturing	IT infrastructure enhances innovation and business performance
Zeng and Lu (2021)	Data from 265 core firms in China's agri-food supply chain	Agriculture/ transportation and storage	IT capabilities significantly improve firm performance
Yu et al. (2021)	Data from 296 cross-border e-commerce firms	Transportation and storage	IT integration improves financial performance via supply chain optimization
Mesároš and Mandičák (2017)	Data from 85 Slovak construction firms	Construction	ICT tools (e.g., enterprise resource planning (ERP) systems, building information modeling (BIM) tools) significantly enhance company performance

Source: own

that while DI positively influences financial outcomes, the magnitude and mechanisms of impact vary across sectors, supporting the need for sector-specific analyses.

Given the economic importance of manufacturing, utilities, and transportation sectors in CEE countries, research on their DI's financial effects is critical. These industries contribute significantly to GDP and employment, and digital transformation in these sectors could enhance regional economic development. Hence, the following hypothesis is proposed:

H2: The impact of DI on financial performance varies among sectors in CEE countries.

1.3 Strategic integration of ICT for enhanced performance

Digitalization levels across the CEE region vary, enterprises in wealthier nations invest more in R&D and exhibit higher levels of digital

adoption, which in turn contributes to improved economic performance and competitiveness (Brodny & Tutak, 2022). The COVID-19 pandemic accelerated digitalization, compelling enterprises to adopt cloud computing, AI, and e-commerce for resilience (Criveanu, 2023; Savvakis et al., 2024). EUROSTAT (in 2022) reported increased online sales and cybersecurity investments supported by EU policies (Kyshakevych et al., 2024). Firms with higher digital adoption saw improved financial performance, including EBITDA and market valuation (Moro-Visconti et al., 2025). SMEs leveraging digital tools outperformed peers in profitability and adaptability (Kádárová et al., 2023). However, digital disparities and cybersecurity risks remain challenges (Criveanu, 2023). The role of ICT in enhancing financial performance is further mediated by factors such as innovation capability, business model alignment,

and organizational culture (Yunis et al., 2018; Wang et al., 2020; Zhang et al., 2023). While technological adoption offers potential for profit generation, challenges such as cost, skills shortages, and cultural barriers may limit its effectiveness (Wen et al., 2021). For instance, ERP systems (Chopra et al., 2022), customer relationship management (CRM) tools and business intelligence (BI) tools (Rajnoha et al., 2016) have been shown to significantly improve profitability and operational efficiency. Given the importance of integrating ICT with strategic decision-making and operational processes, the following hypothesis is formulated:

H3: Technologies facilitating operational integration, such as ERP systems, significantly enhance financial performance by enabling profitability and efficiency gains.

2 Research methodology and materials

2.1 Research methodology

This study examines the relationship between DI and financial performance indicators across three sectors, utilizing multiple linear regression (MLR) and multiple factor analysis (MFA). Previous research indicates that the adoption of digital technologies can positively impact firm performance across various industries. MLR was employed to identify significant DI indicators and quantify their effect on financial performance.

To ensure the validity and reliability of the regression analysis, a series of preliminary checks were conducted on both dependent and independent variables. These included tests for multicollinearity, normality, and homoscedasticity. The normality of regression residuals was assessed using a normal P-P plot, while homoscedasticity was examined through standardized residual plots. Multicollinearity was evaluated by calculating Pearson correlation coefficients, with values exceeding 0.7 suggesting potential multicollinearity and variance inflation factors (VIF) greater than 3 indicating problematic multicollinearity. Decisions regarding the exclusion of variables were based on their impact on the R^2 value.

MLR was chosen over panel regression due to its straightforward approach to estimating coefficients for all independent variables simultaneously while pooling data across multiple years to enhance statistical power and reliability. In contrast, panel regression introduces complexities such as fixed or random effects

and potential endogeneity biases, which could complicate the analysis and make it less suitable for this study.

MFA, drawing on the methodologies of Thurstone (1931) and Escofier and Pages (1994), was used to analyze the interrelationships between variables across different blocks, including DI, indebtedness, profitability, and liquidity. Initially, separate principal component analyses (PCAs) were conducted for each block, followed by a global PCAs on the normalized blocks to explore the relationships between the variable groups. This approach effectively visualized the data structure and identified clusters, making it well-suited for analyzing complex datasets.

All analyses were performed using R version 4.2.3 (R Core Team, 2023), with visualizations generated in RStudio and further refined in Inkscape. MLR was conducted using the “lm” function from the Stats package, while MFA was executed using the “MFA” function from the FactoMiner package. Durbin-Watson and VIF tests were carried out using the Car package.

2.2 Research data

This study analyzes DI and financial performance in 11 CEE countries using data from the EUROSTAT ENT2 and EMIS Benchmark databases. The EUROSTAT ENT2 database includes data from around 150,000 enterprises across the EU, focusing on ICT usage and e-commerce in sectors. Average values for DI indicators were analyzed based on EU surveys. The EMIS Benchmark database provides financial data from 2,000 to 5,000 enterprises in CEE countries, covering sectors. These datasets allow a comprehensive analysis of the link between digitalization and financial performance in the CEE region.

Digital intensity indicators

The study used historical data from the EUROSTAT ENT2 database, focusing on ICT usage and e-commerce in enterprises. The Digital Intensity Index (DII) v3, developed by the European Commission, was the primary metric for measuring digitalization, reflecting enterprise-level adoption of 12 digital technologies. Due to data limitations, certain indicators, such as “use any AI technology” and “buy sophisticated or intermediate cloud computing services,” were excluded. Additionally, collinearity was detected between variables,

Tab. 2: The selected digital intensity indicators from EUROSTAT (ENT2)

Database/indicator code	Variables	Indicator label
ISOC_EC_ESELN2/ E_AWS_GT1_B2C_GT10WS	WEB_SALES	Enterprises where web sales are more than 1% of total turnover and B2C web sales more than 10% of the web sales
ISOC_CICCE_USEN2/ E_CC	CLOUD_COMPUTING	Buy cloud computing services used over the internet
ISOC_EB_IIPN2/ E_CRM	CRM	Enterprises using software solutions like customer relationship management (CRM)
webDB/ E_ERP1	ERP	Enterprises that have ERP software packages to share information between different functional areas
ISOC_CI_IT_EN2/ E_ISPDF_GE30	INTERNET_SPEED	The maximum contracted download speed of the fastest fixed-line internet connection is at least 30 Mb/s
webDB/ E_IUSE_GT50	BUSINESS_INTERNET	Enterprises where more than 50% of the persons employed have access to the internet for business purposes
ISOC_CISMTN2/ E_SM1_ANY	SOCIAL_MEDIA	Use any social media

Source: own based on EUROSTAT (2024)

leading to the exclusion of “enterprises with e-commerce sales of at least 1% of turnover” and “use two or more social media,” leaving seven independent variables. The analysis covered data from 2017 to 2022 and focused on these selected indicators (Tab. 2).

Financial performance indicators

For financial performance, the study used EMIS Benchmark indicators, focusing on profitability, indebtedness, and liquidity ratios. Profitability ratios like ROA and gross profit margin assessed a company's ability to generate profits. Indebtedness ratios, including Leverage, evaluated financial leverage and risk, while liquidity ratios such as the current ratio examined the ability to meet short-term obligations. These indicators offered a comprehensive view of each enterprise's financial health.

Sampling strategy

The sample included enterprises from 11 CEE countries, with data collected between 2017 and 2022. The study applied a purposive sampling strategy, selecting enterprises with complete data. Excluded from the analysis were countries with missing financial data and enterprises lacking key indicators. The final sample comprised

61 observations per sector, ensuring a balanced representation across sectors like manufacturing, transportation, and utilities.

The formula presented below illustrates the dependent and independent variables utilized in MLR:

$$y_i = \beta_0 + \beta_1(WEB_SALES)_i + \beta_2(CLOUD_COMPUTING)_i + \beta_3(CRM)_i + \beta_4(ERP)_i + \beta_5(INTERNET_SPEED)_i + \beta_6(BUSINESS_INTERNET)_i + \beta_7(SOCIAL_MEDIA)_i + \varepsilon_i \quad (1)$$

where: y – dependent variables (current liabilities/total liabilities, current ratio, gross profit margin, leverage, and ROA); $\beta_1, \beta_2, \dots, \beta_7$ – the parameters of the 7 independent variables; ε – the error term; i – sector (utilities, manufacturing, and transportation).

Tab. 3 describes variables in the manufacturing, utilities, and transportation sectors across CEE countries. The Tab. 3 comprises 61 observations for each sector separately, with the exception of financial ratios data for Bulgaria, the Czech Republic, Estonia, Latvia, and Lithuania in 2022, which is excluded due to missing information.

Tab. 3: Description of variables in sectors – Part 1

Variables	Mean	Std. deviation
Manufacturing (N = 61)		
Current liabilities/total liabilities	0.6873	0.0775
Current ratio	1.4873	0.3120
Gross profit margin	0.3243	0.1388
Leverage	0.9582	0.2386
Return on assets	0.0619	0.0191
WEB_SALES	0.0524	0.0344
CLOUD_COMPUTING	0.5489	0.2483
CRM	0.1974	0.0673
ERP	0.2560	0.1372
INTERNET_SPEED	0.5415	0.1971
BUSINESS_INTERNET	0.1730	0.0837
SOCIAL_MEDIA	1.0330	0.2271
Utilities (N = 61)		
Current liabilities/total liabilities	0.4784	0.1554
Current ratio	1.0318	0.3888
Gross profit margin	0.4574	0.3055
Leverage	1.1953	0.5843
Return on assets	0.0210	0.0669
WEB_SALES	0.0234	0.0204
CLOUD_COMPUTING	0.6495	0.3138
CRM	0.2840	0.0968
ERP	0.2825	0.1640
INTERNET_SPEED	0.6160	0.1801
BUSINESS_INTERNET	0.2560	0.0595
SOCIAL_MEDIA	0.8539	0.2093
Transportation (N = 61)		
Current liabilities/total liabilities	0.4840	0.1700
Current ratio	1.0550	0.4003
Gross profit margin	0.4485	0.2631
Leverage	1.4650	0.9396
Return on assets	0.0274	0.0226
WEB_SALES	0.0500	0.0444
CLOUD_COMPUTING	0.4656	0.2560
CRM	0.1463	0.0643
ERP	0.1422	0.0753

Tab. 3: Description of variables in sectors – Part 2

Variables	Mean	Std. deviation
Transportation (N = 61)		
<i>INTERNET_SPEED</i>	0.5460	0.1966
<i>BUSINESS_INTERNET</i>	0.3485	0.1662
<i>SOCIAL_MEDIA</i>	0.8845	0.2188

Source: own

3 Results

3.1 Manufacturing sector

Impact of DI on indebtedness. The adoption of digital solutions significantly influences indebtedness. Using CRM and ERP (*CRM* and *ERP*) software positively affected the current and total liabilities ratio, while businesses with over 50% of employees using the internet for business purposes (*BUSINESS_INTERNET*) experienced a negative impact. ERP also increased leverage,

whereas social media (*SOCIAL_MEDIA*) usage reduced it.

Impact of DI on liquidity. High-speed internet access (*INTERNET_SPEED*) and social media (*SOCIAL_MEDIA*) engagement positively influenced liquidity, as measured by the current ratio.

Impact of DI on profitability. ERP software improved gross profit margin, whereas business internet access had a negative effect.

Tab. 4: Statistical results of the research in the manufacturing sector

Dependent variable	Independent variable	Unstandardized coefficients		VIF index	t-statistic	Significance (p-value)
		β	Std. error			
Current liabilities/total liabilities ($R^2 = 0.430$; F -statistic = 5.6; $p < 0.01$; Durbin-Watson = 1.99)	Constant	0.586	0.053		11.054	0.000
	<i>CRM</i>	0.718	0.131	1.178	5.487	0.000
	<i>ERP</i>	0.223	0.072	1.529	3.097	0.003
	<i>BUSINESS_INTERNET</i>	-0.345	0.162	2.760	-2.131	0.038
Leverage ($R^2 = 0.397$; F -statistic = 4.90; $p < 0.01$; Durbin-Watson = 2.30)	Constant	1.380	0.171		8.091	0.000
	<i>E_ERP1</i>	0.633	0.231	1.529	2.737	0.008
	<i>SOCIAL_MEDIA</i>	-0.491	0.143	1.567	-3.439	0.001
Current ratio ($R^2 = 0.394$; F -statistic = 4.84; $p < 0.01$; Durbin-Watson = 2.44)	Constant	0.736	0.222		3.322	0.002
	<i>INTERNET_SPEED</i>	0.458	0.194	1.303	2.363	0.022
	<i>SOCIAL_MEDIA</i>	0.586	0.185	1.567	3.159	0.003
Gross profit margin ($R^2 = 0.237$; F -statistic = 2.26; $p = 0.044$; Durbin-Watson = 2.05)	Constant	0.193	0.112		1.733	0.091
	<i>ERP</i>	0.463	0.151	1.514	3.062	0.004
	<i>BUSINESS_INTERNET</i>	-0.890	0.346	2.761	-2.574	0.013
Return on assets ($R^2 = 0.408$; F -statistic = 5.12; $p < 0.01$; Durbin-Watson = 1.96)	Constant	0.039	0.013		2.968	0.004
	<i>CRM</i>	0.092	0.033	1.178	2.815	0.007
	<i>ERP</i>	-0.066	0.018	1.529	-3.643	0.001

Source: own

CRM usage enhanced ROA, but ERP possession negatively impacted ROA.

Tab. 4 summarizes the regression coefficients and model fit measures. The Durbin-Watson statistics confirmed the independence of residuals, and model fit indices indicated a moderate yet significant fit. VIF values below 3 suggested no multicollinearity issues.

3.2 Utilities sector

Impact of DI on indebtedness: The findings indicate a positive and statistically significant relationship between e-commerce (*WEB_SALES*), ERP (*ERP*), and internet connection speed (*INTERNET_SPEED*) with the ratio of current liabilities to total

liabilities. Specifically, *WEB_SALES*, *ERP*, and *INTERNET_SPEED* were positively associated with this ratio. On the other hand, cloud computing (*CLOUD_COMPUTING*), use of CRM (*CRM*), and social media (*SOCIAL_MEDIA*) were negatively associated with the ratio.

ERP and *INTERNET_SPEED* also positively influenced leverage, while *SOCIAL_MEDIA* had a negative impact on leverage.

Impact of DI on liquidity: Social media had a positive and statistically significant impact on the current ratio.

Impact of DI on profitability: ERP had a negative and significant impact on the gross profit margin. No significant effects of DI indicators were observed on ROA.

Tab. 5: Statistical results of the research in the utilities sector

Dependent variable	Independent variable	Unstandardized coefficients		VIF index	t-statistic	Significance (p-value)
		β	Std. error			
Current liabilities/total liabilities ($R^2 = 0.410$; F-statistic = 5.26; $p < 0.01$; Durbin-Watson = 1.95)	Constant	0.521	0.122		4.274	0.000
	<i>WEB_SALES</i>	2.140	0.827	1.054	2.588	0.012
	<i>CLOUD_COMPUTING</i>	-0.135	0.066	1.596	-2.039	0.046
	<i>CRM</i>	-0.382	0.182	1.154	-2.102	0.040
	<i>ERP</i>	0.408	0.112	1.263	3.634	0.001
	<i>INTERNET_SPEED</i>	0.206	0.094	1.063	2.198	0.032
	<i>SOCIAL_MEDIA</i>	-0.211	0.087	1.225	-2.429	0.019
Leverage ($R^2 = 0.473$; F-statistic = 6.81; $p < 0.01$; Durbin-Watson = 1.93)	Constant	1.160	0.433		2.680	0.010
	<i>E_ERP1</i>	1.144	0.399	1.263	2.865	0.006
	<i>INTERNET_SPEED</i>	0.682	0.333	1.062	2.046	0.046
	<i>SOCIAL_MEDIA</i>	-1.099	0.308	1.225	-3.569	0.001
Current ratio ($R^2 = 0.237$; F-statistic = 2.35; $p = 0.036$; Durbin-Watson = 1.90)	Constant	0.965	0.347		2.784	0.007
	<i>SOCIAL_MEDIA</i>	0.643	0.247	1.225	2.608	0.012
Gross profit margin ($R^2 = 0.236$; F-statistic = 2.30; $p = 0.041$; Durbin-Watson = 2.02)	Constant	0.898	0.284		3.106	0.003
	<i>ERP</i>	-0.530	0.252	1.256	-2.101	0.041
Return on assets ($R^2 = 0.118$; F-statistic = 1.01; $p = 0.435$; Durbin-Watson = 1.96)	Constant	0.078	0.064		1.222	0.227
	<i>CRM</i>	-0.187	0.096	1.154	-1.953	0.056

Source: own

According to Tab. 5, all dependent variables except ROA showed significant and moderately good model fit. Additionally, all VIF indices were below the threshold of 3, indicating the absence of multicollinearity.

3.3 Transportation sector

Impact of DI on indebtedness: The analysis revealed that *ERP*, internet speed (*INTERNET_SPEED*), and using social media (*SOCIAL_MEDIA*) showed positive effects on the current/total liabilities ratio, with strong statistical significance. Conversely, cloud computing (*CLOUD_COMPUTING*) and business

internet access negatively impacted the ratio, with cloud computing having a moderate negative effect and business internet access (*BUSINESS_INTERNET*) showing a stronger negative influence. While *CRM* had a significant negative effect on leverage, the overall regression model was not significant.

Impact of DI on liquidity: Business internet access (*BUSINESS_INTERNET*) showed a positive and significant effect on the current ratio, while e-commerce (*WEB_SALES*) negatively and significantly impacted the ratio.

Impact of DI on profitability: The study indicated that *CRM*, *ERP*, and high-speed internet

Tab. 6: Statistical results of the research in the transportation sector

Dependent variable	Independent variable	Unstandardized coefficients		VIF index	t-statistic	Significance (p-value)
		β	Std. error			
Current liabilities/total liabilities ($R^2 = 0.402$; F -statistic = 5.09; $p < 0.01$; Durbin-Watson = 2.34)	Constant	0.320	0.107		3.007	0.004
	<i>CLOUD_COMPUTING</i>	-0.264	0.077	2.244	-3.439	0.001
	<i>ERP</i>	0.606	0.264	1.529	2.301	0.025
	<i>INTERNET_SPEED</i>	0.327	0.122	1.303	2.669	0.010
	<i>BUSINESS_INTERNET</i>	-0.584	0.154	2.760	-3.792	0.000
	<i>SOCIAL_MEDIA</i>	0.297	0.099	1.567	2.994	0.004
Leverage ($R^2 = 0.173$; F -statistic = 1.59; $p = 0.160$; Durbin-Watson = 1.72)	Constant	3.056	0.692		4.416	0.000
	<i>CRM</i>	-4.629	2.102	1.325	-2.202	0.032
Current ratio ($R^2 = 0.386$; F -statistic = 5.75; $p < 0.01$; Durbin-Watson = 2.03)	Constant	0.567	0.254		2.230	0.030
	<i>WEB_SALES</i>	-3.665	1.126	1.345	-3.255	0.002
	<i>CLOUD_COMPUTING</i>	0.367	0.183	1.180	2.008	0.050
	<i>BUSINESS_INTERNET</i>	1.556	0.367	2.006	4.238	0.000
Gross profit margin ($R^2 = 0.602$; F -statistic = 11.46; $p < 0.01$; Durbin-Watson = 1.56)	Constant	0.175	0.134		1.303	0.198
	<i>CLOUD_COMPUTING</i>	-0.245	0.097	1.180	-2.530	0.014
	<i>CRM</i>	0.873	0.408	1.325	2.139	0.037
	<i>ERP</i>	2.457	0.333	1.208	7.383	0.000
	<i>INTERNET_SPEED</i>	0.467	0.154	1.775	3.025	0.004
	<i>BUSINESS_INTERNET</i>	-0.836	0.194	2.006	-4.305	0.000
Return on assets ($R^2 = 0.085$; F -statistic = 0.70; $p = 0.669$; Durbin-Watson = 2.04)	Constant	0.025	0.018		1.423	0.161
	<i>CRM</i>	0.092	0.053	1.325	1.738	0.088

Source: own

connection (*INTERNET_SPEED*) positively affect the gross profit margin. In contrast, cloud computing (*CLOUD_COMPUTING*) and business internet access (*BUSINESS_INTERNET*) negatively influenced the gross profit margin. No significant impact of DI on ROA was observed in the analysis.

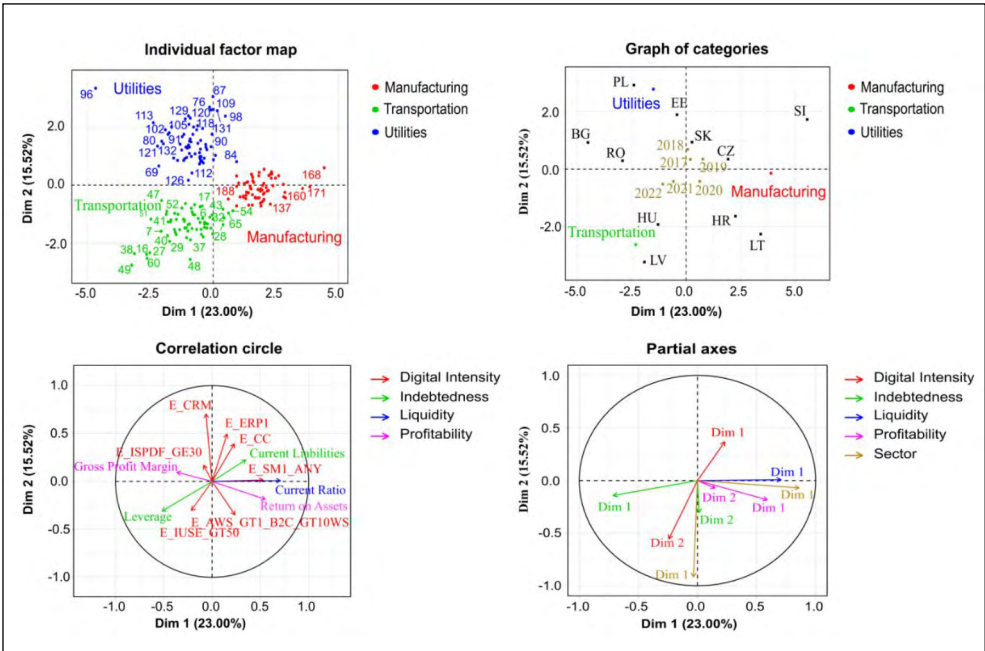
Tab. 6 summarizes the regression coefficients and model fit measures with all VIF indices below the threshold of 3.

3.4 Results from the MFA analysis

Fig. 1 contains four plots. The first plot (individual factor map) displayed the companies colored by sectors. The second plot (correlation circle) presented the relationship between each variable block and digital intensity indicators. The third plot (partial axes plot) showed which variable block belongs to which dimension. The fourth plot (graph of categories) depicted each categorical variable on a common plot (years, countries, sectors). Overall, the two dimensions of MFA accounted for nearly 40% of the variance, which was considered

satisfactory. The two MFA dimensions effectively distinguished the three sectors.

The first dimension was related mainly to *SOCIAL_MEDIA*. The second dimension can be related to the remaining indicators of digital intensity. Regarding the financial indicators, liquidity and profitability belonged to the first dimension, while indebtedness can be related to the second dimension. The manufacturing sector can be described by a relatively higher current ratio and Liabilities, higher ROA and *SOCIAL_MEDIA*, and lower gross profit margin and leverage. Companies in the utilities sector had relatively higher *CLOUD_COMPUTING*, *CRM*, and *ERP* values. Transportation companies had the highest leverage and *BUSINESS_INTERNET*. Analysis of variance (ANOVA) showed that the most influential indicator was current liabilities, with an *F*-statistic of 67.43 ($p < 0.001$). The second most influential indicator was ROA, with an *F*-value of 45.76 ($p < 0.001$), followed by *E_CRM* with an *F*-value of 43.38 ($p < 0.001$). *INTERNET_SPEED* ($F = 3.10$;



$p = 0.048$) and gross profit margin ($F = 8.34$; $p < 0.001$) had a smaller but still significant role in distinguishing the 3 sectors.

4 Discussion

While previous research has been limited, this study aimed to fill the gap and provide valuable insights into the influence of DI across multiple sectors. This study confidently explored the impact of DI on financial performance in three sectors, namely the utilities, manufacturing, and transportation sectors in the Central and Eastern European countries. The research findings suggested that the impact of DI on the financial performance of different sectors varied significantly depending on the sector and the financial performance index (Fig. 1). The statistical analysis results indicated that DI significantly impacted financial performance in the studied sectors. Thus, $H1$ was accepted. This finding was consistent with prior research (Khanna & Sharma, 2022; Mesároš & Mandičák, 2017; Xiliang et al., 2023), which demonstrated a substantial impact of IT/ICT on the company's output.

4.1 Manufacturing sector

The influence of DI on financial performance in the manufacturing sector of CEE countries is multifaceted and shaped by various factors. Notably, different DI indicators yielded contrasting effects on firms' indebtedness. Adopting software solutions like CRM and ERP systems positively influenced firms by increasing current liabilities relative to total liabilities. These systems enhance data management and interdepartmental communication, enabling firms to expand operations and invest in growth opportunities, thereby raising liabilities. Such technologies are critical for maintaining competitiveness and achieving organizational goals. Conversely, while providing employees with internet access for business purposes may offer efficiency gains and cost savings, it is associated with lower current liabilities relative to total liabilities, reflecting reduced reliance on external financing – a potentially advantageous outcome in the long term. In today's digital landscape, a stable internet connection is indispensable for business operations. These findings align with the research of Dabbous et al. (2023) and Saura et al. (2022).

Regarding liquidity, certain DI indicators, such as internet connection speed and

social media usage, positively correlated with the current ratio. Firms with faster internet connections and active social media engagement displayed improved short-term liquidity positions. Social media, in particular, enhances customer engagement and drives sales, thereby boosting liquidity.

DI indicators exhibited both positive and negative impacts on profitability. Firms utilizing ERP systems experienced higher gross profit margins, driven by process streamlining and resource allocation improvements, which resulted in cost savings and operational efficiencies. However, extensive internet usage for business purposes negatively affected gross profit margins, possibly due to increased operating costs or inefficiencies caused by excessive online activities. CRM usage positively impacted ROA, as it improved customer relationship management and marketing effectiveness, leading to increased sales and profitability. Conversely, ERP systems had a negative impact on ROA, potentially reflecting challenges such as high implementation costs and initial inefficiencies, which may offset their eventual benefits in asset utilization. These effects underline the importance of context and implementation in determining the financial outcomes of DI.

4.2 Utilities sector

Various factors shape the multifaceted effects of digital intensity on the financial performance of utilities firms. Firms in this sector must carefully evaluate the costs, benefits, and risks associated with adopting and utilizing digital technologies to enhance financial performance and maintain competitiveness in an evolving digital landscape.

The results revealed a mixed impact on indebtedness. Data indicated that firms employing digital intensity tools such as e-commerce, ERP systems, and high-speed internet tend to exhibit higher levels of indebtedness, driven by increased current liabilities. This may reflect significant investments in e-commerce infrastructure, ERP implementation, and internet connectivity. These findings align with Grant and Yeo (2018) conclusion that e-commerce development in Eastern European countries lags behind the US and Western Europe. Moreover, web sales appear less favored in the utilities sector compared to the hospitality and services sectors.

Interestingly, firms utilizing digital technologies like cloud computing, CRM, and social media showed lower debt levels, evidenced by a significant negative relationship with current liabilities. These technologies offer benefits such as cost savings, efficiency improvements, and enhanced financial management. The study highlighted a nuanced relationship between DI and financial leverage. Firms with ERP systems and fast internet connections tend to exhibit higher leverage, suggesting their inclination toward technology investment and growth opportunities, often supported by debt financing. Conversely, active social media engagement reduces financial leverage, potentially reflecting a focus on brand-building and customer engagement without heavy reliance on debt.

In terms of liquidity, the analysis showed a positive and significant relationship between social media activity and the current ratio, indicating that firms with active social media presences tend to have stronger short-term liquidity. Social media may enhance customer engagement, drive sales, and improve cash flow management, thereby strengthening liquidity positions.

Regarding profitability, the study revealed a significant negative impact of ERP systems on the gross profit margin, likely due to the substantial costs associated with implementation, maintenance, and operational challenges. However, no measurable impact of DI indicators was observed on ROA. While this suggests that these technologies may not directly affect asset utilization or profitability within the utilities sector in the CEE region, further research is needed to explore their potential influence fully.

4.3 Transportation sector

The impact of DI on the financial performance of firms in the transportation sector in the CEE region is a complex and multifaceted issue. While some digital intensity indicators positively influence indebtedness, liquidity, and profitability, others have opposing effects.

Regarding indebtedness, the analysis revealed a nuanced relationship between DI indicators and current liabilities relative to total liabilities. A significant positive impact of adopting ERP systems, high-speed internet connectivity, and social media usage on indebtedness suggests that firms leveraging these technologies often face higher current liabilities. This may be attributed to increased

investments in operations, expansion projects, or marketing initiatives requiring short-term financing. Conversely, the use of cloud computing and basic business internet access was associated with lower current liabilities, likely due to cost reductions, efficiency improvements, and better financial management. Additionally, firms employing CRM systems tended to have lower financial leverage, as CRM adoption can enhance revenue generation and financial stability through improved customer management and retention.

The study also indicated that business internet access positively influences short-term liquidity. Improved operational efficiency, streamlined transactions, and real-time communication enabled by internet connectivity likely contribute to better cash flow management and liquidity.

In terms of profitability, digital technologies such as CRM, ERP systems, and high-speed internet showed mixed effects. A significant positive relationship was observed between these technologies and gross profit margin, suggesting their role in enhancing profitability through operational efficiency, customer management, and data-driven decision-making. Conversely, cloud computing and business internet access had a significantly negative impact on profitability, potentially due to increased operating costs, cybersecurity risks, or disruptions linked to internet access.

The findings supported the hypothesis *H2* that DI has varying impacts on financial performance across sectors, aligning with prior research by Khanna and Sharma (2022). Notably, ERP emerged as a key driver of profitability, consistent with an earlier study by Mesároš and Mandičák (2017), which highlighted the superior performance of enterprises utilizing ERP. However, ERP implementation may lead to short-term debt burdens in the manufacturing and transportation sectors and fail to enhance profitability in the utilities sector. This underscores the importance of carefully evaluating ERP investments, given the significant capital requirements for compatible IT infrastructure and potential impacts on liabilities. Consequently, hypothesis *H3* was partially accepted.

Conclusions

This study offers valuable insights into the influence of DI on the financial performance of enterprises in the utilities, manufacturing, and

transportation sectors across 11 Central and Eastern European (CEE) countries, using data from EUROSTAT and EMIS from 2017 to 2022. The research demonstrated that the impact of DI on financial performance varies significantly across sectors, supporting the hypothesis that digital technologies influence sectoral financial outcomes differently. These findings underline the importance of tailoring digital strategies to the unique characteristics of each sector, as the application of digital technologies is not a one-size-fits-all model.

Theoretical contributions of this study are to contribute to the growing body of literature on digital transformation by emphasizing the sector-specific effects of DI on financial performance. It highlights the nuanced relationship between digital technologies and financial metrics, such as profitability, indebtedness, and liquidity. Additionally, the results reinforce the idea that while digital technologies offer numerous opportunities to enhance competitiveness, their adoption requires careful planning and consideration of industry-specific needs.

Practical implications for managers, the findings stress the importance of developing a customized digital strategy that aligns with the specific demands of each sector. Manufacturing firms may focus on ERP systems for improved operational efficiency, while utilities companies could benefit from cloud computing and CRM for better financial management. Transportation firms should leverage high-speed internet and CRM technologies to boost profitability and customer management while being mindful of potential debt burdens from ERP investments. Managers should ensure that digital transformation is accompanied by the necessary staff training and acquisition of skills specific to each technology. For investors, the study signals that digital investments in the CEE region can significantly enhance profitability and liquidity but must be carefully evaluated to mitigate risks, such as high implementation costs, particularly in the utilities sector. Investments in digital technologies should align with long-term strategic goals, and careful consideration of sector-specific challenges is essential for maximizing returns. For policymakers, the findings suggest that supporting digital transformation in CEE countries requires an understanding of sector-specific needs. Policymakers should provide targeted support, such as incentives for digital infrastructure

investments, and encourage training and skill development programs to ensure that enterprises can fully realize the benefits of digital technologies. Additionally, policymakers should consider how digital adoption may differ between developed and developing regions within CEE to create more tailored strategies for fostering competitiveness.

Recommendations for the studied sectors are the following. Manufacturing sector has to invest in ERP systems to streamline operations but carefully evaluate costs and implementation challenges. Internet access for business purposes can help reduce reliance on external financing. Utilities sector has to focus on CRM and cloud computing for cost efficiency and improved financial management. Caution is advised when adopting ERP systems due to high costs and potential negative effects on profitability. Transportation sector must prioritize high-speed internet and CRM for better customer engagement and profitability. Monitor the cost implications of adopting ERP systems to avoid excessive debt burdens.

Limitations and future research are the following. This study is limited by its focus on only three sectors and the CEE region, which may not fully capture the broad spectrum of digital technology benefits across industries. Future research should extend the analysis to more sectors and compare the impact of digital transformation between developed and developing countries. Moreover, the quality of human resources and research and development may influence the relationship between DI and sector performance, warranting further investigation in future studies.

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Exploring philanthropic behavior and tax incentives: Motivations and trends in individual giving in the Czech Republic

Blanka Jarolimova¹

¹ Tomas Bata University in Zlín, Faculty of Management and Economics, Department of Finance and Accounting, Czech Republic, ORCID: 0000-0001-9940-5734, jarolimova@utb.cz (corresponding author).

Abstract: *Philanthropy is defined as accommodating behaviour towards other members of society, usually through charitable donations. Charity forms a significant part of the income for the non-profit sector in many countries and is often directly supported through government tax policies. This article focuses on new empirical findings and applicable conclusions. It discusses the development of individual giving, motives, causes, and effects of philanthropic behaviour of individual donors in the Czech Republic. The tax incentive in the form of a tax deduction for donations means that the taxpayer bears part of the value of the donation, and part is transferred to the state by the taxpayer using the tax savings equal to the tax rate. Emphasis is placed on how current government policy, through charitable tax deductions from income tax, directly affects the volume of philanthropy in the economy. Philanthropy in the Czech Republic has unique characteristics influenced by its historical, cultural and economic context. This paper examines the motivations behind individual giving in the Czech Republic and evaluates the role of tax incentives compared to other motivators such as personal satisfaction and altruism. Utilizing a survey of 1,050 respondents, combined with regression and correlation analyses, the study reveals that tax incentives are a minor motivator for most donors, with only 2% identifying them as their primary reason for giving. Instead, personal satisfaction and altruism dominate as the most significant motivations. Additionally, while higher-income donors are more likely to utilize tax benefits, many remain unaware of these opportunities. The findings suggest the need for increased awareness campaigns and better integration of tax benefits into fundraising strategies. The study contributes to philanthropy by providing empirical insights specific to the Czech Republic and comparing these findings with existing literature.*

Keywords: *Giving, charitable giving, philanthropy, donation support, tax relief.*

JEL Classification: D64, H24, L31.

APA Style Citation: Jarolimova, B. (2025). Exploring philanthropic behavior and tax incentives: Motivations and trends in individual giving in the Czech Republic. *E&M Economics and Management*, 28(4), 131–147. <https://doi.org/10.15240/tul/001/2025-5-022>

Early Access Publication Date: October 3, 2025.

Introduction

Philanthropy plays a crucial role in many countries by providing private support for a wide range of activities that benefit the public. Unlike government programs (which pursue public goals through public funding) and profit-driven

ventures (which aim for private gain), philanthropy uniquely combines private actions for the public good. Most OECD countries encourage this sector by offering preferential tax treatment: philanthropic organizations are often tax-exempt for their activities, and individuals

or corporations donating to these causes can receive tax incentives that reduce the cost of their contributions.

Building on previous research and empirical data, this study explores whether tax incentives truly motivate individuals to give or whether other factors, such as personal satisfaction and altruism, play a more decisive role. Additionally, it examines demographic influences such as age, income, and education, providing a comprehensive picture of the philanthropic landscape in the Czech Republic.

Individual giving in the Czech Republic represents a significant phenomenon. Increasingly, individuals are dedicating their financial resources, time, and assets to support charitable activities and non-profit organizations. Individual giving evolves uniquely, influenced by historical, cultural, and economic factors. This article aims to provide an overview of the current state of individual giving, analyse the main motives of donors, and identify key areas that attract their support.

This study delves into the landscape of individual giving in the Czech Republic to understand individual donors' motives, behaviour, and demographics. It is based on primary data collected from a survey of 1,050 respondents and secondary data from various sources, including the Czech Statistical Office, the Financial Administration of the Czech Republic, and non-profit organizations.

Private giving constitutes an essential source of funding for public benefit activities or non-governmental non-profit organizations, both in the form of donations from individuals and corporate giving. Currently, in the Czech Republic, the only state support tool in the field of giving is the tax deduction of the donation value from the tax base. This tax relief for donations was implemented in tax legislation as early as 1993 within the framework of introducing the standard tax system of the market economy and has thus far remained the only tax tool supporting philanthropy. Therefore, support for giving has a firm place in our tax system; however, this support cannot be considered conceptual. This system is designed to favour donations provided to non-profit organizations, thereby contributing to the sustainable financing of their activities. At the same time, it faces criticism and proposals for improvement, particularly regarding administrative complexity and the availability of information on possible tax advantages.

There is no universally agreed-upon rationale for providing preferential tax treatment to charitable entities. Economic theory offers limited justification for tax relief for philanthropy, whether for the entities themselves or donations, primarily in situations where public goods are underprovided or where the activities of a philanthropic entity generate positive externalities. The under-provision of public goods suggests a combination of "market failure," "government failure," and "volunteer failure," meaning that neither the private sector, government, nor volunteer sector alone can supply an optimal level of public goods to maximize societal welfare. From the research perspective, it can be stated that giving in the Czech Republic remains outside the interest of the academic community, as there are no systematic statistical data on individual giving. There is also no other systematic research dedicated to this issue. Essentially, descriptive statistics on giving can be obtained from two basic sources, which offer only aggregated data. The first source is data from the Czech Statistical Office (CSO) (Czech Statistical Office, 2023), which provides so-called satellite aggregate data on non-profit organizations as part of statistical surveys. Another source is aggregated data from tax returns published annually by the Financial Administration of the Czech Republic (FA CR, 2023). As confirmed by Hladká et al. (2017), another source of information is data published directly by non-profit organizations, i.e., foundations, donor online platforms, and the nationwide association of donors – Donors Forum. However, the presented data significantly differ. The difference between the data published by both institutions in 2020 was EUR 68,000 and the gap widens annually.

The Czech government is aware of the situation, which is why, in 2022, it established a working group for private giving (Government Council for Non-Profit Organizations, 2023), which aims to propose measures to increase the motivation of individual donors to donate financial resources for public benefit purposes. An example of such measures may be raising awareness among individual donors about the possibility of deducting the value of the provided donation from the tax base. Individual donors often do not utilize this deduction option, which could explain the discrepancies in the numbers reported by the CSO and the FA CR. Furthermore, the current situation

does not allow for considering volunteer work as a deductible item from the tax base. Without quality research, however, everything remains in the realm of assumptions.

According to the Worldwide Governance Indicator (World Bank Group, 2023), the situation concerning the level of individual giving in the Czech Republic from a global perspective is not encouraging, as it has long been at the bottom of the individual giving ranking compiled from European countries. If we were to look for specific data reflecting the level of giving in the Czech Republic compared to other European countries, we could refer to the research conducted by the European Research Network on Philanthropy (ERNOP, 2017), according to which the ratio of giving to GDP in the Czech Republic was very low compared to other European countries. The Czech Republic donates more than three times less per capita to GDP than the United Kingdom, more than twice less than Germany or Denmark, and is comparable to countries such as Hungary or Spain.

The justification of tax deductions is a long-discussed topic. Donating reduces the taxpayer's tax liability and diminishes the taxpayer's available resources (Ackerman & Auten, 2011). Therefore, it is justifiable to consider the value of the gift when calculating the taxpayer's tax liability if the donation is eligible for a tax deduction and genuinely serves charitable or public benefit purposes. However, existing research (Andreoni, 2015; Andreoni & Payne, 2013; Auten et al., 2002; Feldstein & Clotfelter, 1976; List, 2011) suggests that tax benefits for donors rank low among the primary motivations. Tax deductions in the form of philanthropy have a positive effect but do not have a sufficiently strong motivational impact. Donors respond to tax incentives if the donation amount is personally significant and planned. Spontaneous donations are typically not made solely for tax savings. They are also limited mainly to high-income taxpayers and higher tax rates. The reward for giving in the form of lower tax liability for taxpayers with low tax rates is zero, and the tax incentive provides them with little or no motivation to donate.

Two key issues with tax incentives for donors are that they can be regressive and potentially undemocratic. Tax incentives may be regressive because higher-income taxpayers receive greater benefits than those with lower

incomes, both in absolute and proportional terms, as deductions tend to benefit those in higher tax brackets more significantly. This raises concerns that tax incentives effectively channel public funds to preferred philanthropic causes, giving higher-income donors outsized influence over how tax revenue is directed. This influence may be problematic, especially if donors' priorities do not align with broader societal needs. Increasing government oversight of eligible entities for tax-advantaged donations could help mitigate these concerns.

1 Theoretical background

Economic theory provides a limited rationale for granting philanthropy tax deduction, mainly when insufficient public goods or philanthropic activities produce beneficial spillover effects. Studies by Andreoni (1990, 2015), Bekkers and Wiepking (2011a), and Feldstein and Clotfelter (1976) have established that tax incentives are often secondary motivators, overshadowed by intrinsic motivators like empathy and social responsibility. However, existing research lacks comprehensive data from the Czech Republic, where historical, cultural, and economic factors may uniquely shape philanthropic behaviour. This study aims to bridge that gap by providing empirical evidence from a large sample of Czech donors.

