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Obsah Contents

SUBJECTIVE JOB SATISFACTION OF EMPLOYEES AND THEIR WILLINGNESS TO ACCEPT A NEW JOB FROM THE PERSPECTIVE OF SELECTED SOCIO-DEMOGRAPHIC CHARACTERISTICS

Kristína BULKOVÁ

Abstract

This paper investigates statistically significant relationships between respondents' age, level of education, and length of work experience and their subjective job satisfaction. In addition, it examines employed respondents' decisions regarding the acceptance of a better job offer in relation to age, education, and work experience. Subjective job satisfaction was measured using a Likert-type scale, while the decision to accept a better job was assessed using three response options: yes, no, and undecided The findings reveal several statistically significant results. The highest level of subjective job satisfaction was identified amon respondents aged twenty-nine to forty-four years. Willingness to accept a better job was most pronounced among respondents in younger age categories. Furthermore, the highest proportion of respondents reporting positive job satisfaction was observed among those with university education. A high level of job satisfaction was also evident among respondents with more than four years of work experience. This group simultaneously demonstrated a willingness to accept a better job offer.

Key words:
Job Satisfaction, to accept a better job, socio-demographic characteristic (age, length of practice, level of academy degree)

JEL Classification J10, J28, J80 https://doi.org/10.52665/ser20250201

INTRODUCTION

Understanding criteria reflecting employees' demographic, professional, and qualification characteristics constitutes a fundamental prerequisite for effective development and functioning at both the micro level (enterprise, firm, organization) and the macro level (the social system as a whole) within the field of human resource management. The trends highlighted by empirical research findings (specific authors) serve as an important source of inspiration and guidance, as well as a concrete framework for enhancing work motivation in the context of the above-mentioned criteria.

If organizations aim to influence and increase work efficiency and support organizational development, it is essential to understand the key determinants related to employees' age, length of work experience, and level of education. This knowledge enables the selection of appropriate managerial approaches for guiding and influencing individuals as well as work groups.

In this context, Ipsirli and Namal (2023) emphasize that if data obtained from questionnaires or subjective evaluations are not interpreted in relation to the individual characteristics of employees, it is generally not possible to make satisfactory assessments of job satisfaction. It is therefore assumed that personal characteristics independent of the work context—such as gender, level of education, years of employment, age, health status, and marital status—exert a substantial influence on the level of job satisfaction. This is because socio-demographic and personal factors are closely associated with individuals' perceptions of working life and working conditions, characteristic behavioral patterns, differing intentions, goals, and motivational structures.

1. LITERATURE OVERVIEW

There are numerous definitions of job satisfaction in academic literature, reflecting considerable variation across individuals. Moreover, the frequent use of related or overlapping terms, such as workplace environment, business climate, work ethic, quality of work life, work satisfaction, or working conditions - instead of the concept of job satisfaction itself has made it increasingly difficult to establish a precise and universally accepted conceptual framework.

Seeman (2021) defines job satisfaction as an individual's emotional state resulting from the evaluation of performed work, work experience, interpersonal relationships at work, and related factors. Similarly, Meier and Spector (2015) conceptualize job satisfaction as individuals' attitudes toward their work and its various aspects, as well as the degree to which they like or dislike their job. Locke defines job satisfaction as "a function of the range of specific satisfactions and dissatisfactions that an individual experiences with respect to the various dimensions of work," emphasizing the relationship between what individuals expect from their job and what they actually receive (Locke, cited in Muhammad & Ahmed, 2024., Alzyoud, 2018).

Obeng et al. (2024) note that job satisfaction is a concept that has attracted substantial attention in management studies, social psychology, and academic practice. It is a multifaceted construct, with scholars offering diverse definitions, commonly referring to a favorable and pleasurable emotional state individuals experience toward their employment.

In essence, job satisfaction represents a general work-related attitude. An individual who is satisfied with their job tends to exhibit a positive attitude toward work, whereas dissatisfaction is typically associated with a negative work attitude. More specific work attitudes are linked to particular aspects of work. For example, some individuals derive satisfaction from responsibility, while others find fulfillment in teamwork. Consequently, different aspects of work provide varying degrees of satisfaction depending on individuals' personal characteristics, abilities, and interests. In this context, Kaupilla (2025) argues that, based on research on job attitudes, markedly different conclusions may be drawn, as employees observe and evaluate their leaders from varying attitudinal perspectives depending on whether they are satisfied or dissatisfied with their jobs. Egemen (2024) further emphasizes that job satisfaction and job performance vary considerably across different categories of employees. The lowest levels of job satisfaction and job performance were identified among skilled laborers, whereas the highest levels were observed among engineers and architects. Moreover, a strong positive correlation between job satisfaction and job performance was found across all respondent categories. Henning (2024) highlights that job satisfaction has been shown to increase with age. Enhancing job satisfaction requires the creation of an appropriate work environment, including suitable working conditions, positive interpersonal relationships, cooperation among employees, effective leadership styles, fair compensation and motivation systems, and task allocation that aligns with employees' competencies. Job satisfaction is generally associated with improved employee performance, which in turn further reinforces satisfaction at work. Matud et al. (2024) conclude that job satisfaction plays a significant role in the mental health, psychological well-being, and overall life satisfaction of adult working women and men.

However, there are also cases in which highly productive employees do not experience job satisfaction, as their work may not fulfill them intrinsically.

Job satisfaction within organizations also contributes to reduced absenteeism and employee turnover. More satisfied employees tend to exhibit lower absenteeism rates and a reduced inclination to change jobs. Furthermore, job satisfaction significantly affects individuals' psychological well-being. Emotionally balanced employees are better able to concentrate on their work, achieve higher quality outcomes, experience fewer workplace accidents, and maintain more positive relationships with colleagues, supervisors, and subordinates. Ultimately, job satisfaction also exerts a positive influence on employees' private lives.

Robbins (2015) argues that understanding the factors influencing job satisfaction is particularly important for average employees rather than exceptional performers, as organizations tend to invest more effort into enhancing the job satisfaction of high-performing employees due to their strategic value. The most widely used method for assessing the level of job satisfaction remains the questionnaire-based approach. Salleh (2024) note the findings revealed that each independent variable had a positive and statistically significant effect on job satisfaction. Specifically, talent retention emerged as the most influential predictor of job satisfaction.