Conditions for applying tax benefits on donations are usually set by the income tax act of each country, where they are defined both in terms of content and value. The conditions are set for individuals as non-taxable parts of the tax base, where the total value of provided donations must be at least EUR 40 or 2% of the tax base. In total, deducting a maximum of 15% of the tax base is possible. The upper limit was increased to 30% in the years 2020 to 2026. In terms of content, the donation (gratuitous contribution) must meet other conditions; especially, it must be provided for a purpose specified by the income tax act, such as, e.g., science, research, culture, education, youth, healthcare, ecological, and humanitarian. Looking at the OECD Taxation and Philanthropy Report (OECD, 2020), it is straightforward that the Czech Republic is among the countries with the broadest range of worthy purpose categories to support giving.

Degasperi and Mainardes (2017), Feldstein and Clotfelter (1976), Mainardes et al. (2017) in their research point out that generally,

the primary source of income for charitable organizations is individual donations. According to them, this limits the scope of these organizations' activities, as the amount of funds from this group tends to be limited and unpredictable.

Bekkers and Wiepking (2011b) argue that philanthropic acts can be inspired by concern for the well-being of recipients. This leads to understanding what Grace and Griffin (2006) pointed out, that individual characteristics and demographic factors can provide a range of information for explaining donation behaviour. In cases of economic recession, this behaviour may not hold true, as Morgan and Breeze (2009) indicate that individuals tend to donate less during economic crises. This claim is supported by findings from Banks and Tanner (1999) and Smith and McSweeney (2007), who argue that when the economy is in recession, organizations seeking to raise funds must pay more attention to fundraising as donors tend to be more concerned with their financial situation.

For non-profit organizations to correctly target donors, it is essential to know their motivations. Giving can be defined as complex behaviour motivated by various social, economic, and psychological factors. There is a relatively rich body of research dedicated to donation motivations. Bekkers and Wiepking (2011a) reviewed approximately 550 articles to understand better donor behaviour and the attributes associated with these donors. They subsequently grouped variables into eight mechanisms of giving: awareness of need, solicitation, costs and benefits (tax relief), altruism, reputation, psychological benefits, values, efficacy. These mechanisms can provide a basic theoretical framework for future research explaining charitable giving. Other researchers such as Bennett (2009), Casale and Baumann (2013), Grace and Griffin (2009), Knowles et al. (2012), Konrath and Handy (2018), and Verhaert and Van den Poel (2011) also tried to understand the behaviour, motivations, and reasons why individual donors contribute to charity by identifying variables directly related to this individual behaviour. The last-mentioned divided motivations into private and public. Among the private are reputation, tax relief, and efforts to reduce negative or good feelings. Among the public are altruism, influence on changes, and creating new relationships. Degasperi and Mainardes (2017) limit their work to identifying external motivational factors that

support individual monetary donations. They systematize eight external factors influencing individual giving, which appear in the literature and affect monetary donations: trust, reward, leadership influence, organizational characteristics, environmental influences, personal benefit, characteristics of beneficiaries, and future interest. They conclude that no single factor is significantly dominant.

Motivations driven by private and public benefits or external and internal factors are not always distinct and can often overlap. In other words, individuals may be motivated by various reasons for giving, encompassing both personal and societal benefits and external and internal drivers simultaneously. A review of the studies mentioned above reveals several common themes.

Altruism (sense of need) and empathy (awareness of need): altruism is one of the most frequently mentioned motivations for giving. Individuals who donate for altruistic reasons are motivated by the desire to help others without expecting any reward or benefit for themselves. Empathy, or the ability to empathize with others' situations, is key in this type of giving. Research shows that people with high levels of empathy are more frequent donors and give larger amounts. Other studies also point to the importance of empathy in moral decision-making and prosocial behaviour (Khalid & Dickert, 2022; Xiao et al., 2021).

Social pressures and reciprocal behaviour (being asked): social pressures and reciprocal behaviour are other significant motivations. Social norms and expectations can influence individuals to give, especially if giving is common in their social group. Reciprocal behaviour, where an individual donates in anticipation that their action will be reciprocated somehow, is also common. Studies have shown that personal requests for donations are more effective than impersonal ones (Andreoni et al., 2011), suggesting that social pressure and personal relationships significantly influence donation behaviour (Meer & Rosen, 2018). Research further suggests that social pressures can significantly impact individuals' decision to donate (Andreoni, 2015; Eckel et al., 2017).

Personal satisfaction (good feeling) and reputation: giving can also bring personal satisfaction and a sense of meaningfulness, known as the "warm glow" effect. This concept describes the joy and satisfaction an individual

experiences when helping others. This feeling can be so strong that it motivates people to give repeatedly (Andreoni, 1990). Recent studies confirm that intrinsic rewards play a significant role in the motivation to give (Giebelhausen et al., 2017).

Economic factors (tax relief): economic conditions and personal financial situations also influence the decision to donate. People with higher incomes and wealth tend to donate larger amounts, partly due to their greater financial capacity but also due to tax incentives and social prestige associated with philanthropy. Research also indicates that economic uncertainty can reduce the willingness to give, while economic stability can increase it (Wiepking & Bekkers, 2011b). Recent studies confirm that the economic situation plays a key role in donation decisions (Almunia et al., 2020; Duquette, 2016; Haruvy & Popkowski Leszczyc, 2022; Hood et al., 1977).

Motivations for giving are multifaceted and include altruistic desires to help others, social pressures and reciprocal behaviour, personal satisfaction, affinity and loyalty to organizations, economic factors, and the influence of marketing strategies. Understanding these motivations can help organizations plan their fundraising activities more effectively and increase donation rates.

2 Research and methodology

The research design aims to investigate the motivations behind individual giving in the Czech Republic and assess how tax benefits influence donation behaviour. Primary and secondary data sources were used to ensure robustness and depth.

The aim is to confirm, refine and supplement the data in relation to individual donations in the Czech Republic based on primary research and aggregated data from tax returns published annually by the Financial Administration of the Czech Republic (FA CR, 2023). It aims to build on the generally discussed need to increase interest from government institutions and academia in both individual and corporate giving within the context of the Czech Republic and other EU countries.

The research aimed to determine how often donors give, for what purposes and motives, and to understand their knowledge regarding the possibility of claiming donation deductions from the tax base. The obtained data were

further processed using appropriate statistical methods. The methodological framework includes regression and correlation analysis to examine the impact of variables such as sex, age, income and education on the volume and frequency of donations. These methods allow a deeper understanding of the relationships between demographic and economic factors and giving behaviour. The combination of primary and secondary data provides a comprehensive view of individual donor behaviour and their awareness of tax benefits.

Methodologically, the research is based mainly on analysing primary research results conducted in the spring of 2023 on a research sample of 1,050 respondents. The resulting sample was determined by stratified proportional random sampling, which allowed for a deeper analysis of the data and a smaller sampling error given the homogeneity of the groups from which respondents were selected. The questionnaire contained closed questions, which are characterized by a complete list of possible answers from which the respondent selects to obtain a relevant evaluation. Respondents were asked 24 closed questions in the field of giving and were asked to choose one or more options or answered on a Likert scale ranging from 1 (reflecting complete disagreement) to 5 (describing complete agreement).

The survey was conducted through an online method of questionnaire data collection called computer assisted web interviewing. For the creation of the online questionnaire and data collection, a self-service professional tool, Instant Research, was used, which allows for the acquisition of relevant data from across the Czech Republic while utilizing the updated Ipsos panel of respondents Populace.cz, which currently includes more than 100,000 respondents. Through the online survey, participants provided demographic data and then completed the questionnaire. Questions can be clustered into three main categories: impact of tax benefits, demographic categories, and motivation for individual giving.

The research sample consisted of 548 men and 452 women. The median income of donors is between EUR 800 and EUR 1,000, which is also the most frequently chosen answer. The median age is 45 years. More than half (56.6%) of the participants had a secondary school education or higher. The analysis includes only respondents who

have previously made a charitable donation ($N = 894$; 85.1% of the sample).

Several strategies can be employed to mitigate potential biases in self-reported data. Firstly, careful survey design, including neutral language, balanced response scales, and randomized question order, helps minimize biases. Secondly, to ensure anonymity and confidentiality to reduce social desirability bias, where respondents may provide answers they believe are socially acceptable rather than truthful. Finally, utilizing indirect questioning techniques and randomized response methods also enhances the accuracy of sensitive responses by providing respondents with plausible deniability. The possible reliability of self-reported data was, in addition, cross-validated with objective data from tax records.

3 Results and discussion

Before evaluating data from a questionnaire, secondary data published by the Via Foundation (Nadace Via, 2023) were studied, particularly from annual activity reports and data from the FA CR (2023).

3.1 Secondary data

According to information provided by the FA CR (2023), in all monitored periods, financial donations provided by legal entities significantly exceed donations provided by individuals. That does not correspond with findings by Degasperis and Mainardes (2017), Feldstein and Clotfelter (1976), Mainardes et al. (2017), or at least not entirely. Moreover, it supports the assumption that not all individuals claim donations in their tax returns as items reducing the tax base. It is generally believed that corporate donors are aware of the possibility of claiming donations

as deductible items and, therefore, always utilize this option if they donate. Data on the state of corporate giving are thus more informative.

Suppose we monitor the habits related to individual giving from data published by the largest online donation platform in the Czech Republic (darujme.cz, Nadace Via) over the past 10 years, it is clear that most donors make one-time donations. However, one-time donations have declined over the years, from nearly 90% initially to 71% in 2023. At the same time, data show that men tend to donate more sporadically but are willing to donate larger one-time donations. Conversely, women tend to donate regularly, but their amounts are smaller. This confirms the assertion of Landry et al. (2005), who stated in their research that giving can be positively influenced by many factors, including the gender of the requester, as men tend to donate more when receiving requests from attractive women. Data obtained from primary IGA research conducted in 2023 in the Czech Republic confirm these findings, although the ratio of one-time to recurring donations is not as pronounced. Here, 38% of respondents indicated periodic donations.

When evaluating the data from tax statistics published by the FA CR (2023) over the past 20 years (Tab. 1), a steady year-on-year increase in donations provided in real terms is visible, apart from 2008 and 2011. The decline in 2008 can be explained in the context of findings presented by Morgan and Breeze (2009), which show that the expected global financial crisis caused it. However, if we focus on the years 2020 to 2022, we see that during the global recession, the ongoing COVID-19 pandemic (1/2020 to 5/2022), and the onset of the conflict in Ukraine (2/2022), individual

Tab. 1: Individual giving in the Czech Republic from 2003 to 2022

Year	Annual increase (%)	Year	Annual increase (%)	Year	Annual increase (%)	Year	Annual increase (%)
2003	1.00	2008	0.98	2013	1.05	2018	1.07
2004	1.08	2009	1.04	2014	1.06	2019	1.03
2005	1.21	2010	1.01	2015	1.02	2020	1.16
2006	1.13	2011	0.97	2016	1.09	2021	1.11
2007	1.10	2012	1.07	2017	1.16	2022	1.25

Source: own based on FA CR (2023)

giving in the Czech Republic significantly increased with an average one-time donation amount of EUR 48 and a periodic donation amount of EUR 12 in 2023.

The following table (Tab. 2) presents the annual percentage increase in the number of tax returns where individual donors claimed a deduction for donation over a twelve-year period from 2010 to 2021. The percentage increase is mostly positive across all years, indicating a general upward trend in individuals claiming donation deductions. The year 2021 shows a relatively high increase of 1.11, which could be influenced

by charitable giving motivated by the COVID-19 pandemic or enhanced awareness of tax benefits. 2013 shows the highest increase of 1.17. It is the year when a 7% solidarity tax surcharge on high-income individuals was implemented. This additional tax burden may have incentivized taxpayers to seek ways to reduce their taxable income, such as by making charitable donations, which are deductible under Czech tax law.

Data published by darujme.cz further confirms that donors are more sensitive when confronted with news of natural disasters or during certain holidays such as Christmas (Tab. 3).

Tab. 2: Number of tax returns with claimed donation deduction by individual donors from 2010 to 2021

Year	Annual increase (%)	Year	Annual increase (%)	Year	Annual increase (%)	Year	Annual increase (%)
2010	1.00	2013	1.17	2016	1.06	2019	1.05
2011	1.03	2014	0.99	2017	1.06	2020	1.03
2012	1.03	2015	1.04	2018	1.06	2021	1.11

Source: own based on FA CR (2023)

Tab. 3: Willingness to donate by time of the year

Year	Month	Purpose	Year	Month	Purpose
2012	December	Christmas	2018	December	Christmas
2013	June	Flooding	2019	December	Christmas
2014	December	Christmas	2020	December	Christmas
2015	April	Earthquake in Nepal	2021	June	Tornado (the SE part of the CR)
	December	Christmas	2022	February	Start of the conflict in Ukraine
2016	December	Christmas		March	Start of the conflict in Ukraine
2017	December	Christmas	2023	December	Christmas

Source: own based on portal darujme.cz

3.2 Primary data – Impact of tax benefits on individual giving

In the research, only 37% of respondents stated that the possibility of a donation deduction is an opportunity for them to reduce their tax base. At the same time, 65% of respondents consider tax deductions insufficient motivation for giving. From other answers (Fig. 1), it emerged that more than 75% of respondents do not know

the amount of tax they would save if they donated. Only 17% could correctly determine the amount of the tax deduction. Respondents were also asked questions to assess their knowledge of the minimum limit for deduction eligibility. Question No. 10 assessed knowledge of the minimum limit for all donations, and question No. 11 assessed the minimum limit for a single donation.

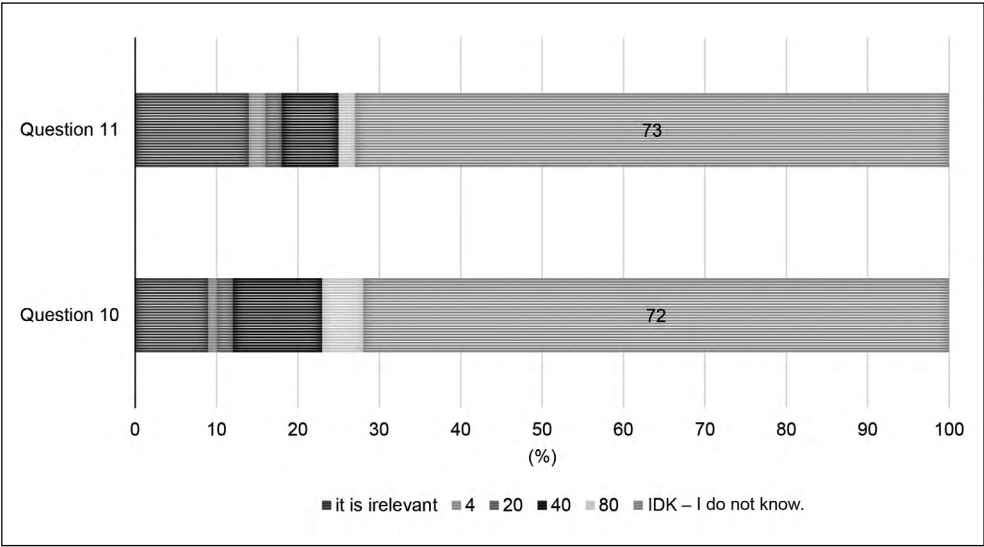


Fig. 1: Donors' awareness of the minimum donation amount

Source: own based on Primary IGA research

Awareness of the minimum donation amount to qualify for a tax deduction is very low. In both cases, more than 70% of respondents answered that they do not know (IDK) any minimum limit, and the remaining 20% knew about the limit but stated it incorrectly. Only 11% and 14%, respectively, correctly answered the questions. Questions related to donors' awareness were also aimed at assessing their knowledge of the increase in the maximum donation limit from 15% to double in 2021 and 2023. The responses clearly showed that 66% of respondents were unaware of the increase in the maximum limit. When asked whether recent events such as the COVID-19 pandemic or the conflict in Ukraine positively influenced their giving, 18% of respondents answered positively for the former, and almost 30% responded positively by increasing their donations for the latter.

Respondents were also asked about the most frequently donated amounts of money or non-monetary donations. From the responses, as seen in Fig. 2, it is evident that monetary donations typically range between EUR 40 and EUR 200. These amounts can be used as deductible items from the tax base. Non-monetary donations most commonly fall into the categories

of EUR 4 and EUR 40. In the first case, this likely involves people being asked to contribute on the street during various one-day campaigns, such as street collections or donor SMS. Considering the second response of EUR 40 and combining it with the answer regarding the form of donation, respondents indicated in almost 17% of cases that it involved blood donations. Every blood donation, however, has a tax-deductible value of EUR 120. It can thus be evaluated that most respondents are unaware of the deductible value of blood donation.

When asked whether tax deduction is the primary motivation for giving, only 2% of respondents answered positively. The primary motivations cited were "the need to do a good deed" and "the feeling that they could help or influence something." 41% of respondents admitted that when donating, it is important to know whether they can deduct the donation from the tax base, but it is not the main reason for donating. The possibility of tax deduction is associated with obtaining a confirmation from the recipient, giving respondents confidence that their funds will be genuinely used for the intended purpose. Most respondents (86%) consider the possibility of deduction when donating as a correct step for the state.

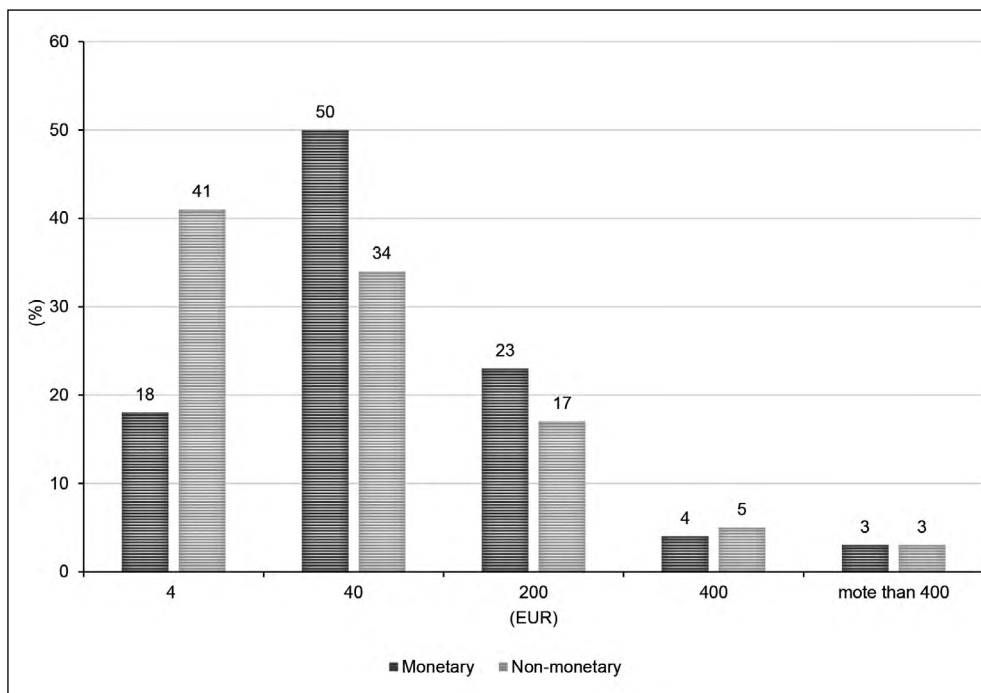


Fig. 2: Average amounts of monetary and non-monetary donations (EUR)

Source: own based on Primary IGA research

3.3 Primary data – Impact of demographic factors (age, education and income) on individual giving

The influence of demographic factors on individual giving was another aspect considered during primary research, namely age, education and income levels. One of the research premises was that the philanthropic behaviour of older taxpayers may significantly differ from that of younger ones. Decisions about current donations and charitable bequests are likely to be more interdependent than at a younger age. According to research conducted by Feldstein and Clotfelter (1976), splitting the population into older and younger groups did not significantly improve the model's explanatory power. The data from the recent primary research support the Feldstein and Clotfelter (1976) outcome as seniors' responses did not differ substantially from those of other age groups.

To either prove or disprove the abovesaid and measure the impact of demographic data

such as age and income a regression analysis was performed:

$$Y = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \dots + \beta_k \cdot X_k + \varepsilon \quad (1)$$

where: dependent variable is the amount donated by the individual; independent variable age of the individual and individual's income; estimation of the amount of the donation at zero values of the predictors are constants.

Tab. 4 presents the results of the regression linear model and regression coefficients with 95% confidence intervals. The coefficient of 0.291 for the age variable suggests that age does not significantly affect the donation amount (p -value 0.825). When considering income, the coefficient of -8.4663 indicates that with each increase in income by one unit, the donation amount decreases by approximately 8.47 units (p -value < 0.001). R -squared (R^2) is 0.030, meaning that the model explains only 3% of the variability in the donation

Tab. 4: The impact of age and income on individual giving

Variable	Coef.	Std. error	t-value	P > t	95% LCL	95% UCL
Intercept	704.355	67.538	10.429	0.000	571.803	836.907
Age	0.291	1.312	0.222	0.825	-2.284	2.865
Income	-8.466	1.606	-5.272	0.000	-11.618	-5.315

Source: own based on Primary IGA research

amount. This suggests that income has a statistically significant adverse effect on the donation amount, while age does not have a statistically significant effect.

Subsequently, the relationship between the donation amount, income and education was analyzed. The regression model:

$$Y = \beta_0 + \beta_1 \cdot X + \beta_2 \cdot D_1 + \beta_3 \cdot D_2 + \dots + \beta_k \cdot D_k + \varepsilon \tag{2}$$

where: dependent variable – amount donated by the individual; continuous independent variable – individual's income; dummy variables – categories for education levels; constants – baseline donation for the reference group; aimed at predicting the influence of education and income on the amount of donation (Tab. 5) and thus included two key variables: monthly income and education in four categories (HS – high school, VC – vocational certificate, HE – higher education, ES – elementary school).

Income has a positive and statistically significant effect ($\beta = 0.075$; $p < 0.001$). Secondary education (HS) and higher education (HE) are also statistically significant predictors. Individuals with a secondary school education donate

on average EUR 15.72 (Ed_HS 392.753) more, and those with a university education even EUR 17.48 (Edu_HE 436.554) more than the reference group ($p < 0.05$ for both). Other educational categories were not statistically significant. Their effect on the donation amount may be around zero or explained by chance. The model achieved an $R^2 = 0.081$, meaning that income and education together explain about 8.1% of the variability in donation levels, which is common in behavioural models where there are many influences beyond economic factors. To test the hypothesis that higher education leads to higher income, a one-factor analysis of variance (ANOVA) was conducted with results $F(4, n) = 32.51$ and $p < 0.001$. Differences between groups are statistically significant, indicating that education level systematically affects income. Persons with university education have the highest average income, while persons with primary education have the lowest. Education acts through a dual mechanism indirectly through higher income and directly, as a cultural or value factor influencing donation decisions. This relationship supports the thesis that donor behaviour is both economically and socially conditioned.

Tab. 5: The impact of education and income on individual giving

Variable	Coef.	Std. error	t-value	P > t	95% LCL	95% UCL
Intercept	538.530	209.705	2.568	0.010	126.938	950.123
Income	0.075	0.011	7.160	<0.001	0.055	0.096
Ed_HS	392.753	153.911	2.552	0.011	90.668	694.837
Edu_VC	-49.627	148.861	-0.333	0.739	-341.801	242.546
Edu_HE	436.554	215.844	2.022	0.043	12.912	860.197
Edu_ES	-241.149	273.657	-0.881	0.378	-778.261	295.962

Source: own based on Primary IGA research

Tab. 6: The impact of age, education and income on individual giving

Variable	Coef.	Std. error	t-value	P > t	95% LCL	95% UCL
Const	193.821	407.686	0.475	0.635	-606.704	994.345
Age	-4.251	6.505	-0.653	0.514	-17.024	8.523
Education	67.004	99.546	0.673	0.501	-128.462	262.471
Income	0.050	0.009	5.616	0.000	0.033	0.068

Source: own based on Primary IGA research

To get a more detailed view of the data, another multivariate regression analysis was performed (Tab. 6).

$$Y = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \beta_3 \cdot X_3 + \varepsilon \quad (3)$$

where: the dependent variable being the amount of donation and the independent variables being age, income and education.

We therefore interpret that age and education do not have a statistically significant effect on the donation amount. Income has a positive and statistically significant effect on the donation amount. Each increase in income of EUR 40 is associated with an average increase in donation of EUR 2. The R-squared value indicates that the model explains only a small part of the variability in the data (5.6%), which again means that other factors not included in the model affect the donation amount.

A possible explanation for the differences is multicollinearity. If age, income and education are correlated, this may cause the individual coefficients not to be statistically significant, even though a simple analysis shows a significant relationship. When other variables are included, we can better control for their influence. This may reveal that some variables (income) have a more substantial influence than others (education), which may lead to a change in the significance of the coefficients.

That is why, subsequently, multicollinearity diagnostics were performed to find out the variance inflation factor (VIF) for each variable (Tab. 7).

$$Y = \beta_0 + \beta_1 \cdot PC1 + \beta_2 \cdot PC2 + \varepsilon \quad (4)$$

where: dependent variable – amount donated; PC1 and PC2 – principal components or predictors; intercept – expected value of dependent variable when PC1 and PC2 are 0; β_1 , β_2 – regression coefficients.

The results of multicollinearity diagnosis show the following values: age – VIF = 7.25, education – VIF = 9.29, income – VIF = 8.14. VIF values between 5 and 10 may indicate a moderate level of multicollinearity, which should be investigated further. In our case, all three predictors are above in the range, indicating some multicollinearity among the variables. Principal component analysis (PCA) was used to reduce dimensionality and remove multicollinearity. Regression analysis was performed using principal components as explanatory variables.

PC1 is the first principal component that explains the largest possible variation in the data. It is a linear combination of the original variables (in this case, education and income) with maximum variance. PC2 is the second principal component that explains as much of

Tab. 7: Variance inflation factor

Variable	Coef.	Std. error	t-value	P > t	95% LCL	95% UCL
Const	2,555.838	84.664	30.192	0.000	2,390.695	2,720.981
PC1	-153.138	84.368	-1.815	0.070	-318.595	12.319
PC2	356.484	84.370	4.224	0.000	191.024	521.943

Source: own based on Primary IGA research

the remaining variability in the data as possible, while being orthogonal (independent) of PC1. PC1 may represent the combined effect of education and income, which explains most of the variation in donation. PC2 may represent another combined effect of these variables that explains additional differences in the gift amount independent of PC1.

PC1 has no statistically significant effect on the donation amount ($p = 0.070$), although it is close to the significance threshold. PC2 has a statistically significant effect on the donation amount ($p < 0.001$), indicating that this principal component contributes significantly to the variability in the donation amount. PCA helped to reduce the dimensionality of the data and remove the multicollinearity between the original variables (education and income). These components capture the most significant possible variability in the data while being independent. In the regression analysis, we find that PC2 significantly affects the donation amount, suggesting that some combined effects of education and income significantly impact the donation amount.

3.4 Primary data – Impact of motivation on individual giving

The research aimed to find the impact of motivation on individual giving. Donor motivation has been a longstanding research subject, explored through various organizational and societal lenses (Chapman et al., 2018; Degasperri & Mainardes, 2017; Green & Webb, 1997; Mainardes et al., 2017). To find the motivation of individual giving in the Czech Republic, the respondents were asked to select the most important motivation for them. They were offered eight possible answers based on previous research conducted, namely by Degasperri and Mainardes (2017) and Bekkers and Wiepking (2011a), who systemized eight external factors influencing individual giving, which appear in the literature and affect monetary donations as mentioned in the previous section.

Studies by Okunade and Berl (1997) and Wiepking and Maas (2009) and others suggest a positive correlation between higher educational attainment and charitable giving, indicating that education plays a significant role in influencing individuals' propensity to donate. However, we cannot consent to the previous outcomes when testing the relationship between "education level and motivation."

The null hypothesis of independence between education and motivation cannot be rejected due to a p -value of 0.44 greater than the commonly used significance level (0.05). In other words, based on this test, there is no statistically significant evidence of a relationship between education and motivation. Nor can it be concluded based on the chi-square test that there is a statistically significant relationship between "gender and motivation," as the p -value of 0.11 is still greater than the commonly used significance level of 0.05.

The differences between men and women when giving were also studied. As found, women and men differ in their decisions when making donations. Research conducted in the United States and the United Kingdom has consistently shown that women are more likely to donate and tend to give higher amounts than men (Mesch et al., 2006, 2011; Piper & Schnepf, 2007). However, findings from the Netherlands indicate that gender differences in giving are more complex than previously assumed (De Wit & Bekkers, 2016). While women are more likely to donate and support a broader range of sectors, men generally contribute more. Unlike recent studies in the United States, Dutch males donate larger sums than their female counterparts. In our research, it was found that men donate 1.7 times more than women when asked. For men, one of the most mentioned motivations is feeling good about myself. Conversely, for more than 40% of women, the driving force behind giving is the feeling that they can help someone or something or make an impact. For men, this reason is cited only one-third of the time. In addition, one-fifth of men, compared to women, donate because of an occasional need to do a good deed. Their giving is, therefore, more impulsive than women's. Giving of women is more diverse. For example, the motivation to take advantage of tax benefit is more prevalent among women than men, indicating that women are more likely to consider the financial benefits of donating. Motivation needs of others also appear to be more common among women, which could reflect greater empathy or social awareness in this group. Overall, the analysis suggests that while the primary motivations for giving are similar for both genders, women tend to have a broader range of reasons for giving than men. This may be important for non-profits when creating gender-targeted campaigns.

The “motivation vs. age” analysis shows the relationship between age categories and motivations for giving. In the 0–18 years age category, motivations are almost evenly distributed, with no strong preference for any particular motivation. In the 19–30 years and 31–45 years age categories, we see those motivations “feeling good about myself” and “feeling that I can help something (someone) and can make a difference” are the most common. This may indicate that younger adults and the middle age group often donate for personal satisfaction and the belief that they can make a difference. In the 46–60 years age category, the same motivations are still present. However, there is also a slight increase in the possibility of benefiting from tax relief motivation, which may be related to a growing awareness of the financial benefits of giving. In the oldest category (61+ years), motivations show a greater diversity, which may reflect the broader range of life experiences and values of older people.

Many previous studies have looked at the relationship between income and charitable giving, either as a simple comparison between income and percentage of income donated or else in terms of the income elasticity of giving (McClelland & Brooks, 2004; Neumayr & Pennerstorfer, 2021). The current research looked at the “motivation compared to net income” from a different perspective. The analysis shows the relationship between the different categories of net income and the motivations for giving. In the lower income categories (EUR 400 and EUR 800), motivations “feeling good about myself” and “feeling like I can help something (someone) and make a difference” dominate. This may indicate that people with lower incomes donate mainly out of personal satisfaction and the belief that they can make a difference, even if they have limited financial resources. The same motivations remain important in the middle-income categories (EUR 800–1,200 and EUR 1,200–1,600), but other motivations, such as the possibility of tax relief, are beginning to emerge. This may indicate that people with higher incomes are considering more of the financial benefits of donating. In the highest income categories (EUR 1,600–2,000 and more than EUR 2,000), there is an increased variety of motivations, including the motivation for tax deduction. This may suggest that higher-income earners have more reasons to donate, including personal satisfaction, social impact and financial benefits.

When testing the relationship between the “motivation and donation amount” in the “up to EUR 4” category, motivations “feeling good about myself” and “feeling like I can help something (someone) and make a difference” are again the most common. These motivations also remain dominant in the category “up to EUR 40.” As the amount of the donation increases, other motivations, such as the possibility of tax relief, start to appear. In the “up to EUR 200” and “up to EUR 400” categories, there is an increasing variety of motivations, including the motivations “other” and “needs of others.” This may suggest that people who donate higher amounts have a wider range of reasons for donating. There is a significant increase in motivation possibility of tax benefit in the highest categories of “up to EUR 2,000” and “EUR 2,000 or more,” suggesting that tax relief is becoming an important reason for donating large amounts. Overall, the data show that as the amount of the donation increases, the variety of motivations increases, which may be important for the donation solicitation strategy.

It is evident that regardless of age, gender, education or donating amount, motives “feeling good about myself” and “feeling like I can help something (someone) and make a difference” are the most prevalent. The typical donor in the Czech Republic is characterized by a balance of altruistic and self-interested motivations, with personal satisfaction and empathy being the primary drivers. Understanding these motivations and demographic characteristics can help non-profit organizations tailor their approaches to better engage with donors and increase charitable contributions.

Conclusions

Philanthropy, supported by private giving, whether individual or corporate, is a crucial part of the philanthropic sector. Private giving is not a “Cinderella” but an equal partner to governments in this area. However, private giving is often overlooked by the academic community, with existing research mainly focusing on the American experience. The situation in the Czech Republic is no different. There is still a lack of truly comparable data at the international level. This article aimed to stimulate interest in this area. The research indicates that awareness of tax benefits for donations is low. The Government Council for Non-Governmental and Non-Profit

Organizations of the Czech Republic 2023 has established a working group for private giving to propose measures to increase the motivation of individual donors to donate resources for public benefit purposes. Statistics from the Czech Statistical Office show that a large part of charitable giving is in the form of volunteer work. This area should be the focus of further research and consideration of the possibility of including volunteering in the tax base, as is possible in some countries, where it is possible to claim not the value of time but some costs associated with volunteering. Also, Bauer et al. (2013) examined the relationship between voluntary labour and charitable donations across 19 European countries using data from the European Social Survey (ESS). They found a positive correlation between donating time and money at individual and country levels.

Non-profit organizations need to improve their collaboration with their donor base and find new ways of long-term cooperation. Motivations led by private and public benefits do not always have to be distinct and sometimes overlap. Individuals can have many motivations for giving and simultaneously be motivated by both private and public benefits.

The findings reveal that donors are typically middle-aged, with a median age of 45, and most possess a secondary education or higher. Their median income ranges between EUR 800 and EUR 1,000 per month. Donations are often irregular, and many do not maintain long-term relationships with specific organizations. The typical donation amounts for monetary contributions range between EUR 40 and EUR 200, with a significant portion of donations directed towards health, children and youth, the disabled or disadvantaged, and animal protection. The primary motivations for giving include personal satisfaction, altruism, and the desire to make a difference. Although tax relief is considered important, it is not the primary driver for most donors. Social pressures and personal requests also play a significant role, particularly among men, who are likelier to make larger, one-time donations than women, who prefer smaller, regular contributions. Younger donors, specifically those aged 19–45 years, are primarily motivated by personal satisfaction and the belief in making a difference. Higher-income donors tend to consider tax benefits more than their lower-income counterparts.

Understanding the typical donor profile can help tailor fundraising strategies, leveraging the primary motivations of personal satisfaction and altruism. Non-profit organizations can emphasize the impact of donations and provide emotional rewards for donors to foster long-term engagement. Awareness campaigns about tax benefits are recommended to increase the frequency and amount of donations, especially among higher-income individuals. Building long-term relationships with donors is crucial, and non-profits should focus on creating lasting connections through regular updates, demonstrating the impact of contributions, and engaging donors in meaningful ways.

This study contributes to understanding philanthropic behaviour in the Czech Republic by providing empirical evidence supporting tax benefits' limited influence on individual giving. The results suggest that increasing awareness of available tax deductions may enhance the effectiveness of tax incentives. However, policymakers and non-profit organizations should also emphasize other motivational factors, such as personal satisfaction and altruism, in their fundraising strategies.

Despite its contributions, this study has several limitations that should be acknowledged. Firstly, the reliance on self-reported data introduces potential biases, including social desirability and recall bias, which may affect the accuracy of respondents' answers. Secondly, the study is limited to the Czech Republic, restricting the generalizability of findings to other countries with different cultural, economic, or legal contexts related to philanthropy. Additionally, the research provides a snapshot of donor behaviour at a single point in time, lacking longitudinal data that could reveal changes in motivations and giving patterns over time. Furthermore, respondents' awareness of tax benefits was limited, which may have influenced their reported motivations. The potential for multicollinearity between variables such as age, education, and income could also affect the interpretation of statistical results. Survey design limitations, including closed questions, may restrict respondents from fully expressing their motivations. Future research should focus on longitudinal, comparative, and qualitative approaches to explore philanthropy's underlying psychological and emotional drivers.

In conclusion, individual giving in the Czech Republic has the potential to grow further

through targeted strategies that address donor motivations and enhance long-term engagement. By leveraging these insights, non-profit organizations can better harness the philanthropic potential of individuals, contributing to a more robust and sustainable charitable sector.

Acknowledgments: Supported by grant IGA/FaME/2021/013 – Corporate giving from the income tax perspective and willingness to give in companies operating in the Czech Republic.

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Mahalanobis distance and Stutzer ratio modelling in emerging markets portfolios

Dejan Zivkov¹, Boris Kuzman², Jonel Subic³

¹ University of Novi Sad, Novi Sad School of Business, Serbia, ORCID: 0000-0003-2357-3250, dejanzivkov@gmail.com (corresponding author);

² Institute of Agricultural Economics, Serbia, ORCID: 0000-0002-8661-2993, kuzmanboris@yahoo.com;

³ Institute of Agricultural Economics, Serbia, ORCID: 0000-0003-1342-1325, jonel_s@iep.bg.ac.rs.

Abstract: This study examines the performance of multi-asset portfolios in global emerging markets, emphasizing their exposure to systemic risk and risk-adjusted returns. The analysis encompasses portfolios from regions such as Southeast Asia, the Middle East and Central Asia, Central and Eastern Europe, Africa, and Latin America. The research uses daily data, covering a 10 years period. Two advanced methodologies are applied in the portfolio construction – the Mahalanobis distance and the Stutzer ratio. The financial turbulence index constructed for the systemic risk measurement reveals a pronounced allocation bias toward a single asset, driven by its distinctive attributes. Interestingly, the asset with the highest weight in the portfolio originates from frontier markets, which are less integrated into the global financial system and thus more insulated from global economic shocks. The Stutzer ratio, through its calculation of the decay parameter theta, provides insights into whether an emerging market portfolio is characterized by high volatility and frequent market fluctuations or is more aligned with long-term investment strategies that emphasize stability and consistent performance. The results indicate that all emerging markets portfolios have higher Stutzer ratio than the developed portfolio, which indicates better risk-adjusted results. However, the theta parameter is mostly lower in the emerging markets portfolios, suggesting higher risk in these markets. The highest Sharpe ratio is found in the African countries portfolio, while the best portfolio, when using the more advanced Stutzer ratio, is with Latin American countries. This study provides insightful guidance for international investors exploring opportunities in emerging markets, focusing on systemic risk and evaluating returns through a risk-adjusted lens.

Keywords: Mahalanobis distance, risk-adjusted performance, multi-asset portfolio optimization.

JEL classification: C61, G32, D53.

APA Style Citation: Zivkov, D., Kuzman., B, Subic, J. (2025). Mahalanobis distance and Stutzer ratio modelling in emerging markets portfolios. *E&M Economics and Management*, 28(4), 148–162. <https://doi.org/10.15240/tul/001/2025-4-010>

Introduction

Over the last couple of decades, emerging markets have implemented numerous reform measures, making them more appealing to global investors. Several reasons make them favourable for investment. First, emerging markets often experience faster economic growth compared to developed economies, driven by industrialization, urbanization, and increasing consumer demand (Časni & Vizek,

2014). Younger and growing middle-class populations lead to rising consumption, creating opportunities for companies to expand and generate higher profits (Eshun et al., 2023). Many emerging markets are investing heavily in infrastructure projects (Babucea et al., 2017), leading to opportunities in construction, real estate, and related sectors, while government-led reforms aimed at liberalizing markets or improving governance can spur economic growth and

attract more foreign investment. Some emerging markets are leapfrogging traditional technologies and adopting cutting-edge solutions, creating unique investment opportunities.

On the other hand, emerging markets often face various vulnerabilities due to their developing nature and structural characteristics. They commonly struggle with issues such as inflation, exchange rate fluctuations, and heavy debt burdens (Rocha & Moreira, 2010). From a stock market perspective, these markets are often characterized by a lack of liquidity (Urban, 2017), which makes executing large trades challenging. According to Salisu et al. (2022), stock prices in emerging markets also tend to be more volatile, influenced by speculative behaviour and external shocks. Moreover, emerging markets are particularly sensitive to geopolitical risks, as many of them are heavily reliant on commodity exports (Pitterle et al., 2015). Geopolitical risks can disrupt commodity markets, adversely affecting the revenues and economic stability of these countries. In addition, geopolitical tensions or conflicts can heighten uncertainty, leading global investors to withdraw funds from emerging markets and shift to safer assets in developed economies.

All emerging markets have their own pros and cons when it comes to investment, and the performance of these investments differs significantly between countries due to varying economic, political, social, and structural factors. The goal of the paper is to identify which emerging markets portfolio offers the best opportunities for investors, analysing two perspectives – the level of systemic risk each portfolio is exposed to and its risk-adjusted performance. We construct six-asset portfolios comprising stock indices from emerging markets across five global regions: Southeast Asia, the Middle East and Central Asia, Central and Eastern Europe, Africa, and Latin America. For comparison, we also examine a portfolio consisting of developed G7 countries. While this topic is not new in the literature (Alqahtani et al., 2020; Liu, 2019; Salisu et al., 2020; Zhao et al., 2019), this paper seeks to contribute by employing two unconventional and sophisticated methodological approaches – the Mahalanobis distance (MD) as a measure of systemic risk and the Stutzer ratio as a significant improvement over the classical Sharpe ratio.

Examining systemic risk in emerging markets is important for investors because

emerging markets are sensitive to global economic conditions, such as changes in interest rates, commodity prices, or investor sentiment (Mensi et al., 2021). Investors who effectively analyse and manage systemic risks can better navigate volatility in these markets, while taking advantage of their growth potential. On the other hand, the analysis of risk-adjusted performance is equally important because it helps balance the higher growth potential of these markets with the significant risks they pose. Specifically, this calculation enables investors to make informed decisions, optimize portfolios, and avoid excessive risks while capitalizing on growth opportunities.