2. GOAL AND METHODOLOGY

Subjective job satisfaction and willingness to accept a new job were examined using a questionnaire survey. The questionnaire was anonymous and administered to employed respondents regardless of industry or type of organization. The research sample was selected using convenience sampling, the principle of which consists in recruiting participants based on opportunities that arise during the research process (Miovský, 2006).

Respondents' subjective job satisfaction was measured using an item assessed on a Likert-type scale, whereby respondents indicated their level of agreement or disagreement with statements related to their job satisfaction. Responses were subsequently categorized into three groups: *agree*, *neutral*, and *disagree*. Respondents' decision to accept a better job offer was assessed using a closed-ended question with three response options: *yes*, *no*, and *undecided*.

The total number of respondents included in the analysis was n = 394. Respondents were classified according to:

- age (up to twenty-eight years, twenty-nine to forty-four years, and forty-five to sixty-five years)
- level of education (secondary vocational education without a leaving examination, upper secondary education with a leaving examination, and university education)
- length of work experience (< 1 year, 1–2 years, 2–4 years, and > 4 years).

Descriptive and inferential statistical methods were employed to analyze the collected data. To examine relationships between nominal and ordinal variables, the chi-square test of independence (χ^2 test) was applied. The level of statistical significance was set at $\alpha = 0.05$, and statistical decisions were based on comparisons between the obtained p-values and the predefined significance level.

For the appropriate application of the chi-square test, its basic assumptions were verified. In particular, the sample size exceeded the minimum requirement ($n > 40$), ensuring the suitability of the test for the present analysis.

Hypotheses

H_1: It was assumed that a statistically significant relationship exists between respondents' age and their subjective job satisfaction. Hypothesis H_1 was confirmed.

H_2: It was assumed that a statistically significant relationship exists between respondents' age and their decision to accept a better job. Hypothesis H_2 was confirmed.

H_3: It was assumed that a statistically significant relationship exists between respondents' level of education and their subjective job satisfaction. Hypothesis H_3 was not confirmed.

H_4: It was assumed that a statistically significant relationship exists between respondents' level of education and their decision to accept a better job. Hypothesis H_4 was not confirmed.

H_5: It was assumed that a statistically significant relationship exists between respondents' length of work experience within the organization and their subjective job satisfaction. Hypothesis H_5 was confirmed.

H_6: It was assumed that a statistically significant relationship exists between respondents' length of work experience within the organization and their decision to accept a better job. Hypothesis H_6 was confirmed.

3. FINDINGS

Verification of Hypothesis H1

For the verification of the first hypothesis, three age categories of respondents were compared. The analysis aimed to determine whether a statistically significant relationship exists between age categories (up to 28 years, 29–44 years, and 45–65 years) and respondents' subjective job satisfaction.

Table 1: Subjective Job Satisfaction and Respondents' Age

Respondents' attitude	Up to 28 years	29-44 years	45-65 years	Total	χ2 -test
Agree [n]	89	106	91	286	0,0000
Agree [%]	61%	78%	82%	73%	
Neutral stance [n]	19	19	10	48	
Neutral stance [%]	13%	14%	9%	12%	
Disagree [n]	39	11	10	60	
Disagree [%]	27%	8%	9%	15%	
Total [n]	147	136	111	394	
Total [%]	100%	100%	100%	100%	

Source: Own elaboration

As shown in Table 1, the probability value p is lower than the selected level of significance, p (0.0000) < α (0.05). Therefore, it can be concluded that there is a statistically significant relationship between respondents' age and their subjective job satisfaction.
Using the chi-square test, a statistically significant association between age and respondents' subjective job satisfaction was confirmed. The highest level of subjective job satisfaction was observed among respondents aged 29–44 years, followed by those aged 45–65 years. The lowest level of subjective job satisfaction was recorded among respondents up to 28 years of age, who also expressed the highest level of disagreement with their job satisfaction.

Verification of Hypothesis H2
For the verification of the second hypothesis, three age categories of respondents were compared. The analysis aimed to determine whether a statistically significant relationship exists between age categories (up to 28 years, 29–44 years, and 45–65 years) and respondents' decision to accept a better job.

Table 2: Respondents' Age and Their Decision to Accept a Better Job

Respondents' attitude	Up to 28 years	29-44 years	45-65 years	Total	χ2 -test
Yes [n]	93	42	27	162	0,0000
Yes [%]	63%	31%	24%	41%	
Undecided [n]	35	57	36	128	
Undecided [%]	24%	42%	32%	32%	
No [n]	19	37	48	104	
No [%]	13%	27%	43%	26%	
Total [n]	147	136	111	394	
Total [%]	100%	100%	100%	100%	

Source: Own elaboration

As shown in Table 2, the probability value p is lower than the selected level of significance, p (0.0000) < α (0.05). Therefore, it can be concluded that there is a statistically significant relationship between respondents' age and their decision to accept a better job. The respondents

who were significantly the most willing to accept a better job were those in the age category up to 28 years. In contrast, the highest proportion of respondents unwilling to accept a better job was observed among those aged 45–65 years. Among respondents aged 29–44 years, attitudes toward accepting, not accepting, and being undecided about a better job offer were approximately evenly distributed.
The findings are also noteworthy in that they confirm the basic assumption of the study: the age group up to 28 years included the lowest number of respondents who would refuse a better job offer, whereas the age group 45–65 years included the highest number of respondents who expressed a negative attitude toward accepting a better job.

Verification of Hypothesis H3
For the verification of the third hypothesis, three categories of respondents' educational attainment were compared. The analysis aimed to determine whether a statistically significant relationship exists between the level of education (secondary vocational education without a leaving examination, upper secondary education with a leaving examination, and university education) and respondents' subjective job satisfaction.