The Mahalanobis distance is used to calculate the level of systemic risk in each portfolio. It was originally developed as a statistical tool to classify human skulls into distinct groups based on their physical characteristics (Mahalanobis, 1927). In the realm of finance, this concept can be adapted to analyse features such as the statistical moments of assets in a portfolio or the characteristics of portfolios held by investors. When portfolio weights are optimized using outdated or shifting distributions, they can become highly suboptimal, while trading strategies relying on past market patterns that no longer exist are likely to incur losses. To address this issue, Kritzman and Li (2010) introduce the concept of “financial turbulence,” measured using the Mahalanobis distance. The financial turbulence index (FTI) captures the degree of multivariate irregularity or unexpected behaviour in financial market data. In other words, the Mahalanobis distance can be characterized as a statistical measure used to determine the distance between a point and a distribution, taking into account the correlations among variables (Stöckl & Hanke, 2014). In finance, this measure can identify unusual observations in multivariate datasets, such as outliers in portfolio returns or economic indicators (Kanga et al., 2023). Giglio et al. (2016) assert that this methodology has several useful characteristics that make it superior to other methods in detecting turbulence and systemic risk. First, it incorporates the covariance structure of the variables, making it effective in financial systems where variables are highly correlated. Second, it adjusts for different scales of the variables, ensuring that no single variable disproportionately influences the results. Third, it detects extreme deviations from

the norm, which indicates stress or vulnerability in financial systems.

There is substantial evidence in the literature indicating that stock returns in emerging markets often deviate from a normal distribution (Dridi & Boughrara, 2023; Li et al., 2021; Tanos et al., 2024; Yiming et al., 2024). This challenges the practical applicability of the Sharpe ratio because it is based on the variance, assigning equal weight to deviations both above and below the mean (Sharpe, 1966). This assumption, however, may not align with real-world investor preferences, particularly when the focus is on protecting against losses. The Stutzer ratio, introduced by Stutzer (2000), redefines the concept of risk by focusing on the likelihood of failing to meet a specified target return. Unlike the Sharpe ratio, which views all volatility as risk, the Stutzer ratio emphasizes downside risk. As Stutzer (2000) demonstrates, when a portfolio is expected to outperform a benchmark over time, the probability of underperformance diminishes exponentially as the sample period grows. This decay rate, represented mathematically as θ , is proposed as a performance measure, and Stutzer (2000) provides a method to construct portfolios that maximize this decay rate. The Stutzer ratio has several advantages over the traditional Sharpe measure, according to Haley and McGee (2006). First, it is not constrained by the assumption of normally distributed returns, making it a more flexible and robust performance metric. Second, it accounts for investor preferences for positive skewness, which are overlooked in the mean-variance paradigm. Third, it discourages strategies that generate high returns at the cost of taking extreme risks.

The main contribution of the paper lies in the methodologies employed. First, it evaluates the level of systemic risk in emerging market portfolios using the elaborate Mahalanobis distance approach. Second, it assesses the risk-adjusted performance of the portfolios using the advanced, but rarely used Stutzer ratio metric. To the best of our knowledge, neither methodology has been applied in this context, which provides the motivation for this research.

Apart from the introduction, the paper is organized as follows. The second section provides a review of the existing literature. The third section outlines the methodologies used, focusing on Mahalanobis distance and Stutzer ratio-optimized portfolios. The fourth

section presents the dataset and descriptive statistics. Section five is dedicated to presenting the research findings in two subsections. The final section offers the conclusions.

1 Theoretical background

This section presents studies that use emerging equity markets in global portfolios. For instance, Christoffersen et al. (2014) analyse trends and changes in correlations over time using weekly return data from both developed and emerging markets. They argue that including emerging markets alongside developed markets enhances diversification opportunities. Abuaf et al. (2019) conducted an empirical analysis to determine if emerging-market portfolios lie on the mean-variance efficient frontier and assessed which specific markets offer superior diversification benefits. Their findings highlighted Mexico and China as the most significant contributors to portfolio diversification. Gupta and Donleavy (2009) found that, even with rising correlations, Australian investors can still gain advantages by including international emerging markets in their portfolios. Guidi and Ugur (2014) examine the integration of South-Eastern European (SEE) stock markets, specifically those in Bulgaria, Croatia, Romania, Slovenia, and Turkey, with developed markets in Germany, the UK, and the USA. Their study reveals that, despite dynamic cointegration observed during much of the global financial crisis (September 2008 to May 2010), investors could still achieve diversification benefits between September 2007 and June 2013. Jayasuriya and Shambora (2009) build upon existing research regarding enhancements to the efficient portfolio frontier within globally diversified portfolios. Their findings indicate that, over the past eight years, a U.S. investor could have achieved superior returns at the same level of risk by including emerging and frontier markets in their portfolio. Hadhri and Ftiti (2019) explore the profitability of investing in emerging markets. Beyond the traditional first and second moments considered in asset allocation, their analysis emphasizes the third moment: realized skewness. Their results suggest that emerging markets tend to outperform developed markets over various time horizons, particularly during periods of financial crises.

Thomas et al. (2022) explore how frontier markets contribute to enhancing the diversification benefits of international portfolios,

particularly in the Asia-Pacific and European regions. Their findings show that while frontier markets provide greater diversification potential than emerging markets, they are more suitable for investors with a higher tolerance for risk. Buchanan et al. (2011) demonstrate that adding emerging markets to a global portfolio offers the combined advantage of lowering risk while boosting returns. Ngene et al. (2018) present detailed findings on the interactions of shocks and volatility between the stock markets of 24 frontier markets and the U.S. They contend that the conditional correlation between the U.S. and each of these frontier markets is typically low or negative, suggesting that U.S. investors can benefit from diversification by including frontier markets in their portfolios. Chan-Lau (2012) contends that allocating a larger portion to emerging markets may enable investors to surpass their benchmarks in growth phases, while keeping the potential for downside risks relatively low. Berger et al. (2013) conclude that emerging markets provide diversification advantages by reducing risk. Their analysis reveals that the volatility in emerging markets is mostly driven by idiosyncratic factors, reinforcing their capacity to mitigate overall portfolio risk. Kohlert (2011) concludes that emerging markets can offer valuable diversification benefits, though their effectiveness largely depends on the specific composition of frontier market indices. If an inappropriate index is selected, its return patterns and correlations may fail, leading to unexpectedly poor performance during turbulent times.

From the perspective of Mahalanobis distance and Stutzer ratio portfolios, few papers have utilized these methodologies. Shi and Weidong (2022) introduce an innovative approach named weighted turbulence, which integrates a dynamic network framework with a weighted Mahalanobis distance to assess systemic risk across global energy markets. According to their findings, this technique effectively captures sharp increases in systemic risk while remaining resilient to distortions caused by noisy data. Their model demonstrates strong practical value for real-world applications in systemic risk analysis. Stöckl and Hanke (2014) explore both current and prospective uses of the Mahalanobis distance within financial contexts. They organize these applications based on the characteristics and origins of the input variables involved. Their analysis

highlights how this statistical measure can offer valuable insights and practical benefits for actors operating in financial markets. On the other hand, Benson et al. (2008) utilize the Stutzer ratio framework to examine optimal portfolio design and assess the performance of Australian equity funds. Through a comparative analysis of the Stutzer and Sharpe ratios, they reveal how deviations from normal return distributions carry meaningful economic implications. Their findings underscore the influence of return non-normalities on both portfolio formation and performance assessment methodologies. Alcock et al. (2013) investigate potential manipulation within U.S. REITs by contrasting performance assessments derived from the manipulation-proof performance measure (MPPM) with those based on conventional metrics such as the Sharpe ratio, Jensen's alpha, the information ratio, and the Stutzer index. Their analysis uncovers indications that certain manipulation tactics may exploit leverage in a strategic and opportunistic manner.

2 Research methodologies

2.1 Mahalanobis distance

Kritzman and Li (2010) suggest that the Mahalanobis distance can serve as an effective measure of unusualness in financial markets. Considering an asset return (r_t) at a given day t , the deviation of how much this return deviates from the norm is to calculate the standardized squared deviation: $(r_t - \mu)^2/\sigma^2$, where: μ – the expected return; σ^2 – the return variance. A higher ratio indicates a more “unusual” return, implying that the instantaneous return variance surpasses its long-term average. Notably, this ratio corresponds to the squared Mahalanobis distance for a single asset. To extend this concept to a portfolio with n assets, one could sum the Mahalanobis distances of all individual assets, yielding the squared Euclidean distance, as in Equation (1):

$$Eu_t^2 = \sum_{i=1}^n \frac{(r_{t,i} - \mu_i)^2}{\sigma_i^2} \quad (1)$$

However, this approach disregards the dependencies between assets, which are crucial for assessing the systemic risk of a group of assets in a portfolio, according to Stöckl and Hanke (2014). The direction of deviations in asset returns from their means holds critical information about their interrelationships, which requires

a multivariate distance measure to capture. The squared Mahalanobis distance incorporates this consideration, as in Equation (2).

$$MD_t^2 = (r_t - \mu)' \Sigma^{-1} (r_t - \mu) \quad (2)$$

In cases where the covariance matrix is diagonal (with zero off-diagonal elements), MD simplifies to the squared Euclidean distance. Yet, its key advantage lies in its ability to account for joint deviations in asset returns, r_i and r_j (for $i, j = 1, \dots, n$ and $i \neq j$). When calculating the Mahalanobis distance, demeaned returns are taken into account, ensuring that the calculation reflects how far a data point is from the centre of the distribution. Without demeaning, the Mahalanobis distance would measure the distance from the origin, which is not meaningful when analysing data that naturally clusters around its mean. Using demeaned returns allows the Mahalanobis distance to identify unusual returns relative to the expected behaviour (mean and covariance structure), and also to detect outliers or anomalies (e.g., extreme deviations from normal returns).

By summarizing the unusual behaviour of all assets into a single metric, the Mahalanobis distance provides a comprehensive measure of systemic irregularities. Moreover, it does not rely on strict distributional assumptions and is particularly well-suited for elliptically distributed random variables, which can be fully characterized by their location parameter μ and scatter matrix Σ . When this measure is used in the context of portfolios, MD is referred to as (squared) financial turbulence index (FTI):

$$FTI = \sqrt{\frac{1}{w_D^2} (w_D(r_t - \mu))' \Sigma^{-1} (w_D(r_t - \mu))} \quad (3)$$

where: r_t – the vector of asset returns; μ – the mean vector of the distribution; Σ – covariance matrix of the variables and Σ^{-1} – the inverse of the covariance matrix; w_D – the diagonal matrix of weights w_i .

2.2 Stutzer ratio

After calculating the level of systemic risk for each portfolio, we aim to compare their risk-adjusted performance using the Stutzer ratio. The Stutzer ratio offers a refined alternative to the Sharpe ratio, addressing several of its

shortcomings. While the Sharpe ratio evaluates risk-adjusted returns by comparing excess returns to volatility, the Stutzer ratio takes a broader perspective by incorporating the full characteristics of return distributions, including skewness and kurtosis (Haley & McGee, 2011). It leverages an exponentially tilted likelihood ratio to account for risks that the Sharpe ratio often overlooks (Bondarenko, 2014). A key limitation of the Sharpe ratio is its sensitivity to outliers, which can distort the assessment of risk-adjusted returns. In contrast, the Stutzer ratio reduces this issue by focusing on the overall distribution of returns rather than solely relying on volatility (Benson et al., 2008). This makes the Stutzer ratio particularly effective in capturing the reliability of long-term returns. Unlike the Sharpe ratio, which can reward portfolios with erratic performance as long as the returns are high, the Stutzer ratio emphasizes consistency. It is specifically designed to favour portfolios that deliver stable returns over time, offering a more accurate representation of risk-adjusted performance for portfolios with non-normal return distributions.

We design portfolios with the objective of maximizing the Stutzer ratio. This metric is calculated in relation to a chosen benchmark asset, where $r_{p,t}$ denotes the return of portfolio at time T , adjusted by the benchmark returns. The mean excess return (\bar{r}_p) is subsequently defined as:

$$\bar{r}_p(T) = \frac{1}{T} \sum_{t=1}^T r_{p,t} \quad (4)$$

Stutzer (2000) explains that when a portfolio has a positive expected excess return, the law of large numbers implies that the probability of observing a negative sample excess return, $\bar{r}_p(T)$, approaches zero as the sample period T increases. From this standpoint, an investor aiming to minimize the risk of underperformance might construct a portfolio designed to reduce the likelihood of non-positive average excess returns as quickly as possible. The rate at which this probability diminishes, referred to as I_p , is known as the “portfolio performance index.” This index quantifies how rapidly the chance of underperformance converges to zero and is defined mathematically in Equation (5).

$$I_p = \max_{\theta} \left(-\ln E \left(e^{\theta \bar{r}_p(T)} \right) \right) \quad (5)$$

where: $\theta < 0$

For investors aiming to minimize benchmark underperformance, the optimal portfolio is the one with the highest decay rate. Stutzer (2000) shows that if stock returns are normally distributed, I_p is directly linked to the traditional Sharpe ratio, ensuring that portfolio rankings remain identical whether assessed using the Stutzer ratio or the Sharpe ratio. From a portfolio construction perspective, I_p can be utilized as a practical tool for designing portfolios in advance. Consider N potential assets for inclusion in the portfolio, each with a time series of T observed excess returns, $r_{i,t}$ for asset i . The portfolio's excess return at any given time t is then calculated as follows:

$$r_{p,t} = \sum_{i=1}^N w_i r_{i,t} \quad (6)$$

where w_i – the weight assigned to asset i within the portfolio. The sample estimate of the expression on the right-hand side of Equation (6) is calculated in the following manner:

$$\hat{I}_p = \max_{\theta} \left(-\ln \frac{1}{T} \sum_{t=1}^T e^{\theta \bar{r}_p(T)} \right) \quad (7)$$

The optimal asset weights, according to the portfolio performance index criterion, are found by solving the maximization problem outlined in Equation (8). When optimizing the Stutzer portfolio, it is crucial to choose suitable initial values for both the asset weights and the portfolio performance index. Stutzer (2000) suggests starting with the asset weights that maximize the Sharpe ratio as an initial approximation in Equation (8). Similarly, a reasonable starting value for θ is typically set as the negative of the mean excess return divided by its variance.

$$I_m = \max_{w_1, \dots, w_n} \max_{\theta} \left(-\ln \frac{1}{T} \sum_{t=1}^T e^{\theta \bar{r}_p(T)} \right) \quad (8)$$

2.3 Dataset

This study analyses daily closing prices of stock indices from both emerging and developed markets to form six-asset portfolios. The sample includes 30 stock indices representing

emerging markets across five global regions: East Asia, the Middle East and Central Asia, Central and Eastern Europe, Africa, and Latin America. For comparison, six indices from G7 countries are incorporated to represent developed markets. The selected indices from East Asia are: JKSE (Indonesia), KLCI (Malaysia), SET (Thailand), VNI (Vietnam), PSEi (Philippines) and STI (Singapore). The Middle East and Central Asia indices are: SENSEX (India), DSEX (Bangladesh), KSI (Pakistan), KASE (Kazakhstan), TADAWUL (Saudi Arabia) and DFM (United Arab Emirates). The emerging European indices are: WIG (Poland), PX (the Czech Republic), BUX (Hungary), BET (Romania), SOFIX (Bulgaria) and SBITOP (Slovenia). The African indices are: EGX (Egypt), MASI (Morocco), NSE (Nigeria), NSX (Namibia), BRVM (Côte d'Ivoire) and JSE (South Africa). The Latin American indices are: BOVESPA (Brazil), IPC (Mexico), IPSA (Chile), COLCAP (Columbia), Lima general (Peru) and JSEAJC (Jamaica). At the end, the G7 indices are: S&P500 (USA), NIKKEI225 (Japan), DAX (Germany), CAC (France), FTSE100 (UK) and FTSE-MIB (Italy). All selected indices are composite stock indices that track the overall performance of multiple stocks across various sectors, providing a broad measure of market performance.

The dataset spans a significant period, from January 2015 to December 2024, with all data sourced from the Investing.com platform. Stock prices are converted into log-returns, denoted as $r_{i,t}$, using the formula: $r_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, where P_i refers to the stock price. To maintain consistency across the dataset, all time-series of a single portfolio are synchronized based on available observations. The MSCI All Country World Index serves as the benchmark asset for constructing the Stutzer portfolio, providing a comprehensive measure of global equity performance across both developed and emerging markets.

Tab. 1 presents the four-moment descriptive statistics of the selected indices. It can be observed that all kurtosis values exceed the benchmark of 3, indicating the presence of extreme risk. The Mahalanobis distance provides a comprehensive measure of systemic risk for each portfolio, accounting for both the mean characteristics of the indices and their correlation interdependencies. Additionally, the third moment also reveals non-normal

Tab. 1: Descriptive statistics

	Mean	Std. dev.	Skew.	Kurt.		Mean	Std. dev.	Skew.	Kurt.
South East Asia portfolio					Mid Asia portfolio				
JKSE	0.004	0.413	-0.229	13.043	SENSEX	0.016	0.412	-1.372	14.110
KLCI	0.000	0.295	-0.372	14.161	DSEX	0.009	0.339	1.115	21.763
SET	-0.007	0.404	-1.992	30.942	KSI	0.008	0.414	-0.437	6.949
VNI	0.013	0.495	-0.982	7.411	KASE	0.025	0.387	0.147	12.956
PSEi	-0.005	0.522	-1.558	19.449	TADAWUL	0.018	0.409	-0.239	9.237
STI	-0.001	0.358	-0.883	12.902	DFM	0.016	0.416	-0.710	10.187
CEEC portfolio					African portfolio				
WIG	0.009	0.514	-1.132	16.836	EGX	0.042	0.592	-0.261	6.879
PX	0.012	0.408	-0.977	14.094	MASI	0.001	0.302	-1.671	29.100
BUX	0.027	0.532	-1.437	16.306	NSE	0.014	0.440	0.593	9.182
BET	0.013	0.426	-1.902	24.793	NSX	0.019	0.656	-0.414	8.417
SOFIX	0.008	0.329	-2.120	33.370	BRVM	-0.008	0.306	0.278	7.165
SBITOP	0.012	0.354	-1.699	21.705	JSE	0.015	0.487	-0.118	10.444
Latin America portfolio					DEC portfolio				
BOVESPA	0.020	0.651	-0.599	15.247	S&P500	0.020	0.493	-0.829	19.413
IPC	0.005	0.428	-0.272	5.527	NIKKEI225	0.010	0.568	-0.480	12.189
IPSA	0.014	0.492	-0.202	17.361	DAX	0.014	0.530	-0.606	14.326
COLCAP	0.010	0.495	0.185	22.730	CAC	0.013	0.519	-0.895	15.049
Lima general	0.019	0.487	-0.371	13.254	FTSE100	0.004	0.435	-0.918	16.850
JSEAJC	0.022	0.425	0.355	40.537	FTSE-MIB	0.013	0.613	-1.666	23.385

Source: own

behaviour, suggesting that the normally-based Sharpe ratio results may diverge from the more complex Stutzer ratio, which takes into account significantly more factors than the classical Sharpe ratio. Both the Mahalanobis distance and the Stutzer ratio incorporate the correlation matrix when optimizing a portfolio, and these results may help explain the portfolio outcomes. Therefore, Tab. 2 presents the pairwise Spearman correlations for each portfolio. The average correlations between indices are: 0.287, 0.119, 0.226, 0.096, 0.240 and 0.589 for SEAC, MEAC, CEEC, AFC, LAC and DEC portfolio, respectively. According to these results, the developed markets have the highest average correlation, while all emerging markets are significantly less integrated. This might affect the performance of the portfolios.

3 Empirical results

3.1 Mahalanobis distance results

This section presents the financial turbulence index results for the six portfolios, calculated using the Mahalanobis distance methodology. The structure of the calculated portfolios is shown in Tab. 3, while the average values of the FTI are presented in Tab. 4. Fig. 1 illustrates the time-varying evolution of the FTI across the sample.

Before finding reasons for the result in Tab. 3, it is worth of knowing that the key factors affecting *MD* are demeaned returns (deviations from the mean), high variance (variables with higher variance contribute less to *MD*), correlation matrix and outliers. The mean of assets is important in calculating a portfolio because it acts as the centre or reference point from which deviations are

Tab. 2: Pairwise Spearman rank correlation

	JKSE	KLCI	SET	VNI	PSEI	STI		SENSEX	DSEX	KSI	KASE	TADAWUL	DFM
JKSE	1	–	–	–	–	–	SENSEX	1	–	–	–	–	–
KLCI	0.374	1	–	–	–	–	DSEX	0.079	1	–	–	–	–
SET	0.310	0.349	1	–	–	–	KSI	0.124	0.058	1	–	–	–
VNI	0.178	0.185	0.202	1	–	–	KASE	0.192	0.051	0.087	1	–	–
PSEI	0.344	0.372	0.279	0.144	1	–	TADAWUL	0.214	–0.004	0.047	0.137	1	–
STI	0.320	0.395	0.387	0.168	0.306	1	DFM	0.226	0.056	0.079	0.164	0.270	1
	WIG	PX	BUX	BET	SOFIX	SBITOP		EGX	MASI	NSE	NSX	BRVM	JSE
WIG	1	–	–	–	–	–	EGX	1	–	–	–	–	–
PX	0.419	1	–	–	–	–	MASI	0.092	1	–	–	–	–
BUX	0.434	0.390	1	–	–	–	NSE	0.027	0.055	1	–	–	–
BET	0.292	0.310	0.285	1	–	–	NSX	0.133	0.052	–0.018	1	–	–
SOFIX	0.087	0.119	0.114	0.119	1	–	BRVM	0.021	0.043	0.029	–0.004	1	–
SBITOP	0.168	0.180	0.151	0.204	0.118	1	JSE	0.142	0.065	–0.002	0.816	–0.002	1
	BOVESPA	IPC	IPSA	COLCAP	Lima	JSEAJC		S&P500	NIKKEI	DAX	CAC	FTSE100	FTSE-MIB
BOVESPA	1	–	–	–	–	–	S&P500	1	–	–	–	–	–
IPC	0.416	1	–	–	–	–	NIKKEI	0.214	1	–	–	–	–
IPSA	0.367	0.391	1	–	–	–	DAX	0.584	0.319	1	–	–	–
COLCAP	0.349	0.332	0.306	1	–	–	CAC	0.585	0.333	0.934	1	–	–
Lima	0.379	0.381	0.301	0.336	1	–	FTSE100	0.543	0.322	0.820	0.858	1	–
JSEAJC	0.013	–0.005	–0.003	–0.010	0.050	1	FTSE-mib	0.542	0.273	0.863	0.879	0.770	1

Source: own

measured. *MD* measures the distance of each observation from the centre of a multivariate distribution, where the mean represents this centre in multivariate analysis. By calculating demeaned returns, the estimation ensures that the distance is measured relative to the central tendency of the data. Typically, assets with high mean returns are preferred unless their variance or correlation makes them risky.

Tab. 1 presents the optimized results of the Mahalanobis distance portfolios, revealing a distinct pattern. In other words, it can be seen that in all portfolios, one asset holds a very high share, while all other assets have negligible weights. In all cases, the dominant asset in the portfolio has a relatively high mean, low variance, low correlation and high kurtosis. For example, in the SEAC portfolio, the majority of the investment is

concentrated in the Vietnamese index (VNI), which has the highest mean (0.013) and the lowest average correlation with other assets (0.175). The SENSEX index in the MECAC portfolio has relatively high mean (0.016), low variance (0.412) and high kurtosis (14.110). In the CEEC portfolio, the Bulgarian SOFIX has the highest share due to the lowest variance (0.329) and the highest kurtosis (33.370). This is also the case with MASI in the AFC portfolio. The Jamaican JSEAJC index has the highest mean of 0.022 and a very low average correlation of 0.009, which explains its dominance in the portfolio (99.71%). In the DEC portfolio, S&P500 has the share of 83.56%, with the highest mean (0.020) and the second-lowest average correlation (0.411).

Fig. 1 illustrates the dynamic FTI for each optimal portfolio. It is clear that the highest

Tab. 3: Structure of Mahalanobis distance portfolios

SEAC		MECAC		CEEC		AFC		LAC		DEC	
JKSE	0.48	SENSEX	95.06	WIG	0.10	EGX	0.10	BOVESPA	0.10	S&P500	83.56
KLCI	0.30	DSEX	0.09	PX	0.40	MASI	99.69	IPC	0.10	NIKKEI225	0.65
SET	0.69	KSI	0.42	BUX	0.24	NSE	0.02	IPSA	0.00	DAX	4.28
VNI	97.80	KASE	0.95	BET	0.34	NSX	0.06	COLCAP	0.06	CAC	4.11
PSEi	0.30	TADAWUL	1.51	SOFIX	98.08	BRVM	0.00	Lima gen.	0.03	FTSE100	3.88
STI	0.43	DFM	1.97	SBITOP	0.84	JSE	0.13	JSEAJC	99.71	FTSE-MIB	3.53

Note: Acronyms SEAC, MECAC, CEEC, AFC, LAC and DEC denote South East Asian countries, Middle-East and Central Asian countries, Central and Eastern European countries, African countries, Latin American countries and developed countries, respectively.

Source: own

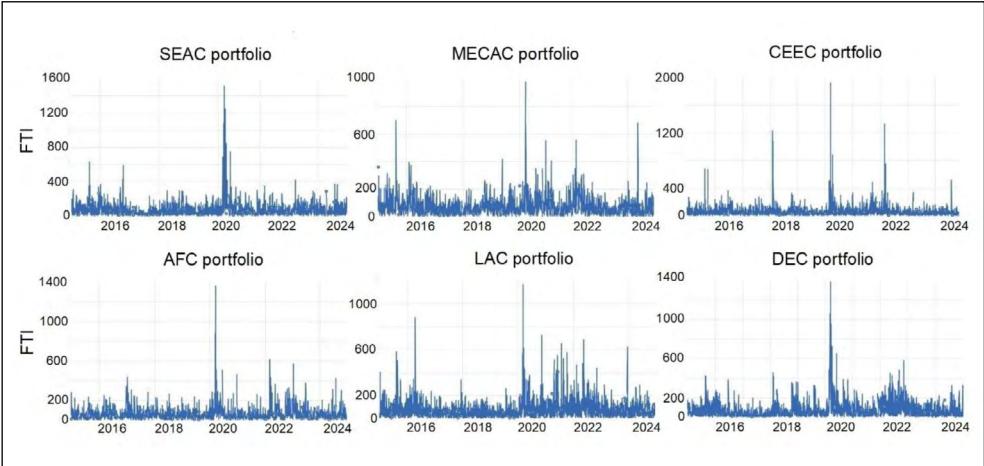


Fig. 1: Calculated financial turbulence index of optimal portfolios

Source: own

impact from systemic risk occurred during the COVID-19 pandemic. The pandemic was a major shock to global stock markets, and these results are consistent with Uddin et al (2021), Hsu and Tang (2022) and Yu and Xiao (2023). Additionally, higher systemic risk is also observed during the Russia-Ukraine war, which triggered an energy crisis and turmoil in global energy commodity markets.

Fig. 1 shows how the level of systemic risk fluctuates over time, but it hardly can be used for accurate comparison to determine which group of countries has experienced

the highest impact from global systemic risk. Additionally, the high concentration of a single asset in all portfolios may distort the picture of which group of countries is most affected. Therefore, Tab. 4 calculates the average level of systemic risk for both the optimal portfolios and the equal-weight portfolios. The latter is expected to more realistically reflect which group of countries suffers the most from global systemic risk. It should also be noted that the level of FTI in all optimal portfolios is lower than that in the equal-weight portfolios, indicating the effectiveness of the optimization.

Tab. 4: Financial turbulence index of equal-weight and optimal portfolios

	SEAC	MECAC	CEEC	AFC	LAC	DEC
Optimal portfolios						
FTI (%)	83.13	76.74	77.56	64.87	64.07	82.72
Equal weight portfolios						
FTI (%)	88.91	89.26	88.40	87.94	87.04	88.73

Source: own

According to the optimal portfolio results, the LAC and AFC portfolios experienced the lowest level of global systemic risk. This essentially means that the JSEAJC and MASI indices are highly resistant to global shocks, as these two indices occupy the largest share in the portfolio. These findings align with Kohlert (2011), who asserts that emerging markets can deliver valuable diversification benefits, though their effectiveness largely depends on the composition of frontier market indices. Similarly, Berger et al. (2013) argue that emerging markets offer diversification advantages by lowering risk, as their volatility is predominantly influenced by idiosyncratic factors, further enhancing their ability to reduce overall portfolio risk. The equal-weight portfolio results indicate that all portfolios experienced a relatively equal amount of systemic risk, but the LAC portfolio performed slightly better than the others. In the equal-weighted portfolio, we do not find evidence that developed countries are more susceptible to global crises compared to emerging markets.

3.2 Stutzer ratio results

Identifying extreme turbulence in portfolios suggests that the Sharpe ratio may provide an inaccurate risk-adjusted assessment, as it assumes normality. Therefore, we apply a more complex and sophisticated metric, the Stutzer ratio, which penalizes investments with skewed or heavy-tailed distributions, commonly observed in stock markets. In order to be thorough in the analysis, we estimate both Sharpe and Stutzer portfolios to examine how their structure and performance differ, and Tab. 5 shows these results.

The Sharpe ratio is easy to understand because it favours assets with a high mean return and low risk in a portfolio. All dominant assets in Sharpe portfolios have the highest

mean returns, as Tab. 5 indicates. For instance, the VNI index is the only asset in the SEAC portfolio because it has by far the highest mean return (0.013). KASE holds a significant share of 83.02% with a mean return of 0.025, while BUX dominates with 96.10% due to its high mean return of 0.027. EGX has a high mean return of 0.042, followed by JSE with a mean return of 0.015, resulting in respective portfolio shares of 53.07% and 26.67%. JSEAJC, Lima General, and BOVESPA occupy positions in the portfolio based on their risk-adjusted performance. In the DEC portfolio, the S&P500 holds a 100% share, driven by its highest mean return (0.020) and relatively low risk (0.493).

On the other hand, the structure of all Stutzer portfolios differs significantly from that of the Sharpe portfolio, indicating that additional factors, such as higher moments and the decay parameter, play an important role. Assets with the highest share in the Sharpe ratio also tend to have a high share in the Stutzer ratio portfolio. However, it can be noted that in most cases (except the AFC portfolio) assets that have a zero share in the Sharpe portfolio appear in the Stutzer portfolio, suggesting that the latter accounts for more factors than the classical Sharpe ratio.

Tab. 6 presents the Sharpe and Stutzer ratios for their respective portfolios. The results clearly show that the Sharpe ratio is greater in the Sharpe portfolios, whereas the Stutzer ratio is higher in the Stutzer-optimized portfolios. These findings strongly indicate the effectiveness of both portfolio optimization approaches. When comparing Sharpe performance across portfolios, the AFC portfolio stands out with the highest Sharpe ratio, recorded at 0.089. In the Stutzer portfolio, the LAC portfolio achieves the highest ratio, with the JSEAJC index holding the largest share at nearly 67%. The Jamaican index possesses several favourable characteristics that elevate it to the top

Tab. 5: Structure of Sharpe and Stutzer portfolios

SEAC		MECAC		CEEC		AFC		LAC		DEC	
Panel A: Sharpe portfolios											
JKSE	0.00	SENSEX	8.47	WIG	0.00	EGX	53.07	BOVESPA	31.37	S&P500	100.00
KLCI	0.00	DSEX	0.00	PX	0.00	MASI	0.00	IPC	0.00	NIKKEI225	0.00
SET	0.00	KSI	0.00	BUX	96.10	NSE	3.60	IPSA	0.00	DAX	0.00
VNI	100.00	KASE	83.02	BET	3.90	NSX	16.67	COLCAP	0.00	CAC	0.00
PSEi	0.00	TADAWUL	8.51	SOFIX	0.00	BRVM	0.00	Lima gen.	32.23	FTSE100	0.00
STI	0.00	DFM	0.00	SBITOP	0.00	JSE	26.67	JSEAJC	36.40	FTSE-MIB	0.00
Panel B: Stutzer portfolios											
JKSE	8.77	SENSEX	8.07	WIG	0.00	EGX	81.77	BOVESPA	12.81	S&P500	78.46
KLCI	0.00	DSEX	17.18	PX	0.00	MASI	0.00	IPC	0.00	NIKKEI225	18.70
SET	0.00	KSI	3.41	BUX	51.39	NSE	0.00	IPSA	0.00	DAX	2.84
VNI	91.23	KASE	43.71	BET	11.85	NSX	0.00	COLCAP	4.49	CAC	0.00
PSEi	0.00	TADAWUL	16.64	SOFIX	9.53	BRVM	0.00	Lima gen.	15.77	FTSE100	0.00
STI	0.00	DFM	10.98	SBITOP	27.23	JSE	18.23	JSEAJC	66.93	FTSE-MIB	0.00

Source: own

in the LAC portfolio – a high mean return (0.022), low risk (0.425), positive skewness (0.355), and a low average correlation with other LAC indices (0.020).

Tab. 7 provides descriptive statistics comparing the Sharpe and Stutzer ratios across all six portfolios. Interestingly, the Sharpe ratio portfolio exhibits a higher mean than the Stutzer counterpart in four out of six cases, as well as lower negative skewness also in four

out of six cases. From a theoretical standpoint, this seems counterintuitive since the Stutzer ratio is designed to favour higher returns and lower negative skewness. However, a critical factor in calculating the Stutzer ratio is the decay factor (theta), which is not considered in the Sharpe ratio. The decay factor determines the weight assigned to historical data when calculating risk-adjusted returns. A lower decay factor places greater emphasis on recent data,

Tab. 6: Values of Sharpe and Stutzer ratios in Sharpe and Stutzer portfolios

	SEAC	MECAC	CEEC	AFC	LAC	DEC
Panel A: Sharpe ratio						
Sharpe portfolio	0.015	0.036	0.043	0.089	0.033	0.020
Stutzer portfolio	0.014	0.017	0.023	0.077	0.024	0.016
Panel B: Stutzer ratio						
Sharpe portfolio	0.0002 (-0.0149)	0.0005 (-0.0365)	0.0009 (-0.0432)	0.0020 (-0.0891)	0.0013 (-0.0328)	0.0003 (-0.0199)
Stutzer portfolio	0.0004 (-0.0574)	0.0030 (-0.3147)	0.0014 (-0.1437)	0.0026 (-0.1402)	0.0115 (-0.4239)	0.0008 (-0.0926)

Notes: The numbers in parentheses denote theta; bold values highlight the larger figure when comparing the six portfolios.

Source: own

Tab. 7: Descriptive statistics of Sharpe and Stutzer portfolios

	SEAC		MECAC		CEEC		AFC		LAC		DEC	
	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer
Mean	0.013	0.012	0.024	0.019	0.027	0.020	0.030	0.037	0.021	0.021	0.020	0.018
Variance	0.495	0.463	0.339	0.239	0.518	0.356	0.423	0.509	0.348	0.325	0.493	0.432
Skew.	-0.982	-1.066	-0.152	-1.024	-1.472	-2.409	-0.705	-0.423	-0.953	-0.149	-0.829	-0.985
Kurt.	7.425	7.803	12.810	12.975	16.587	27.535	8.933	7.573	16.933	27.792	19.412	18.702

Source: own

making the portfolio more responsive to current market trends and changes. This approach is particularly suitable for rapidly changing or volatile markets, as it captures short-term dynamics and adjusts quickly to shifts in risk or return patterns. Conversely, a higher decay factor gives more weight to long-term data, making the portfolio more stable and less sensitive to short-term fluctuations, which is ideal for strategic, long-term portfolios. In addition, the theta parameter is also important in the selection of individual assets in the portfolio. In our case, we maximize theta, which means the optimization reduces weights for assets with significant downside risk or negative skewness, favoring more stable and positively skewed assets.

As shown in Tab. 6, four emerging market portfolios (MECAC, CEEC, AFC, and LAC) have lower theta values compared to portfolios composed of developed market indices. A lower theta indicates that emerging market portfolios are more volatile and operate in rapidly shifting markets where responsiveness is essential. These results are in line with Thomas et al. (2022). On the other hand, the DEC and SEAC portfolios report higher theta values. Higher theta is better suited for long-term portfolios that prioritize stability and reduced sensitivity to short-term noise. Therefore, the selection of theta should align with the investor's time horizon, risk tolerance, and the characteristics of the assets within the portfolio. Emerging markets or highly volatile assets may benefit from a lower theta, while developed markets or more stable assets tend to perform better with a higher theta. Thus, the decay factor probably plays a crucial role in shaping the Stutzer portfolio structures, often taking precedence over

lower negative skewness and higher returns. This might explain the somewhat unexpected results observed in the descriptive statistics of the Sharpe and Stutzer portfolios.

3.3 Discussion

The study finds that certain frontier market indices, such as VNI, MASI or JSEAJC, dominate the optimized Mahalanobis distance portfolios due to their lower integration into the global financial system. This could have various implications for global investors. First, the weak correlations with global stock markets reduces overall portfolio volatility and enhances diversification, especially during periods of global financial turbulence. This is in line with Atipaga et al. (2025), who researched the connection between developed and developing African countries. Second, this could mean that frontier markets are less affected by events like interest rate hikes in developed economies, geopolitical tensions, or global recessions (Talebi et al., 2025). Third, frontier markets are less dependent on foreign portfolio investments, and their economies are more localized and less reliant on global trade or supply chains. According to Harb and Umutlu (2024), this means that frontier markets are typically driven by local factors rather than global trends, which can provide stability in portfolios during global systemic risk events.

However, frontier markets are not without challenges. In other words, frontier markets often characterize political and regulatory instability, limited liquidity and smaller market size as well as underdeveloped financial infrastructure. These factors imply the presence of higher risk in frontier stock markets, as it is suggested by the lower theta parameter in the Stutzer ratio portfolios.

Conclusions

The paper examines the performance of emerging market multi-asset portfolios from the perspective of systemic risk susceptibility and risk-adjusted output. The paper is unique in the literature because two sophisticated methodological approaches are applied in this process – the Mahalanobis distance and Stutzer ratio.

The calculation of the FTI, based on the Mahalanobis distance methodology, reveals that the impact of global systemic risk is lower in optimal portfolios compared to equal-weight portfolios. Furthermore, the optimization process highlights a significant concentration in a single asset within the portfolio, driven by the unique idiosyncratic characteristics of that specific asset. An intriguing finding is that, in four out of five cases, the assets with the highest weight in the portfolio originate from less developed frontier markets. This occurs because frontier markets are less integrated into global financial systems and less dependent on global trade flows. As a result, they serve as a buffer, being less exposed to the volatility of global markets. In four out of five cases, the emerging market portfolios demonstrate lower sensitivity to global systemic risk compared to the developed market portfolio, with Latin American and African countries achieving the best results.

The Stutzer ratio analysis enhances the overall findings by providing insights into the risk-adjusted performance of the selected portfolios. Unlike the traditional Sharpe ratio, the Stutzer ratio offers key advantages, such as relaxing the assumption of normality and incorporating higher moments of the return distribution. A particularly noteworthy feature of this measure is its use of the decay parameter, θ , which highlights subtle portfolio characteristics related to risk and the likelihood of underperformance. The findings reveal that all emerging market portfolios achieve higher Stutzer ratios compared to the developed market portfolio, reflecting superior risk-adjusted performance. However, the θ parameter is generally lower in emerging market portfolios, signaling a higher level of risk associated with these markets. According to the results, the Latin American portfolio has the best Stutzer ratio.

This paper serves as a valuable resource for global investors interested in emerging market investments, offering a detailed analysis from the perspectives of systemic risk and

risk-adjusted performance. It presents the precise structure of both the Mahalanobis distance and Stutzer ratio portfolios, providing insights into which emerging markets deliver the best performance. Both individual and institutional investors can leverage the findings to develop asset allocation strategies that optimize the performance of their investment portfolios.

Acknowledgement: *The paper is a part of research financed by the MSTDI RS, agreed in Decision No. 451-03-136/2025-03/200009 from 4. 2. 2025.*

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Financial innovation and financial inclusion in European countries: How do they interact?

Alina Cristina Nuta¹, Ibrahim Cutcu², Felix Puime-Guillen³

¹ Danubius International University, Faculty of Economics and Business Administration, Romania; Azerbaijan State University of Economics (UNEC), Women Researchers Council, Azerbaijan, ORCID: 0000-0003-3248-644X, alinanuta@univ-danubius.ro (corresponding author);

² Hasan Kalyoncu University, Department of Economics, Turkey, ORCID: 0000-0002-8655-1553, icutcu@gmail.com;

³ University of A Coruna, Faculty of Economics and Business, Spain, ORCID: 0000-0001-7341-9134, felix.puime@udc.es.

Abstract: The most challenging moments in economic history necessitated adaptability to new realities and foreshadowed innovative reactions from economic agents. The recent global health crisis compelled all the stakeholders to find viable solutions to prevent the economic recovery from stalling. As finance serves as the fuel that keeps the economic engine running, exploring the factors affecting financial innovation is pivotal. Europe's digital transition strategy provides a vibrant approach to bolstering the digital economy and financial landscape. This study evaluates the link between financial inclusion and financial innovation in selected European countries moderated by digital technology. Moreover, subsequent factors related to socio-economic development, like the standard of living, education, urbanization, and globalization, are studied to assess their impact on financial innovation. The study used new-generation panel data techniques to analyze the selected European countries from 2000 to 2020. Durbin Hausman's cointegration test shows a long-run relationship. Our findings from fully modified ordinary least square (FMOLS) and dynamic ordinary least squares (DOLS) tests highlighted an inverse relationship between financial inclusion and financial innovation. Thus, expanding the inclusion of people in the financial ecosystem will not increase the usage of innovative financial tools. However, it will only encourage access to essential financial services and products, considering the high levels of financial inclusion in Europe and the newcomers' financial and digital literacy levels. Additionally, the preference for using cash in European countries, which is still at high levels, also explains our results regarding the indirect connection between financial inclusion and financial innovation diffusion. Moreover, a strong direct correlation is observed between education, standard of living, and urbanization. Konya causality analysis results displayed a causal relationship between independent variables and financial innovation in different countries.

Keywords: Digital technology, innovative finance, inclusion, education, Europe.

JEL Classification: Q55, D1, F65, I25.

APA Style Citation: Nuta, A. C., Cutcu, I., & Puime-Guillen, F. (2025). Financial innovation and financial inclusion in European countries: How do they interact? *E&M Economics and Management*, 28(4), 163–179. <https://doi.org/10.15240/tul/001/2025-4-011>

Introduction

The long history of economic thought examined innovation and financial innovation from

different perspectives. Investment in human capital is strongly connected with innovation. Innovation is the key to performance and

development, driven by the “new” element in activity. At the same time, innovation in finance has generally been associated with positive outcomes for a large part of the literature (Bernier & Plouffe, 2019), but it has also been related to negative events, such as crises (Beck et al., 2016).

On the other hand, financial inclusion can augment the innovation of the financial sector by expanding the demand for money and new, personalized, and innovative financial products. Education is the key element, as well as rapid economic development. Additionally, literature has not reached a consensus regarding the impact of financial development on innovation; beyond a positive (Levine, 2005) or negative relationship, some works found a non-linear relationship (Trinugroho et al., 2021), suggesting a positive impact until a certain threshold has been reached, after which the innovation is disheartened.

The definition of financial innovation constantly evolves, making it challenging to standardize measures in the literature. Many studies have analyzed financial innovation's influence on financial inclusion because expanding the range of financial services as much as possible through innovative tools and philosophy will enhance inclusivity. Additionally, few studies analyzing India's context raise doubts about the inclusivity capacity of innovation in finance, specifically concerning women, unbanked, and vulnerable communities (Kanungo & Gupta, 2021; Venkatraman & Reddy, 2021). However, no study has analyzed the impact of financial inclusion on financial innovation broadly. To fill the literature gap, our study aims to empirically evaluate the existence of causality between financial inclusion and innovative financial products and its interpretation in the pursuit of sustainable development goals in the rapid expansion of digital technology. A marginal aim is to investigate the role of globalization, education, and living standards on financial innovation. Additionally, the study will assess the role of urbanization as a driver for social modernization on financial innovation. Thus, this approach argues that extending inclusion in the financial ecosystem will not result in more innovative financial product usage, but contrary, especially when there is a high level of inclusion, as is the case with selected developed countries from Europe, beyond which additional players in the system will not demand more

innovation, but only basic financial services. A relevant reason to sustain this finding is related to the fact that additional consumers are usually vulnerable people or belong to vulnerable communities, especially in developing countries. However, this is not the only reason, considering the specific consumer preference for financial tools in European countries, which is closely related to cash usage. This study aims to ascertain the main factors that affect financial innovation in European countries, analyzing the role of the standard of living, urbanization, internet usage, financial inclusion, and globalization.

The research contribution to the literature can be highlighted in the following ways. The study addresses an unexplored connection between financial inclusion and financial innovation, giving rationales behind the negative impact of inclusion on financial innovation at a certain level of inclusion and considering the specific profile of financial instrument users from Europe. This is an important finding for institutional stakeholders, which should address the financial skills gap of financially excluded people and create relevant programs for them. Moreover, the diversity of cash users' profiles within European countries and their high preference for not owning or using digital payment tools requires the continued adaptation of the cash strategy of European authorities, according to their diminished propensity to be active actors in the financial digital landscape. Additionally, this paper used data considering the use of electronic payment instruments from the European Central Bank as a proxy for the financial innovation variable and the access and depth components of the financial development index to construct a proxy for the financial inclusion variable, which has not been used in previous studies. Moreover, new generation panel data analysis techniques were used in the methodology. The study's methodology, which aims to determine the link between financial innovation and financial inclusion in EU states, includes descriptive statistics analyzed via graphical presentations of the variables. Subsequently, cross-section dependence test, panel unit root test, homogeneity test, panel cointegration test, coefficient estimator analysis (fully modified ordinary least square – FMOLS and dynamic ordinary least squares – DOLS), and panel causality tests are performed. As can be seen,

current and new-generation analyses were used in all analyzers.

Thus, the primary focus of this research is to investigate the relationship and impact of financial innovation on financial inclusion in selected EU countries. In this context, the main hypothesis of the study is that there is a long-term relationship between financial innovation and financial inclusion. The structure of the paper continues with the literature review. In the following section, the econometric approach is presented. Next section points out the results and discussion, followed by the conclusions and policy implications presented in the last section.

1 Theoretical background

The theory of the national innovation system explains the advancement of innovation (Watkins et al., 2015). Education (human capital) has greater importance for innovation, as models of endogenous growth suggested (Romer, 1994) by generating technological change, in contrast with learning-by-doing models (Arrow, 1962) in which technologies have a secondary role.

Previous studies approached innovation in finance as a response to regulation (Silber, 1983), explained by the fact that new practices or new financial tools appear when different constraints affect the financial decisions of firms and households. Financial inclusion is strongly correlated with financial stability, both positively and negatively (Nuta et al., 2024). The widely allocated financial resources feature of financial inclusion positively affects financial stability by contributing to more equitable and less risky interactions, an increase in formal institutions' involvement, and reduced costs (Hua et al., 2023; Oanh et al., 2023; Saha & Qin, 2023; Yin et al., 2020; Yu et al., 2023). Conversely, when financial inclusion is based on improperly regulated fintech innovation, adverse effects, such as volatility, risk spillover, as well as excessive credit, and inflation, will negatively impact financial stability (Boot et al., 2021). Moreover, a good-bad financial inclusion distinction is established in the literature (Hua et al., 2023; Oanh et al., 2023). They argue that after a certain threshold, the expansion of financial inclusion became "bad finance," accompanied by over-indebtedness and systemic risk. In addition, Hua et al. (2023) discovered an inverted U-shaped link between these two variables.

Financial inclusion plays a crucial role in the real economy by providing access to resources for those in need. However, it has limitations when it comes to fostering innovation. Moreover, there can be a crowding-out effect, where the demand for money for general spending by individuals without an investment mindset may limit the potential for borrowing for productive purposes. In this context, financial literacy becomes essential.

Financial innovation and financial inclusion are not always compatible. As Anderloni and Carluccio (2007) highlighted, inclusion in the financial market and access to financial services become difficult for specific categories of people in an innovative-intensive landscape. Moreover, a very complex financial network will supply more personalized services for households and firms but is also subject to induced contagion processes and financial shocks. As well, the intricacy of certain "opaque" financial products will lead to increasing risks, not only to exclusive access and inequality (Botta et al., 2022). Conversely, research of Niankara (2023) on the Arab regional payment system that used Global Findex surveys pointed out the importance of financial inclusion in enhancing digital payment solutions, considering the Helical theory framework of Carayannis and Campbell (2012). The debate on financial innovation, inclusion, and globalization still lacks consensus in the literature. Moreover, globalization (especially financial globalization), besides the diversification of financial resources and extension of the range of instruments available for business financing and investments, can diminish the costs of transactions, improve risk sharing and the information transfer and transparency between counterparties, and can facilitate the uniformization of standards disclosure and a stronger discipline. Contrariwise, financial globalization may not have similar effects on financial development or innovation because of the relevance of the internal domestic markets (e.g., financial, capital, and labor), which are more powerful and can catalyze in different ways the financial environment, as highlighted in Wei (2018) research. As the literature suggested, globalization tends not to be such a pivotal factor for developed nations.

In a study of Tesega (2022) on 33 African countries evaluating the association between financial globalization and financial development, the author found mixed effects:

a reduced level of financial globalization had a negative impact on financial development, while higher levels of globalization positively affected financial development. A more recent study (Zheng et al., 2023) found a significant boost of globalization to technological innovation, enhanced by the robustness of the institutional quality of a specific country. The main channel by which the positive effect becomes evident is financial development. Nevertheless, a study by Ghosh (2017) suggested that globalization can diminish the resources dedicated to innovative firms. Additionally, a greater concentration of the financial ecosystem may generate an expansion of the financing cost, including for innovative activities. The innovative impetus of a country is not only a matter of human capital deployment but also dependent on the country's development level and also, on internal and external financial resources. Considering the social advancement of a country (standard of living), which reflects the domestic potential of that country to become more innovative and use technology-based tools, this study also identifies the external financial capabilities to evaluate their potential in shaping financial innovation by including globalization in the model. The rationale behind including the standard of living in the model

is that innovation is a resource-consuming process (O'Sullivan, 2006) and may occur in the presence of certain disposable income at the individual or societal level. Innovation enhances development. The feedback effect is also noticeable. Thus, a higher standard of living and economic empowerment will support and boost innovation by enhancing the quality of education and upskilling people, attracting more innovation (Madgavkar, 2023).

2 Research methodology

2.1 Data

Some of the variables selected for this study were previously used to explain the effects of various features on financial development in different groups. However, the literature used them separately without covering the complex relationships that are discussed and explained in this research. Moreover, by adding urbanization and gross national income, the results will shed light upon the influence social development has on financial innovation, which is paramount for the characteristics of modern society. The primary constraint of the data range of the research is the standard data problem. The analyses are based on annual data for the period 2000–2020 due to the standard data constraint of the variables of selected

Tab. 1: Dataset and sources

Variables	Definition	Source
Financial innovation (<i>FIN</i>)	The use of electronic payment instruments in a specific country	European Central Bank
Financial inclusion (<i>FINC</i>)	The average of financial institution access and depth and financial markets access and depth indices	IMF
Individuals using internet (<i>IU</i>)	The number of internet users in a country	World Bank
Mean years of schooling (<i>MYS</i>)	The educational attainment levels of people aged 25 and more	UNDP (United Nations Development Programme)
Globalization (<i>GLB</i>)	Measures three aspects of globalization (social, economic, and political)	KOF Swiss Economic Institute
Urban population (% total population; <i>URB</i>)	People living in urban areas	World Bank
Gross nation income per capita (constant 2017 international USD; <i>GNI</i>)	Standard of living in selected countries	UNDP

Source: own

European countries. In this regard, financial innovation (*FIN*) is used as the dependent variable, and financial inclusion (*FINC*), individuals using the internet (*IU*), mean years of schooling (*MYS*), and globalisation (*GLB*) variables are used as independent variables. For the globalization measurement, we used the KOF globalization index (Gygli et al., 2019). Additionally, urbanization (*URB*) and gross national income (*GNI*) variables, known to affect the dependent variable of financial innovation, are incorporated in the model as control variables. The explanatory notes of all variables included in the model are displayed in Tab. 1.

In the research, the model created within the hypothesis framework is constructed as follows.

$$LNFIN_{it} = \beta_0 + \beta_1 FINC_{it} + \beta_2 LNIU_{it} + \beta_3 MYS_{it} + \beta_4 LNGLB_{it} + \beta_5 LNURB_{it} + (1) + \beta_6 LNGNI_{it} + \varepsilon_{it}$$

where: $i = 1, 2, 3, \dots, N$ denotes cross-sectional data; $t = 1, 2, 3, \dots, T$ indicates time dimension; and ε – error term. In the analyses, financial innovation (*FIN*), gross national income (*GNI*), urban population (*URB*), globalization (*GLB*), and individuals using the internet (*IU*) variables are logarithmized and transformed into the model.

For the other variables, we did not use logarithms since they are ratios or indices. The study's methodology, which aims to determine the relationship between financial innovation and financial inclusion in EU countries, is as follows: descriptive statistics are analyzed via graphical presentations of the variables. Subsequently, cross-section dependence test (CD_{lm1} and LM_{adj}), panel unit root test, homogeneity test, panel cointegration test, coefficient estimator analysis (FMOLS and DOLS) and panel causality (Konya) tests are performed.

2.2 Descriptive statistics and graphical analysis

In econometric applications, changes and fluctuations of variables over the years are observed through graphical analyses. The graphical view and interpretations of the variables of the research are shown in Fig. 1.

When Fig. 1 is analyzed, it is observed that the highest level of *LNFIN* variable is observed in France and Germany, while it reaches its lowest point in Malta. Furthermore, Luxembourg differs from other countries in *LNGNI* variable. While *LNURB* variable fluctuates at the same level in almost all countries, Romania and Portugal are at the minimum level. Regarding the *LNGLB* variable, it is understood that

Tab. 2: Basic statistical tests for variables

Variables	Observations	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera
<i>LNFIN</i>	420	7.0316	7.4164	10.1621	2.5960	1.7772	-0.4473	2.4336	19.6201 (0.0000)
<i>LNGNI</i>	420	10.5101	7.4164	11.4422	9.4034	0.3988	-0.4441	2.9533	13.8430 (0.0009)
<i>LNURB</i>	420	4.3021	7.4164	4.5858	3.9661	0.1661	-0.1205	2.0552	16.6372 (0.0002)
<i>LNGLB</i>	420	4.4030	7.4164	4.5124	4.0867	0.0832	-1.3259	4.6672	171.6984 (0.0000)
<i>LNIU</i>	420	3.8402	1.2384	4.5896	-0.5057	1.1032	-2.8005	10.5196	1,546.4240 (0.0000)
<i>FINC</i>	420	0.5215	7.4164	0.8454	0.0356	0.2011	-0.5817	2.1922	35.1087 (0.0000)
<i>MYS</i>	420	11.5274	7.4164	14.1322	6.7827	1.4855	-0.8202	3.4058	49.9667 (0.0000)

Note: *LNFIN* – financial innovation; *LNGNI* – gross national income; *LNURB* – urban population; *LNGLB* – globalization; *LNIU* – individuals using the internet; *FINC* – financial inclusion; *MYS* – mean years of schooling.

Source: own

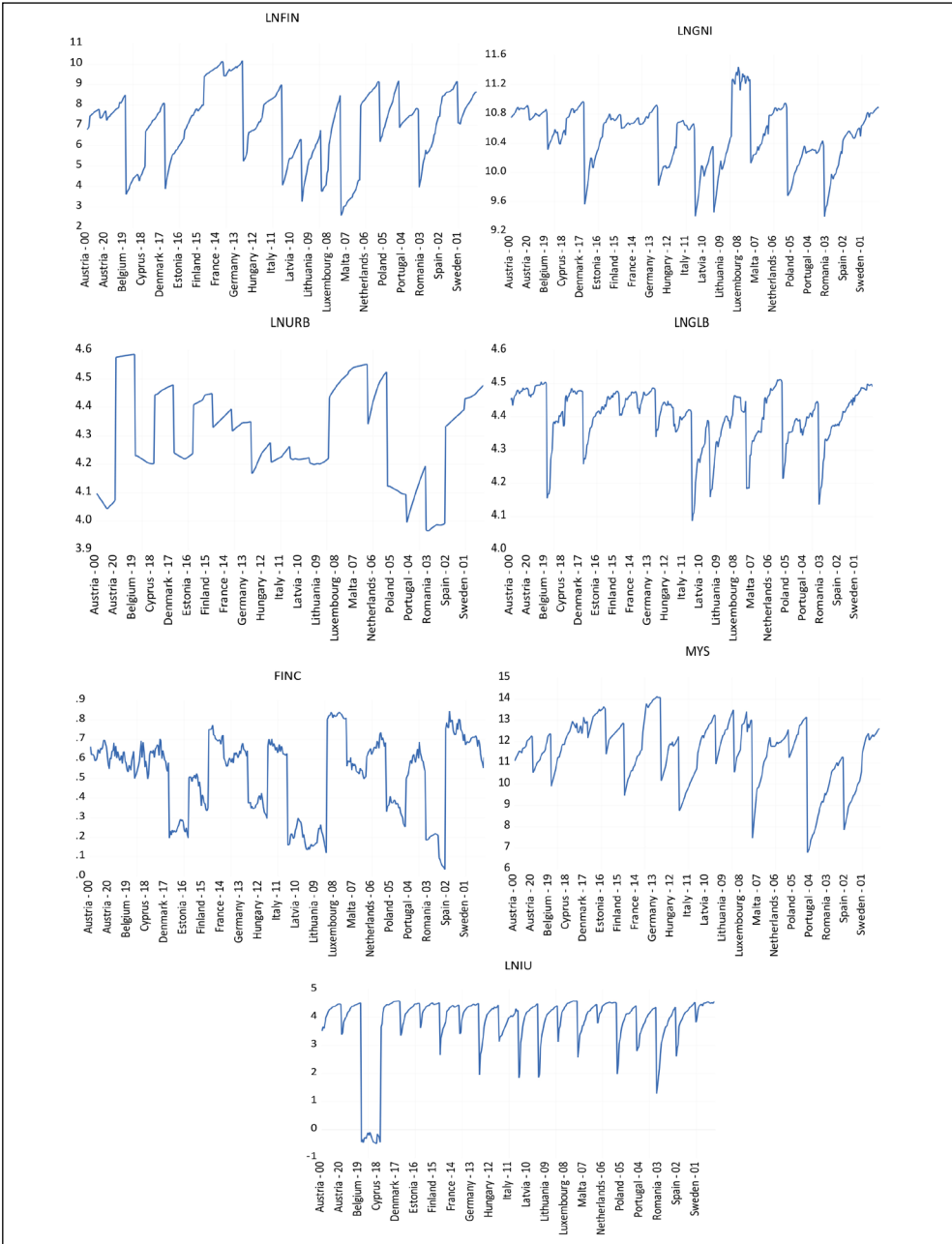


Fig. 1: Graphical representation of variables

Note: *LNFIN* – financial innovation; *LNGNI* – gross national income; *LNURB* – urban population; *LNLGB* – globalization; *LNIU* – individuals using the Internet; *FINC* – financial inclusion; *MYS* – mean years of schooling.

Source: own

countries such as Romania and Lithuania, which joined the EU afterward, are at low levels. While *FINC* variable generally fluctuates in all countries, it peaks in Luxembourg and at the bottom in Romania and Spain. In *MYS* variable, all countries except Portugal fluctuate around the same band. In *LNIU* variable, similar fluctuations are observed in all countries except Cyprus. In Cyprus, *LNIU* variable has negative values.

The basic descriptive statistics are displayed in Tab. 2. When the data are evaluated, according to the kurtosis value, it is seen that *LNLGB* and *LNIU* variables are pointed (with values greater than 3), while the other variables are flattened (with values less than 3). According to the skewness value, all variables are negatively (right) skewed since they are less than zero. The results of the Jarque-Bera test indicate that all the variables are significant and do not conform to a normal distribution.

2.3 Empirical approach

In this part of the research, where the link between *FIN* and *FINC* is examined, annual data for selected EU countries for the period 2000–2020 are used. The main reasons for preferring European Union countries in the selection of the country sample are as follows: i) the high share of EU countries in the world economy; ii) being made up of countries that continuously increase their *FIN* investments in the world; iii) high level of *FINC* with the adoption of a common currency.

Within the scope of the research hypothesis that there is a long-run relationship between *FINC* and *FIN*, the model built in the study is first presented, and the methodology to be used is explained.

3 Results and discussion

3.1 Cross-section dependence test

The existence of a cross-sectional relationship between variables was further analyzed. With globalization, the interdependence of countries is increasing, increasing the interdependence between variables. In other words, the effect of positive or negative shocks experienced in one country is expected to affect other countries due to the interdependence process. In the research, the independence relationship between the European Union countries should also be analyzed, and some evaluations should be made based on the findings. The country group involved in the study's analysis is 20 countries. For this reason, the cross-sectional dimension is $N = 20$. The time dimension is 21 ($T = 21$) since the periods of 2000–2021 are analyzed. Since $T > N$ (Pesaran, 2004) CD_{lm} and LM_{adj} tests of Pesaran et al. (2008) are employed in the study.

Pesaran (2004) was used and formulated as the Equations (2–3):

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N P_{ij}^2 \quad (2)$$

Tab. 3: Results of cross-section dependence test – Part 1

Variables	CD tests	CD_{lm1} (BP, 1980)	CD_{lm2} (Pesaran, 2004)	CD (Pesaran, 2004)	LM_{adj} (Pesaran et al., 2008)
<i>LNFN</i>	T-statistics	3,451.304*	167.301*	58.367*	166.801*
	Probability	0.000	0.000	0.000	0.000
<i>LNGNI</i>	T-statistics	2,419.465*	114.369*	41.535*	113.869*
	Probability	0.000	0.000	0.000	0.000
<i>LNURB</i>	T-statistics	2,870.727*	137.518*	22.492*	137.018*
	Probability	0.000	0.000	0.000	0.000
<i>LNLGB</i>	T-statistics	3,212.898*	155.071*	56.270*	154.571*
	Probability	0.000	0.000	0.000	0.000

Tab. 3: Results of cross-section dependence test – Part 2

Variables	CD tests	CD _{lm1} (BP, 1980)	CD _{lm2} (Pesaran, 2004)	CD (Pesaran, 2004)	LM _{adj} (Pesaran et al., 2008)
LNIU	T-statistics	3,317.846*	160.455*	55.545*	159.955*
	Probability	0.000	0.000	0.000	0.000
FINC	T-statistics	1,099.278*	16.644*	23.381*	46.144*
	Probability	0.000	0.000	0.000	0.000
MYS	T-statistics	3,163.137*	152.518*	54.561*	152.018*
	Probability	0.000	0.000	0.000	0.000

Note: *, **, and *** indicate that the series are stationary at 1, 5, and 10% significance levels; *LNFIN* – financial innovation; *LNGNI* – gross national income; *LNURB* – urban population; *LNGLB* – globalization; *LNIU* – individuals using the internet; *FINC* – financial inclusion; *MYS* – mean years of schooling.

Source: own

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \rho_{ij} \right) \quad (3)$$

where: *T* and *N* represent the time and the number of cross-section units (*N*).

Looking at Tab. 3, which tests the cross-sectional dependence relationship in selected EU countries, it is seen that the probability values of the variables are statistically significant at the 1% level, which admits cross-sectional dependence. This is also consistent with the theory and with the current world

environment. That is to say, it can be derived that a shock to one EU country will influence other countries.

3.2 Panel unit root analysis

In panel data analyses, unit root tests are performed to eliminate the spurious regression problem. In this research, the CIPS unit root test is used because of the previously determined cross-sectional dependence. The CIPS unit root test is used because it provides consistent analysis results for cases with *T* > *N*.

As the unit root test results are shown in Tab. 4, according to the CIPS statistic results

Tab. 4: Unit root test results

Variables	Level	1 st differential
LNFIN	-2.469	-4.809**
LNGNI	-2.553	-5.158*
LNURB	-2.553	-3.846***
LNGLB	-1.865	-4.430**
FINC	-3.504	-6.473*
MYS	-2.679	-5.373*
LNIU	-2.400	-3.680***

Note: *, **, and *** indicate that the series are stationary at 1, 5, and 10% significance levels; 1, 5, and 10% critical values are -4.96, -4.00 and -3.55, respectively; *LNFIN* – financial innovation; *LNGNI* – gross national income; *LNURB* – urban population; *LNGLB* – globalization; *LNIU* – individuals using the internet; *FINC* – financial inclusion; *MYS* – mean years of schooling.

Source: own

calculated for the whole panel, all variables are unit-rooted at their level values. When the variables are differenced at first order, *LNGNI*, *FINC*, and *MYS* variables become stationary at 1% significance level, *LNFIN* and *LNGLB* variables become stationary at 5% significance level, and finally, *LNURB* and *LNIU* variables become stationary at 10% significance level. The condition is met since variables become stationary at the same level $I(1)$.

3.3 Homogeneity test

The homogeneity test aims to identify whether a modification in one country has a comparable impact on other countries. In this scenario, it is anticipated that coefficients will exhibit heterogeneity in models designed for countries with distinct economic structures. Conversely, coefficients are expected to display homogeneity in models created for groups of countries sharing similar economic structures. This study employs the slope homogeneity test (Delta test) introduced by Hashem Pesaran and Yamagata (2008) to assess homogeneity. The Equations (4–5), for these tests, are given below.

$$\hat{\Delta} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}} \right) \quad (4)$$

$$\hat{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - E(Z_{iT})}{\sqrt{Var(\tilde{Z}_{iT})}} \right) \quad (5)$$

Tab. 5 presents the homogeneity test results. The coefficients are heterogeneous. This indicates that the effect of a change in the variables included in the model on *FIN* differs in each country.

3.4 Durbin-Hausman cointegration test and coefficient estimator analysis results

In this analysis, the Durbin-Hausman cointegration test developed by Westerlund (2008) is used to analyze the long-run relationship between the variables. Many reasons distinguish the Durbin-Hausman test from others and make it more robust. The most important is that the test considers the cross-sectional dependence between variables and is a second-generation panel cointegration test (Westerlund, 2008). Since heterogeneity is captured according to the Delta test results in the research, the DH group test statistical results will generate more reliable results in the cointegration test.

Recognizing that employing group statistics is more suitable for analysis due to the observed changes in slope coefficients and the heterogeneity of variables in Tab. 6, the study considers

Tab. 5: Results of the homogeneity test

	Test statistics	Probability value
Delta	10.697*	0.000
Delta_{adj}	13.410*	0.000

Note: *, **, and *** indicate that the panel coefficients are heterogeneous at 1, 5, and 10% significance levels, respectively.

Source: own

Tab. 6: Durbin-Hausman cointegration test results

Test statistics	Statistics value	Probability value
Durbin-Hausman group	980.919*	0.000
Durbin-Hausman panel	17.172*	0.000

Note: *, **, and *** indicate a long-run relationship between the variables at 1, 5, and 10% significance level, respectively.

Source: own

the results of the Durbin-Hausman group statistic, upon scrutinizing the probability values of the Durbin-Hausman panel statistic. It is deduced that a long-term relationship exists between the variables as the value is below 0.05. Consequently, it is inferred that a lasting association exists between *FIN* and *FINC*. Identifying long-term relationships between variables suggests that the essential condition for coefficient estimation has been met. The FMOLS method, introduced to the literature by Phillips and Hansen (1990), generates consistent and reliable results in coefficient estimation of small samples, estimating the long-run impact of the independent variables (Yurdakul, 2018). DOLS estimates the coefficient by considering the leads and lags of the first differences of the variables, being more effective small observations models (Pata & Tütüncü, 2017).

When Tab. 7 is analyzed, according to the FMOLS coefficient estimator, the following variables have a relationship with the dependent variable financial innovation (*LNFIN*) in the specified direction and significance level: i) *LNGNI*, *LNURB*, and *MYS* at 1% significance level; ii) the positive direction between *LNIU* at a 10% significance level; iii) there is a negative correlation between *FINC* at a 1% significance level.

According to the DOLS coefficient estimator, the following variables are related to the dependent variable financial innovation (*LNFIN*) in the specified direction and significance level:

- i) *LNLGB* is negatively correlated at 5% significance level;
- ii) a positive relationship between *LNGNI*, *MYS*, and *LNIU* at 1% significance level;
- iii) a positive relationship between *LNURB* at 5% significance level;
- iv) *FINC* is negatively correlated at the 10% significance level.

The results highlighted in Tab. 7 show how socio-economic variables influence *FIN*. The most important result consists of an indirect relationship between financial inclusion and innovation. In this sense, in European countries included in the panel, it was observed that an increase in *FINC* (considering that European countries included in the model dispose of a certain level of inclusiveness) would not increase *FIN*. This upshot is possible because newcomers in the financial ecosystem are vulnerable people or socio-enterprises searching for financial resources for their basic needs and usually have low financial literacy profiles. In fact, according to the latest European Commission survey on financial literacy (the Eurobarometer from 2023), only 18% of EU citizens have a high level of financial literacy. Among the countries surveyed (the Netherlands, Sweden, Slovenia, and Denmark) only three achieved the highest levels of financial literacy, with percentages of 28, 27, and 27%, respectively. In contrast, a significant portion of EU citizens exhibit low levels of financial literacy, with Finland at 27%, Latvia at 24%,

Tab. 7: FMOLS-DOLS estimation results

Variables	FMOLS estimator			DOLS estimator		
	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
<i>LNLGB</i>	-0.0632	0.3922	0.8720	-2.4663**	0.7624	0.0014
<i>LNGNI</i>	1.2020*	0.1068	0.0000	2.3088*	0.1828	0.0000
<i>LNURB</i>	10.2504*	2.4408	0.0000	15.0373**	5.3412	0.0043
<i>MYS</i>	0.4347*	0.0365	0.0000	0.2330*	0.0499	0.0000
<i>LNIU</i>	0.07471***	0.0438	0.0890	0.2371*	0.0659	0.0004
<i>FINC</i>	-1.4658*	0.2285	0.0000	-0.5808***	0.3094	0.0617

Note: *, **, and *** indicate a significance level of 1, 5, and 10% respectively; *LNFIN* – financial innovation; *LNGNI* – gross national income; *LNURB* – urban population; *LNLGB* – globalization; *LNIU* – individuals using the internet; *FINC* – financial inclusion; *MYS* – mean years of schooling.

Source: own

Belgium at 22%, Spain at 22%, and Poland at 20%, although the European countries are developed countries. Our outcomes are also confirmed by Kanungo and Gupta (2021) and Venkatraman and Reddy (2021) but are in contrast with Carayannis and Campbell (2012). According to these important results, intensive literacy programs, both for financial and digital skills, are needed. In this manner, many aspects will be solved: better spending decisions, proper investments, and increased demand for innovative and specialized financial products that can bring more social gains and may help target sustainable development goals (Hua et al., 2023; Luu et al., 2023). Additionally, other relevant results of this study point out the positive correlation between socio-economic variables and *FIN*. In this respect, education is a crucial factor that can enhance financial *FIN*, having the potential of multiplication and more personalization and secure financial products and services. The standard of living is influenced by technology and *FIN* and, at the same time, can encourage *FIN*, bearing in mind the fact that the “new” element, specific to innovation, can be cost-dependent. The study’s results identify a positive relationship between the economic development level of the analyzed countries and the appetite for *FIN*, which also confirms Madgavkar’s (2023) findings. Urbanization is found to be directly correlated with *FIN*. Cities’ development increases the greed for sophisticated financial instruments and alternative financing especially in the context of the need for greener and more human-centered living places. Finance seems to evolve across the increasing trend of urbanization, as Grafe and Mieg (2019) have found. Societal and development changes potentiate the innovation of financing infrastructure and tools. Local stakeholders, as well as companies, investors, and civil society, are important in the decision-making process for further innovation in urban financing. According to the DOLS econometric approach, globalization was negatively correlated with *FIN*, which is in line with Wei (2018). The findings related to the negative connection between globalization and *FIN* are also consistent with the conclusion of Atsu and Adams (2023). They suggested a similar effect of foreign direct investments on innovation.

Further, the study shows a positive relationship between internet intensity/use and *FIN*

in European countries. As can be observed, digital performance, internet usage, and the scope for which the internet is used in European countries present different characteristics, even if there is not a significant difference between the best-positioned country (Denmark, 96.44% of individuals are using the internet) and the worse positioned (Bulgaria, where 78.97% of individuals are using the internet), while the average at the European Union is 88.59%, according to DESI (2023). Individuals are using the internet for internet banking at various levels across Europe, with Norway being top-ranked at 95.84%, followed by Finland and Denmark at similar percentages. On the opposite side, Romania occupies the last spot with only 19.19% of individuals using the internet for banking purposes, close to Bulgaria (22.44%), while the average EU-27 is 59.66% in 2022. These figures offer a concrete perspective of the internet utility in Europe and must also be correlated with the level of basic digital skills evaluated by DESI (2023), which show high levels in Finland, the Netherlands, Ireland, and Denmark (from 79.18% to 68.65%), while Bulgaria and Romania are placed on the last positions (31.18% and 27.82%, respectively). The conclusion highlights the importance of digital skills in using the internet not only for socializing but also for taking care of day-to-day activities, such as paying bills, money transfers, e-commerce, investments, and being more efficient and productive. In this sense, national institutions should increase citizens’ digital skills to properly implement the digital transformation strategy, which can positively affect society.

3.5 Kónya causality test

Kónya (2006) devised this test to explore causal relationships between variables, utilizing the seemingly unrelated regressions (SUR) estimator proposed by Zellner (1962). One notable advantage of this test is its applicability to heterogeneous panels, allowing for separate causality tests for individual countries within the panel.

Tab. 8 shows a unidirectional causality relationship from *LNF* to *FIN* in Italy at the 5% level and in Estonia, Lithuania, and Spain at the 10% level. These results align with Carayannis and Campbell (2012), presenting the advantages of a more innovative financial

Tab. 8: Kónya causality results

Country	Wald statistics	Critical values			Wald statistics	Critical values		
		1%	5%	10%		1%	5%	10%
	H0: $\Delta LNFIN$ does not Granger-cause $\Delta FINC$					H0: $\Delta FINC$ does not Granger-cause $\Delta LNFIN$		
Estonia	74.703***	136.764	104.091	74.710	1.102	628.498	358.315	271.266
Italy	130.466**	151.045	108.055	90.855	29.069	1556.290	850.882	635.556
Lithuania	93.797***	143.062	120.077	79.036	88.469	1603.970	761.667	371.579
Spain	88.973***	164.349	127.054	87.604	0.014	728.096	533.366	321.083
H0: $\Delta LNFIN$ does not Granger-cause $\Delta LNGNI$					H0: $\Delta LNGNI$ does not Granger-cause $\Delta LNFIN$			
Austria	14.867	161.487	107.042	73.008	78.950***	177.272	118.152	77.476
Belgium	124.073***	226.889	169.307	119.274	7.445	130.217	77.333	51.671
Cyprus	110.416***	146.150	116.240	82.893	11.530	154.351	130.411	90.702
Denmark	79.677***	174.348	93.892	78.644	78.398***	217.710	96.768	76.057
Estonia	10.370	164.214	130.447	105.374	95.057**	121.310	91.503	72.537
Finland	54.720	139.293	89.622	79.074	89.247***	166.666	110.851	86.442
France	117.889**	289.224	101.977	85.352	5.298	185.771	113.231	94.089
Germany	105.725**	283.083	102.024	87.253	53.865	180.800	126.265	110.511
Hungary	69.835	141.606	87.854	77.016	142.029*	140.237	108.778	79.467
Italy	75.869	114.921	101.777	85.301	148.012*	131.203	112.237	75.954
Lithuania	94.516***	150.726	99.344	85.941	40.111	171.069	114.214	82.367
Luxembourg	47.592	111.676	80.694	68.276	144.700**	478.506	99.135	81.523
Portugal	85.816***	170.196	106.843	83.353	8.793	166.606	141.483	94.922
Romania	4.151	178.788	101.368	71.295	75.881***	203.785	114.716	74.871
H0: $\Delta LNFIN$ does not Granger-cause $\Delta LNLGB$					H0: $\Delta LNLGN$ does not Granger-cause $\Delta LNFIN$			
Denmark	91.647***	197.632	104.472	79.750	29.894	575.619	296.358	225.049
Hungary	92.006***	165.62	100.929	91.661	4.682	1299.074	668.684	403.629
Lithuania	47.648	146.004	118.711	99.363	563.881**	677.086	390.770	307.448
Luxembourg	46.08	126.725	102.400	75.650	1024.512*	1012.928	484.753	304.680
Malta	135.912*	110.400	89.754	78.934	717.630**	1171.860	620.492	377.478
Netherlands	113.669**	141.320	87.930	66.284	341.468***	929.489	396.318	326.449
Poland	34.949	190.550	112.149	95.074	199.551***	408.959	332.183	198.352
Romania	202.194*	125.664	103.164	85.532	3.069	1678.927	1065.714	437.505
H0: $\Delta LNFIN$ does not Granger-cause ΔMYS					H0: ΔMYS does not Granger-cause $\Delta LNFIN$			
Lithuania	0.629	154.794	99.877	70.819	358.701*	184.874	115.400	84.029
Luxembourg	1.022	214.372	147.075	83.158	146.406*	124.290	100.352	64.601
Romania	90.553*	172.957	104.443	80.043	-11.051	134.460	121.672	73.129
Sweden	36.800	261.304	103.430	85.589	79.785*	273.890	101.558	75.132
H0: $\Delta LNFIN$ does not Granger-cause $\Delta LNIU$					H0: $\Delta LNIU$ does not Granger-cause $\Delta LNFIN$			
Finland	14.983	216.490	119.143	90.425	92.956***	264.477	133.870	89.577
Luxembourg	92.038***	150.095	111.418	91.608	2.545	163.629	110.774	94.195
Netherlands	82.977***	154.273	120.231	75.652	1.963	197.656	105.310	59.345
Portugal	49.988	158.460	95.542	78.719	90.746**	122.590	87.482	72.495
Sweden	97.234***	161.016	108.281	90.181	121.305**	145.997	86.320	76.446

Note: *, **, and *** indicate that there is causality from the first variable to the second variable at 1, 5, and 10% significance levels, respectively; *LNFIN* – financial innovation; *LNGNI* – gross national income; *LNURB* – urban population; *LNLGB* – globalization; *LNIU* – individuals using the internet; *FINC* – financial inclusion; *MYS* – mean years of schooling.

Source: own

environment for the inclusivity issue. The emergence of new financial tools has increased access to financial funds for households and firms, favoring economic transactions and increasing people's standard of living. There is no causality relationship between *FINC* and *LNFIN* in any country.

Additionally, it shows a unidirectional causality relationship from *LNFIN* to *LNGNI* at a 5% level in France and Germany and at a 10% level in Belgium, Cyprus, Denmark, Lithuania, and Portugal. From *LNGNI* to *LNFIN*, a unidirectional causality relationship is found at the 1% level in Hungary and Italy, at the 5% level in Estonia and Luxembourg, and at the 10% level in Austria, Denmark, Finland, and Romania. The financial development of a country is critical for its development and especially for the just transition process, which is an essential goal for European Union member states. Moreover, the inverse relationship is also confirmed by our results and integrates the capacity of the level of economic development to attract and impel innovative finance features.

Moreover, Tab. 8 demonstrates a unidirectional causality relationship from *LNFIN* to *LNGLB* at 1% level in Malta and Romania, 5% level in the Netherlands, and 10% level in Denmark and Hungary. There is a unidirectional causality relationship from *LNGLB* to *LNFIN* at 1% level in Luxembourg, 5% level in Lithuania, 10% level in the Netherlands and Poland. While globalization enhances the openness of an economy, financial transactions must adjust and adapt to the new standards and conditions, alongside internalizing new techniques and frameworks from the external economic associate.

Besides, Tab. 8 shows a unidirectional causality relationship from *LNFIN* to *MYS* only in Romania at 1% level. There is a unidirectional causality relationship from *MYS* to *LNFIN* at 1% level in Lithuania, Luxembourg, and Sweden. Education is fundamental for innovation, and financial innovation depends on education from the perspective of creating new features, instruments, and organizational channels to facilitate resource utilization and financial stability. More highly skilled people will increase awareness of properly utilizing more specialized tools.

Finally, Tab. 8 displays a unidirectional causality relationship from *LNFIN* to *LNIU*

at 10% level in Luxembourg, the Netherlands, and Sweden. There is a unidirectional causality relationship from *LNIU* to *LNFIN* at 5% level in Portugal and Sweden and at 10% level in Finland.

Our findings demonstrate the emergence of the interconnection between *FIN* and internet intensity. Most financial instruments require access to an internet connection, which is critical for process implementation. According to European Central Bank statistics, in the European area, the number of ATMs increased from 198,994 to 276,602 from 2000 to 2021; in the same period, the number of point-of-sale (POS) terminals increased from 3.3 million to more than 13 million. Card payments are most intensely used in Portugal (70%), while Slovakia and Finland (38%) have the highest share of credit transfers. In Germany, we can observe the most considerable level of direct debits, while the highest percentage of E-money transactions can be observed in Luxembourg (93%), followed by Italy, with 15%. According to a report on new digital payment methods at the European countries' level, the features desired by the general public from a new payment method are related to the potential to exist as a one-stop solution with reduced costs and that is not too complex. Meanwhile, traders are oriented towards minimized costs, instant payments, security, and easy integration into their operations.

Conclusions

This study used FMOLS and DMOLS techniques to evaluate the link between *FINC* and *FIN*. Other socio-economic variables were also assessed based on their correlation with *FIN* in selected European countries from 2000 to 2020. While the main part of the literature analyzed the role of *FIN* in pursuing *FINC*, only a few studies evaluated some factors influencing *FIN*. In contrast, the literature did not dig deep into considering the potential or limitation of *FINC* to boost innovation. Thus, this study examines the impact of digital technology, *FINC*, standard of living, and other economic and social variables on *FIN*. According to the main findings, the widespread use of financial services will not entail an increase in *FIN*, and the study identified several explanations. On the one hand, the newcomers in the financial ecosystem are usually people who lack tech skills or financial literacy (confirmed by the European Commission Eurobarometer

figures released in 2023) and are searching for traditional financial products; on the other hand, they do not consider innovative financial services due to their risk-adversity and security reasons or the fear of losing or not being able to control their data, also in line with Macchia-vello and Siri (2022), Preziuso et al. (2023) and Tran and De Koker (2019). The right to choose how households can access financial services, guaranteed by European regulation, can be one factor of the propensity for consuming traditional financial products instead of innovative ones using digital tools, also in line with Zamora-Pérez et al. (2024) findings. In order to develop a positive connection between *FINC* and *FIN*, these factors (e.g., skills, literacy, security, personal data status/control, and privacy) must be addressed by the regulators at the national and European levels. Rigorous actions are needed to preserve individual integrity and enhance the personal capacity of equitably self-integrating in the financial ecosystem. Additionally, tighter regulations should address these technology-led financial stability concerns (Ahnert et al., 2022).

The results suggested a strong causal correlation between *FINC* and *FIN* in countries like Estonia, Italy, Lithuania, and Spain. Moreover, *FIN* is significantly correlated with the standard of living in Austria, Denmark, Estonia, Finland, Hungary, Italy, Luxembourg, and Romania. The main findings represent valuable support for policymakers, enhancing the practical value of this research. In this sense, several specific policy options are arising from the study results. Based on the demonstration that enhancing financial literacy at the national level is critical for attaining the social permeability for using innovative finance tools, the authorities should expand the target of formal and informal financial education programs to less addressed categories. In Europe, central banks and various financial authorities are involved in such programs to check the impact and adjust the key features for broader social significance. For example, the Bank of Italy conducts a triennial survey on financial literacy (IACOFI), observing the effects of informal programs for increasing digital financial skills. As a result, financial literacy improved during the last five years, creating the premises for further usage of innovative financial tools (Banca d'Italia, 2023). In Romania, the Institute for Financial Studies created a framework for offering various school

programs as supplementary sources of financial education besides the formal curriculum. Other national authorities can replicate these good practices to enhance financial education and address the gaps among social groups, considering that younger people in European countries do not own a digital payment tool (Zamora-Pérez et al., 2024).