Table 3: Subjective Job Satisfaction and Level of Education

Respondents' attitude	Secondary vocational (no leaving exam)	Upper secondary (with leaving exam)	University education	Total	$\chi 2$ -test
Agree [n]	12	65	210	287	0,2702
Agree [%]	67%	67%	75%	73%	
Neutral stance [n]	4	12	32	48	
Neutral stance [%]	22%	12%	11%	12%	
Disagree [n]	2	20	37	59	
Disagree [%]	11%	21%	13%	15%	
Total [n]	18	97	279	394	
Total [%]	100%	100%	100%	100%	

Source: Own elaboration

As shown in Table 3, the probability value p is higher than the selected level of significance, $p > \alpha$ (0.05). Therefore, it can be concluded that there is no statistically significant relationship between respondents' level of education and their subjective job satisfaction, as the p-value exceeds the threshold of 0.05.
Although descriptive results indicate that the highest proportion of respondents who expressed subjective job satisfaction can be observed among those with university education, this difference cannot be considered statistically significant. Respondents with upper secondary education with a leaving examination appear to be the least satisfied with their job. In the case of respondents with secondary vocational education without a leaving examination, attitudes toward subjective job satisfaction are relatively balanced, with the majority expressing satisfaction and a smaller proportion reporting dissatisfaction.

Verification of Hypothesis H4
For the verification of the fourth hypothesis, respondents were classified into three educational categories. The analysis aimed to assess whether a statistically significant association exists between the level of educational attainment (secondary vocational education without a leaving examination, upper secondary education with a leaving examination, and university education) and employees' decision to accept a better job.

Table 4: Level of Education and the Decision to Accept a Better Job

Respondents' attitude	Secondary vocational (no leaving exam)	Upper secondary (with leaving exam)	University education	Total	χ2 -test
Yes [n]	7	43	112	162	0,9069
Yes [%]	39%	44%	40%	41%	
No [n]	5	22	77	104	
No [%]	28%	23%	28%	26%	
Undecided [n]	6	32	90	128	
Undecided [%]	33%	33%	32%	32%	
Total [n]	18	97	279	394	
Total [%]	100%	100%	100%	100%	

Source: Own elaboration

As shown in Table 4, the probability value p is higher than the selected level of significance, p (0.9069) > α (0.05). Therefore, it can be concluded that there is no statistically significant relationship between respondents' level of education and their decision to accept a better job, as the p-value exceeds the threshold of 0.05. Across all educational categories (secondary vocational education without a leaving examination, upper secondary education with a leaving examination, and university education), the proportions of respondents who are willing, undecided, or unwilling to accept a better job are approximately equal.

Verification of Hypothesis H5

For the verification of the fifth hypothesis, four categories of respondents' length of work experience were compared. The objective was to determine whether a statistically significant relationship exists between the length of respondents' work experience (< 1 year, 1–2 years, 2–4 years, > 4 years) and their subjective job satisfaction.

Table 5: Respondents' Length of Work Experience and Their Subjective Job Satisfaction

Respondents' attitude	< 1 year	1-2 years	2-4 years	> 4 years	Total	χ2 -test
Agree [n]	26	42	74	144	286	0,0001
Agree [%]	57%	61%	70%	83%	73%	
Neutral stance [n]	11	8	11	18	48	
Neutral stance [%]	24%	12%	10%	10%	12%	
Disagree [n]	9	19	20	12	60	
Disagree [%]	20%	28%	19%	7%	15%	
Total [n]	46	69	105	174	394	
Total [%]	100%	100%	100%	100%	100%	

Source: Own elaboration

As indicated in Table 5, the probability value p is lower than the selected level of significance, p (0.0001) < α (0.05). Therefore, it can be concluded that a statistically significant relationship exists between respondents' length of work experience and their subjective job satisfaction. The significantly highest proportion of satisfied respondents is observed among those with work experience exceeding four years. At the same time, this category includes the lowest proportion of respondents who expressed a negative attitude toward their job satisfaction. Conversely, the lowest level of subjective job satisfaction is found among employees with less than one year of work experience.

Verification of Hypothesis H6

For the verification of the sixth hypothesis, four categories of respondents' length of work experience were compared. The analysis aimed to determine whether a statistically significant relationship exists between respondents' length of work experience (< 1 year, 1–2 years, 2–4 years, > 4 years) and their decision to accept a better job.

Table 6 : Respondents' Length of Work Experience and Their Decision to Accept a Better Job

Respondents' attitude	< 1 year	1-2 years	2-4 years	> 4 years	Total	χ2 -test
Yes [n]	26	42	54	40	162	0,0000
Yes [%]	57%	61%	51%	23%	41%	
No [n]	7	12	20	65	104	
No [%]	15%	17%	19%	37%	26%	
Undecided [n]	13	15	31	69	128	
Undecided [%]	28%	22%	30%	40%	32%	
Total [n]	46	69	105	174	394	
Total [%]	100%	100%	100%	100%	100%	

Source: Own elaboration

As shown in Table 6, the probability value p is lower than the selected level of significance, p (0.0000) < α (0.05). Therefore, it can be concluded that a statistically significant relationship exists between respondents' length of work experience and their decision to accept a better job. The respondents with four or more years of work experience are the least willing and at the same time the most undecided to accept a better job. The highest proportion of respondents willing to accept a better job is observed among those with one to two years of work experience. Among respondents with two to four years of work experience, acceptance of a better job is the most prevalent response, while neutral and negative attitudes are represented at comparable levels.

4. DISCUSSION

The results indicate that a statistically significant relationship exists between respondents' age and their subjective job satisfaction. It was expected that subjective job satisfaction would differ across the examined age categories. Accordingly, three age groups were analyzed (up to 28 years, 29–44 years, and 45–65 years) in order to identify respondents' attitudes toward their subjective job satisfaction. It may therefore be inferred that age represents a factor influencing employees' job satisfaction.

The highest level of subjective job satisfaction was observed among respondents aged 29–44 years, while the lowest level was identified among respondents up to 28 years of age. This youngest group also expressed the highest level of dissatisfaction with their job satisfaction. Contrary to expectations, the highest level of positive job satisfaction was not found among respondents aged 45–65 years. The observed tendencies between the independent variable (respondents' age) and the dependent variable (subjective job satisfaction) thus differ from previous empirical findings.

Ipsirli and Namal (2023) report that younger and older employees tend to experience higher levels of job satisfaction compared to middle-aged individuals. In most studies addressing this issue, job satisfaction follows a U-shaped pattern in relation to age. Younger employees typically report high levels of satisfaction, often attributed to the enthusiasm associated with entering the workforce. As work experience increases, job satisfaction tends to decline among middle-aged employees due to rising expectations and changing perspectives. In later stages of working life, job satisfaction often increases again as personal demands decrease and factors such as reduced mobility in the labor market or awareness of age-related employment barriers become more salient (Ipsirli & Namal, 2023).

Our findings further demonstrate that age significantly influences respondents' decisions to accept a better job. It was assumed that willingness to accept a better job would vary across age categories, which was confirmed. The greatest willingness to accept a better job was observed among respondents up to 28 years of age. Conversely, respondents aged 45–65 years were the most unwilling to accept a better job and most frequently expressed a negative attitude toward such a decision. Among respondents aged 29–44 years, attitudes toward

accepting, rejecting, or being undecided about a better job offer were approximately evenly distributed.
Related findings by Li et al. (2021) suggest that younger employees who have not yet attained leadership positions are more positively influenced by leadership behavior than older employees or those in managerial roles, highlighting the importance of leadership behavior in fostering engagement among early-career employees. Moreover, the relationship between leadership behavior and work engagement is significantly moderated by managerial status, with the influence of leadership behavior increasing when individuals hold leadership positions (Navickas et al., 2023; Piotrowski et al., 2021).
In the next part of the analysis, attention was devoted to the relationship between respondents' level of education (secondary vocational education without a leaving examination, upper secondary education with a leaving examination, and university education) and subjective job satisfaction. Although descriptive results indicate differences in subjective job satisfaction across educational levels, no statistically significant relationship between education level and subjective job satisfaction was confirmed. The highest proportion of respondents reporting positive job satisfaction was found among those with university education, whereas the lowest level of satisfaction was observed among respondents with upper secondary education with a leaving examination. This may be attributed to higher expectations that are not sufficiently met by actual working conditions.
In this context, Clark et al. (as cited in Ipsirli & Namal, 2023; Wall et al, 2022) note that vocational training, qualifications, and work experience can influence job satisfaction in a manner similar to age and gender. It is often assumed that individuals with higher levels of education and experience may exhibit lower job satisfaction due to disproportionately increasing expectations and demands.
The decision to accept a better job was also examined in relation to respondents' level of education. The results indicate that no statistically significant relationship exists between educational attainment and the decision to accept a better job. This finding was unexpected, as it might have been assumed that respondents reporting lower job satisfaction would demonstrate a stronger willingness to accept a better job offer.
Finally, the relationship between subjective job satisfaction and length of work experience (< 1 year, 1–2 years, 2–4 years, > 4 years) was analyzed. The highest proportion of satisfied employees was observed among respondents with more than four years of work experience, while the lowest level of satisfaction was found among employees with less than one year of experience. Additionally, distinct patterns emerged regarding willingness to accept a better job. Respondents with four or more years of work experience were the least willing and most undecided about accepting a better job, whereas the highest willingness to accept a better job was identified among respondents with one to two years of work experience.

CONCLUSION

The results of the questionnaire survey confirm the existence of statistically significantrelationships between selected socio-demographic characteristics of employees and both subjective job satisfaction and willingness to accept a better job. The analysis shows that age and length of work experience represent significant factors influencing employees' work-related attitudes, while the level of education does not demonstrate a statistically significant effect in this context.
A statistically significant relationship was identified between respondents' age and subjective job satisfaction. The highest level of job satisfaction was observed among respondents aged twenty-nine to forty-four years, whereas the lowest level was recorded among respondents up to twenty-eight years of age. Age also significantly influenced respondents' decisions regarding the acceptance of a better job, with younger employees showing the greatest willingness to accept a new job offer and respondents aged forty-five to sixty-five years demonstrating the strongest reluctance to change jobs.
The results further indicate that respondents' level of education is not significantly associated with either subjective job satisfaction or willingness to accept a better job. Although respondents with university education reported a higher proportion of positive job satisfaction, the

differences among educational categories were not statistically significant. Similarly, attitudes toward accepting a better job were distributed relatively evenly across all levels of education.

In contrast, length of work experience was found to be significantly related to both examined variables. Employees with more than four years of work experience reported the highest level of subjective job satisfaction and simultaneously showed the lowest willingness to accept a better job, frequently expressing indecision. Conversely, respondents with shorter work experience - particularly those with one to two years of practice -were more inclined to accept a better job, while respondents with less than one year of experience expressed the lowest level of job satisfaction.

Overall, the findings highlight the importance of age and work experience as key socio-demographic determinants of job satisfaction and job mobility decisions, while educational attainment appears to play a less decisive role.

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READINESS OF PEOPLE IN CITIES TO USE DIGITAL SERVICES IN BUILDING SMART CITIES

Eva GRMANOVÁ

Abstract

People in cities who do not have the opportunity to use established digital services may be disadvantaged. For this reason, the readiness of city residents to implement digital services is important. The aim of our study is to determine the specifics of EU countries in the readiness of city residents to use digital services from the point of view of using the internet for basic activities and from the point of view of basic digital skills in building a smart city. The method used is regression analysis. The Breusch-Godfrey test is used to determine autocorrelation. Romania and Bulgaria are the countries in the EU where the readiness of city residents to implement digital services is the weakest. Expanding digital skills training for employees could contribute not only to the digitalization of the country but also to the building of smart cities.

Key words:
smart city, smart people, internet activities, EU countries

JEL Classification O3, O33 https://doi.org/10.52665/ser2020202

INTRODUCTION

Digital development is currently characteristic for all developed countries in the world. Digital development is one of the key specifics of the present era. It has a great societal impact. It allows for the improvement of services in various areas of the economy. The development of information and communication technologies and artificial intelligence affect economic growth. The proper use of digital technologies can improve the use of various natural resources. At the same time, economies can increase their efficiency and sustainability. From this perspective, it is important to monitor the connection between the use of digital technologies in the development of society and the improvement of the quality of life.