In addition, there is a need to correlate the digital skills of citizens and their demand for digital products and services to improve the benefits of using technology for various economic actions. The relevance of using the internet in a larger economic sphere is pivotal for economic development and *FIN* stir. In this sense, financial institutions must include incentives for digitalizing the transactions to ease access and encourage the electronic transfer of money. Besides national actions, European decision-makers must expand the funding coverage of the Digital Europe Programme and include various financing opportunities to support the financial digital instruments and ease digital innovation in payments. Our findings confirm Zamora-Pérez et al. (2024) results, showing that transactions in cash are widely used in the euro area despite the spread of digital payment tools. According to this study, the most relevant factors supporting these cash preferring patterns are financial literacy and digital skills, alongside with individual personal choices. As our findings highlighted, the financial inclusivity of individuals must be correlated with an increase in financial literacy and financial-specific digital skills in European countries, which have a different approach to cash usage than other developed economies. The demand-side limitations, like personal habits, for adopting innovative financial tools are significant for this phenomenon and must be considered. Additionally, access to cash must remain an ongoing pursuit for European financial authorities (see Eurosystem cash strategy) to keep the financial ecosystem balanced at the European level. As supported by the European Central Bank's latest survey (Zamora-Pérez et al., 2024), cash remains a key payment method for European citizens (52% at points of sale) and companies (88%), even if it has been on a slight downward trend in recent years. The most important reasons for this preference are related to security, reliability, and privacy. Digital payments are correlated to privacy concerns by the Europeans. The simple expansion of users in the financial

landscape will not increase the use of innovative financial products based on new technologies. What requires the involvement of the authorities in organizing financial and digital literacy programs and co-involvement of consumers in the ongoing changing process of their habits and preferences, becoming more and more familiar with the new digital products and their advantages, especially to be prepared for the issuing of central bank digital currencies.

Engaging additional individuals and firms in using financial services and products at this level of inclusivity in European countries is less important for developing innovative finance tools. However, it is relevant from the perspective of the “no one left behind” principle of sustainable development goals. The importance of payment preferences of European consumers represents one of the main supports of our study results. According to two recent studies published by European Central Bank (Zamora-Pérez et al., 2024) the individuals’ preference for cash payments and the reticence in using digital technologies is widely known in the euro area, and this would be an expected behavior of newcomers in the European financial landscape also. This explains why more financially included people will not conduct automatically to an increase in the demand for innovative financial services and products. The inertia of payment habits is still present in the European financial ecosystem, which the financial authorities must further analyze, understand, and address. However, financial institutions should develop innovative and risk-sharing tools and methods to spur accountable usage and be better involved in users “financial education path, while governments and regulators should focus on new users” healthier and innovative financial behaviors. Furthermore, digital financial literacy should be integrated into both formal and informal education programs in partnership with various stakeholders to facilitate the acceptance and use of technology-driven financial services.

The study limitations refer to the sample of countries included in the analysis. In this sense, an approach of emerging countries, where *FINC* is at reduced levels, should be carried out. Moreover, using different indicators for the *FIN* variable could bring more light to the research literature. Another important objective for future research could be evaluating a feedback effect between *FIN* and *FINC*.

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Make ads skippable or not: The impact of ad type on brand recall, salience and conversion rate

Radka Bauerova¹, Veronika Koprivova²

¹ Silesian University in Opava, School of Business Administration in Karvina, Department of Business Economics and Management, Czech Republic, ORCID: 0000-0003-3110-5756, bauerova@opf.slu.cz (corresponding author);

² Silesian University in Opava, School of Business Administration in Karvina, Department of Business Economics and Management, Czech Republic, ORCID: 0000-0002-0920-5032, koprivova@opf.slu.cz.

Abstract: In today's world, people are using digital platforms more than ever to communicate with friends, network, shop, learn and more. The average time spent on these platforms is increasing. Companies are naturally reflecting this fact in order to reach as many people as possible through these platforms and their advertising messages. However, users are constantly bombarded with advertising messages that fragment their attention. It is, therefore, important to study the effects of different types of video advertising, with or without skipping, on consumers' purchasing decisions and to create ads that perform better but do not distract the audience. Therefore, the aim of this paper is to investigate the effect of skipping ads in terms of brand memorability and brand salience on subsequent conversion performance in an e-commerce store. The results of the study show that consumers achieve lower brand recall and conversion rates when shown a non-skippable ad than a skippable ad. On the other hand, while skippable ads are associated with higher levels of actual brand recall, from a more holistic perspective, the non-skippable ad type is better suited to increase brand salience, which appears to be more important for subsequent future purchase execution at the retailer.

Keywords: Brand salience, brand recall, skippable ad, non-skippable ad, experiment.

JEL Classification: M37, M31.

APA Style Citation: Bauerova, R., & Koprivova, V. (2025). Make ads skippable or not: The impact of ad type on brand recall, salience and conversion rate. *E&M Economics and Management*, 28(4), 180–197. <https://doi.org/10.15240/tul/001/2025-5-009>

Early Access Publication Date: April 15, 2025.

Introduction

The development of technology and digitalisation has influenced the change of established concepts and has also greatly influenced advertising and the way it is presented. It is necessary to keep an eye on current trends, but also on wiles that could harm companies when presenting their products. Consumers of advertising are becoming more and more demanding, and we have recently seen them

move to different platforms than has been the norm.

The shift from traditional advertising to online channels was motivated by consumer preferences for digital media. Features of the internet, such as ubiquity and immediacy, and the development of technological devices (e.g., smartphones) have changed consumer habits and encouraged new forms of interaction with other users, firms and content creators

(Flavián et al., 2012; Hussain & Lasage, 2014). People spend more time on social media than watching television (TV). While the number of individuals who watch TV constantly decreases, the internet is used by 62.5% of total population. Facebook is used by 58.8% of total internet users, taking 66.3% of these Facebook users use it daily. The number of people around the world using social media per se grew from the previous year (2021) by 10%. Lin (2017) discusses the profound impacts of digital communication technologies on marketing strategies, stating that traditional channels such as television are progressively being replaced by online platforms for advertising purposes. This transition reflects changing consumer behaviors and content consumption patterns that favor the immediacy and accessibility of online platforms.

Worldwide digital advertising spending is growing steadily. This growth reflects the benefits of online advertising, including their potential to engage users with audio-visual ads (Taylor, 2015). These trends also mark a significant departure from the advertising industry, which has traditionally sought to maintain control over the advertising process and consumer experience, leaving the consumer as a passive and powerless observer (Kwon et al., 2014). Despite this, advertisers still apply their established offline advertising practices to online settings (Belanche et al., 2017a) without considering the interactive needs of online audiences (Cho & Cheon, 2004; Gvili & Levy, 2018). “Ad blindness” spreads rapidly when viewers refuse to pay attention to ads or anything that resembles them (Resnick & Albert, 2014).

Research by Rehman et al. (2023) demonstrates that advertising saturation significantly impacts brand recall. Their findings indicate that excessive exposure to advertisements leads to information overload, negatively affecting a consumer’s ability to recall and recognize brands. The study revealed a substantial negative correlation ($r = -0.353$, $P < 0.05$), indicating that as ad volume increases, brand recall declines significantly among the respondents. Belanche et al. (2020) found that viewers showed differences in brand recall based on the type of ad format, emphasizing the necessity for advertisers to adapt their strategies according to the viewer’s engagement level with these ads. The users are now more selective about the advertising messages they receive and may even react negatively to online advertising. It results

in the situation the consumers are “ad blinded.” This phenomenon spreads rapidly when viewers refuse to pay attention to ads or anything that resembles them (Resnick & Albert, 2014).

The rise of ad blindness and declining TV viewership signals a changing trend, requiring product presentation adaptations. Some advertisers are already shifting their marketing to the online space, allowing users the option to skip ads. This choice influences various aspects of customer behavior. This paper examines how the ability to skip ads affects brand recall, brand salience, and conversion rates. Brand recall measures how well a consumer remembers a brand in a specific context (Prashar et al., 2012). Brand recall can be aided or unaided. Aided recall provides the brand name, while unaided recall uses a non-brand name to identify the brand (Gesmundo et al., 2022). Our study uses both approaches, starting with unaided recall and then aided recall. Brand salience, defined by Romaniuk and Sharp (2004) as the brand’s likelihood of being thought of in buying situations is in this paper measured by their method. Their method includes various representative attributes/tasks that are used to reflect on the brand, its position relative to competing brands, and to focus on whether or not the brand has value.

The aim of this paper is to examine the impact of ad skippability in terms of brand recall and brand salience on subsequent conversion performance in an e-shop. Therefore, the paper first focuses on video ad formats on social media in general, followed by an introduction to the findings on the impact of skippable and non-skippable advertising on consumers, along with an evaluation of the effectiveness of these two types of advertising. The third section of the paper presents the design of the experiment. The experiment design presents the specific steps of the experiment, defines the variables under study, and determines the minimum sample of participants. Subsequently, the results of the investigation conducted using eye-tracking technology are presented and discussed. Implications of the results for practice, limitations, and possible future directions for further research in this area are outlined.

1 Theoretical background

In order to increase the level of user control over advertising and thus its effectiveness, some internet platforms such as Facebook

or YouTube have developed innovative interactive features (likes, shares). The introduction of this mechanism has not only influenced consumer opinions and attitudes, but has also changed the industry (Pashkevich et al., 2012). It allows users to easily share, tag likes or handle complaints, or helps them to make decisions (Pauwels et al., 2016) and disseminate business messages to thousands more users (Schivinski & Dabrowski, 2016).

YouTube's monetization model is based on the insertion of advertising messages during exposure to audio-visual content sought by visitors. Placing video ads in front of viewed content has proven to be successful, but it is also the most disruptive form of advertising on this social platform. To solve this problem, YouTube introduced skippable video ads in December 2010. This prototype interactive format allows users to watch the ad to the end or skip it after 5 s, increasing their active role (Belanche et al., 2017a). A survey of Statista (2019) states that among global marketing professionals, 29% considered skippable pre-roll ads on YouTube to be the most effective ad format on the platform, compared to 7% who favored non-skippable ads.

Banerjee and Pal (2021) discuss that skippable ads allow viewers to exert control over their engagement, suggesting that viewer perception can influence the effectiveness of various ad formats. Another analysis by Kumar et al. (2021) affirms that different advertisement formats exhibit varying effectiveness, indicating that timing, content, and nature of the advertisement significantly impact CTR (click through rate), thus supporting the idea that the dynamics of video advertising are fluid and ever-changing.

Lin et al. (2021) highlight the variances in pricing across different ad formats and emphasize that non-skippable ads generally command higher CPM (cost per mile) rates due to their uninterrupted delivery of content. The analysis illustrates that the minimum cost per view for non-skippable ads can start as low as EUR 0.004, whereas the cost for skippable video ads tends to begin at around EUR 0.008, reflecting the added value attributed to viewer control in skippable formats. It is essential to acknowledge that these values are not static; rather, they are influenced by a myriad of factors, such as content quality, the timing of ad placements, targeted demographic

audiences, and the prevailing demand for ad space within a specific context.

Skippable ads have changed user choice, where consumers have the choice to watch or skip an ad. The following subsections focus on the effectiveness of these video ad formats.

1.1 The impact of skippable advertising on its effectiveness

As mentioned before, a skippable ad type offers users the option to skip the ad or continue watching it after a certain period of time. Some studies (Puccinelli et al., 2015; Teixeira et al., 2010) consider ad viewing (or skipping) as a clear indicator of ad effectiveness. Other research (Pashkevich et al., 2012) on skippable video ads confirms that their controllability increases user satisfaction with the site and reduces the negative consequences of advertising by 30%. Other studies (McCoy et al., 2008; Morimoto & Chang, 2006) show that feeling in control of online advertising reduces users' irritation with advertising. Thus, advertising effectiveness has been a target for advertisers and a topic of research interest among advertising scholars in recent decades (Danaher, 2017).

Previous literature in this area indicates that consumers' attitudes towards advertising, intrusiveness and loyalty are three key variables related to advertising effectiveness in a digital context (Ashley & Tuten, 2015; Belanche et al., 2017a; Goodrich et al., 2015). Researchers have examined some aspects of this format, user preferences within skippable ads (Pashkevich et al., 2012), personal and situational variables that influence skipping behaviour such as ad repetition (Arantes et al., 2018; Belanche et al., 2017b), and chaos in ads (Ha, 2017). Several studies have also considered ad length (Goldstein et al., 2015) and content, such as the use of humour (Campbell et al., 2017), various arousal cues (Belanche et al., 2017a), and factors that influence viewers' intention to watch these ads (Lee & Lee, 2011).

Various influences can affect ad skipping. Banerjee and Pal (2021) revealed a tendency for emotional skipping of skippable ads, whereby viewers did not actually skip the ads but engaged in other online/offline activities while the ads were displayed in the background. This newly identified phenomenon in video advertising is similar to the concept of emotionally unsubscribing customers in email marketing.

The revelation of emotional skipping suggests that the viewership of skippable ads cannot be clearly interpreted. A fully played ad does not necessarily mean that it was watched. This also has important implications for the online advertising model and ROI tracking.

However, according to Statista (2019) skippable video ads are the most effective ad format, scoring higher on entertainment and engagement than overlay ads. While attitudinal factors showed no significant differences compared to non-skippable ads and microspots, skippable ads achieved about 10% higher click-through rates and 20% more site visits. Marketing experts also consider skippable video ads (played just before the YouTube video itself) to be the most effective YouTube ad format across all generations of consumers. Moreover, one significant factor influencing Generation Z's preference for skippable ads is their affinity for entertaining content. Research by Hermawan et al. (2023) suggests that Generation Z viewers are more inclined to engage with advertisements that contain entertainment elements, thereby improving their overall attitude towards these ads. These findings make skippable video ads an attractive ad format for targeting young adult consumers for both advertisers and content creators.

1.2 The impact of a non-skippable ad on its effectiveness and recall

Senarathna and Wijetunga (2024) claimed that while ad clutter does not have a direct negative impact on a viewer's attitude towards the YouTube channel, it indirectly contributes to ad irritation, affecting the overall experience negatively. This aligns with findings from studies suggesting that viewers tend to prefer ad formats that allow some level of control, which can foster a more favorable attitude towards such ads (Long et al., 2024). When viewers find ads irritating, they are less likely to recall the brand being advertised, impacting the effectiveness of the advertisement. This is supported by research comparing brand recall between skippable and non-skippable ads, showing differences in how each type affects recall (Belanche et al., 2020).

This sub-section looks at the effect of non-skippable advertising on its effectiveness and recall, and looks more closely at the comparison of click-through rates across the two types of ads studied.

Pashkevich et al. (2012) used a follow-up search as a measure of ad effectiveness and found skippable ads were as effective, if not more so, than non-skippable ads. They also found that viewers strongly preferred skippable ads to non-skippable ones. Overall, users like the freedom to end the ad after 5 s, especially in the non-personalized state. Belanche et al. (2019) reported that brand recall is positively affected by the amount of time spent watching the ad. Intrusiveness of ad is one of the variables, which decreases the time spent watching ad, because the users want to avoid intrusive ads. That is why, in the case of non-skippable ad, when they are not allowed to take this option, this fact alone can make ad intrusive.

On the other hand, Vroegrijk's (2020) meta-study with over 10,000 respondents from Germany, the Netherlands, and the UK found non-skippable ads more memorable. Respondents browsed sites with video ads, noting if and when they skipped them. Subsequently, respondents were asked which brands they remembered from the ads, how they recalled the message of the ad, and which ads they were familiar with. In all cases, participants performed slightly better in the case of non-skippable ads. The differences in results by ad type were no more than 10% in either case.

Based on the research conducted, it can be summarised that consumers have three different choices when watching video ads. The first choice is to skip the ad if the ad allows this action. The second choice is to watch skippable or non-skippable ads. The last choice is to deliberately ignore the ad, where the ad is playing in the background but the consumer is engaged in other activities during the duration of the ad.

1.3 Developing the hypotheses

Previous research shows that users often skip skippable and non-personalized ads. Belanche et al. (2017b) found that situational factors like time of day significantly influence ad acceptance, as users skip ads more when they are in a hurry. Lee et al. (2022) expanded on this, showing that time urgency and audience availability affect ad viewing. They found that both the ad's content and viewers' personal and contextual factors influence the decision to skip or view ads.

Using a mobile device drives users to skip ads and spend less time viewing them.

Due to the instantaneous nature of mobile media and the limited screen size of mobile devices, viewing ads on these devices can make the viewing experience irritating, leading users to skip them (Nam et al., 2019).

The non-skippable ad type does not offer this option to users. The irritation of that ad, amplified by the temporal certainty during the long ad (i.e., 60 s), decreased attitudes toward the ad, which in turn reduced purchase intention. Temporal certainty decreases irritation of the ad during the short one, while it increased this irritation during the long ad, which in turn reduced the effectiveness of the ad (Jeon et al., 2019).

Consumers' reactions to video ads are obviously related to reactions in the brain, and within the default mode network theory (DMN), it is possible to see specific connections. This theory has already been investigated by many authors from different points of view, and it has also been shown that the DMN correlates negatively with other networks in the brain, such as attention networks (Broyd et al., 2009). The implication of the given is that if a consumer is compelled to engage with a non-skippable ad, their attention span may decrease, potentially leading to a negative impact on their ability to remember the item or brand.

It follows that if the consumer does not have a choice (in the case of non-skippable ad), then according to the DMN theory, DMN activity could be activated, which could lead to less memorability of advertising messages and, consequently, low conversion. Conversely, when a consumer has a choice, DMN activity should not be activated, which could lead to greater memorability with subsequent higher conversion.

The first hypothesis is based on this theory and is formulated as follows:

H1: Consumers have lower ad recall and conversion rates when viewing a non-skippable ad than a skippable ad.

According to Romaniuk and Sharp (2004), attitudes are about evaluating the brand (questions such as "Do you think it is a good brand?" are used), while salience, or significance or distinctiveness, of a brand is largely about thinking about the brand (e.g., it is measured by asking "In a given buying situation, are you likely to notice or buy a product with the brand?"). Based on their conceptualization of brand salience,

they expect that measuring this salience will yield the following benefits: i) higher correlation with brand familiarity than brand attitude, as it is related to brand knowledge rather than brand evaluation; ii) higher correlation with longer-term repertoire of brands than brands used at any point in time, as brand salience should permeate long-term memory structures. Therefore, brand salience may also be characterized by its ability to predict the future composition of the brand repertoire. More stability over time on individual level than a reaction to individual brand attributes.

Given these findings, the next hypothesis is formulated as follows:

H2: The higher the brand salience and brand recall, the higher the conversion.

Previous studies in the field of ad types focused on examining the circumstances of ad avoidance (Campbell et al., 2017), ad choice (Bellman et al., 2021), personal, situational factors (Belanche et al., 2017b) and contextual factors (Lee et al., 2022) influencing the decision to skip or not to skip the ad. Thus, the investigation is mainly about searching the elements affecting this process and its causes. Another study focuses on investigating the consequences from the brand recall perspective (Belanche et al., 2020) and Gesmundo et al. (2022) expand it with brand awareness. Our research explores brand attributes in the research area somewhat more extensively, from a more holistic perspective. To brand recall, we add brand salience and conversion rate.

2 Research methodology

The experimental design was used to obtain core data suitable for assessing the stated hypotheses. This method is one of the most effective to have control over variables. In addition, it allows the determination of cause and effect, which is important for the possible confirmation of formulated hypotheses. In order to conduct the study, it was important to plan an appropriate experimental design to be applied to explore the grey area of the topic under study. Gazepoint's eye-tracking technology was used to implement the experiment. Using this technology, the experiment investigated the path of the eye pupil when watching video advertisements.

The quality of the eye-tracking results was enhanced using the PEEP (post experience eyetracker protocol) method. After eye-tracking,

participants provided additional information on their actions through questioning. The experiment occurred in a controlled university room with a single computer equipped with an eye-tracking device. Participants were isolated and tested individually at scheduled times. After watching commercials and a short film, each participant moved to another room to purchase three products and complete a questionnaire. They were asked to keep the experiment confidential for 14 days to avoid influencing other participants.

A random sample of Generation Z subjects was recruited from students (details removed for anonymity). Participants aged 20 to 25 years were eligible. The self-selected volunteers were randomly assigned to control and experimental groups to enhance internal validity. A list of all participants was created for each of the 8 experiment dates. Students were randomly assigned to groups based on a key: the first to the skippable advertising group, the second to the non-skippable group, and the third to the control group, repeating this pattern as needed. Data were analyzed using Gazepoint analysis (version 6.7.0) and IBM SPSS (version 21.0). Written informed consent was obtained from all participants.

2.1 Specifications of the technology applied

The Gazepoint control system used to monitor the pupil of the eye is high-performance. The GP3 eye tracker sampling rate is 60 Hz. Accuracy is 0.5 to 1 degree. Spatial resolution (RMS) is 0.1. The used eye tracker has binocular eye tracking mode.

It is recommended to use contact lenses instead of glasses when using Gazepoint pupil tracking technology. Otherwise, the software may not correctly detect what it is sensing. Eye tracking equipment with glasses may not be

able to record the path of the pupil of the eye, or the results may be distorted. Therefore, all participants affected by this measure were asked in advance to wear contact lenses for the purposes of the experiment.

2.2 Variables in the experiment

An important part of the experimental design is determining the appropriate number of participants to be included in the study. Schreiber et al. (2006) suggest that each parameter should have at least 10 participants. According to Hair et al. (2018), as few as five research participants per variable can be considered as a lower limit, but they lean towards a 15:1 ratio (i.e., 15 participants for one variable) or, better yet, 20:1 as the most acceptable way to determine sample size.

The variables chosen for the intended experiment were skippable advertising, budget, and time. Overall, it was therefore necessary to recruit at least 30 Generation Z participants for the research to ensure a lower bound on the sample size. The sample size in this study can be considered adequate given the parameters set. In fact, the experiment involved 33 participants in the skippable advertising, 22 participants in the non-skippable advertising, and 11 participants in the control sample. The sample of respondents consisted of 45.3% males and 54.7% females between the ages of 20 and 25. Tab. 1 shows the proportion of respondents by age in each of the groups examined.

Tab. 1 shows that the distribution of respondents according to their age is very similar across groups.

2.3 Phases of the experiment

In the first phase of the experiment, the participants were randomly divided into two groups. The first group viewed only skippable ads,

Tab. 1: The participants' characteristics

Group	Age (years)					
	20	21	22	23	24	25
Non-skippable ad (%)	18.18	42.42	15.15	18.18	3.03	3.03
Skippable ad (%)	9.09	54.55	9.09	9.09	13.64	4.55
Control (%)	9.09	45.45	9.09	27.27	9.09	0.00

Source: own

the second group viewed only non-skippable ads (control group). The participants had no idea what the real goal of the experiment was. They were told that they had to watch a short film, but before the film started, they could also watch some commercials. For ads that were skippable and where there was a real possibility of skipping, participants could skip these ads at their discretion after the first 5 s. A “skip ad” button was inserted into the video ads to indicate the possibility of skipping after a set time limit. This button had the same design as the button for the ads on the YouTube platform and was chosen deliberately as it is familiar and subconscious to users through this platform. The button was chosen to be in the Czech language due to the fact that the experiment was conducted in the Czech Republic.

By analogy, the experimental design was the same in the non-skippable ad group, except that participants in this group were played the same ads as the previous group, but without the option to skip them. After all the experiments were conducted, the proportion of correct responses for both groups of participants was then examined for the first question in the questionnaire, which examined the recall of the video ads.

In the second phase of the experiment, each participant was instructed to purchase three products online, spanning the categories of food, household goods, and travel accommodation. The selected categories were chosen for specific reasons. Participants were given freedom in their online search for these products. The independent variables manipulated in this phase included budget and time. In addition, a control group faced no constraints. Participants were randomly assigned to each constraint or control group. Those with a set budget of EUR 793 (equivalent to CZK 20,000 as of 22 December 2021) were compared to those with an unrestricted budget. For time constraints, one group had to complete their purchases within 15 min. Researchers documented participant selections and constraints on prepared forms.

Subsequently, all participants completed a final online questionnaire. In this questionnaire, participants first had to answer three questions that explored their awareness of the advertisements they had seen. The approach is mainly based on an international

meta-study conducted by DVJ Insights (Vroegrijk, 2020). Specifically, the following questions were asked:

- i) What brands appeared in the ads you just saw?
- ii) For which ads did you understand the message the ad was intended to convey?
- iii) Which ads did you already know before this experiment?

Subsequently, brand saliency was examined using the metrics of Romaniuk and Sharp (2004). According to them, buyers may use multiple cues at the same time and on different purchase occasions. The types of attributes that may be relevant for measurement include purchase/consumption situations, benefits, or functional features. Therefore, participants were asked to complete the following sentences in the questionnaire:

- i) I would buy grocery online for my household at ...;
- ii) I would buy a gift for a friend who lacks housewares at ...;
- iii) I would go to e-shop ... for the most comfortable holiday.

Romaniuk and Sharp (2004) argue that memory retrieval involves a competitive process where related items in memory compete when stimulated by each stimulus. They suggest that asking respondents to judge the association between a brand and an attribute individually may not fully capture the effects of competitive interference. Thus, to mimic the actual shopper experience, the research included a component where participants ranked e-shops based on their preference for the advertisements. This ranking was conducted using a rating scale. The authors also note that many brand salience measurement tools focus solely on assessing brand aspects, suggesting that most attributes should reflect common thoughts when considering a brand/choice. They propose that evaluations often extend beyond specific brands to encompass internal and external circumstances. Thus, they advocate for measuring the primary characteristic of a brand using a yes/no indicator rather than an association measure. In this research, participants were instructed to respond solely with yes or no. Questions for this salience measurement section were sourced from the company's official website to reflect its self-presentation.

All questions in the final questioning are formulated in such a way as to appropriately

clarify the participants' motivations within each activity during the experiment.

2.4 Selected product categories

For the experiment, ads of specific e-shops that fall into three online product categories were selected. The focus was on dynamic online product categories, illustrating current trends in this area. Therefore, these categories were selected by conducting an analysis of online category growth over the last 5 years in the Czech Republic. The selected categories include food/groceries, homeware, and travel and accommodation categories.

For each product category, three well-known e-shops selling products on the Czech online market were selected. Thus, in the experiment, participants watched a total of 9 advertisement videos. In the case of skippable videos, the videos were modified to simulate the situation of ad skippability to examine the influence of this variable on the participant's purchase decisions for predefined variables (juice, pan, seaside holiday) in the second phase of the research. The videos were edited in the sense that the same design button that appears on YouTube when the ad can be skipped was added to the video. This button appears after the first 5 s of each ad that can be skipped. No other manipulation of skippable videos has taken place. No video manipulation was done for the design with non-skippable ads. For the control group, there is a mix

of unskippable ads (no manipulation) and skippable ads (modification by adding a skip button after 5 s).

3 Results and discussion

Tab. 2 shows descriptive statistics on the percentage of skip, brand recall, number of pints of brand salience, and conversion between the two groups (skippable ads vs. non-skippable ads). For the variable indicating the total time to see the ads, we see that the total duration of all ads was 254.10 s (experimental design of non-skippable ads), and the total average time to see for participants with skippable ads was 177.43 s. The difference between participants is at most 45.51 s. Thus, on average, there was a 76.67 s reduction in ad views by participants in the experiment.

It can be seen that total brand recall and number of pints of brand salience in the skippable ads group were lower than in the non-skippable ads group. However, this difference is very small and almost negligible in the general overall view of the results. In the case of conversion, we can see that the group with skippable ads has a higher average than the group with non-skippable ads. However, even in this case the values differ minimally. Therefore, the next section will focus on the results in more depth in terms of the individual brands and the differences between the results, as well as the distribution of participants into groups according to skip time.

Tab. 2: Descriptive statistics

Variables	Experimental design	N	Mean	SD
Time of skipping	Skippable ads	22	177.43	45.51
	Non-skippable ads	31	254.10	0.00
Brand recall	Skippable ads	22	5.27	1.03
	Non-skippable ads	31	5.55	1.73
Number of pints of brand salience	Skippable ads	22	7.41*	1.76
	Non-skippable ads	31	7.77*	2.13
Conversion	Skippable ads	22	1.91	1.07
	Non-skippable ads	31	1.71	0.97

Note: * removed the points for comparing brands with each other; it does not affect the overall result, only the result for the specific e-shop.

Source: own

Examining the primary data in more depth, attention was first given to examining awareness of display ads and conversion. In order to confirm the first hypothesis (*H1*), it was necessary to investigate the effect of ad type on recall and conversion rates. First, a Pearson's chi-square test was conducted to determine whether ad type has an effect on brand recall. In this case, hypothesis *H0* was formulated as:

H0: The level of brand recall does not depend on the type of advertisement.

However, the result of the test shows (Tab. 3) that the type of advertisement has an effect on brand recall (Sig. < 0.05).

Based on the value of the contingency coefficient, it can be said that the relationship between the type of ad seen (skippable/non-skippable) and the resulting number

Tab. 3: The results of the Pearson chi-square test (effect of ad type on brand recall)

	Value	df	Asymp. sig.
Pearson chi-square	13.345	6	0.038
Contingency coefficient	0.442	–	0.038

Source: own

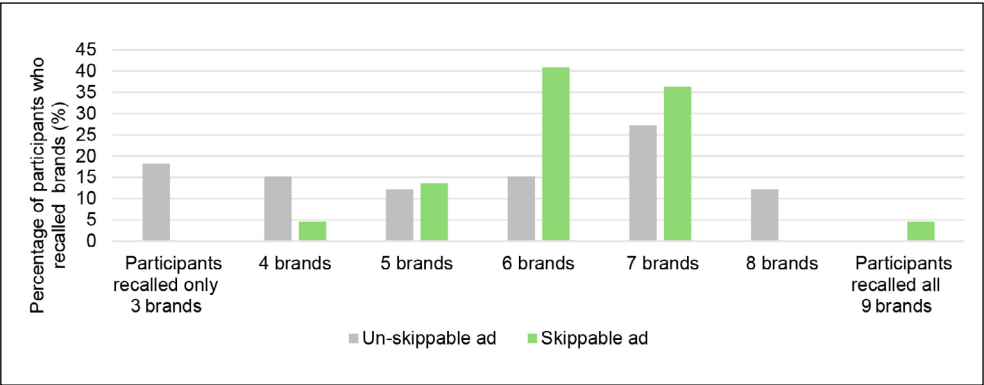


Fig. 1: Number of brands remembered after watching a skippable ad versus a non-skippable ad

Source: own

of remembered brands approaches a moderately strong relationship (0.44). The specific number of brands remembered by participants in the experiment in the groups with viewed non-skippable and skippable advertisements is shown in Fig. 1.

When comparing the results of the skippable and non-skippable groups, Fig. 1 shows that there are differences in the degree of brand recall between these groups. Those participants who watched the skippable type of ad showed higher rates of remembering more brands

than participants who watched the non-skippable type of ad. A large difference can be seen when we focus attention on the percentage of participants who were able to recall six or more brands. We see that 81.82% of participants, of those who were able to skip the commercial, remembered six or more brands that appeared in the commercials. In contrast, only 54.54% of participants from the non-skippable ad group achieved this result. When we compare these results with those of the control group, in which participants viewed a mix of non-skippable and

skippable ads, we can see that the control sample is quite similar to the sample of participants with non-skippable ads. It can, therefore, be concluded that skippable advertising has an impact on brand recall and increases the degree of brand recall.

In the next step, the effect of brand recall from the viewed ad on conversion was investigated. Participants were asked to purchase juice, a pan, and a holiday on any e-store. Based on the results of Pearson chi-square tests (Tab. 4), it was found that only in the case of the food/

Tab. 4: The results of the Pearson chi-square tests (brand recall on conversion)

Product category	Tests results	Value	df	Asymp. sig.
Food/groceries	Pearson chi-square	14.039	6	0.029
	Contingency coefficient	0.461	–	0.029
Household goods	Pearson chi-square	3.892	6	0.691
	Contingency coefficient	0.264	–	0.691
Travel and holiday accomodation	Pearson chi-square	1.644	6	0.949
	Contingency coefficient	0.175	–	0.949

Source: own

groceries product category does conversion depend on brand recall (Sig. = 0.029 < 0.05).

A closer examination of brand recall for individual brands and subsequent conversion shows that in the case of the food/groceries product category, on average only 3% of participants purchased groceries from a different e-shop than the three e-shops studied. Within the household goods and travel and holiday accommodation product categories, consumer preferences seem to have influenced the results, as there are more e-shops selling these product categories than those selling food. Specifically, in the travel and holiday category, an average of 13% of participants shopped at other e-shops, and in the household goods category, an average of 23% of participants did so. Participants were not constrained in their choice of the e-shop from which they purchased the product, and, therefore, some purchases were also made outside the three e-shop brands studied. These purchases are summarised in the last column under other e-shops.

This section presents the results of brand recall and subsequent conversion in the food/groceries product category analysis, where participants were tasked with buying juice online. Since the online food/grocery market in the Czech Republic is not yet saturated, purchases from other brands were less significant compared to previous sectors studied.

In the skippable ad group, Tesco and Rohlik achieved over 10% higher brand recall and more than 8% higher conversion rates. However, for the basket e-shop, both brand recall and conversion rates were slightly lower in the skippable ad group, with a difference of less than 1%. Additionally, the analysis showed that even participants who did not initially purchase from the studied e-shops eventually bought from them. This indicates that a strong brand comes to mind when needed. When participants searched for suitable e-shops for groceries, they ultimately chose familiar e-shops, highlighting the importance of brand salience in purchase decisions.

Interestingly, although participants could purchase products from any e-shop, the analysis shows higher purchase numbers for brands they saw advertised before buying. This is notable given the Czech household goods market's saturation with many e-shop brands. The relationship between brand recall and subsequent purchase (conversion) is particularly striking. For Tescoma, brand recall was slightly higher in the skippable ad group, but conversion was nearly 4% lower. For Orion, both brand recall and conversion were higher in the non-skippable ad group. Kulina had the fewest participants in both groups and no conversions, indicating that its advertising did not stand out against competitors. Additionally, previous experience

and loyalty to other e-shops influenced purchase decisions, as evidenced by the number of purchases from e-shops not included in the study.

In the tourism sector, participants were tasked with purchasing seaside holiday accommodations from any e-shop. The analysis shows that participants who viewed skippable ads had higher brand recall and conversions for two of the three brands studied compared to those who viewed non-skippable ads. For the Invia brand, brand recall and conversion rates were similar between the two groups, though slightly higher for non-skippable ad viewers. The sector's saturation with different brands likely influenced the number of purchases made on other e-shops as well.

The influence of ad type when looking more closely at the e-shop brands examined was always confirmed for two of the three e-shop brands examined across all three industries studied. At the same time, a higher level of brand amenity was confirmed to have an influence on higher conversion rates for the majority of conversions examined. Therefore, it can be concluded that hypothesis *H1* is confirmed. Consumers experience lower ad recall and conversion rates when viewing non-skippable ads than when viewing skippable ads.

An interesting association emerges between the low recall and conversion rates for

Kulina and Orion brands and the area of interest (AOI) results from eye-tracking for participants with skippable ads (Tab. 5). High AOI values were recorded for participants who focused on the skip option for these ads. Similarly, Tesco showed a very low conversion rate with high values for participants focusing on and revisiting the skip option. Despite Tesco's over 90% brand fit due to its established presence in the Czech offline market, its low conversion rate online is intriguing. This suggests a significant offline influence on brand equity but highlights the link between low conversion at Tesco and the AOI findings.

On the other hand, lower AOI eye-search rates are observed for ads for brands that have used the fun appeal in the first few seconds.

The proportion of participants who chose to watch the ad and those who skipped it varies. In 61% of the cases, participants consistently skipped ads focused on household items and travel. Slightly fewer participants, specifically 46%, skipped ads focused on online groceries. The overall average of participants who skipped an ad at some point is 56%.

The final area of examination was brand salience, assessed through various criteria where points were allocated based on participants' responses to questions regarding brand salience, following Romaniuk and Sharp's (2004) metric. Initially, participants recorded

Tab. 5: Area of interest (AOI) results

Brand advertising	AOI* statistics					
	Viewers/total viewers	Average time to 1 st views (s)	Average time viewed (s)	Average fixations	Revisitors	Average revisits
BlueStyle	8/22	9.241	0.205	1.375	2	1.000
Čedok	4/22	14.920	0.202	1.250	1	1.000
Invia	7/22	6.482	0.105	1.143	2	1.500
Košík	9/22	17.351	0.214	1.889	3	2.000
Kulina	10/22	12.169	0.300	1.700	4	2.000
Orion	15/22	9.464	0.310	1.800	3	3.333
Rohlík	10/22	9.347	0.305	1.400	3	1.000
Tesco	14/22	6.546	0.417	1.857	5	1.800
Tescoma	4/22	12.192	0.255	1.500	1	1.000

Note: * area of interest was set up to "skip button."

Source: own

their preferred e-shop for groceries, housewares gifts, and holidays. If an e-shop involved in the experiment was mentioned, it received 1 point per mention. Next, participants ranked ads based on preference, with e-shops earning points proportional to the number of times their ad was ranked highest. Lastly, participants indicated agreement or disagreement with pre-formulated statements, with e-shops receiving points for each affirmative response. The earned brand salience points are depicted in Figs. 2–3, alongside brand recall and overall conversion rates.

In the group of participants exposed to non-skippable ads (Fig. 2), the brand salience score appears to offer more reliable insights into total conversion compared to brand recall alone. For instance, although participants showed high brand recall for Tesco and BlueStyle, their overall conversion rates did not align. This disparity may stem from brand recall being based on immediate reactions to prepared ads, whereas brand salience reflects a deeper, longer-term engagement with the brand. Thus, we posit that brand salience may better predict future purchases with a specific brand than mere brand recall.

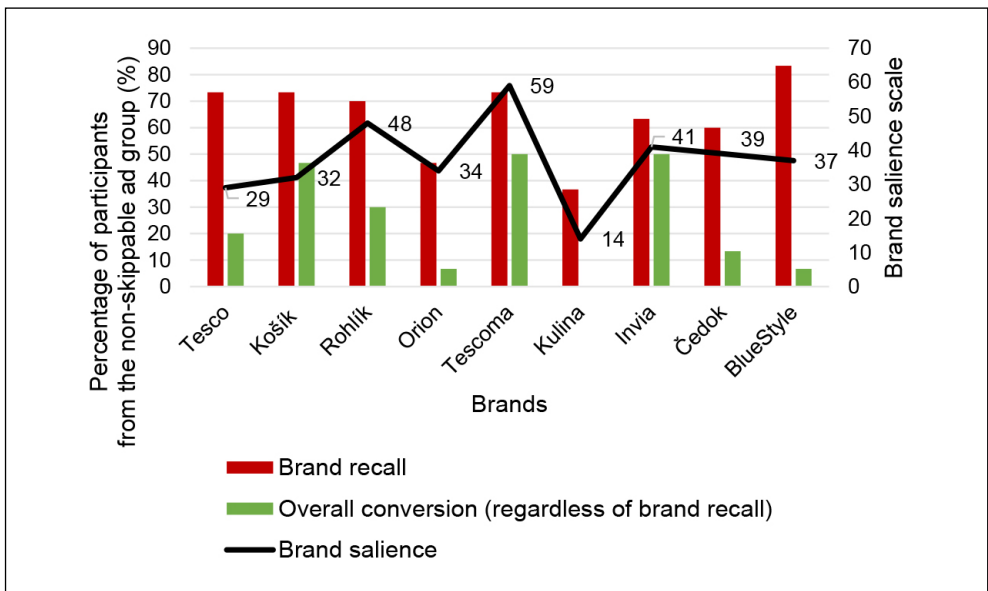


Fig. 2: The link between brand salience, brand recall and overall conversion (a group of participants with a non-skippable ad)

Source: own

The same situation occurs in the case of the results within the group of participants in the skippable ad type experiment (Fig. 3). However, it is interesting to note that in most cases here, individual brands achieve lower brand salience scores. This finding suggests that although skippable ads are associated with higher levels of actual brand recall, from a more holistic perspective, the non-skippable ad type is better suited for increasing brand salience, which appears to be more important

in subsequent future purchase execution at a retailer of a given brand.

By examining Figs. 2–3, it can be concluded that in most cases, achieving a higher brand salience score is related to greater brand recall, which is associated with greater conversion. This relationship is evident for both participants who were shown only skippable ads and those who were shown only non-skippable ads. However, the time when the participant skips the ad also plays a role in skippability.

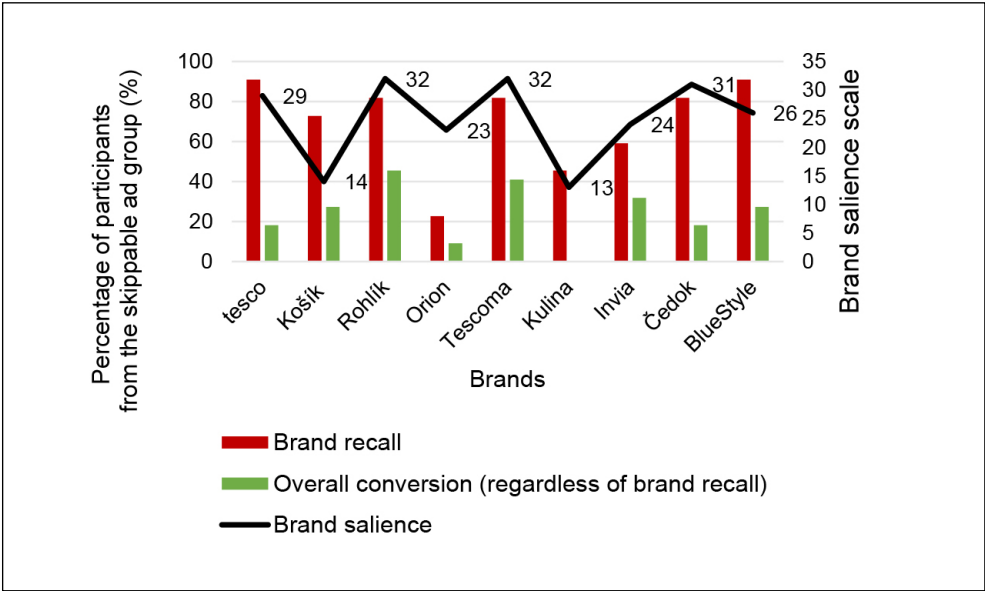


Fig. 3: The link between brand salience, brand recall and overall conversion (a group of participants with a skippable ad)

Source: own

Tab. 6: ANOVA test results

Brand advertising	Variables		Sum of squares	df	Mean square	F	Sig.
Tesco	Brand recall	Between groups	3.429	2	1.714	5.4	0.015
		Within groups	5.714	18	0.317		
		Total	9.143	20			
Invia	Conversion	Between groups	11.435	3	3.812	5.54	0.007
		Within groups	12.383	18	0.688		
		Total	23.818	21			
	Salience	Between groups	27.685	3	9.228	4.414	0.017
		Within groups	37.633	18	2.091		
		Total	65.318	21			

Source: own

The results, considering the time to skip a skippable ad in the case of a particular ad, are shown in Tab. 6.