Effective use of digital technologies aimed at economic growth and quality of life is necessary in all regions. However, as stated by the World Bank Group (2024), in 2024 the degree of urbanization of the world is approaching 58%. Due to the large proportion of people living in cities, it is particularly important to monitor the use of digital technologies in the development of cities and the improvement of the quality of life in cities. The topic is also highly relevant from the point of view of demographic development. Most developed countries are addressing the issue of population ageing and reducing workforce. Within the EU, the burden on the working-age population from people of post-productive age is increasing. According to Eurostat (2025), while in 2015 there were 29 people aged 65 and over for every 100 people aged 15 to 64, in 2024 it was 33.9 people. The situation is similar in individual regions. Maintaining the size of the workforce or mitigating its decline in cities can have a positive impact on urban development. Digital development is also important, which can improve the quality of life in cities. According to Marchesani et al. (2026), the connection between the implementation of digital technologies and smart living positively affects the attractiveness of cities.

Another reason for the need to introduce a smart city is the fact that “the exponential development of the cities and increasing number of flows, causes congestion and lowers the level of quality of life in the city” (Kauf, 2019, p. 143). Innovation and new approaches are therefore essential to maintain the quality of life in cities.

Velasquez Mendez et al. (2025) point out that the introduction of digital technologies in building a smart city should be sensitive. The authors emphasize that when introducing digital technologies, there may be a mismatch between the introduction of digital technologies and the preferences of communities. The introduction of some technologies may worsen the quality of life of people, or their implementation may fail due to inefficient management (Mora et al., 2025).

However, the most significant factor influencing the construction of a smart city is people. As stated by the Ministry of Investments, Regional Development and Informatization of the Slovak Republic (2023, p. 21, author's translation), "The success of smart city initiatives with the support of the Internet of Things largely depends on the active participation and approach of citizens." User experiences enable citizens to benefit from new approaches introduced in cities. The introduction of digital technologies in cities in many areas requires individual skills in working with the internet and access to the internet. Without them, the use of many applications could be unrealistic or ineffective.

Similarly, Manville et al. (2014, p. 86) emphasize that “above all, a smart city is a smart Similarly, Manville et al. (2014, p. 86) emphasize that “above all, a smart city is a smart community of people.” It is not possible to build smart cities without a vision, smart people and process (Manville et al., 2014, p.76). According to the authors, the term smart people refer to people with their digital skills, education, training, human resource management, which contribute to innovation and creativity.

A large share of innovation in cities requires that people living in cities have an internet connection and that they have the necessary digital skills. According to the Ministry of Investments, Regional Development and Informatization of the Slovak Republic (2023), smart self-government is becoming very necessary in cities, which affects several areas. Its implementation requires that citizens have the necessary digital skills. To do this, it is necessary to increase digital equality through educational opportunities (Shen et al., 2025).

The aim of the study is to determine the specifics of EU countries in the readiness of urban residents to use digital services in building a smart city from the perspective of using the internet for basic activities and from the perspective of basic digital skills. The intention is to point out which EU countries can be considered, from the above perspectives, as countries with the weakest readiness of their residents. Part of the output of the study is to determine the approaches that are important from the perspective of urban residents' readiness to use digital services and building a smart city

1. LITERATURE OVERVIEW

As stated by Ziosi et al. (2022), there are several concepts of smart cities that characterize smart cities from different perspectives. Several authors, when defining the term smart cities, focus mainly on specifying important dimensions. According to Ulya (2024, p. 1001), the dimensions used by various authors when characterizing smart cities can be divided into six categories: 1/ smart economy, 2/ smart people, 3/smart environment, 4/ smart governance, 5/ smart living and 6/ smart branding. These categories are also called main dimensions (Ziosi et al., 2022). Manville et al. (2014) and Kumar (2020) list the following dimensions when mapping smart cities: 1/ smart economy, 2/ smart mobility 3/smart environment, 4/ smart people, 5/ smart living, 6/ smart governance. The main difference in both characteristics is in one dimension. The approach of Manville et al. (2014) emphasizes mobility. The approach of Ziosi et al. (2022) emphasizes branding.

Smart city concepts have several common characteristics. One of them is that smart cities are about development and improvement (Guenduez & Mergel, 2022). Most smart city characteristics contain words such as “optimization, improvement, enhancement, or development” (Guenduez & Mergel, 2022, p. 2). Another fact is that smart cities use advanced digital technologies in various areas. Ulya et al. (2024) citing Achmad et al. (2018) state that the use of ICT is the main idea of the smart city concept.

As already mentioned, there are different approaches to defining the term smart cities. We consider the statement given by Manville et al. (2014, p. 18) “the idea of Smart Cities is rooted in the creation and connection of human capital, social capital and information and Communication technology (ICT) infrastructure in order to generate greater and more sustainable economic development and a better quality of life" to be a concise characteristic. The characteristic emphasizes the connection of the three basic types of capital with information and communication technologies with the aim of achieving sustainable development and improving the quality of life.

Digital technologies in building a smart city focus on optimized resource use, improving public services, increasing city resilience and improving the quality of life (Kaiser & Deb, 2025 citing Kaiser, 2024).

Based on the above, it follows that smart cities and quality of life are interconnected. Purnomo et al. (2016) state that smart living contributes to improving the quality of life with its approaches. This primarily concerns the provision of healthcare, quality housing, cultural activities and social cohesion. According to Purnomo et al. (2016), the most common indicators of smart living are indicators characterizing healthcare services, social security and safety, housing quality and public transportation system. People are the most important in innovations in these areas. The economic, social, cultural and technological performance of cities should serve the interests of city residents (Kourtit & Nijkamp, 2012).

People must have the necessary skills and must take the initiative to use innovative approaches. Smart people, according to Purnomo et al. (2016), build human capital and social cohesion. They use lifelong learning, participate in public life, use creativity and flexibility. The most common indicators of smart people are indicators characterizing the education system, facilities and creativity.

Based on the above, it follows that the basis for the use of new technologies in cities, which enable their application in the economic growth of cities and in increasing the quality of life in cities, are the skills of people living in cities. Part of the digital readiness of managers within public administration in cities are their information and digital skills. Digital management is currently becoming the basis for improving the performance of the public sector in cities through the integration of technologies (Aldhi et al., 2025). The motives for implementing smart cities are increasing the efficiency of public administration, increasing the quality of services to residents and visitors to cities, and increasing the quality of life (Kubišová, 2022). Local governments play an important role in building smart cities. Their approaches to building smart cities are often similar. De Oliveira et al. (2024) citing Chien (2008, 274) state that local governments often tend to implement similar policies in pursuit of economic growth.

Building a smart city concept promotes innovation, increases competitiveness and sustainability of development (Lin & Zheng, 2025). Cooperation with city residents and obtaining feedback from city residents in improving the quality of life becomes important in implementing effective smart city solutions (Esposito et al., 2025).

"According to the EU's Digital Decade objectives, all key public services for businesses and citizens should be fully online by 2030" (Eurostat, 2025d). Readiness is essential to achieve this goal and to make effective use of digital technologies. According to Aldhi et al. (2025), readiness is important at both the individual and organisational levels.

However, the development of smart cities also brings concerns. These are mainly related to the fact that advanced technologies will not be suitable for all citizens. The disadvantage of disadvantaged groups may increase. Disadvantaged groups, such as people on low incomes who do not have access to smart devices, will not have access to smart services (Shen et al., 2025). Limited internet access, limited access to smart devices and low digital skills can widen the digital divide and make it difficult to take advantage of digital services.

Among the important skills at the individual level are people's access to the internet in the city and their use of the internet. According to Eurostat (2025g), the number of households with internet access is growing and approaching saturation. The share of households with internet access in cities was highest in Luxembourg (99.9%) in 2023. The Netherlands was second (99.0%) (Eurostat, 2025g). From the above facts, it can be concluded that households in cities have the possibility to connect to the internet. However, whether their current situation and knowledge allow them to do so is a different question. According to Hernandez and Faith (2023), people with low education may have low digital skills and use the internet less. According to Eurostat (2025i), there was a significant difference in the level of basic digital skills between people with low formal education and high formal education in Ireland, Greece and Malta.

Other groups of people who use the internet to a lesser extent are economically inactive people and people who have not worked in the last four weeks or have not been able to start working within two weeks. These groups of people may have difficulties using digital services and accessing the internet in cities. Access to the internet at home is particularly important, as internet access at employers may have various restrictions.

The study consists of the following sections. The literature review is followed by a section describing the aim and objectives of the work. It also includes an overview of the methods used. This is followed by a section in which the results and discussion are formulated. At the same time, this section contains the limitations of our research. The main approaches are summarized at the end of the study.

2. GOAL AND METHODOLOGY

As part of building a smart city, cities focus on expanding digital services. A group of residents who do not have the opportunity to use established digital services in cities may be disadvantaged. Therefore, in the digitalization of services in cities, residents' access to the internet and their digital skills are important aspects in terms of urban population readiness

It is obvious that people in cities in individual EU countries differ in their readiness to use digital services, and therefore also to promote the concept of a smart city. We assess the readiness of city residents from two perspectives:

1/ from the perspective of the share of people who can use the internet for basic activities, 2/ from the perspective of acquiring basic digital skills.

The aim of our study is to determine, based on the analysis, the specifics of EU countries in the readiness of city residents to use digital services when building a smart city from the perspective of using the internet for basic activities and from the perspective of basic digital skills. Our intention is to point out which EU countries we consider to have the weakest population readiness from the above-mentioned perspectives Building smart cities can be challenging in these countries and measures need to be taken to improve the readiness of city dwellers to adopt digital services. We will also aim to gain insights into which approaches are important in terms of urban readiness.

Our aim is to highlight the importance of urban readiness in individual EU countries and to promote the smart city concept. The disadvantage of some city dwellers could be further increased by the introduction of digital services.

The period analysed is 2014 to 2024. We are aware of the short time series. We have chosen the length of the time series from a year from which data are available for all EU countries.

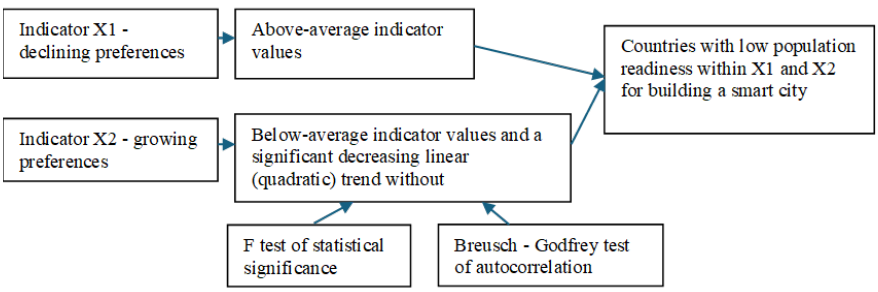


Figure 1: Conceptual model

As an indicator of internet use we chose the indicator Percentage of individuals who used internet in the last 3 months. Individuals living in cities. Internet use: sending/receiving e-mails (Eurostat, 2025a). The values of the indicator are obtained from the EU survey.

According to Eurostat (2025c) “The survey population of individuals consists of all individuals aged 16 to 74”.

As an indicator assessing digital skills we chose an indicator with negative preferences, namely ignorance of digital skills “Individuals living in cities. Individuals with no overall digital skills” (Eurostat, 2025b). The activities used to calculate skills are “Finding information about goods or services (IUIF); Seeking health-related information (IHIF); Reading online news sites, newspapers or news magazines (IUNW1); Activities related to fact-checking online information and its sources (TICCSFOI, TICIDIS, TICNIDIS, TICXND)” (Eurostat, 2025e). According to Eurostat (2025h), by 2030, up to 80% of the population should have at least basic digital skills.

The results of the study will include, in addition to the findings obtained from the analysis of indicators, an assessment of approaches that are important from the perspective of the readiness of city residents to implement digital services in building a smart city.

To achieve the goal, we used secondary data from the Eurostat database (2025a, 2025b).

The analysis will include the answer to the following research questions:

1/ Which countries lag behind others in digital skills?

2/ Which countries lag behind others in internet use in cities?

3/ In which countries is there a negative trend in the development of internet use in cities?

4/ What measures can be introduced for lagging countries and countries with an unsatisfactory trend of the indicator? The conceptual model is in Figure 1.