When the ANOVA tests were performed within each category of time to skip an ad, only three relationships were found. In the case

of Tesco, the time to skip an ad is related to subsequent brand recall. Furthermore, an association was found in the case of ad skip time for Invia and subsequent conversion and salience.

The results in terms of skip time and the variables examined without attention to

Tab. 7: Overall results in terms of ad viewing time and ad type

Video ad skippable time	Percentage of skips (%)	Average brand recall (%)	Average number of points of brand salience	Average conversion (%)
Less than 10 s	25.13	58.24	6.33	17.76
10 s to 20 s	18.85	67.01	4.44	17.54
More than 20 s	11.16	69.76	2.77	31.43
Full video length	44.50	82.05	12.11	29.11
Non-skippable ad	–	64.44	37.00	24.81

Source: own

specific product categories or brand are shown in Tab. 7.

It was found that the highest conversion was achieved when the participant decided to skip the ads after more than 20 s. When this viewing time is reached, brand recall is relatively high but brand salience is low. Only a 2.3% lower conversion is achieved when the participant decides not to skip the skippable ad and even finishes watching it. In this case, brand recall and brand salience are highest. If the subscriber decided to skip the ad, they did so most often within 10 s.

This research focused on examining the used ad type on brand recall, brand salience and conversion rate. Belanche et al. (2019) explored the influences of ad design on brand recall for non-skippable ads, figuring that the influence is significant and, in this ad type, the classical post-arousal structures ought not to be altered. These findings reinforce a previous study designed by Fazio et al. (1992), in which the post-arousal brand name design is a common, effective structure. However, about the skippable ads, the situation was somewhat different, because in the case of skippable ads, the best strategy is placing the brand name before arousal (Belanche et al., 2019).

According to our research, the skippable type of ad is better for higher brand recall, however, the situation is different when the marketer wants to build the brand salience. From this point of view, the effectiveness of ad types has not yet been investigated. Romaniuk and Sharp (2004) characterized brand salience as the likelihood that a brand will be thought of or noticed in relation to others by the consumers in a particular purchase situation.

Of course, this is what the marketers need that consumers are thinking of their brands when doing buying decision. Now, we can assume that the non-skippable type of ad is effective when the marketers try to build this attribute.

Conclusions

In view of the rapidly evolving digital environment, and the resulting shifts of users from one digital platform to another, it is inevitable to monitor the causes of these changes and the behaviour of users on each platform. Different advertising messages are constantly lurking for users, and the examination of their effectiveness is in the crosshairs of both practitioners and academics.

This is a contentious topic with varied perspectives. This paper focuses on evaluating the effectiveness of individual video advertisements in terms of brand recall and salience, encompassing preference and brand perception. The experiment results suggest that beyond the ad content, the option to skip an ad also notably impacts users' perceptions of the brand.

The aim of this paper was to examine the impact of skippability from the perspective of brand recall and brand salience on subsequent conversion performance in an e-shop. The study shows that consumers have lower brand recall and conversion rates with non-skippable ads compared to skippable ones. The ability to skip ads makes them more entertaining, leading to higher brand recall and conversion rates. However, while skippable ads boost immediate brand recall, non-skippable ads are better for increasing brand salience, which is crucial for future purchases. Thus, skippable ads are preferable for short-term incentives, but non-skippable ads are important

for long-term brand salience and conversions. The experiment also found that entertaining ads eliminate the desire to skip, indicating content appeal and timing are vital in ad effectiveness.

Implications. The research area of investigating the effects of ad skippability is very broad. Despite it has been surveyed from many points of view, a huge part of this research study is still unclear, and many questions connected to this subject are not answered yet. Through our research, we wanted to uncover the effects of using skippable or non-skippable ads on brand recall and conversions. The managers can use the findings of our research to handle issues associated with this topic.

There are many goals in the marketing field which can be followed. When the managers are deciding what kind of arrangement they will apply, they have to consider many factors. According to our findings, we can divide the use of the concrete type of ad based on the goal which needs to be achieved. In the case that the brand wants to increase brand recall and conversions, choosing the skippable ad seems to be the better choice for gaining this intention. Nevertheless, when the main aim is to increase the brand salience, the non-skippable ad should be applied. From the point of ad content, higher concern for ads was seen in the case of entertaining ads.

From the above, it follows we are not able to conclude which type of ad, skippable or non-skippable ones, is more effective in general. There is a need to ensure the purpose of the ads, and afterward, it is much easier to choose which kind of ad will be better suited. For the short-term period, the operational intentions, according to our results the skippable ads are considered a preferable choice. However, if the brand wants to follow strategic purposes such as building its salience from a long-term perspective, then non-skippable ads should be selected.

Limitations of the study and recommendations for further research. As with any study, this one has several limitations that should be considered when interpreting the findings. Firstly, a limitation is associated with the research method used. In experimental studies, the presence of hidden variables needs acknowledgment as they may potentially impact the study's outcomes. These variables could include negative perceptions towards advertisements in general and corresponding behaviors

such as skipping ads promptly. For participants exposed only to skippable ads, this hidden variable might have influenced the frequency and duration of skipping. To mitigate this potential effect, a control group was established, and participants were randomly assigned to groups. In the control group, participants had the option to skip only specific ads marked with a skip button. Comparing results between the experimental and control groups reveals that the type of ad viewed influences participants' behavior, although the control group showed a similar distribution of ad recall to the experimental group exposed to non-skippable ads.

The limitation of the study is also related to the choice of the brands, which were selected from three concrete product categories. The results of our research can cover these categories, but in this case, their interpretation as findings for the products, in general, needs to be reserved. Another limitation of the study is the awareness of the brands used. Since these are Czech brands, Czech consumers are familiar with these brands. This situation may reduce the possibility of generalising the results.

As we have already mentioned, there are many options how to investigate the effect of the skippability of ads, and the researchers can decide which are the most important for them to survey. The researchers have several options to explore in further research, like the effects of skippability of ads on brand recognition, their effects on other product categories, or perceptions of this factor within other generations of consumers operating on the market.

Acknowledgments: *Supported by the Student grant competition project SGS/12/2021: "Non-skippable advertisement in the context of performance marketing." The support is gratefully acknowledged.*

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Consumer perception of private labels: A case study of the Czech Republic

Michaela Janska¹, Marta Zambochova²

¹ Jan Evangelista Purkyně University in Ústí nad Labem, Faculty of Social and Economic Studies, Department of Economics and Management, Czech Republic, ORCID: 0000-0003-0288-018X, michaela.janska@ujep.cz (corresponding author);

² Jan Evangelista Purkyně University in Ústí nad Labem, Faculty of Social and Economic Studies, Department of Mathematics and Informatics, Czech Republic, ORCID: 0000-0001-7893-272X, marta.zambochova@ujep.cz.

Abstract: Private brands are currently relatively well accepted by consumers and are generally considered to be of high quality, yet they face various challenges that can threaten their sustainability. This has been confirmed by several authors looking at consumer perceptions of private labels across different countries. The aim of the study was to assess consumers' attitudes and relationships towards private brands and to identify factors that may influence their purchasing decisions. To achieve the objectives, a questionnaire survey was used, where the research sample consisted of 239 people shopping in retail food stores in the Czech Republic, of different gender, age, level of education, and monthly income. It was found that consumers perceive private brands positively in most cases. Using the Friedman test, it was found that consumers care most about low price and quality when buying private brands, while they attach the least importance to the appearance of the packaging. Based on the decision tree, it was revealed that private brands are mostly purchased by women who are employed, students or those on maternity leave, those who have lower incomes and who are under 25 years of age. The results of the logistic regression confirmed that lower price and reasonable quality increase the chance of buying private labels. These findings, such as consumer perception of private brands, and frequency of purchase, are very important to determine appropriate marketing strategy. Based on an effective strategy, retailers can then aim to increase the number of products sold and customer loyalty.

Keywords: Private brands, perception of private brands, purchase decision making, purchase factors, socio-demographic factors.

JEL Classification: M30, M31.

APA Style Citation: Janska, M., & Zambochova, M. (2025). Consumer perception of private labels: A case study of the Czech Republic. *E&M Economics and Management*, 28(4), 198–210. <https://doi.org/10.15240/tul/001/2025-4-013>

Introduction

A brand is a unique name, logo, sign, symbol, design, or combination of these that is used to identify a specific product. A strong brand is required to build customer loyalty. Customers who like a brand will buy it in the long run, bringing money into the company. It is a source of long-term competitive advantage (Shankar et al., 2024).

Private labels (also known as own brands, reseller brands, or distributor brands) are brands created by retailers or wholesalers. Private label brands may bear the retailer's own name or a name developed and used solely by that retailer (Van Loo et al., 2021). There are countless definitions for private labels, so these are products that are owned by the company and not manufactured in-house.

A private label company does not manufacture its products itself, but outsources the production line to another company. The main reasons for this are the lack of capital to build a production plant (funds, professional staff, technology) and the fear of entering a new business (Boon et al., 2018).

The introduction of private labels was a watershed moment in retail history. The rapid growth of retail has increased the presence of these brands in all product categories on the market, and they now appear on the shelves of retail chains more frequently (Gázquez-Abad & Martínez-López, 2021; PLMA report, 2024; Sgroi & Salamone, 2022). Consumers previously perceived private label products to be inferior and lower quality imitations of national brands. Their promotion was primarily based on extremely low prices, which led to consumers having negative attitudes toward their quality (Marques dos Santos et al., 2016). They now compete fiercely with national brands not only on price, but also on quality, distribution, promotion, and packaging. Although consumer perception of private labels has shifted, and they are now frequently regarded as an equal alternative to national brand products, they continue to face a number of challenges and negative attitudes (Abril & Rodríguez-Cánovas, 2016; Akcura et al., 2019; Kádeková et al., 2020; Truong et al., 2017; Valaskova et al., 2018; Van Loo et al., 2021; Wang et al., 2020). The market share of private brands is constantly increasing dynamically, particularly in Europe, and the Czech Republic is no exception, although its growth rate is slower than in the rest of Europe. According to Gielens et al. (2021), this growth is expected to continue. Between 2019 and 2024, the market share of private labels in the Czech Republic ranged between 21%–25%, while in Switzerland, Spain and Portugal the sales share is around 50% (PLMA report, 2024). The main reason for the slower growth in the Czech Republic may be that private labels entered the market later. Nevertheless, it is positive that their share has been growing steadily over the last 10 years.

This study responds to the current situation and tries to explore the different behaviour of Czech consumers compared to other European countries based on the data collected (Gielens et al., 2023). The main objective of the study was to evaluate consumers' attitudes and attitudes towards private label

products and to identify the factors that influence their purchasing decisions.

The study highlights the fact that consumer perceptions have changed towards private labels, and they are now often considered as an equal alternative to national brand products, but still face various problems and negative attitudes. The article primarily focuses on examining the influence of factors on the purchase of private brands as consumers' first choice in the purchase process. The investigation of private brand purchasing as a first-choice brand selection was primarily carried out by Stoppacher et al. (2024) in their study. Studies by Boon et al. (2018), Dimitrieska et al. (2017), Fuduric et al. (2022), Gílenes et al. (2021), Kádeková et al. (2020), Mao et al. (2023), Muszyńska (2019), and others, have investigated the influence of factors (price, packaging, recommendations, demographic factors) that affect consumer perceptions of private brands. Furthermore, our study examines these factors in the Czech environment and thus highlights the different consumer perceptions of brands in other countries. A primary brand should emphasise marketing strategy as an essential element for building brand awareness among consumers.

1 Theoretical background

Retailers began to invest their surplus in building their own brands (Van Loo et al., 2021). As a result, retailers began to reinvest their profits in building their own brands. According to Dimitrieska et al. (2017) and Keller et al. (2020), the main reasons for the emergence of these brands were the need to create low-cost products and services, acquire loyal customers, and capitalise on opportunities for higher profits. The share of private brands is constantly increasing dynamically, particularly in Europe, where private brands are on the rise. Although private label products are already relatively widely accepted by consumers, they still face some challenges that could threaten their sustainability (Boon et al., 2018; Gielens et al., 2021).

In their study, the authors Do Vale et al. (2016), Fuduric et al. (2022), Husain et al. (2022) focused on the effects of price, familiarity, and store image on purchase intention and loyalty. According to the findings, familiarity with the given brand has the greatest influence on purchase intention and loyalty to private

label products. Store image had a significant influence on purchase intention, but no influence on loyalty was demonstrated. The findings also show that lower and more affordable prices are an important factor in retaining customers. Alić et al. (2020) and De Regt et al. (2020) found that private brands are purchased by the majority of consumers and arrived at recommendations to encourage brand loyalty and commitment by creating a favourable brand image.

H1: The majority of consumers purchase private label products.

Rossi et al. (2015) demonstrate the impact of product brand knowledge on perceptions of quality. They concluded that a good brand name increases the perception of quality, whereas if the consumer is unfamiliar with the brand, they perceive the same product to be of lower quality.

According to Boyle et al. (2018) or Muszyńska (2019), consumers frequently base product quality solely on the reputation and prestige of a given brand, whereas new brands frequently have the same or higher quality than well-known brands. The most important factors were found to be price, quality standards, packaging, and design (Valaskova et al., 2018).

Based on the private label factors examined, the second hypothesis was established:

H2: Private label products sold by retailers are of the same quality as manufacturer's brand products.

Kádeková et al. (2020) and Rusobya et al. (2024) also investigated the impact of package visual design on food product perception and consumer behaviour. Packaging is an important element of private label success (Mao et al., 2023). According to Hwang and Kim (2022), package design only has an effect on product perception when it has a high or medium level of visual elaboration, but not when it has a low level.

To confirm the importance of packaging, the following hypothesis was established:

H3: The packaging of private label retailers is as appealing as that of manufacturer brand products.

The private label strategy primarily affects three major large groups: manufacturers, traders, and consumers. Private brands have

some advantages for these people. From the standpoint of a marketer, the main benefits and reasons for including private brands are primarily the ability to differentiate (Geyskens et al., 2018). Gielens et al. (2023) mention price control as one of the main advantages as the company completes its image and has the ability to decide on its own price. Private labels also give you more control over branding and production, as well as more customisation (Dimitrieska et al., 2017). Private brands are typically less expensive than branded products. This is due to the fact that consumers do not have to pay for mass marketing campaigns or other costs associated with national brands (Ma & Siebert, 2024). Other advantages of private brands for consumers are their accessibility and a variety of products (Dimitrieska et al., 2017; Sharma et al., 2020).

Muszyńska (2019) investigated the effect of price on customer brand loyalty when comparing private versus national brands. They concluded that lowering the price of a private label product increases sales, whereas lowering the price of a national brand product increases the customer's perception of product quality. These arguments were tested through the following hypothesis:

H4: The consumer would choose the national brand product if it was heavily discounted and cost the same as the private label product.

According to Cuneo et al. (2019), private label sellers must clearly identify what triggers consumers' intention to purchase these brands in order to increase market share. Although preference factors can be highly variable and depend on the product category, research in the food industry suggests that quality and price are generally very important to consumers.

It turns out that perceived price has no more influence on purchase decisions than negative brand awareness (Abril & Rodríguez-Cánovas, 2016). This fact was tested by the following hypothesis:

H5: Price and quality are among the most important product brand factors.

Alić et al. (2020) and Musso et al. (2022) discuss the demographic differences in customers' purchasing decisions and perceptions of private labels in their research. According to the survey, there are no significant gender

differences in brand image. On the contrary, monthly income was discovered to be a significant influencer of the perceived price of Tesco brand products. Significant differences were also found between respondents' educational levels and their perceptions of the quality of private brands. The influence of socio-demographic factors on purchase behaviour towards private label products was examined based on the hypothesis:

H6: There are differences in consumer buying behaviour towards private label products based on socio-demographic criteria of respondents.

2 Research methodology

To answer the aim of the article, three research questions were identified:

RQ1: What is the perception of consumers towards private brands? In response to RQ1, four working hypotheses (*H1* to *H4*) were developed.

RQ2: What factors (price, quality, packaging appearance, breadth of range, recommendations, etc.) most influence consumers' intention to purchase private brands? In response to RQ2, one working hypothesis (*H5*) was created.

RQ3: According to socio-demographic criteria, which group of consumers purchase private labels the most? In response to RQ3, one working hypothesis (*H6*) was created.

For the fulfilment of research questions RQ1 to RQ3 and their hypotheses, a quantitative method (questionnaire survey) is used (Fig. 1).

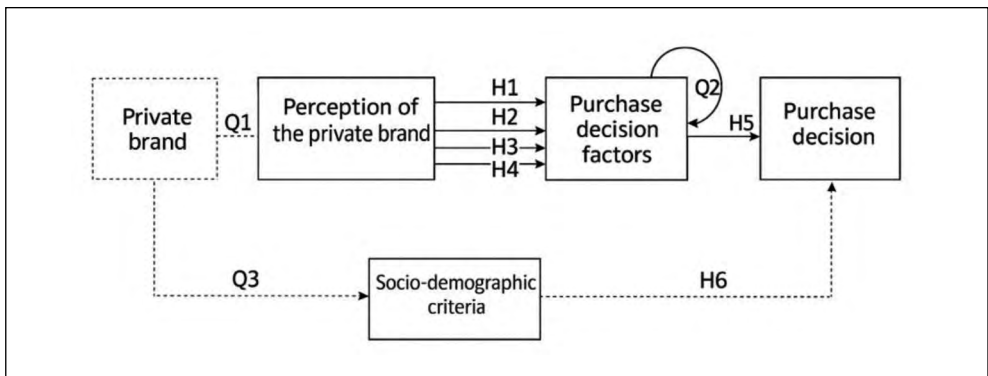


Fig. 1: Research questions and hypotheses

Note: Research questions (RQ1 to RQ3); hypotheses (H1 to H6).

Source: own

The goal of the survey was to determine the primary reasons for purchasing private labels, as well as how frequently consumers buy them and how significant a role they play in their shopping basket. The effort was also made to clarify general consumer opinions, attitudes, and attitudes toward private brands, what factors most influence consumer purchasing behaviour toward private label products, and whether it is affected in any way by the respondents' segmentation criteria, such as gender, age, status, education, place of residence, or net monthly income.

The survey's target group was determined, and respondents to the questionnaire survey

were chosen to be people shopping in retail food chains (Lidl, Tesco, Penny, Kaufland, Billa) in the Czech Republic, of different gender, education, age, and monthly income, to ensure the diversity of respondents and their preferences. The study focused primarily on people who buy private labels. If they did not purchase private brands, they were asked to explain why.

Spearman's rank correlation coefficient and a regression analysis were used to assess the relationship between factors. The Friedman test was used to compare several dependent choices to determine which factors are most and least important to consumers when purchasing food. With the help of subsequent analysis,

groups of factors that customers evaluate similarly were also discovered. The Kruskal-Wallis test for comparing mean values was used to assess differences in the importance of individual factors based on gender, age, education, status, income, or place of residence. A decision tree created in the SPSS program revealed whether socio-demographic criteria (gender, age, education, income, status, and place of residence) influence purchase intention toward private brands.

According to Cumming and Calin-Jageman (2016), if we allow for a 10% width of confidence intervals, then assuming a range of proportions for variables of 0.2–0.5, the recommended research sample size is approximately 200–250. The research results were compared with corresponding research conducted within the EU with a comparable sample size.

The data was collected from roughly mid-June to the end of August 2023. Women made up 69% of the total number of 239 interviewed respondents, with men accounting for the remaining 31%. This is primarily due to the fact that women shop more frequently than men and take care of the household. People aged 26–35 years make up the largest age group, accounting for 28% of the total sample. The 36–45 age group is another large one (23%). Respondents with a secondary school education and a high school diploma have the highest representation in the questionnaire survey (46%). Respondents with a university degree were the second most numerous group, accounting for 28% of the total. 41% of the total monitored sample lives in the countryside, while the remaining 59% live in the city. Fig. 2 depicts the distribution of respondents according to their social status.

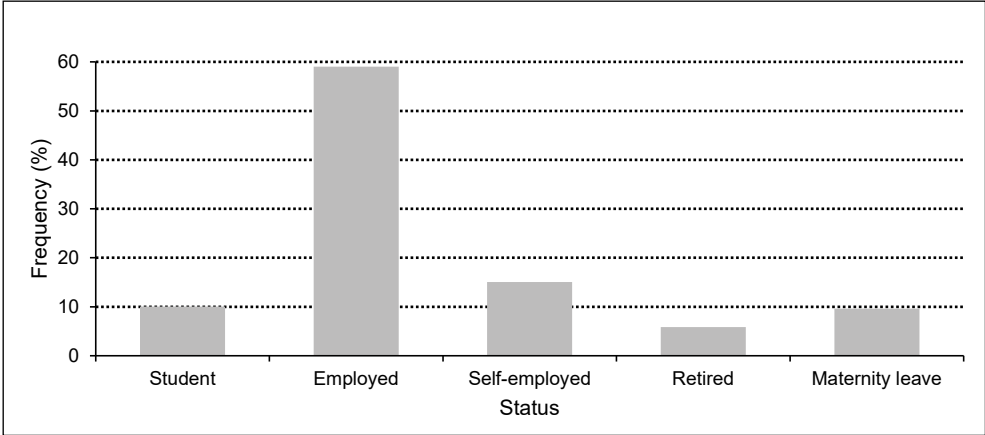


Fig. 2: Social status of respondents

Source: own

Given that private brands are frequently associated with low prices and are perceived as less expensive alternatives to national brands, respondents were also asked about their average monthly net income as part of the socio-demographic data. The most popular category was EUR 800–1,200, which was chosen by up to 31% of respondents. 25% of respondents reported an average monthly income of up to EUR 800, while the same percentage reported a range of EUR 1,200–1,600.

13% of respondents earn between EUR 1,600 and EUR 2,000 per month. Higher incomes are underrepresented, accounting for only 7% of the total. In summary, the sample included respondents with lower, average, and higher monthly net incomes.

3 Results

Answers to the first research question were sought through four hypotheses. *H1* was assessed using 95% confidence intervals. This is

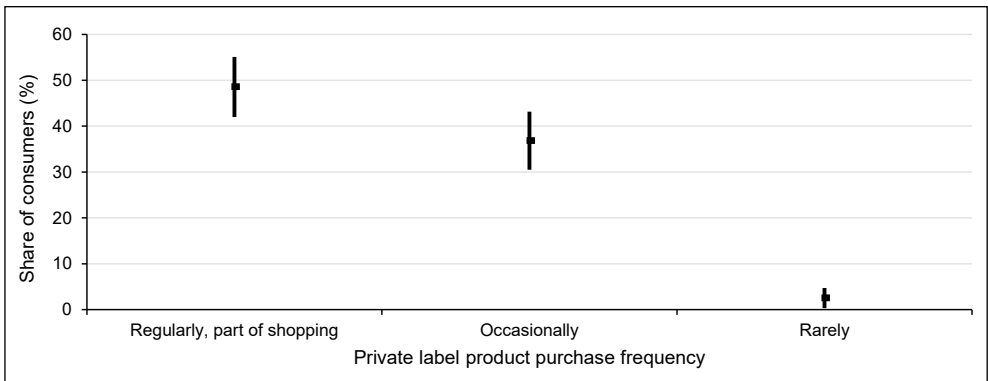


Fig. 3: Consumer shares based on the frequency of purchase of private label products

Source: own

depicted as a graphic representation in Fig. 3. It is obvious that private label products are in high demand.

For *H2*, 57% of respondents agreed or strongly agreed with this statement. Only 10% of people disagree. The others remained neutral. A chi-square goodness-of-fit test revealed that there were significant differences in the representation of each version of the responses. Because the *p*-value of the test performed was significantly less than 0.01, the null hypothesis was rejected. These are very positive results, indicating that the perception of the quality of private label products has significantly improved, and they are no longer perceived as low-quality imitations of national brands.

H3 was supported by 31% of respondents. 33% of respondents, on the other hand, disagreed. The remainder took a neutral stance. As a result, the opinions are very balanced, and this statement cannot be completely confirmed or refuted. The chi-square goodness-of-fit test also failed to refute the null hypothesis that there are no differences in the representation of individual responses. The test yielded a *p*-value of 0.831. In any case, based on the findings, it is certain that private brands have room to improve the appearance of their packaging, as consumers had a negative attitude toward the attractiveness of their packaging.

H4 was used to evaluate a 95% confidence interval. With 95% certainty, the proportion of consumers who prefer a national brand ranges between 55.1% and 67.9%. As can be

seen, the main reason for purchasing a private label is still the price.

To answer research question *RQ2*, several dependent samples were compared using the Friedman test. The *p*-value of the performed test was $<<$ (significantly less than) 0.01. The hypothesis about the comparability of the importance of the monitored factors is thus rejected, and the results (*H5*) show that there are significant statistical differences, as well as different grades for the evaluation of the selected factors. According to the post hoc analysis, quality is the most important factor for consumers when purchasing food. The factors of discounts and promotions and price came in second and third place, respectively. Even during times of economic crisis, customers still prioritise quality of food over price. The manufacturer's brand, country of origin, and recommendations from acquaintances are the next group of attributes that are compared in order. As a result, the brand became an important decision-making factor, as did the country of origin, which could be considered a weakness of private labels because these factors, particularly the manufacturer, are not always indicated on the product packaging. When it comes to food, shoppers rank the appearance of the packaging as the least important factor. This is an intriguing result, because the visual aspect of a product is often a very important factor when purchasing food.

The following inquiry focused on whether socio-demographic factors (gender, age, status,

Tab. 1: Results of the Kruskal-Wallis test, in terms of *p*-values

Factor	Sex	Age	Education	Status	Income	Place of stay
Lower price than with national brand products	0.200	0.757	0.193	0.071	0.073	0.758
Good quality	0.044	0.049	0.008	0.147	0.648	0.629
Price/quality ratio	0.451	0.615	0.139	0.600	0.423	0.658
Packaging appearance	0.027	0.070	0.013	0.641	0.355	0.848
Assortment breadth	0.004	0.298	0.106	0.156	0.659	0.130
Recommendations from others	0.292	0.383	0.026	0.261	0.184	0.314
Product popularity	0.000	0.189	0.074	0.662	0.267	0.881

Note: Dark grey indicates statistically significant differences; light grey indicates statistically less significant differences.

Source: own

education, location of residence, and income) had an impact on consumers' decisions to purchase private brands. Therefore, the Kruskal-Wallis test and subsequent post hoc analysis were used to determine whether the significance of individual factors varies depending on socio-demographic data. The resulting *p*-values are displayed in Tab. 1, with dark grey highlighting for significant statistical differences and light grey for less significant ones.

Gender differences in product quality, package appearance, range of products, and popularity were found to be statistically significant. All of these factors were rated higher for women than for men. There are also differences based on age, with the 46–55 age group placing a higher value on the quality of private label products than other age groups. Similarly, there were only minor statistical differences in the appearance of the packaging. This factor was found to be slightly more important for the 46–55 age group. Differences in factor assessment can also be seen for those with the highest level of educational attainment. Product quality and packaging appearance were found to be more important to consumers with a high school education than to consumers without a high school diploma. Consumers with a higher level of professional education will pay more for recommendations from friends and family. Weak differences in product popularity were also discovered. Consumers with a high school diploma rated this factor as more important. It was also discovered that for customers

with an average net monthly income of up to EUR 800, the low price of private brands is a critical factor in purchasing them, similarly, for housewives. There were no statistically significant differences based on residence. As a result, the importance of individual factors does not differ significantly between village and city dwellers.

Spearman's rank correlation coefficient was used to examine the relationship between individual factors and average monthly net income. It was discovered that the average monthly net income and the price factor have a statistically significant positive relationship. At the same time, it has been demonstrated that consumers who pay attention to product prices also pay attention to quality, price/quality ratio, range of products, recommendations, and product popularity. These factors are also important to consumers, who are concerned with the quality of the products as well as the appearance of the packaging. The correlation analysis also revealed that the price/quality ratio factor is related to the factors of product popularity and recommendations from acquaintances. The link between the appearance of the packaging and the range of products, as well as recommendations and popularity, was established. Customers who monitor a product's popularity will also give a recommendation. A statistically significant relationship was also discovered between product popularity and recommendations from acquaintances. A regression analysis was also performed.

Given the nature of the data, ordinal logistic regression was chosen. The dependent variables were the frequency of private label purchases and the proportion of private label products in the shopping basket (both scaled variables). In both cases, independent variables were chosen to be measures of the seven reasons listed for purchasing private-label products. The resulting models were statistically significant at a level of 1% significance, but their significance was only within the range of 25%–40%. The strongest factor was always found to be the price-quality ratio, followed by the quality of these brands, and then a factor indicating the lower price of private brands compared to national brands. All these factors showed a direct relationship; i.e., a positive opinion of these factors increases the chance of buying private label products. At the 10% level of significance, the factor of the appearance of packaging followed. In this case, however, an inverse relationship was shown, meaning that the appearance of the packaging of private label products decreases the chances of buying them.

A final question was asked to those who answered no to the question of whether they buy private-label products. This ascertained the main reasons. Respondents rated the selected factors on a Likert scale once again. Friedman's test for multiple independent samples and subsequent post hoc analysis was used to evaluate factor comparisons once again. The p -value came out < 0.01 (significantly less than) 0.01. As a result, the null hypothesis was rejected, and the results show that there are statistically significant differences in the factor ratings. Consumers cited poor quality as the primary reason for avoiding private labels. This is not a surprising result, given that truly private brands did not previously stand out for high quality. People may develop prejudices as a result of this, preventing them from trying these products. The second most important factors are the manufacturer's lack of knowledge and the appearance of the packaging. Inadequate knowledge of the manufacturer is a problem for some private brands, who do not state who made the product on the packaging and thus appear very untrustworthy in the eyes of consumers. As a result, listing the manufacturer, particularly if it is a well-known manufacturer, can boost not only trust but also the perceived quality of the product. The attractiveness and

overall appearance of some private brands are also a major weaknesses. This has also been demonstrated for consumers who purchase private-label products. Even though they do not believe that the attractiveness of private brand packaging is completely comparable to the attractiveness of the manufacturer's brand packaging, it frequently appears simple and cheap, which can lead to negative attitudes and prejudices that it is a low-quality product. Price and country of origin were discovered to be unimportant factors in respondents' refusal to purchase private labels. Price ranked last, which is unsurprising given that private brands are known for their low prices.

A decision tree was created for a more detailed answer to $RQ3$ and to evaluate $H6$, respectively in the final processing step, specifically using the CRT algorithm implemented in the SPSS statistical system. The frequency of purchase of private label products was chosen as the explained variable, and all socio-demographic factors, as well as buying opinions, were chosen as explanatory variables.

The resulting tree (Fig. 4) was of high quality, with a risk estimate value of 0.35, indicating that 65% of the objects were correctly classified.

The tree structure indicates that private brands are most frequently purchased by people under 45, with at least a high school diploma, and who are not convinced that a product's high price guarantees its quality. Private brands, on the other hand, are purchased the least by consumers under the age of 45 who do not have a high school diploma or who have one but believe that a higher price represents a higher quality of goods.

4 Discussion

The primary goal of the questionnaire survey was to determine the current state of consumer perception of private brands in the Czech Republic's. Their attitudes and opinions on private brands, frequency of purchase, degree of representation in the basket, and reasons for purchase were all determined. It was discovered during the investigation of consumer buying habits and decision-making that consumers monitor which brands they buy when purchasing food. They are not convinced, however, that a high price guarantees high quality, which is good for private brands because they are typically associated with a lower price. Although consumers report that they buy based on brand, they

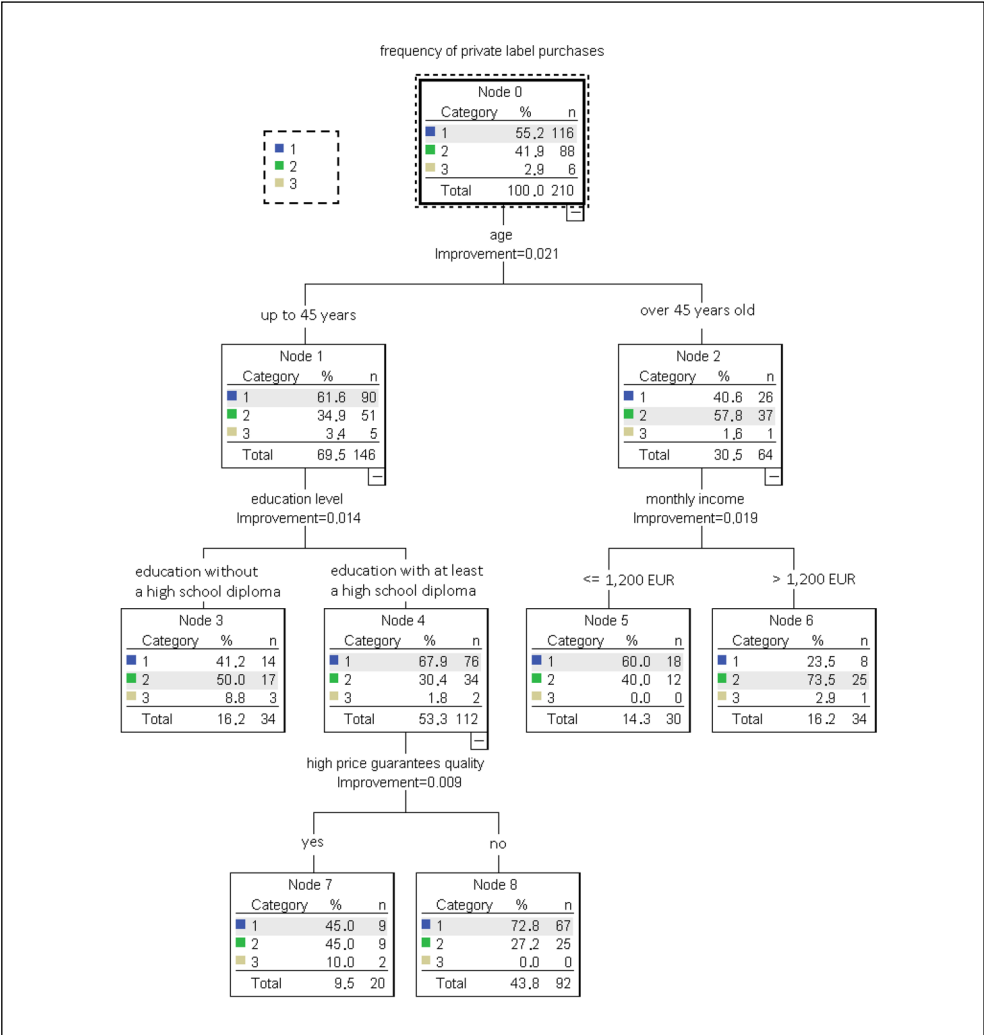


Fig. 4: Decision tree for classifying private label consumers

Note: Category 1 – regularly, part of shopping; category 2 – occasionally; category 3 – rarely.

Source: own

also prioritise quality and price when purchasing food. Discounts and promotions are another important factor in consumer purchasing decisions. On the other hand, they place little emphasis on the appearance of the packaging.

Despite the fact that the majority of respondents have heard of and are familiar with the term “private label,” they still find it difficult to identify some private brands, particularly

those that are less well-known or do not include a retail logo in the name. Similarly, Marion (2024) states that the company must assist the customer in determining what its brand is and is not. Similarly, Swaminathan et al. (2020) state that brand equity is created when customers are aware of the brand and have positive, strong, and distinct associations with it in their minds. Private label labelling is critical to their

success, according to Geyskens et al. (2018). Our research also revealed that while the majority of consumers buy private label products, they account for less than half of the basket content for the majority of customers. As a result, it can be concluded that private brands have not yet completely replaced national brand products, and consumers are still gravitating toward them in limited ways.

According to Valaskova et al. (2018), the primary reasons for purchasing private brands were primarily cost savings, i.e., their low price and price/quality ratio, which the respondents placed the most emphasis on. This is consistent with the authors Ma and Siebert (2024), who state that the reason is that consumers do not have to pay for mass marketing campaigns and other costs associated with national brands. Consumers ranked good product quality as the third most important factor. When it comes to private brands, however, consumers are less concerned with the appearance and attractiveness of the packaging. Other factors important to respondents were also mentioned. Examples include their accessibility, flavour, and proven quality, as well as their support for local producers and growers. They also stated that the product is manufactured by the same company, but has different packaging and is less expensive. According to Ipek and Yilmaz (2021), Muszyńska (2019), Ndlovu and Heeralal (2022), and Valaskova et al. (2018), there are differences in the importance of individual factors based on socio-demographic data. Women, for example, rated quality, appearance of the packaging, range of products, and product popularity as more important than men. Similarly, when purchasing private brands, the 46–55 age group places a greater emphasis on the quality of the products and the appearance of the packaging than other age groups of consumers. Differences were also discovered based on the level of education attained, with consumers with a secondary education and a high school diploma favouring the factors of quality and appearance of the packaging. Consumers with a higher level of professional education will pay more for recommendations from friends and family. According to Kurt and Gino (2023), the most important factor for respondents with lower incomes is low price. Furthermore, it became clear that private brands are most frequently purchased by people under 45, with at least a high school diploma, and who are not convinced that a product's high price guarantees its quality. On the contrary,

consumers under the age of 45 who do not have a high school diploma or who do have one but believe that a higher price also represents a higher quality of goods purchase the fewest private brands. We can conclude from this that it is necessary to persuade consumers of the high quality of private label products which corresponds with the findings of Kiss et al. (2022) or Ndlovu and Heeralal (2022).

Private label products are purchased by consumers across all product categories, but dairy products, meat and sausages, and products from the drugstore and cleaning product sections are the most popular. On the contrary, alcoholic beverages and products for children and pets are two categories in which people do not trust private labels and rarely buy them. Similar conclusions were reached by Kádeková et al. (2020).

Although Rajavi et al. (2019) and Steenkamp (2024) concluded that the direct effects on brand value and its development and brand building primarily have two dimensions, namely brand loyalty and brand image, and the degree of loyalty to private brands can be considered to be rather lower within the framework of our survey. This is because consumers would prefer the discounted national brand product if it was heavily discounted and cost the same as the private label product. Similarly, Pasirayia and Richards (2023) concluded that for many consumers, private labels will never guarantee the same high quality as national brands, and thus prefer the safety and value of a national brand, even if it means paying more. On the contrary, more than half of the respondents believe that the quality of private brands is comparable to that of national brands. Even the appearance of the packaging is rated favourably by consumers who purchase private brands. On the contrary, one of the main reasons why consumers do not buy them is because of this. They identified a fear of low quality and a lack of manufacturer knowledge as major factors discouraging them from purchasing private labels.

This perception is often linked to the prejudices associated with private labels, such as that they are cheap and low-quality products. Brand image is also closely related to perceived quality. At the same time, healthy lifestyles are a growing trend nowadays. Consumers are increasingly being encouraged to watch what they eat, i.e., what the ingredients and values

of a product are. It is, therefore, important that retailers continue to focus on improving quality as well as on good communication, which can increase trust in private label products. Emphasis on quality, availability and customer benefits are key parts of a company's marketing strategy and can contribute significantly to strengthening brand awareness in the marketplace.

One significant limitation of this study is that the scope of the investigation was limited to a single region of the Czech Republic. More research would be required to confirm the findings on a larger scale (Joshi & Garg, 2020). Consumers socially construct perceived brand authenticity (Fuduric et al., 2022; Gielens et al., 2023), so cross-cultural differences are to be expected. Future research should further focus on whether the primary brand can influence taste ratings of selected products. Here, these findings are investigated through the blind test method, which has been used in studies by authors such as Kádeková et al. (2020) and Košičiarová et al. (2020). The conclusions of future research should take into account the fact that private brands emphasise marketing strategy as a fundamental element for building brand awareness among consumers.

Conclusions

The perception of private labels in the Czech Republic is mostly positive, but there are still challenges in competing with national brands. While consumers appreciate the affordability of private labels, there is a need to continuously work on strengthening their perceived quality to fully match national brands.

Price and quality play a key role in private label purchasing, with demographic factors influencing consumer preferences. Women and older age groups have been found to place more emphasis on quality and appearance of the packaging, while men and younger consumers focus more on price. It is therefore important that marketing strategies take account of these demographic differences and target different groups of consumers.

Loyalty to private brands is lower than to national brands, suggesting room for strengthening trust and quality. Consumers are willing to favour discounted national brands if their price is equal to private brands. This highlights the need to build a stronger relationship between consumers and private labels through quality products and effective communication.

Based on our findings, it is recommended to focus on marketing strategies that reinforce quality and trust in private brands, and to take into account demographic differences in consumer preferences. Investment in quality raw materials, innovative technologies and effective communication is needed to convince consumers of the high quality of private brands and to build their loyalty.

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Understanding university students' adoption of ChatGPT: A TAM-based exploration of key factors

Parul Agnihotri¹, Song Chen²

¹ Tongji University, School of Economics and Management, China, ORCID: 0000-0002-8808-9227, parul.priyadarshini@hotmail.com (corresponding author);

² Tongji University, School of Economics and Management, China, chens@tongji.edu.cn.