Regression analysis, model quality verification

Regression analysis was used to achieve the goal. It included verification of the quality of the model. We used regression analysis to express the trend of the time series of the indicator in individual EU countries.

$$y_t = b_0 + b_1 t + e_t,\ t = 1, 2, \dots, T. \qquad (1)$$

We verified the statistical significance of the model with an F-test.

If the linear trend was not statistically significant, we determined the statistical significance of the quadratic trend.

$$y_t = b_0 + b_1 t + b_2 t^2 + e_t,\ t = 1, 2, \dots, T, \qquad (2)$$

where t is the time variable. T is the number of periods, e_t represents the error.

Breusch-Godfrey test

Bűrger (2023) points out that estimating the trend of a time series in which there is autocorrelation is difficult. ”If ρ > 0, ordinary least squares (OLS) estimate of β no longer have a known distribution, so that assertions about trend significance are not possible” (Bűrger, 2023, 1). For this reason, we also focused on verifying autocorrelation in the time series. In the case of statistical significance of the linear model, we determined the autocorrelation of the residuals using the Breusch-Godfrey test. We determined the autocorrelations of the first, second, third and fourth orders.

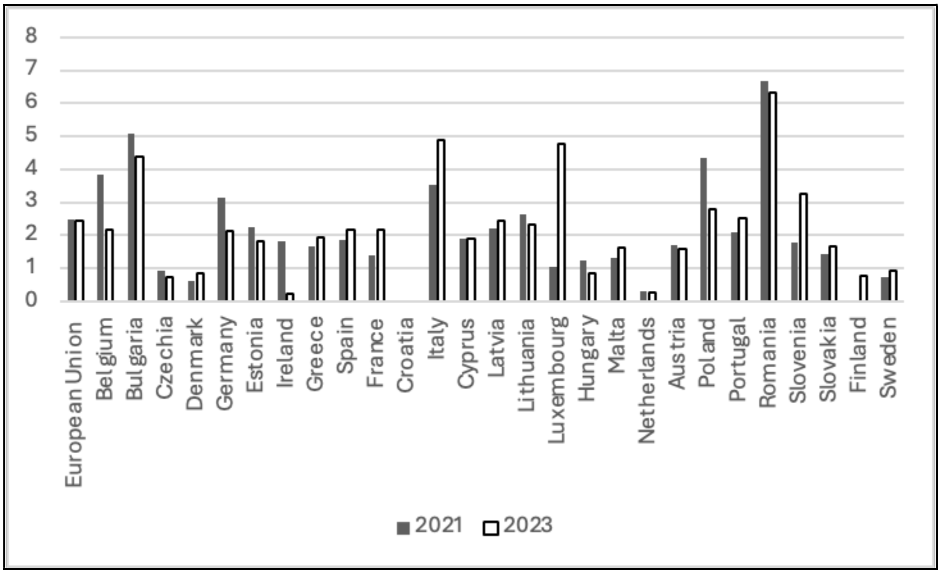
3. FINDINGS AND DISCUSSION

3.1 Individuals with no overall digital skills

The indicator characterizing the share of individuals living in a city without overall digital skills / percentage of individuals allows for the alignment of the country based on the digital skills of residents living in cities. It has decreasing preferences. That is, the higher its value, the more unfavourable its development.

The values of the indicator allow for assessing what share of the city population in the country is not ready to use digital technologies. Data are available for 2021 and 2023.

Figure 2: Individuals with no overall digital skills



Source: Eurostat (2025b)

As Figure 2 shows, the highest values of the indicator were in Romania in both periods. In 2023, there was a slight decrease in the indicator, but the values were still among the maximum. In 2021, Bulgaria was second. In 2023, the indicator value in Bulgaria decreased slightly. However, the indicator value was still among the first four maximums. Luxembourg has a specific position among EU countries. It is among the states with the largest increase in the indicator values between 2021 and 2023. In 2023, it was even the third with the highest value. This means that the share of people who did not have digital skills increased significantly. One reason could be the large number of immigrants in Luxembourg. Immigrants are concentrated mainly in cities, due to job opportunities. According to Eurostat (2025f), more than 50% of immigrants live in Luxembourg. In 2023, the share of immigrants from outside the EU was more than 18% of the total population.

The group of countries with above-average values of the indicator in both years consists of: Bulgaria, Italy, Poland and Romania. In 2021, Belgium, Germany and Lithuania had values above the average. In 2023, Luxembourg, Latvia, Portugal and Slovenia also had values significantly above the average. The lowest values were in Croatia. In 2021, Finland and the Netherlands also had low values.

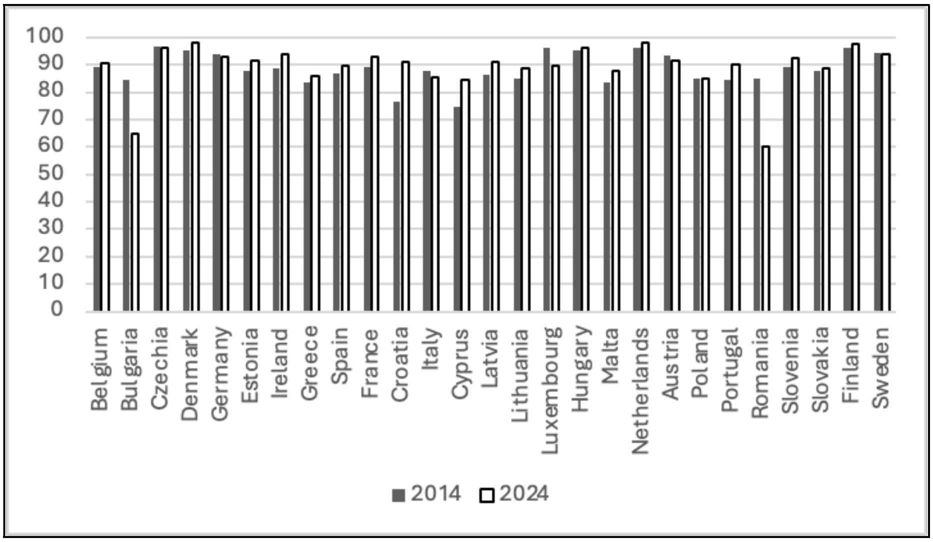
3.2 Percentage of individuals who used internet in the last 3 months. Individuals living in cities

The indicator, Percentage of individuals who have used the internet in the last 3 months - individuals living in cities, has a growing preference. That is, the higher its value, the more favourable its development. The values of the indicator allow us to assess what proportion of the city population in the country uses the internet for basic activities.