Abstract: The rapid rise of AI chatbots like ChatGPT has spurred growing interest in understanding the factors that influence their adoption, especially in educational settings. This study focuses on identifying the key elements that shape university students' intentions to use ChatGPT, using the technology acceptance model (TAM) as the theoretical foundation. The research integrates core constructs such as perceived ease of use (PEU), perceived usefulness (PU), perceived risk, trust, and technostress to examine their influence on the intention to use (IU) ChatGPT. Survey data from Indian university students were analyzed using the Smart PLS structural equation modeling technique. The findings reveal significant relationships between PEU, PU, and IU. Specifically, PEU emerged as a strong determinant of both PU and IU, underlining the importance of a user-friendly, intuitive interface in promoting ChatGPT adoption. Additionally, perceived risk was found to negatively impact IU, suggesting that addressing concerns related to privacy and misinformation is crucial for fostering trust and encouraging use. Although technostress had a smaller effect, it still played a notable role, indicating that the stress associated with using new technologies needs to be managed effectively through support mechanisms. Interestingly, trust did not significantly affect IU, challenging assumptions about its role in AI-driven technology adoption. This raises important questions about the specific factors that contribute to trust in such tools. The study's findings reaffirm the relevance of TAM constructs in understanding ChatGPT adoption while also highlighting the importance of emotional and cognitive factors, such as perceived risk and stress. These findings contribute to the growing academic discussion surrounding AI chatbot adoption and offer actionable insights for AI developers, educators, and policymakers. This research highlights the importance of addressing both technical and emotional factors to ensure broader acceptance and effective use of AI technologies like ChatGPT in learning environments.

Keywords: AI adoption intention, perceived risk, technostress, perceived usefulness, technology acceptance model.

JEL Classification: M15, O33, D81.

APA Style Citation: Agnihotri, P., & Chen, S. (2025). Understanding university students' adoption of ChatGPT: A TAM-based exploration of key factors. *E&M Economics and Management*, 28(4), 211–226. <https://doi.org/10.15240/tul/001/2025-5-023>

Early Access Publication Date: October 3, 2025.

Introduction

Rapid technological innovation and global interconnectedness are driving transformative changes across economic, societal, and environmental spheres, with these “megatrends” expected to intensify in the 21st century (Haluza & Jungwirth, 2023). A prominent example is AI, notably OpenAI’s ChatGPT, which showcases AI’s potential by generating human-like content (Jurgen & Tan, 2023). As AI technology evolves, its potential to revolutionize industries including healthcare, finance, programming, and marketing becomes increasingly evident. In particular, the education sector is on the brink of significant transformation, as AI tools like ChatGPT begin to reshape learning environments and teaching methodologies. Researchers are becoming increasingly interested in the increased accessibility and application of AI in education (Huang et al., 2023). According to research, AI can improve students’ engagement and academic achievement in controlled circumstances. ChatGPT, launched by OpenAI in November 2022, exemplifies these advancements as an AI chatbot that simulates human conversations on various topics, enhancing students’ curiosity and fostering question-asking skills. Students can engage with ChatGPT to explore topics, thereby broadening and deepening their learning experiences. Within an educational context, ChatGPT assists by answering questions, summarizing content, generating practice questions, and offering feedback on writing, creating a personalized and accessible virtual learning environment (Steele, 2023).

Given that most university students own computers and smartphones, they are frequent users of mobile applications and digital tools. ChatGPT serves as a convenient application that can support students in their academic pursuits by providing instant responses to queries about course content in a user-friendly interface. Research on ChatGPT’s educational applications demonstrates its versatility across disciplines, from modelling language learning interactions to tackling coding issues and assisting economics and finance research with scenario generation (Ali et al., 2023; Dowling & Lucey, 2023; Kohnke et al., 2023).

The growing use of AI models, particularly ChatGPT, in education creates both potential and challenges. As educators and students increasingly rely on ChatGPT to improve learning and productivity, assessing student perceptions

and adoption of these technologies becomes critical. User acceptance is crucial to successfully embedding AI in academic contexts, where trust, perceived use, and perceived ease of use are critical elements (Chan & Hu, 2023; Sallam et al., 2024).

Hence, this study explores university students’ adoption of AI tools in educational settings within India, examining the roles of trust, perceived risk, technostress, perceived usefulness, and perceived ease of use. Guided by the technology acceptance model (TAM) (Davis, 1989), it examines how perceived risk, technostress, and trust influence students’ attitudes toward AI adoption. Focusing on India’s dynamic educational landscape, a setting characterized by rapid technological advancement, diverse student backgrounds, and challenges in digital accessibility, this study brings a unique perspective to the global conversation on AI adoption in education. By investigating barriers like technostress and perceived risk, it highlights potential obstacles to AI integration. While prior studies have used TAM to assess AI adoption in developed countries (Ma et al., 2024), this study uniquely applies TAM to examine ChatGPT adoption within a developing-country context, offering novel insights into user perspectives that may inform future AI developments.

To explore these dynamics, the study addresses the following research questions:

RO1: How do university students in India perceive the usefulness and ease of use of ChatGPT?

RO2: How do perceived risk, technostress and trust impact the intention to use ChatGPT?

By addressing these issues, this study hopes to provide theoretical and practical insights into AI adoption in educational settings, particularly in emerging markets such as India. The findings are also intended to broaden the TAM framework and show its importance in comprehending AI technology in various cultural situations.

For the empirical investigation, a survey was administered to Indian university students, who are well-positioned to provide insights about AI perspectives due to their experience with digital technologies. The links between the model’s constructs were analyzed using partial least squares structural equation modelling (PLS-SEM). This research is structured as follows: the first section presents theoretical

background and hypothesis development. The second section outlines the research methods. In the third section, the results and analysis are discussed. The fourth section covers the discussion and the final section addresses the conclusion, implications and limitations.

1 Theoretical background

Technology acceptance theories, particularly the technology acceptance model (TAM) introduced by Davis (1989), have been widely used to understand technology adoption. TAM suggests that perceived usefulness (PU) and perceived ease of use (PEU) are key factors shaping adoption intentions, with external factors indirectly influencing adoption by affecting PU and PEU. TAM has been widely applied across various technologies. For example, Pillai and Sivathanu (2020) applied TAM to chatbots in the hospitality industry, adding AI-specific aspects like perceived intelligence and anthropomorphism, demonstrating TAM's appropriateness for AI advancements. Similarly, Moussawi et al. (2021) investigated personal intelligent agents (PIAs) and discovered that perceived enjoyment and human-like AI traits strongly influenced user intentions, emphasizing the importance of anthropomorphism in AI acceptance.

TAM has also been effective in other technical contexts, such as virtual reality (Sagnier et al., 2020) cloud computing (Almarazroi et al., 2019), digital platforms (Song & Kong, 2017), where external factors such as security, data accessibility, and customer experience were found to influence user acceptance. These studies highlight TAM's applicability across different fields. Recent studies on AI adoption in educational settings (Jo, 2023b; Rahman et al., 2022) examined ChatGPT usage in Bangladesh and identified trust as a key mediating factor between users' reported enjoyment and their attitudes toward adoption. Trust is vital for AI acceptance, especially given that AI systems rely on algorithms and automated decision-making, which can foster user skepticism and distrust. Despite the extensive application of the technology acceptance model (TAM), gaps remain in understanding AI adoption in education, particularly concerning technostress and perceived risks. Technostress, caused by system complexity and accessibility issues, negatively impacts adoption, especially among students with limited technical skills

(Verkijika, 2019). It also contributes to reduced academic performance and learning burnout (Qi, 2019; Upadhyaya & Vrinda, 2021), suggesting the need for further exploration of its role in AI adoption in educational contexts. Another critical area that requires more attention is perceived risk. Studies (Cheng & Jiang, 2020) have shown that privacy concerns can lower user satisfaction and future usage intentions, but there is limited research on how perceived risk explicitly affects the adoption of AI tools like ChatGPT, specifically in the context of students. Major concerns regarding misinformation and inaccurate AI outputs exacerbate the risk landscape, highlighting the need for more in-depth research into risk perception within AI-driven educational systems.

The TAM framework and its extensions offer a robust foundation for understanding technology adoption. In the context of AI-driven tools like ChatGPT, constructs such as PU, PEU, trust, technostress, and perceived risk are critical to shaping user attitudes. As AI integration in education continues to grow, understanding these factors is crucial, particularly for promoting AI adoption among university students in developing regions. Thus, this study explores the gaps around technostress and risk perception that could yield valuable insights into facilitating smoother AI adoption in educational settings.

1.1 Perceived usefulness and perceived ease of use, and intentions to use ChatGPT among university students

The technology acceptance model (TAM), developed by Davis (1989), highlights two key factors, perceived usefulness (PU) and perceived ease of use (PEU), as drivers of technology adoption. PU refers to users' belief that technology will enhance their performance, making them more likely to adopt it. Studies in AI research confirm the strong impact of PU on adoption intentions. For example, users' perceptions of AI chatbots' usefulness enhance their willingness to adopt them (Pillai & Sivathanu, 2020). In the case of ChatGPT, its ability to support academic tasks boosts its perceived usefulness and encourages adoption (Rahman et al., 2022). PU's influence on adoption is evident across various fields. In accounting, AI tools that improve efficiency and accuracy drive adoption (Damerji & Salimi, 2021). In healthcare, practitioners are more

likely to use technologies that benefit patients, such as those for older adults (Ha & Park, 2020). Similarly, in mobile commerce, the perceived convenience of apps fosters adoption (To & Trinh, 2021). These examples highlight PU's critical role in technology acceptance, suggesting that emphasizing its benefits can encourage adoption in various contexts.

Perceived ease of use (PEU), defined as the ease with which users interact with technology enhances technology adoption by reducing cognitive effort. Technologies like ChatGPT, with intuitive interfaces, are more likely to be adopted due to their usability (Sallam et al., 2024). Studies consistently show that ease of use influences adoption intentions, especially in AI research. For instance, Chatterjee et al. (2020) found that employees were more likely to adopt an AI-based customer service system when it was easy to use. In line with TAM, the ease of use of ChatGPT positively shapes adoption intentions (Ma et al., 2024).

In the technology acceptance model (TAM), perceived ease of use is seen as a key factor that can enhance perceived usefulness (Davis, 1989). This link suggests that when a system is easy to use, users are more likely to perceive it as beneficial for their tasks or job performance (Venkatesh & Davis, 2000). Studies support this relationship across various AI applications (Chatterjee et al., 2020; Sallam et al., 2024). Together, these TAM constructs emphasize the importance of both functionality and ease of use in driving technology acceptance. Hence we hypothesize:

H1: Perceived usefulness has a positive and significant impact on the intention to use ChatGPT among university students.

H2: Perceived ease of use has a significant positive influence on intentions to use ChatGPT among university students.

H3: Perceived ease of use would positively influence the perceived usefulness to use ChatGPT among university students.

1.2 Perceived risk, technostress, trust, and intentions to use ChatGPT among university students

Adopting AI-driven tools like ChatGPT involves complex psychological factors, particularly perceived risk, trust, and technostress, which shape students' willingness to integrate these tools into academics.

Perceived risk (PR) reflects users' concerns over potential negative outcomes, including

privacy breaches, data misuse, and misinformation (Featherman & Pavlou, 2003). For students using ChatGPT, these risks may involve performance issues (e.g., accuracy), social concerns (e.g., peer perceptions), and privacy fears (Sallam et al., 2024). Such risks are especially relevant in education, where students must weigh benefits against ethical risks, such as potential plagiarism, adding friction to AI adoption (Shin, 2021).

Trust counterbalances perceived risk by promoting confidence in technology's reliability and ethical standards (Alalwan, 2017). For ChatGPT, trust in its accuracy and data security is shown to positively influence student adoption (Jo, 2023a; Rahman et al., 2022). Trust enables students to appreciate ChatGPT's academic benefits and enhances comfort with its functionalities, thus facilitating adoption.

Technostress represents the cognitive and emotional strain from adapting to new technology, a common issue in educational and professional settings (Tarafdar et al., 2019). For students, adapting to tools like ChatGPT may increase technostress, affecting academic performance and deterring adoption (Boonjing & Chanvarasuth, 2017; Yao & Wang, 2023). This stress can lead to hesitancy, as students may associate new tools with mental strain, even if they offer functional benefits (Steelman & Soror, 2017).

Perceived risk, trust, and technostress provide a nuanced view of technology adoption. Trust boosts perceived value by fostering confidence, while perceived risk and technostress create friction by raising concerns. These factors emphasize the need to balance positive and negative influences in educational technology models, guiding universities and developers to mitigate risks and stress while building trust to enhance AI adoption among students. Thus, we hypothesize:

H4: Perceived risk has a negative effect on the intention to use ChatGPT among university students.

H5: Trust has a positive effect on the intention to use ChatGPT among university students.

H6: Technostress has a negative effect on the intention to use ChatGPT among university students.

The proposed conceptual framework for this study is illustrated in Fig. 1.

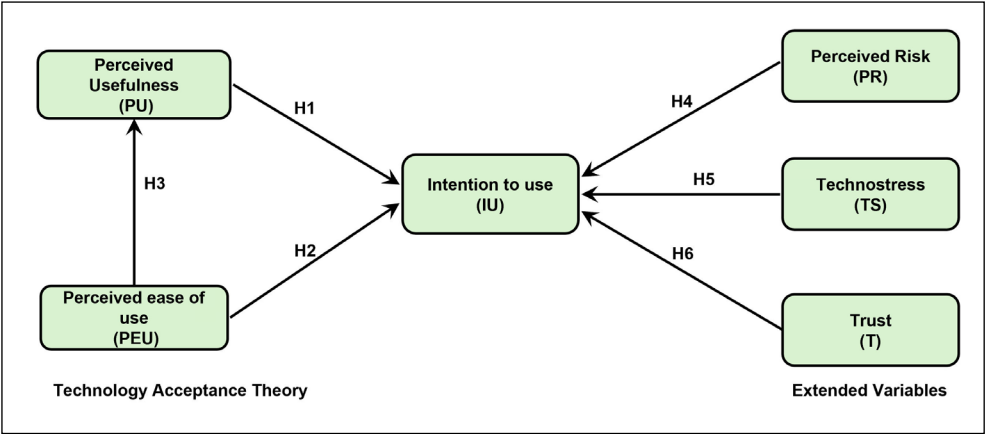


Fig. 1: Theoretical framework (extended technology acceptance model)

Source: own

2 Research methodology

2.1 Research approach

Survey research has long been a cornerstone in information systems studies, particularly for understanding the dynamics of technology acceptance and adoption. Many researchers have used survey research to identify, measure, and analyze the factors influencing individuals' decisions to embrace new technologies (Bhaskar et al., 2024; Rahman et al., 2022). By following established best practices and drawing insights from seminal works, such as influential technology acceptance model, this research has utilized survey-based methods. This study builds on that tradition, utilizing survey-based methods as a systematic framework for examining the complex array of factors that shape university students' intentions to adopt ChatGPT.

2.2 Questionnaire designing

The survey developed for this study measured six key factors influencing university students' adoption of ChatGPT: intention to use, perceived usefulness, perceived ease of use, perceived risk, technostress, and trust. Respondents rated each item on a five-point Likert scale, where 1 indicated "strongly disagree" and 5 indicated "strongly agree." The latent variables in the model were assessed using multiple items derived from established scales. When necessary, the wording of existing questions was

adapted to better align with the study's context. Intention to use, based on Davis (1989), was measured using a 3-item scale that assessed students' likelihood of adopting ChatGPT for academic work and assistance. Perceived usefulness, and perceived ease of use were both also adapted from Davis (1989) and were measured with a 4-item scale each. Perceived risk, based on (Bhaskar et al., 2024), was measured with a 3-item scale examining students' concerns about data privacy, security, and the potential for inaccurate information when using ChatGPT. Technostress adapted from Tarafdar et al. (2019), included a 3-item validated scale that captured the stress and pressure students felt when using ChatGPT for academic tasks. Lastly, trust, derived from Alalwan (2017), was measured using a 3-item scale to evaluate students' confidence in ChatGPT's reliability, security, and overall trustworthiness in an academic setting. Tab. 1 presents the sample items, reliability coefficients, and references for the main variables used in this study.

2.3 Data analysis

Data analysis was performed using Smart PLS 3.2.8, chosen for its robust capabilities in structural equation modeling (SEM) and handling small, non-normal datasets. Smart PLS facilitates theoretical model validation, path coefficient calculation, and predictions with tools like bootstrapping. The analysis

Tab. 1: Measures and reliabilities of main variables

Variable	Number of items	Type of items	Sample item	Cronbach's alpha	Reference
<i>PU</i>	4	5-point Likert scale	ChatGPT is helpful for completing assignments more efficiently.	0.855	Davis (1989)
<i>PEU</i>	4	5-point Likert scale	I find ChatGPT easy to use for academic tasks.	0.874	Davis (1989)
<i>IU</i>	3	5-point Likert scale	I intend to use ChatGPT to assist with my studies frequently.	0.850	Davis (1989)
<i>PR</i>	3	5-point Likert scale	There is a risk that ChatGPT could provide inaccurate or misleading information.	0.818	Featherman and Pavlou (2003)
<i>TS</i>	3	5-point Likert scale	Using ChatGPT for academic purposes makes me feel overwhelmed.	0.789	Tarafdar et al. (2019)
<i>T</i>	3	5-point Likert scale	I believe ChatGPT is reliable for academic assistance.	0.900	Alalwan et al. (2017)

Note: *PEU* – perceived ease of use; *PU* – perceived usefulness; *PR* – perceived risk; *TS* – technostress; *T* – trust; *IU* – intention to use.

Source: own based on results from SMART PLS-SEM

included confirmatory factor analysis (CFA) and path analysis, evaluating both inner and outer models. Using partial least squares SEM (PLS-SEM), the theoretical model was specified to define relationships between latent constructs and indicators (Hair, 2017). Smart PLS then estimated parameters and assessed significance using the PLS algorithm, evaluating model fit, R^2 values, and path significance to ensure a comprehensive model assessment.

2.4 Sampling and data collocation

This study examines university students' intentions to adopt ChatGPT in private institutions, focusing on universities in the New Delhi National Capital Region, a sector that has seen significant growth. Private institutions have been recognized as key drivers of innovation in integrating technology into the teaching – learning process. In India, the rapid expansion of privately owned higher education institutions over the past decade has created an environment where technology adoption is both critical and evolving (Bhaskar et al., 2024). Further, as the sampling frame of students from private universities is not publicly available, hence we adopted a purposive sampling approach.

This method allowed us to specifically target students who were already aware of ChatGPT, ensuring that responses were well-informed and relevant to the research objectives. Data collection was conducted through an offline questionnaire survey, employing a Likert scale ranging from “strongly agree” (5) to “strongly disagree” (1). Following prior studies (Marcoulides & Chin, 2013), we conducted a G*Power analysis based on our conceptual model, assuming an expected effect size of 0.15 and a 5% significance level. The results indicated a minimum requirement of 138 participants for five predictor variables. Our study, with 284 respondents, exceeds this threshold, reinforcing the robustness and reliability of our findings.

Data was collected through an offline Likert-scale survey (“strongly agree” to “strongly disagree”). Of 340 responses, 284 were complete, yielding an effective response rate of 83.52%, meeting SEM sample size requirements for a thorough analysis.

2.5 Demographics

Tab. 2 presents the demographic characteristics of the 284 university students in the study. The sample was nearly evenly split by gender,

Tab. 2: Demographic summary of respondents

Measure	Items	Frequency (N)	Percentage (%)
Gender	Male	145	51
	Female	139	49
	Total	284	100
Discipline	Management	81	29
	Pharmacy	61	21
	Engineering	53	19
	Architecture	40	14
	Journalism	49	17
	Total	284	100
Age (years)	18–20	128	45
	20–25	137	48
	30 and above	19	7
	Total	284	100

Source: own

with 51% male (145) and 49% female (139). The largest academic group was management (29%, 81 participants), followed by pharmacy (21%, 61), engineering (19%, 53), journalism (17%, 49), and architecture (14%, 40). Most participants were aged 18–25 years, with 45% (128) aged 18–20 years, 48% (137) aged 20–25 years, and 7% (19) aged 30 or older.

3 Results and analysis

3.1 Measurement assessment, and evaluating multicollinearity

The initial phase of conducting confirmatory factor analysis (CFA) involves defining the outer model, which specifies the relationships between observed items and their corresponding latent factors, while also assessing their reliability. Given that our data was collected through a self-reported survey, there was potential for common method bias. To address this, we applied Harman's single-factor test, using factor analysis to extract a single principal component. A threshold of less than 50% indicates an acceptable level of common method bias. Our analysis yielded a result of 39.2%, suggesting that common method bias was not a significant concern in this study.

The study's measurement model was evaluated using several reliability and validity

indicators for each construct: perceived ease of use (PEU), intention to use (IU), perceived usefulness (PU), perceived risk (PR), trust (T), and technology self-efficacy (TS). The factor loadings for each item across constructs were above the commonly accepted threshold of 0.7, indicating strong individual item reliability. For internal consistency reliability, Cronbach's alpha values ranged from 0.789 to 0.900, confirming the constructs' reliability. The composite reliability (CR) values, all above 0.8, further supported the reliability of each construct. The results are summarized in Tab. 3

Further analysis employing both the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) affirms the discriminant validity of the constructs. According to the Fornell-Larcker criterion, the square root of each construct's average variance extracted (AVE) is higher than its correlations with other constructs, demonstrating distinctiveness. For instance, the square root of AVE for perceived ease of use (PEU) is 0.852, exceeding its correlations with both intention to use (IU) and perceived usefulness (PU). Similarly, the HTMT values remain below the recommended threshold of 0.85, with the highest value of 0.516 observed between perceived usefulness and trust. Together, these findings confirm that each construct is

Tab. 3: Confirmatory factor analysis for the survey instrument validity and reliability

Constructs	Coding	Loading	Cronbach's alpha	rho_A	CR	AVE	VIF
PEU	PEU1	0.884	0.874	0.880	0.914	0.726	2.694
	PEU2	0.828					2.262
	PEU3	0.895					2.690
	PEU4	0.799					1.781
IU	IU1	0.901	0.850	0.854	0.909	0.770	2.389
	IU2	0.888					2.308
	IU3	0.843					1.799
PU	PU1	0.824	0.855	0.876	0.901	0.695	2.412
	PU2	0.833					2.507
	PU3	0.804					1.937
	PU4	0.872					2.195
PR	PR1	0.913	0.818	0.916	0.882	0.717	1.981
	PR2	0.907					2.151
	PR3	0.703					1.594
TS	TS1	0.848	0.789	0.817	0.875	0.699	1.772
	TS2	0.793					1.632
	TS3	0.867					1.599
T	T1	0.927	0.900	0.911	0.937	0.833	2.977
	T2	0.908					2.954
	T3	0.903					2.575

Note: PEU – perceived ease of use; PU – perceived usefulness; PR – perceived risk; TS – technostress; T – trust; IU – intention to use.

Source: own based on results from SMART PLS-SEM

Tab. 4: Fornell-Larcker criterion

Constructs	PEU	IU	PU	PR	TS	T
PEU	0.852					
IU	0.712	0.878				
PU	0.630	0.682	0.834			
PR	0.156	0.208	0.176	0.847		
TS	0.108	0.203	0.136	0.376	0.836	
T	0.435	0.368	0.460	0.143	0.027	0.913

Note: PEU – perceived ease of use; PU – perceived usefulness; PR – perceived risk; TS – technostress; T – trust; IU – intention to use; the items in diagonal represent the square root of the average variance extracted.

Source: own based on results from SMART PLS-SEM

Tab. 5: Heterotrait-monotrait ratio (HTMT)

Constructs	PEU	IU	PU	PR	TS	T
PEU						
IU	0.821					
PU	0.711	0.784				
PR	0.167	0.221	0.191			
TS	0.135	0.244	0.168	0.457		
T	0.489	0.415	0.516	0.185	0.085	

Note: *PEU* – perceived ease of use; *PU* – perceived usefulness; *PR* – perceived risk; *TS* – technostress; *T* – trust; *IU* – intention to use.

Source: own based on results from SMART PLS-SEM

sufficiently distinct from the others, thereby affirming the model's discriminant validity. Variance inflation factor (VIF) scores for all items remained well below the threshold of 3, confirming no issues with multicollinearity. Collectively, these results support the model's suitability and the constructs' reliability and validity, confirming the robustness of the measurement model for understanding ChatGPT adoption in academic contexts. The results are summarized in Tab. 4 and Tab. 5.

3.2 Structural model assessment

The R^2 value of the endogenous latent variables was determined to understand the structural model's predictive applicability. The R^2 values show how much variance in the dependent variables is explained by the predictors in your model. For intention to use (IU), the model

explains 62.5% of the variance ($R^2 = 0.625$), indicating strong explanatory power, with a slightly adjusted value of 61.7% after accounting for the number of predictors.

The results of the path analysis summarized in Tab. 6 and Fig. 2 indicate several significant relationships between the constructs. Perceived ease of use (PEU) positively influences both intention to use (IU) and perceived usefulness (PU), with path coefficients of 0.461 and 0.630, respectively, and significant p -values (0.000). This demonstrates that when users find the system easy to use, they are more likely to intend to use it and perceive it as useful. Similarly, perceived usefulness (PU) also has a positive and significant effect on intention to use (IU), with a path coefficient of 0.371 (p -value = 0.000), further reinforcing the idea that users are more inclined to adopt the system if they find it useful.

Tab. 6: Results of hypotheses testing

Path coefficients	Original sample (O)	T-statistics (O/STDEV)	p-values
Perceived usefulness → intention to use	0.371	3.970	0.000
Perceived ease of use → perceived usefulness	0.630	10.178	0.000
Perceived ease of use → intention to use	0.461	4.646	0.000
Perceived risk → intention to use	-0.380	4.839	0.000
Technostress → intention to use	-0.089	2.132	0.033
Trust → intention to use	0.004	0.090	0.929

Source: own based on results from SMART PLS-SEM

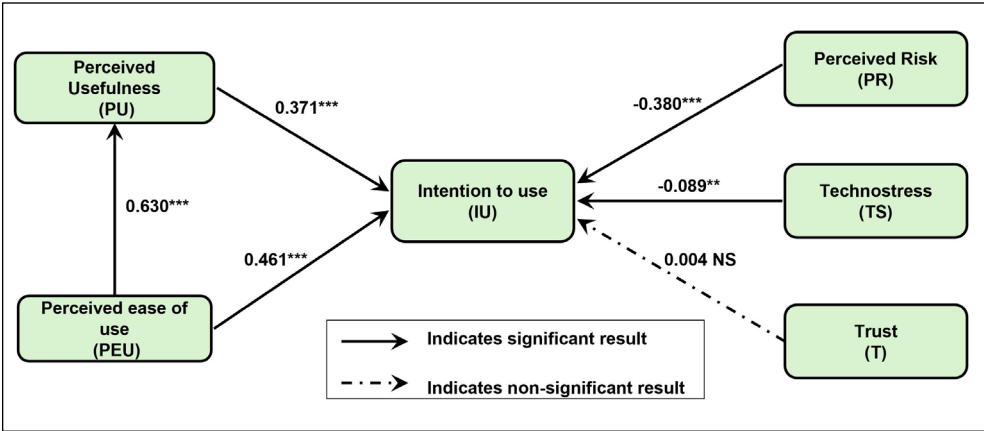


Fig. 2: Results of conceptual model

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Source: own based on results from SMART PLS-SEM

Perceived risk (PR) negatively impacts intention to use, with a path coefficient of -0.380 ($p = 0.000$), indicating higher risks reduce adoption. Technostress (TS) also has a negative effect, though weaker, with a path coefficient of -0.089 ($p = 0.033$). However, trust does not significantly affect intention to use (path coefficient = 0.004 , $p = 0.929$), showing it does not contribute meaningfully to adoption in this context. Overall, the analysis supports most hypotheses, except for the non-significant role of trust.

4 Discussion

The results of this study reveal several key factors that influence the intention to adopt ChatGPT among university students, offering important insights into technology adoption within educational contexts. What makes this research particularly novel is its exploration of the adoption of an advanced AI tool like ChatGPT, specifically in the context of higher education. While prior studies have used the technology acceptance model (TAM) to assess AI adoption in developed countries, this study uniquely applies TAM to examine ChatGPT adoption within a developing-country context, offering novel insights into user perspectives that may inform future AI developments. Moreover, while much of the technology acceptance literature has focused on traditional

tools or platforms, this study introduces a fresh perspective by examining the role of perceived risk, trust, and technostress, factors often overlooked in established models like TAM. By incorporating these psychological and cognitive barriers into the framework, the study offers a deeper understanding of how students navigate the acceptance of AI tools, which is essential in today's educational landscape that is increasingly dependent on emerging technologies. The results of hypotheses *H1* and *H2* highlight the strong positive influence of perceived usefulness (PU) and perceived ease of use (PEU) on students' intentions to use ChatGPT. Notably, PEU emerged as a significant factor, directly impacting both intention to use (IU) and PU. This finding aligns with existing research, which emphasizes the importance of usability in technology adoption, when students perceive ChatGPT as easy to use, they are more likely to see it as useful, increasing the likelihood of adoption (Saif et al., 2024).

Perceived usefulness (PU) is a pivotal factor influencing AI adoption across sectors, including accounting, healthcare, and customer relationship management (Chatterjee et al., 2020; Damerji & Salimi, 2021; Ha & Park, 2020). In educational contexts, PU has been shown to significantly impact students' adoption intentions, as seen in studies from Malaysia and Pakistan, where perceived

effectiveness of AI tools encourages student adoption (Dahri et al., 2024). Additionally, in AI chatbot research, usefulness positively affects user satisfaction and adoption rates (Xing & Jiang, 2024). These insights highlight that, for ChatGPT adoption among Indian university students, emphasizing its academic benefits, such as enhancing research and writing skills, can be instrumental. Such findings support the technology acceptance model (TAM) and suggest that when students view ChatGPT as useful for academic purposes, they are more likely to integrate it into their learning activities, reinforcing the importance of PU in AI adoption within higher education.

Findings for hypothesis *H3* indicate that perceived risk significantly reduces students' intentions to adopt ChatGPT, as concerns about data privacy, misinformation, and ethical issues deter usage. Key concerns include risks of cheating, plagiarism, and misleading content, such as fabricated citations, which can result in academic penalties (Bhaskar et al., 2024; Gravel et al., 2023; Rahman et al., 2022). In addition to these, broader issues, including cybersecurity risks, response bias, and inaccuracies, further discourage adoption (Mijwil et al., 2023; Ray, 2023; Sallam et al., 2024). In other words, regardless of how useful or reliable ChatGPT might be, elevated levels of perceived risk significantly reduce students' likelihood of adopting the technology.

Hypothesis *H4* confirms that technostress negatively impacts students' intentions to adopt ChatGPT, with those experiencing tech-related stress being less inclined to use it. As educational technologies proliferate, students become more vulnerable to technostress, which has been shown to hinder academic performance and cognitive engagement (Boonjing & Chanvarasuth, 2017; Yao & Wang, 2023). High technostress can also weaken the positive effect of perceived usefulness on adoption, as it reduces students' perception of technology's benefits (Steelman & Soror, 2017; Verkijika, 2019). These findings align with our study, suggesting that students under technostress may struggle to recognize ChatGPT's advantages, thereby lowering their adoption intentions.

Surprisingly, trust did not significantly influence students' intentions to use ChatGPT, contrasting with studies in Korea and Bangladesh that identify trust as crucial in AI adoption (Jo, 2023b; Rahman et al., 2022). The role

of trust in AI adoption is highly context dependent. One possible explanation for its non-significance in this study is that students may already possess a baseline level of trust in AI, or they may prioritize factors such as ease of use and perceived usefulness over trust itself. This aligns with the findings of Viswanath Venkatesh et al. (2003), who noted that in certain contexts, perceived ease of use and usefulness tend to have a stronger influence than trust. Moreover, ChatGPT is viewed by students as a supplementary tool rather than a critical decision-making system. Unlike AI applications in high-stakes fields like finance or healthcare, where trust is crucial due to potential risks, ChatGPT can be considered a low-stakes tool for academic tasks. This perception leads students to focus on functionality, accuracy, and efficiency, rather than on establishing deep trust in the system. Further, the ability to cross-check information across multiple sources in education further reduces the need for trust in ChatGPT.

Overall, these findings contribute to a nuanced understanding of the factors influencing ChatGPT adoption in educational settings. By addressing perceived risks and technostress, while emphasizing ease of use and usefulness, stakeholders can better facilitate the acceptance of AI tools like ChatGPT within universities. This study adds to the growing body of literature on AI adoption in education, suggesting directions for both future research and practical implementation to enhance student engagement with emerging technologies.

Conclusions

This study offers a nuanced understanding of how university students in India perceive the usefulness and ease of use of ChatGPT, while also exploring the impact of perceived risk, technostress, and trust on their adoption intentions within educational contexts. By moving beyond traditional TAM constructs, our findings provide a more comprehensive view of technology adoption in higher education, highlighting key psychological and cognitive barriers that influence AI acceptance. This research extends prior studies by incorporating these additional factors, offering deeper insights into how students navigate their interactions with emerging technologies like ChatGPT in academic settings. Addressing the first research question, the findings reveal that perceived usefulness

(PU) and perceived ease of use (PEU) are key drivers of adoption, with students particularly appreciating ChatGPT's ability to support academic tasks such as research, writing, and problem-solving. This aligns with the foundational principles of the technology acceptance model (TAM), which suggests that the more useful and easy to use a technology is, the more likely users are to adopt it. In the context of a developing country like India, these factors take on even greater importance as students increasingly rely on accessible, user-friendly technologies to complement their educational experiences. As higher education institutions in India continue to embrace digital tools, the ease of integrating such technologies into students' academic workflows becomes crucial for widespread adoption. Moreover, the study highlights the complex balance between perceived risk and trust, with students expressing concerns about data privacy and security, yet showing a willingness to overcome these barriers due to the perceived academic benefits of using ChatGPT. This nuanced understanding of the factors driving AI adoption in a developing country context offers valuable implications for educators, policymakers, and technology developers aiming to foster effective integration of AI in educational environments.

Regarding the second research question, the study reveals that perceived risk plays a significant role in influencing students' intentions to use ChatGPT. Concerns about data privacy, potential for academic misconduct, and the reliability of information produced by ChatGPT contribute to a cautious stance among students. Issues such as plagiarism, security risks, and the potential for misleading content highlight ethical and practical challenges that may deter students from fully embracing ChatGPT. Addressing these perceived risks through clear guidelines, transparency in data usage, and safeguards against misuse could help mitigate these concerns, thereby supporting broader acceptance within academic settings.

Technostress, another key factor, also impacts students' adoption intentions. As students encounter more digital tools in their academic environments, adapting to rapidly evolving technologies can lead to feelings of stress and overwhelm. The findings suggest that this stress can diminish students' engagement with ChatGPT, reducing their likelihood of adoption. Supporting students through training, resources, and

simplified user interactions may alleviate technostress, allowing them to use ChatGPT more effectively and with greater confidence.

Interestingly, trust did not emerge as a significant predictor of ChatGPT adoption intentions, contrary to prior research highlighting trust as a key factor in AI acceptance. This unexpected result may indicate that Indian university students already possess a baseline level of trust in generative AI due to familiarity or that usability and usefulness hold more influence over their decisions than trust. Alternatively, students may prioritize the practical aspects of ChatGPT over trust concerns, given their familiarity with similar tools. Future research could further investigate how baseline trust in AI impacts adoption decisions, particularly within educational contexts.

In conclusion, this study highlights key factors influencing ChatGPT adoption among university students in India. By improving ease of use and showcasing educational benefits, institutions can encourage integration of AI tools. Additionally, addressing perceived risks and reducing technostress is crucial for creating a supportive environment. These findings contribute to the growing literature on AI adoption in education, offering guidance for developers, educators, and policymakers to implement AI tools effectively in higher education.

Theoretical implications. This study contributes to the growing body of knowledge on technology acceptance by reinforcing key principles of the technology acceptance model (TAM), particularly in the context of ChatGPT usage. The strong, positive relationships between perceived ease of use (PEU), perceived usefulness (PU), and intention to use (IU) validate the relevance of these constructs in understanding user behavior towards AI technologies like ChatGPT. By confirming these associations, this study supports the applicability of TAM in contemporary AI applications, offering empirical evidence that can guide future research exploring how users adopt and interact with AI-driven tools across different sectors.

Furthermore, the inclusion of perceived risk and technostress introduces a broader perspective to the technology acceptance literature. The significant influence of perceived risk on IU suggests that users' concerns about privacy, security, and potential misuse of AI, such as ChatGPT, are critical factors that need to be addressed for successful adoption.

Additionally, the finding that technostress negatively impacts IU highlights the importance of considering the emotional and psychological barriers users might face when engaging with complex technologies. These findings emphasize the need for more comprehensive models that account for both cognitive and emotional factors, offering a richer understanding of user behavior.

The observation that trust did not have a significant effect on IU in this context invites further exploration into the role of trust when interacting with AI technologies like ChatGPT. Future research could explore how trust functions in various environments, such as educational or professional settings, and whether its significance varies across different use cases. This would help refine technology acceptance models to more accurately capture trust's influence across diverse contexts. Although trust did not play a significant role in this study, it highlights how contexts such as the application domain, user perceptions, and cultural attitudes—can shape the role of trust in technology adoption.

Practical implications. The findings from this study reveal several practical strategies for encouraging AI adoption among university students in India. First, ease of use significantly impacts both perceived usefulness and students' intentions to adopt AI tools, suggesting that simplifying AI interfaces and ensuring smooth, intuitive user experiences are critical. Educational institutions and AI providers should focus on making these tools as accessible and user-friendly as possible. Additionally, perceived usefulness strongly influences students' intentions to use AI, indicating that promoting the practical benefits of these tools can further drive adoption. Offering workshops, real-life examples, and hands-on training that illustrate the tangible academic advantages of AI could enhance students' positive perceptions and encourage broader acceptance.

The negative relationship between perceived risk and intention to use suggests that addressing concerns about data privacy, security, and the ethical use of AI is critical for reducing adoption barriers. Educational institutions should emphasize transparent policies and provide assurances to alleviate students' perceived risks. Technostress also emerged as a barrier, with its negative effect on intention to use, indicating that students may experience stress when adapting to new technologies.

Universities should develop training programs that enhance students' digital skills and AI literacy to reduce technostress and improve AI adoption. Offering workshops, AI-focused coursework, and hands-on learning opportunities can increase students' confidence in using tools like ChatGPT effectively. Further, establishing clear guidelines on the ethical use of AI tools in academic settings, addressing concerns such as plagiarism, misinformation, and data privacy. Providing AI ethics modules as part of university curricula can help students navigate these challenges.

For policymakers, this study emphasizes the need for national AI education policies that promote equitable and responsible AI use across universities. Policies should focus on bridging the digital divide by improving digital infrastructure and ensuring equal access to AI tools. To address perceived risks, policies should ensure clear guidelines on data privacy and ethical AI use in academia. Additionally, to reduce technostress and improve adoption, policymakers should invest in digital literacy programs and AI-focused workshops. These targeted strategies will help facilitate smoother AI adoption in higher education and ensure its benefits are accessible to all students.

Limitations. Despite the valuable insights provided by this study, there are several limitations to consider. First, a more diverse sample, including students from different regions, institutions, and socio-economic backgrounds, could improve the generalizability of the findings. Second, the use of purposive sampling in this study, which targeted students already familiar with ChatGPT, introduces the potential for self-selection bias. To address this limitation, future studies could employ random sampling methods to include a broader and more representative sample of students, regardless of their prior familiarity with AI tools. Additionally, this study relies on the technology acceptance model (TAM), which, while widely used, has limitations. Future research could explore alternative or extended models such as the unified theory of acceptance and use of technology (UTAUT), which incorporates constructs like social influence, facilitating conditions, and performance expectancy, offering a broader understanding of AI adoption. Another limitation involves the role of technostress, which was found to negatively affect students' intention to use ChatGPT. Future studies could explore how

digital skills and technological readiness moderate the relationship between technostress and adoption intentions. Lastly, the cross-sectional nature of this study restricts the ability to make causal inferences. Longitudinal studies could provide deeper insights into the factors influencing the continued use and long-term adoption of AI tools in educational contexts.

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Corporate digital responsibility and cloud computing adoption: An alignment analysis in the EU context

Sann Thawdar Htoo¹, Hana Kopackova²

¹ University of Pardubice, Faculty of Economics and Administration, Department of Systems Engineering and Informatics, Czech Republic, ORCID: 0009-0004-9104-7572, sannthawdar.htoo@student.upce.cz (corresponding author);

² University of Pardubice, Faculty of Economics and Administration, Department of Systems Engineering and Informatics, Czech Republic, ORCID: 0000-0001-6648-4990, Hana.Kopackova@upce.cz.

Abstract: Cloud computing is a transformational and rapidly evolving digital technology that enables driving innovation, scalability, and operational efficiency across various industries. Despite its benefits, the widespread adoption of cloud services presents complex ethical, social, and environmental challenges that organizations must address to ensure responsible and sustainable digital transformation. This study aims to develop a systematic approach to cloud adoption by integrating corporate digital responsibility (CDR) principles into strategic decision-making processes. Through a qualitative methodology, the research investigates and maps the key benefits and challenges of cloud adoption to the core dimensions of CDR, including environmental sustainability, data protection, inclusiveness, and digital governance. The resulting framework bridges the gap between technological advancement and corporate accountability by guiding organizations in adopting cloud technologies in a way that is both effective and ethically grounded. The findings highlight significant differences in prioritizing responsibility-related topics across European countries, with particular attention to environmental concerns, regulatory readiness, and cultural values. These differences suggest that national contexts are critical in shaping how responsible digital practices are understood and implemented. The study contributes to both theoretical understanding and practical application by offering a structured tool for decision-makers who aim to align cloud adoption with broader societal and environmental objectives. The proposed framework offers practical value for organizations seeking to integrate innovation with ethical and sustainable principles. By addressing the full spectrum of social, environmental, and governance considerations, this research provides meaningful insights for decision-makers, policymakers, and scholars working to advance responsible digital practices across diverse European settings.

Keywords: Digital transformation, technological innovation, corporate responsibility, sustainability, cloud strategy.

JEL Classification: O32, O33, M14, Q56, L86, F55.

APA Style Citation: Htoo, S. T., & Kopackova, H. (2025). Corporate digital responsibility and cloud computing adoption: An alignment analysis in the EU context. *E&M Economics and Management*, 28(4), 227–241. <https://doi.org/10.15240/tul/001/2025-4-015>

Introduction

Cloud computing (CC) has emerged as one of the key technological advancements in today's digital world, transforming how individuals

and businesses operate. Since its first applications, CC has been driven by the need for scalable, efficient, and cost-effective IT solutions, which makes it part of exponential technologies.

The adoption of cloud services has been an increasing trend for many years already, and no indication that it should change in the near future has occurred (Zbořil & Svatá, 2022).

This growth is supported by advancements in AI, IoT, specialized data centers, and big data integration. Integrating artificial intelligence (AI) with CC has led to transformative capabilities by enabling intelligent resource management, predictive analytics, and automated scaling, which improve operational efficiency and reduce costs. The internet of things (IoT), virtual machines, and mathematical optimization are accelerating the growth of CC (Taleb & Mohamed, 2020). Similarly, CC enables efficient handling of big data by offering scalable infrastructure and eliminating the need for costly, on-premise hardware (Sandhu, 2022).

The integration of CC introduces complex ethical and operational challenges, particularly regarding data privacy, security, and sustainability. Organizations operating within a shared responsibility model where both cloud providers and users must ensure data protection and compliance must be careful in implementing robust security measures and ethical governance. Emerging Industry 4.0 technologies further intensify these concerns by raising issues related to digital equity, security vulnerabilities, and responsible technology deployment (Verdoliva & Schiavone, 2021). As a result, businesses must prioritize digital ethics, transparency, and sustainability to maintain credibility in an increasingly data-driven world. While digital transformation, including cloud adoption, enhances innovation quality (Pu & Zulkafli, 2024) and operational efficiency, businesses must ensure transparency, accessibility, and ethical use of technology to maintain trust and address societal concerns.

CDR is a growing concept that addresses corporations' ethical, social, and environmental obligations in the digital era. As digital technologies become increasingly embedded in business operations, understanding and implementing CDR is essential for managing risks and capitalizing on opportunities in the digital transformation process (Cheng & Zhang, 2023; Herden et al., 2021). Responsibilities such as unbiased data acquisition, protection, maintenance, accurate interpretation, and addressing value conflicts in data-driven decision-making should be part of the corporate culture. In industries like banking, digital

transformation has improved efficiency and financial performance, but a clear strategic vision is needed to mitigate risks such as financial exclusion and cybersecurity threats, ensuring that responsible digital adoption benefits customers equitably (Niemand et al., 2021).

While cloud adoption is widely discussed in scientific literature, there is a critical gap that needs to be considered, considering a missing link between cloud adoption decisions and CDR principles. In this article, we aim to study how CC, as it is currently implemented in Europe, aligns with the principles of CDR. Specifically, we will investigate whether European CC research considers the broader responsibilities of digital technologies, including legal, social, and environmental. To our knowledge, no CDR research has focused on cloud adoption. Therefore, we had to find a novel way for this evaluation. We followed the process of decontextualization and recontextualization of cloud adoption decision factors and linked them with CDR topics. As the decision factors, we examine the benefits and challenges of cloud adoption as mentioned in scientific literature. Our study is divided into four steps:

- i) S1: define the preliminary framework of CDR topics for the CC adoption domain;
- ii) S2: prepare a systematic literature review on the benefits and challenges of CC adoption in the EU;
- iii) S3: create a map of links from benefits and challenges to CDR topics and finalize the CDR-CCA framework;
- iv) S4: evaluate the alignment of CC adoption in the EU with the CDR approach.

The article is structured as follows. Chapter 1 provides theoretical background, discussing cloud adoption, key influencing factors, and the frameworks that should be considered in the decision-making process. Chapter 2 details the research design, including the methodology, data collection methods, and analytical techniques employed. Chapter 3 presents the findings, emphasizing the impact of CDR on CC, discusses the results compared with existing literature, identifies research limitations, and outlines directions for future studies.

1 Theoretical background

CC represents a transformative shift in IT, enabling scalable, on-demand access to computing resources through service-based models such as IaaS, PaaS, and SaaS. While

the benefits include reduced capital expenditures and simplified IT management, concerns persist regarding data security, vendor lock-in, and service reliability. This shift from localized infrastructure to global networks has redefined traditional computing models, raising important questions about performance, interoperability, governance, and ethical use as adoption expands.

A range of interconnected factors shape the adoption of the cloud. The technology-organization-environment (TOE) framework categorizes these into technological (e.g., relative advantage, compatibility), organizational (e.g., top management support, IT readiness), and environmental domains (e.g., regulatory pressures, competitive dynamics) (Christiansen et al., 2022). While public sector decisions often prioritize compliance and interoperability (Ali et al., 2020), SMEs emphasize affordability and external support due to limited internal resources (Khayer et al., 2020). At the same time, concerns about confidentiality, availability, and integration complexity require nuanced decision-making frameworks. Moreover, stakeholders now demand ethical and sustainable technology use, urging organizations to integrate transparency, accountability, and long-term resilience into their digital transformation strategies (Estensoro et al., 2022; Niemand et al., 2021; Plekhanov et al., 2023).

CC adoption is increasingly linked to broader corporate responsibility frameworks, particularly in the EU, where digital ethics and sustainability are central. Corporate social responsibility (CSR) emphasizes a company's obligations beyond profit, incorporating economic, legal, ethical, and philanthropic duties. Evolving from philanthropic roots, CSR now supports strategic goals like innovation, compliance, and stakeholder trust (Alshukri et al., 2024). Closely aligned with CSR, the environmental, social, and governance (ESG) framework provides standardized metrics to assess corporate behavior, showing a positive link with financial performance and sustainability. However, ESG evaluations face challenges due to inconsistent rating methods (Berg et al., 2022).

As digitalization deepens, CDR has emerged to address ethical and societal challenges unique to digital technologies. CDR builds on CSR and ESG but focuses on issues such as data privacy, algorithmic fairness, cybersecurity, and digital inclusion (Cheng & Zhang, 2023;

Lobschat et al., 2021). It guides responsible digital practices across the full technology life-cycle (Gviliya, 2021; Mihale-Wilson et al., 2021), filling gaps left by traditional CSR frameworks. Scholars recommend aligning CDR with ESG categories – governance for data protection and social for equity (Herden et al., 2021).

In cloud contexts, CDR helps balance ethical concerns and performance goals (Wirtz et al., 2023), distinguishing between normative ethics and practical governance (Mueller, 2022). Given the limitations of existing CSR standards like ISO 26000, updated models or standalone CDR frameworks are needed (Carl et al., 2022). CDR is particularly relevant in the context of the Fourth Industrial Revolution, where rapid digital transformation is reshaping corporate responsibilities. As a new paradigm in corporate governance, CDR redefines the relationship between labor and technology while guiding the ethical deployment and use of emerging digital innovations (Orbik & Zozuláková, 2019).

2 Research methodology

The main aim of this research is to answer the question of whether organizations in the EU align their CC adoption decisions with CDR principles. An easy way to answer this question would be to prepare a systematic literature review on this topic. However, a search in the main scientific databases (Web of Science and Scopus) revealed that there are no documents covering this specific topic, which is surprising because the representation of CC research in both databases is high. The prevalent research in this domain focuses on technical specification (e.g., cloud-native architectures, resource management and cost optimization, edge and fog computing integration, and data analytics and big data integration) or selection criteria (e.g., cost and benefits, scalability and flexibility, privacy and security, and reliability and performance).

Our approach to finding the answer lies in the alignment analysis based on decontextualization and recontextualization of CC adoption selection criteria and finding the link with CDR topics (Fig. 1). The process of decontextualizing the benefits and risks of technology adoption allows us to abstract them from their usual decision-making framework. By recontextualizing these elements within CDR, we can evaluate whether cloud adoption strategies align with broader responsibilities. Thus, they

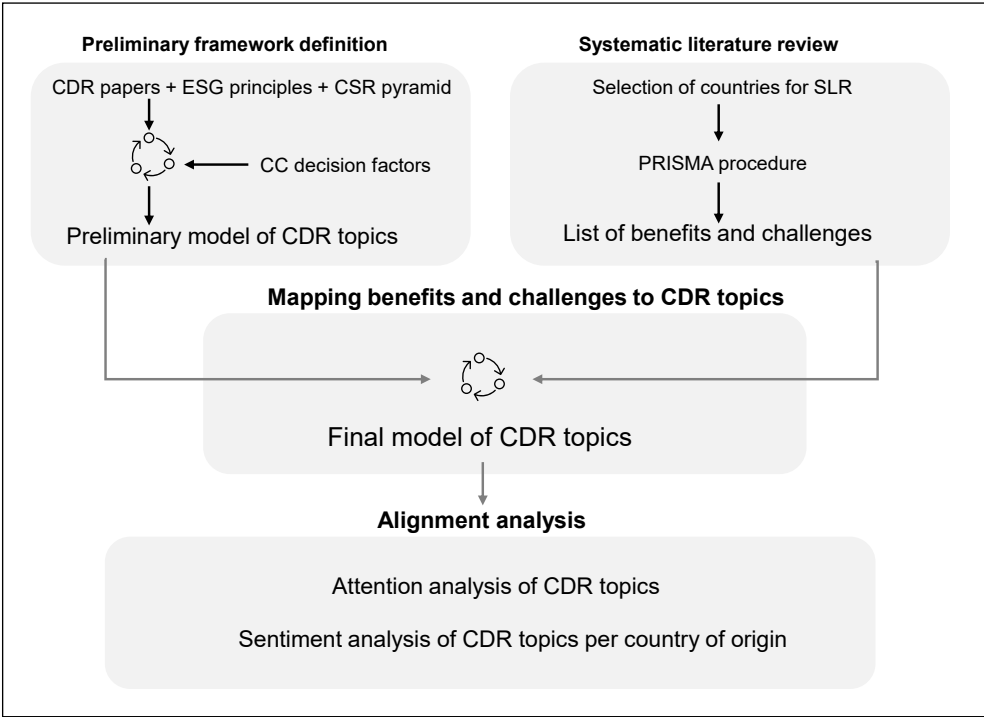


Fig. 1: Research process

Source: own

maximize positive impacts while addressing social, ethical, and environmental concerns. This alignment analysis can prove that even when organizations are focused on direct benefits and risks, they can also foster a responsible and sustainable approach to digital transformation.

The first step of our research involved creating a preliminary model of the CDR-based CC adoption (CDR-CCA) framework. This conceptual framework integrates key ideas from the most essential CDR publications, ESG principles, the CSR pyramid, and established CC adoption decision criteria. In developing our model of the CDR topic, we adopted an iterative, collaborative approach to ensure rigor and objectivity. Initially, each author independently conducted a double-blind assignment of key components and relationships within the model, working without influence from the other's perspectives. Following this phase, we compared our assignments, critically discussed our findings, and restructured the model to address

overlaps, gaps, and ambiguities. In cases where disagreements arose, we engaged a third independent researcher to provide an unbiased perspective and help resolve the differences. This systematic process ensured the model was comprehensive and balanced.

In the second step, we needed to get the list of benefits and challenges (barriers) that influence organizations' decisions about adopting or not adopting CC in the EU. As Eurostat gathers data about the use of technologies under digital economy and society statistics, we expect to find a comprehensive list with the data for the whole EU there. However, in these statistics, we found only three types of benefits (reduction of ICT costs, flexibility due to scaling services up or down, easy and quick deployment of solutions) and five barriers (high cost of buying, Insufficient knowledge of CC, risk of a security breach, uncertainty about applicable law, jurisdiction, dispute resolution mechanism, uncertainty about the location

of the data). As a result, we decided to change the strategy and used a systematic literature review to get the list of benefits and risks of CC adoption instead. Nevertheless, we used Eurostat data to narrow the review's focus to papers from European countries with high, middle, or low penetration of CC services.

We prepared a systematic literature review based on the PRISMA method (Fig. 2). We used Scopus and Web of Science as the primary information sources due to their extensive coverage of scholarly articles and journals. Additional exploration was conducted on Google Scholar to expand the literature review and gather more insights. The search period was limited to publications from 2009 to 2023, ensuring that the recent and relevant studies were included. The search used the "Title, Abstract, Keywords" search form to retrieve relevant literature within the specified parameters.

The search strategy employed a combination of search terms to capture various aspects of CC adoption within the context of the European Union. We used nine separate queries, one for each country. The format of each search query is "cloud AND (computing OR adoption OR drivers OR challenges OR benefits OR risks OR factors) AND [selected country]." The selected country keywords used in the queries are: (Sweden* OR Swed*), (Finland* OR Finnish*), (Netherland* OR Dutch*), (Denmark* OR Danish*), (Italy* OR Italian*), (Czech*), (Greece* OR Greek*), (Romania*), and (Bulgaria*). In the European Commission Digital Library, a specific search strategy was created, employing content type filters such as "Report/ Study," the topic "Cloud Computing," and a time frame ranging from 2013 to 2023.

The exclusion criteria (EC) and inclusion criteria (IC) were specified as follows:

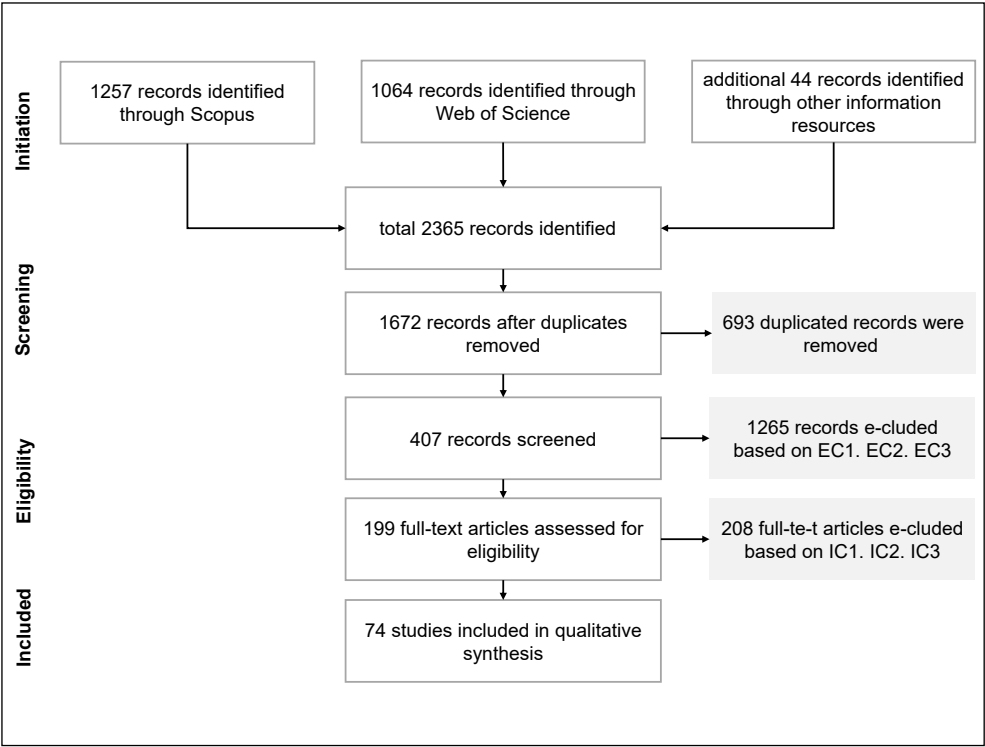


Fig. 2: Prisma procedure

Source: own based on PRISMA guidelines

- i) EC1: excludes studies not written in English to ensure consistency and accessibility for analysis;
- ii) EC2: excludes studies not conducted on cloud computing or cloud adoption;
- iii) EC3: excludes studies that do not concentrate on the selected countries;
- iv) IC1: includes studies specifically addressing cloud adoption within the context of the selected EU countries;
- v) IC2: includes studies examining both drivers and challenges of cloud adoption within focused countries;
- vi) IC3: this includes studies examining at least cloud adoption drivers or challenges within focused countries.

In step 3, we applied a bridging approach. By analyzing the benefits and challenges of CC adoption, we inferred the alignment of CC adoption decisions with CDR principles. This indirect method was necessary given the current lack of direct literature on this topic. We assigned each benefit and challenge to topics of the preliminary CDR-CCA framework. We applied the same double-blind assignment approach as within the formulation of the framework with one additional task: to evaluate if the topic name is accurate or should be adjusted. In the discussion phase, we renamed some topics and aggregated two into one. At the end of this procedure, we consolidated categorized insights into a final CDR-CCA framework, ensuring each topic is defined clearly and backed by extracted data from our analysis.

A total of 74 studies were selected for analysis. To provide transparency on the inputs used in the alignment analysis, we compiled a summary table (<https://www.researchgate.net/publication/393518068>) of all included studies. This table presents the country of focus, sector or organization type, year of publication, key benefits and challenges identified, and their contribution to one or more CDR dimensions. The selection of countries aimed to reflect a balanced representation of CC adoption levels across the EU27. Accordingly, nine countries were chosen to reflect high, moderate, and low adoption contexts. In the final step, we conducted an alignment analysis from two distinct perspectives. First, we examined each article's attention to the three types of responsibilities – economic, legal, social, and environmental. In this analysis, we aggregated both positive and negative views. For example, if a document

discussed cost efficiency as both a benefit and a challenge, it was counted twice. This approach allowed us to identify whether any type of responsibility received disproportionately higher attention than others. The second perspective of our alignment analysis focused on measuring sentiment (benefits/challenges) within each CDR topic, mapped to the country of origin. Here, we assessed whether research in particular countries predominantly emphasized benefits and challenges or employed a mixed approach. Additionally, we explored variations in focus across countries and the most highlighted topics in each.

The second perspective of our alignment analysis focused on measuring sentiment to evaluate perceptions of the benefits and challenges related to CC adoption in the context of CDR. We classified each identified factor from the literature as a benefit (B), a challenge (C), or both (B/C) based on the context and tone of the source articles. This method allowed us to differentiate between positively and negatively framed themes and to identify areas of ambivalence, especially in social dimensions such as digital inclusion and well-being. Sentiment analysis is a well-established technique in qualitative research for capturing subjective meanings and evaluative orientations in textual data (Gaspar et al., 2016), making it suitable for exploring how topics related to responsible digitalization are framed across different national contexts. While the attention analysis mapped the distribution of CDR topics across the literature corpus and categorized them by thematic prominence, the sentiment analysis added a spatial layer by revealing how researchers in different countries perceive these topics. This allowed us to see the big picture, both across CDR dimensions and geographic contexts, and to better understand national differences in digital responsibility discourse. Rather than isolating a few dominant topics, our intent was to offer a panoramic view of how responsible digital transformation is being discussed across Europe, including patterns of imbalance, neglect, or emphasis within specific countries and dimensions.

3 Results and discussion

This chapter outlines the selection of reviewed papers focused on EU countries, the development of preliminary frameworks based on existing models and principles, and

the presentation of results, including the mapping of CC benefits and challenges, the alignment analysis, and the related discussion.

3.1 Paper contributions

The systematic literature review was drawn from diverse countries, showcasing the geographical breadth of research contributions (Fig. 3). Sweden (SE) and Italy (IT) led the way, each contributing 16 papers to the analysis. Finland (FI) and the Netherlands (NL) followed, with 8 papers each, while Romania (RO) added 9 papers to the dataset. Greece (EL) and Czechia (CZ)

contributed 7 and 6 papers, respectively, with Denmark (DK) providing 3. Bulgaria (BG), with just a single paper, represented the lowest level of participation. This distribution highlights the diverse geographical origins of the research included in the document analysis, reflecting a broad spectrum of contributions from multiple countries within the scope of the PRISMA review. The complete PRISMA 2020 checklist, which guided this systematic review, is described in detail by Page et al. (2021) and can be accessed at <https://doi.org/10.13140/RG.2.2.23915.66086>.

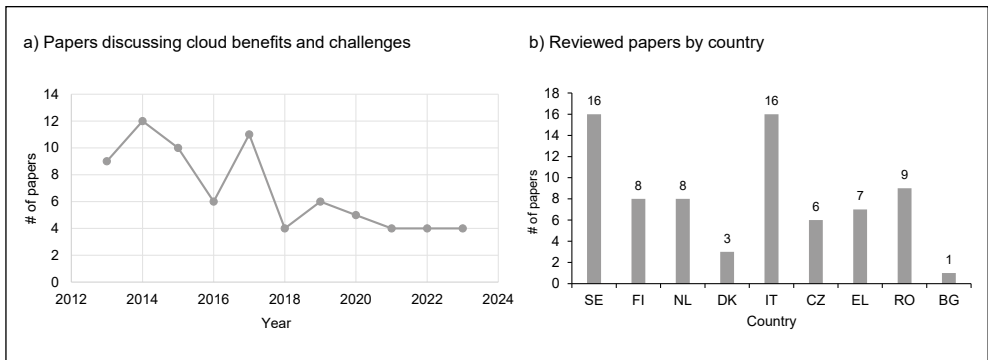


Fig. 3: Distribution of selected papers

Source: own

Examining temporal trends, the number of papers discussing the benefits and challenges of CC fluctuated over the years, reflecting evolving research interests and technological progress. The year 2014 stood out with the highest contribution of 12 papers, marking a peak in scholarly attention toward the potential and limitations of CC during that time. Notable contributions were also made in 2013 and 2017, which saw 9 and 11 papers published, respectively. However, interest seemed to wane in subsequent years, as 2018, 2020, and 2021 each produced only 4 papers. The surge of research in 2014 and 2015 coincided with the rising prominence of CC as a transformative trend in IT. Studies during this period focused on key aspects of the cloud ecosystem, including frameworks, deployment models, emerging technologies, and industry trends. This peak in research activity highlights a critical period of exploration and innovation in the CC domain.

3.2 Preliminary framework

The preliminary framework depicted in Fig. 4 was developed by integrating the CDR principles, CSR pyramid, ESG frameworks, and CC decision factors. CDR extends CSR into the digital realm, ensuring data privacy, AI ethics, and governance (Herden et al., 2021; Lobschat et al., 2021; Wynn & Jones, 2023) while serving as both a regulatory necessity and a strategic advantage for trust and reputation (Carl et al., 2022). As cloud plays a central role in the Fourth Industrial Revolution, integrating CDR into cloud adoption ensures that digital transformation is both ethical and compliant (Orbik & Zozuľáková, 2019). By aligning business ethics and transparency with cloud adoption, the framework mitigates risks associated with digitalization (Mueller, 2022), particularly in balancing profitability and ethical AI governance within cloud services (Wirtz et al., 2023).

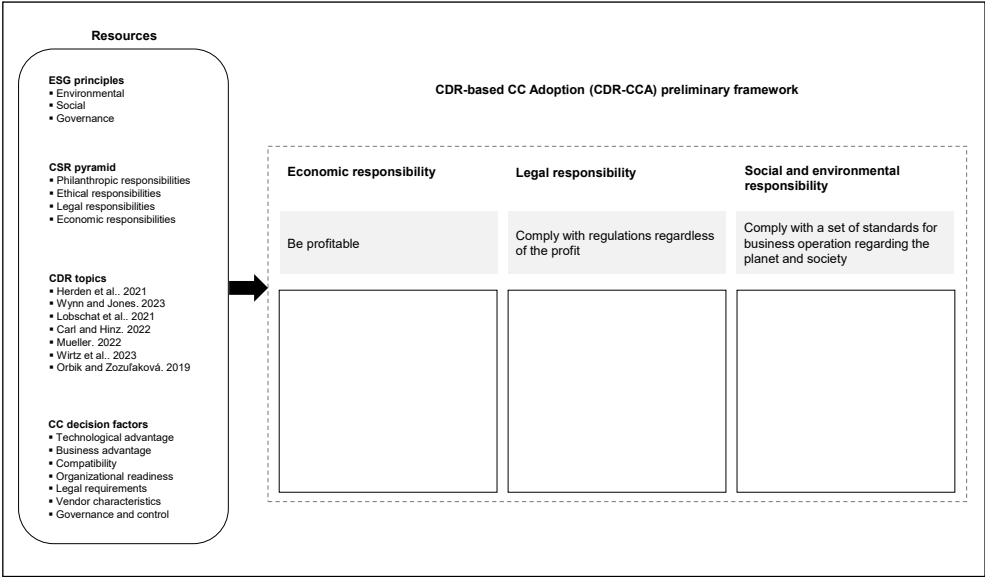


Fig. 4: Preliminary framework

Source: own

Prior research shows that diverse cloud adoption factors can be effectively grouped into technological advantages, business advantages, compatibility, organizational readiness, legal requirements, vendor characteristics, and governance and control (Ali et al., 2020). The preliminary framework was created by combining these established theories and insights from previous research, resulting in a structured approach to cloud adoption that is consistent with the three core responsibilities: economic responsibility, legal responsibility, and social and environmental responsibility.

3.3 Mapping benefits and challenges to CDR topics

This section presents the mapping of cloud adoption benefits and challenges onto key CDR topics. Through a manual extraction process, we identified 312 benefits and 226 challenges. The detailed mapping is available in an online repository. Fig. 5 illustrates the CDR-CCA framework and the associated cloud benefits and challenges. We categorized the responsibilities into three main areas: economic, legal, and social and environmental. An iterative approach was used to determine

the most suitable subcategories. In this approach, each author independently proposed subcategories, followed by a collaborative meeting to discuss discrepancies. Together, we refined the list of subcategories, assigned benefits and challenges to them, and engaged in further discussions. Based on these discussions, we restructured the subcategories to enhance clarity and accuracy.

3.4 Alignment analysis

The results revealed distinct patterns in how different CDR dimensions (economic, legal, and social and environmental responsibilities) are emphasized in cloud adoption decisions (Fig. 6). Economic responsibility dominates the benefits perspective, highlighting the strong focus on cost efficiency and financial advantages as key drivers of cloud adoption. Similar views bring the prevalence of benefits perspective in social and environmental responsibility, emphasizing accessibility, flexibility, perceived usefulness, and convenience. This positive perception indicates growing significance as organizations strive to align technological adoption with sustainability and broader corporate social responsibility goals. In contrast, legal

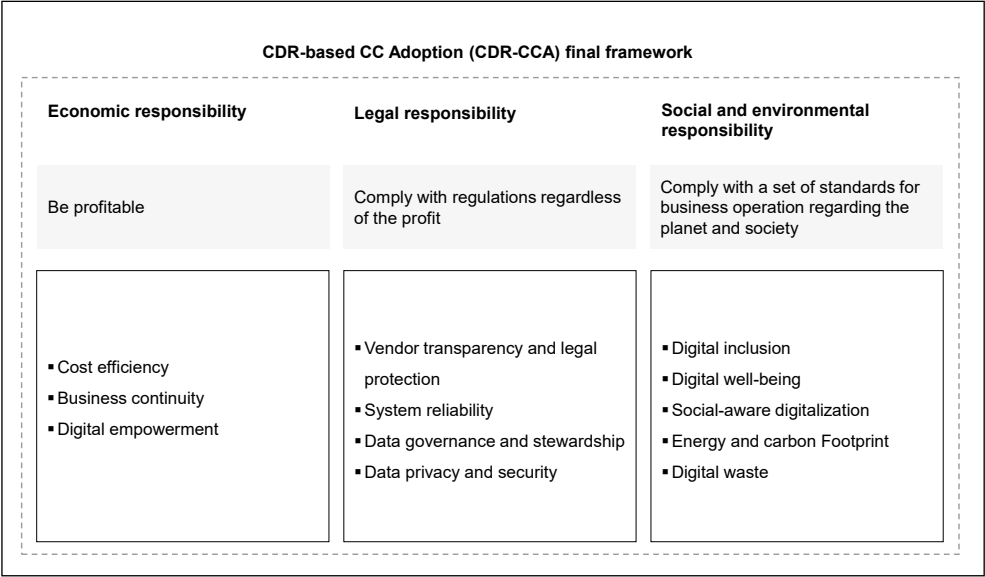


Fig. 5: CDR-CCA framework

Source: own

responsibility emerges as the primary challenge, wieth significantly higher mentions than the other dimensions, reflecting widespread concerns about compliance, regulations, and liability issues.

The detailed analysis of social and environmental responsibility reveals a notable imbalance in how its subcomponents are addressed in CC adoption discussions. While this responsibility receives attention comparable

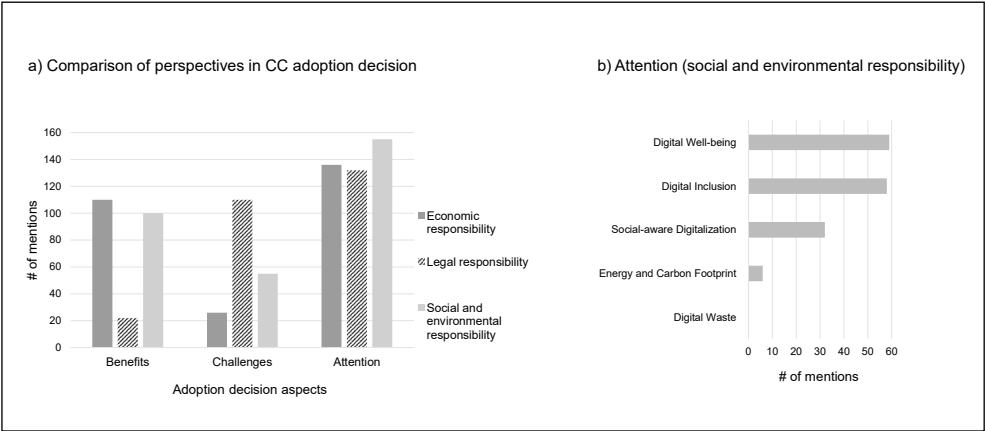


Fig. 6: Responsibility dimensions in cloud adoption decision

Source: own

to economic and legal aspects, the environmental dimension appears significantly underrepresented. Key topics such as digital well-being and digital inclusion dominate the discourse, with high levels of attention reflecting the growing emphasis on equitable access to digital technologies and the impact of CC on user experiences and societal participation. Similarly, social-aware digitalization, which integrates social values into technology deployment, receives moderate attention. However, topics directly tied to environmental sustainability, such as energy, carbon footprint, and digital waste, are strikingly overlooked. This suggests a gap in the prioritization of environmental impacts in cloud adoption decisions despite the increasing focus on sustainability and climate change.

This disparity indicates a need for greater integration of environmental considerations into discussions on cloud adoption. As organizations and policymakers seek to align technological advancements with CSR goals, the environmental implications of CC, such as energy consumption in data centers and e-waste generation, deserve higher attention. A narrow focus on social aspects without adequately addressing environmental consequences risks undermining the broader goals of sustainability and responsible innovation. The findings highlight an opportunity for decision-makers to adopt a more holistic approach that balances social and environmental priorities, ensuring that cloud adoption contributes meaningfully to both societal progress and environmental preservation.

3.5 Sentiment analysis

The aim of the sentiment analysis is to study if the perception of positives (benefits) and negatives (challenges) is similar in countries contributing to our literature review. The sentiment analysis highlights how different countries perceive the benefits, challenges, or mixed implications of CC adoption across CDR topics (Tab. 1). Tab. 1 captures the frequency and framing of key CDR-related themes across national contributions. “—” indicates that the respective topic was not discussed in any of the reviewed articles from that country.

The data revealed that most articles tend to focus predominantly on either benefits or challenges, with significantly fewer adopting a mixed perspective that considers both

aspects. However, we can identify two topics being this ambivalent. Digital inclusion and Digital well-being are mainly viewed from both perspectives. These topics address both opportunities and challenges as they involve balancing accessibility, user experience, and societal impacts. The CC's potential to enhance digital inclusion is evident in its ability to provide users with ubiquitous access to data and services from multiple devices, facilitating global connectivity and interoperability. However, concerns about integration challenges and a lack of expertise in cloud adoption create barriers to equitable access. Access to complete business applications without extensive infrastructure and no need for installation and maintenance simplifies processes at all levels, thus enhancing digital well-being. Conversely, a lack of organizational readiness and the complexity of integrating existing systems with cloud-based solutions can create significant obstacles.

When examining the popularity of CDR topics, cost efficiency emerges as a widely recognized benefit across all countries. Similarly, digital empowerment is considered an important and beneficial topic for all countries. There is also consensus on the choice of the most challenging topic: data privacy and security. An unfortunate common characteristic among all countries is the lack of interest in environmental issues. Energy and carbon footprint was referenced only sparsely: it appeared as a benefit in studies from Sweden, Greece, and Romania and the mixed view is present in one study from Italy. These are the only instances in which environmental concerns entered the conversation across all countries included in the analysis. Digital Waste, in contrast, was entirely absent. No articles from any country addressed this issue, leading to its removal from the sentiment table. The geographically limited and superficial treatment of environmental concerns points to an important research gap.

Now, we want to examine the differences in focus among countries. We view these topics as focal points. The Netherlands (NL) position in the dataset reflects a broad but less concentrated focus on CC topics, as no topic was mentioned in more than 50% of articles. This indicates a more generalized approach to the study of CC, where attention is distributed across various topics without a dominant emphasis. This dispersed focus suggests that

Tab. 1:

Sentiment analysis of perceived benefits and challenges in cloud adoption across contributing countries (%)

		SE (16)	FI (8)	NL (8)	DK (3)	IT (16)	CZ (6)	EL (7)	RO (9)	BG (1)
Cost efficiency	B	68.8	75.0	50.0	66.7	50.0	50.0	71.4	66.7	–
	B/C	6.3	–	37.5	33.3	6.3	33.3	–	11.1	–
	C	6.3	–	–	–	12.5	–	–	–	–
Business continuity	B	–	25.0	25.0	–	25.0	16.7	14.3	11.1	–
	B/C	–	–	–	–	–	–	–	–	–
	C	6.3	–	25.0	–	6.3	16.7	–	–	–
Digital empowerment	B	43.8	62.5	37.5	66.7	75.0	83.3	71.4	44.4	–
	B/C	–	–	–	–	–	–	–	11.1	–
	C	–	–	–	–	–	–	14.3	–	–
Vendor related issues and legal protection	B	–	–	–	–	–	–	–	–	–
	B/C	–	–	–	–	–	–	–	11.1	–
	C	56.3	25.0	25.0	–	25.0	33.3	28.6	33.3	–
System reliability	B	–	–	25.0	–	6.3	–	28.6	–	–
	B/C	–	12.5	–	–	–	–	–	–	–
	C	25.0	25.0	25.0	33.3	37.5	66.7	14.3	–	–
Data governance and stewardship	B	12.5	12.5	–	–	12.5	–	14.3	–	100.0
	B/C	–	–	12.5	–	6.3	–	–	11.1	–
	C	31.3	25.0	12.5	–	37.5	–	–	–	–
Data privacy and security	B	–	–	–	–	–	–	–	–	–
	B/C	–	25.0	12.5	–	–	16.7	–	11.1	–
	C	75.0	25.0	37.5	66.7	62.5	66.7	57.1	44.4	–
Digital inclusion	B	50.0	12.5	37.5	–	43.8	16.7	14.3	33.3	–
	B/C	6.3	–	12.5	66.7	6.3	50.0	14.3	11.1	–
	C	–	12.5	12.5	33.3	18.8	16.7	–	11.1	100.0
Digital well-being	B	6.3	12.5	25.0	33.3	37.5	83.3	42.9	33.3	–
	B/C	12.5	37.5	37.5	66.7	6.3	–	–	–	–
	C	37.5	12.5	25.0	–	18.8	–	14.3	–	–
Social-aware digitalization	B	56.3	12.5	37.5	33.3	18.8	33.3	57.1	22.2	–
	B/C	6.3	–	–	–	–	–	–	–	–
	C	–	–	25.0	33.3	12.5	–	–	–	–
Energy and carbon footprint	B	12.5	–	–	–	–	–	14.3	11.1	–
	B/C	–	–	–	–	6.3	–	–	–	–
	C	6.3	–	–	–	–	–	–	–	–

Note: B – Benefit; C – Challenge; B/C – Both benefit and challenge; SE – Sweden; FI – Finland; NL – Netherlands; DK – Denmark; IT – Italy; CZ – Czechia; EL – Greece; RO – Romania; BG – Bulgaria; . “–” indicates that the respective topic was not discussed in any of the reviewed articles from that country. The values in parentheses represent the number of selected studies in each country. The values in bold and italic present topics covered in more than 50% of published articles in the given country.

Source: own

research in the Netherlands explores CC from a diverse range of perspectives, potentially aiming for a holistic understanding of the field rather than a deep dive into specific issues or benefits. A similar approach can be found in articles originating from Romania (RO) with only one major topic: a beneficial view on cost efficiency. On the other side of the spectrum are Sweden (SE), the Czech Republic (CZ), and Greece (EL), having their attention centered around four main topics.

The final analysis of CC adoption sentiment highlights the most prominent topic in each country. In Sweden, the primary focus is on the challenge of data privacy and security. For Finland, the standout topic is the benefit of cost efficiency, which also applies to the Netherlands and Romania. A similar situation is in Greece, although there is a split of interest between this topic and digital empowerment. The highest popularity in Italy also comes from the benefit of Digital empowerment. The Czech Republic shows a split in emphasis between the benefits of digital Empowerment and digital well-being, reflecting equal interest in both areas. Denmark, despite contributing just three papers, shows a concentrated focus on five topics, with a clear highlight on mixed views regarding digital inclusion and digital well-being. In Bulgaria, where only one paper was included, the focus is on the benefit of data governance and stewardship alongside the challenge of digital inclusion.

3.6 Discussion

The rapid expansion of CC has significantly increased energy consumption, particularly in data centers that operate around the clock to maintain performance and availability (Bharany et al., 2022; Zhang et al., 2021). While these data centers are crucial for digital infrastructure, they also contribute substantially to environmental degradation (Monserrate, 2022). To tackle these challenges, both providers and users must adopt environmentally responsible practices.

This study provides insights into how cloud adoption in the EU aligns with, and sometimes neglects, the principles of CDR. By examining the benefits and challenges of cloud computing against the economic, legal, social, and environmental dimensions of CDR, we can identify key implications for corporate strategy and policy design.

The analysis highlights the dominance of economic and legal dimensions. Economic

responsibility is evident in benefits like cost efficiency and operational flexibility, while legal responsibility primarily presents challenges related to data protection and compliance with regulations such as the GDPR.

However, there are noticeable imbalances in the social and environmental dimensions. While digital inclusion and well-being receive attention, environmental issues like energy consumption and digital waste are significantly underrepresented. This indicates a disconnect between sustainability goals and current cloud adoption priorities, even amid rising public demand for greener IT practices. Several factors may explain this gap, including the tendency of organizations to prioritize short-term economic and compliance goals over sustainability (Mueller, 2022), the absence of standardized sustainability metrics for cloud infrastructure (Carl et al., 2022), the obscured environmental costs in outsourced service models (Monserrate, 2022), and limited organizational awareness of the environmental footprint of digital services (Bharany et al., 2022).

Sentiment analysis reveals national differences in cloud computing and CDR perceptions across the EU. Countries like Sweden and the Czech Republic focus on specific topics like legal challenges, while others like the Netherlands adopt broader perspectives. These variances reflect national policies and cultural values, suggesting that responsible cloud strategies should be tailored to regional contexts (Ali et al., 2020). For example, countries such as Sweden and Finland exhibit high levels of regulatory readiness due to established data protection frameworks, proactive digital strategies, and compliance with GDPR (Issaoui et al., 2023). These nations often integrate digital ethics into national policy and demonstrate advanced e-government infrastructure. In contrast, countries like Romania or Bulgaria, while showing growing interest, may face challenges due to fragmented regulations or limited institutional enforcement. Cultural values also shape perceptions of digital responsibility; for example, Nordic countries place strong emphasis on egalitarian access and transparency, influencing their prioritization of digital inclusion and well-being. Southern European contexts, such as Italy and Greece, may demonstrate stronger emphasis on personal empowerment and organizational flexibility, which aligns with their higher attention to digital empowerment benefits.

Another key finding is the dual perception of digital inclusion and well-being, seen as both benefits and challenges. This indicates that while cloud computing can promote inclusivity, it may also exacerbate inequalities if barriers like infrastructure and digital literacy are not addressed, emphasizing the need for targeted support and inclusive design (Samaniego López et al., 2025).

From a policy perspective, we recommend introducing mandatory sustainability reporting requirements for cloud service usage at both the national and EU levels. Policymakers should support the development of Green Public Procurement (GPP) guidelines specifically tailored to digital services (Pouikli, 2021). Additionally, awareness campaigns should be launched to promote digital environmental responsibility across public and private sectors. Finally, cloud providers and adopters should be incentivized to pursue energy-efficient certifications or adopt standardized carbon accounting practices. Public-private partnerships and targeted guidance tailored to national contexts can also improve alignment with CDR principles.

The study shows that while cloud adoption in the EU reflects some aspects of CDR, it lacks a comprehensive approach, particularly regarding environmental impact and inclusive access. This highlights the need for better collaboration among businesses, regulators, and scholars to ensure that digital transformation promotes responsibility, equity, and sustainability in line with EU digital goals and global ESG standards.

Conclusions

This study assessed the alignment of cloud adoption decisions with CDR principles within the EU context. The findings revealed that while cloud adoption offers significant benefits, such as cost efficiency, digital inclusion, and enhanced data security, challenges remain in key areas like data privacy, security, and environmental sustainability. Our analysis highlights a partial alignment between cloud adoption and CDR principles. Economic and legal responsibilities are often well-addressed, but social and environmental aspects, particularly digital equity and sustainability, require further integration into CC strategies. Digital waste management has emerged as an underexplored yet critical gap in current research and practice. These results show a clear need for targeted guidelines

and policies to bridge these gaps and support responsible CC adoption.

We also provide a foundational framework for linking CC adoption factors to CDR principles, offering practical insights for organizations and policymakers to advance sustainable and ethically sound digital transformations. Future research should expand on these findings, focusing on underrepresented CDR topics and exploring their implications for long-term digital responsibility.

Acknowledgments: Supported by grant No. SGS_2025_018 "Student Grant Competition of the University of Pardubice."

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The journal is published quarterly.

Subscription:

From 2024, the print format of the journal is suspended. The individual issues will be available for free in electronic form on the journal's website. The last print issue is Issue 4, Volume 27.

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Published by: Technical University of Liberec

Studentská 2, 461 17 Liberec 1, Czech Republic, ID no. 46747885

Production: Wolters Kluwer ČR, a. s.

U nákladového nádraží 10, 130 00 Praha 3, Czech Republic, ID no. 63077639

ISSN 1212-3609, ISSN (online) 2336-5064

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