We focused on comparing countries and assessing trends. Based on the trend, we can divide EU countries into three groups: countries with a growing trend of the indicator, countries with a decreasing trend of the indicator and

countries here neither a growing nor a decreasing trend.
The first three countries with the highest value of the indicator in 2014 were the Czech Republic, Finland and the Netherlands. On the contrary, the countries with the lowest values of the indicators were Cyprus, Croatia and Malta. In 2024, the Netherlands, Denmark and Finland had the highest value of the indicator. The countries with the lowest values were Romania, Bulgaria and Cyprus. In addition to these three countries, Greece, Italy, Lithuania, Malta, Poland and Slovakia had below-average values at the beginning and end of the period. The values of the indicator in 2014 and 2024 are shown in Figure 3.

Figure 3: Percentage of individuals who used internet in the last 3 months. Individuals living in cities



Source: Eurostat (2025a)

Based on the indicator values, we expressed the linear trend of the indicator in each EU country. We verified the statistical significance of the models. We then checked whether there was first, second, third and fourth order autocorrelation. A positive statistically significant linear trend of the indicator was in eight countries. These are countries where the share of individuals who used the internet in the last 3 months in the city has been growing in the long term. They are listed in Table 1. Among these countries, the Netherlands has a specific position. Not only is the indicator value among the top three countries with the highest values, but the linear trend of the time series has been growing and reaching a maximum in 2024. If the current trend of the indicator were to be maintained, the value in the Netherlands would approach saturation in approximately nine years. The Netherlands therefore significantly exceeds the EU average in basic digital skills and in ICT specialists. “The Netherlands has long been a leader in digital innovation thanks to its strong research base” (European Union, data not specified, a). Building a strong research base focused on innovation currently appears to be a positive step in the Netherlands. The country can be an example for other EU countries.

Table 1: Positive linear trend and Breusch-Godfrey test of Autocorrelation

	C	RC	CD	BGT
France	87.6555***	0.5223***	69.1%	0.178
Croatia	80.1353***	0.9897***	52.6%	0.207
Portugal	83.3913***	0.7583***	85.4%	0.846
Estonia	89.6931***	0.3305**	33.2%	0.286
Ireland	86.4782***	0.5750***	50.2%	0.748
Spain	83.1851	0.4631**	41.3%	0.191
Latvia	84.6893***	0.4544**	42.4%	0.241
Netherlands	**96.192*** **	**0.1857*** **	**72.9%**	**0.163**

Source: own processing according to Eurostat (2025a)

C - constant, RC - regression coefficient, CD - coefficient of determination, BGT- Breusch-Godfrey test of Autocorrelation, LMF, first-order, p-level

Italy has a specific position within the EU, which has a statistically significant quadratic trend. Since 2017, the trend in Italy has been increasing.

A negative statistically significant linear trend of the indicator is in four countries. Of these, two countries have above-average indicator values and two countries have below-average indicator values. These were Bulgaria and Romania.

Graphical representations of developments in countries with a linear statistically significant downward trend are in Figure 4. Parameter estimates are in Table 2.

Table 2: Negative linear trend and Breusch-Godfrey test of Autocorrelation

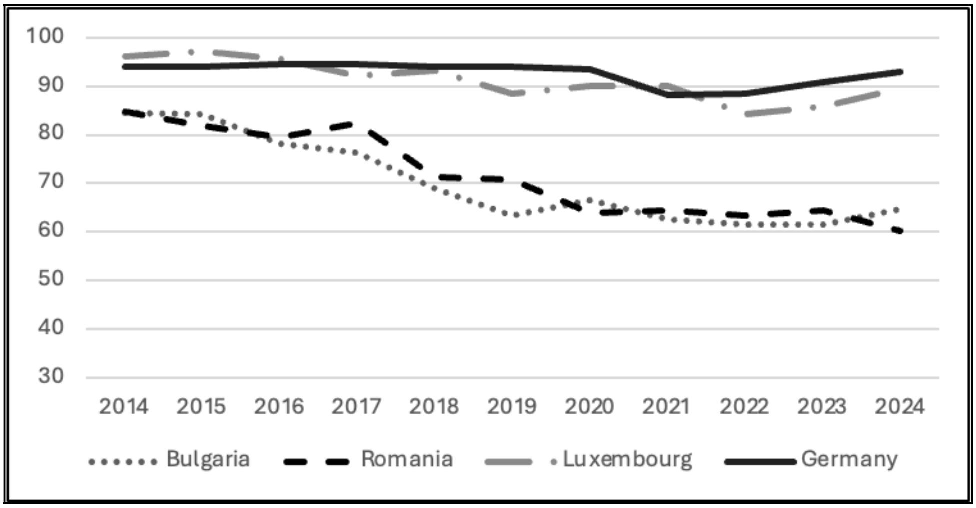
	C	RC	CD	BGT
Bulgaria	84.9184 ***	−2.44518***	80.4%	0.119
Luxembourg	97.7498***	-1.0880***	71.5%	0.475
Romania	87.0796	-2.59282***	88.6%	0.888
Germany	95.3047	-0.4438**	32.0%	0.298

Source: own processing according to Eurostat (2025a)

C - constant, RC - regression coefficient, CD - coefficient of determination, BGT- Breusch-Godfrey test of Autocorrelation, LMF, first-order, p-level

Bulgaria and Romania are also among the countries with above-average values of the indicator Individuals with no overall digital skills (in cities). Based on our criteria, we consider these two countries to be the countries within the EU where the readiness of urban residents to implement digital services is the weakest. It is important that changes occur in both countries that would lead to a reversal in trends.

Figure 4: Negative linear trend of the indicator



Source: Eurostat (2025a)

The lack of readiness of citizens to use digital services in Bulgaria and Romania when building smart cities may have several reasons. According to the European Union (2024a), which refers to the National Statistical Institute (2023), only 9.1% of enterprises in Bulgaria provide their employees with ICT training. The implementation of digitalization in small and medium-sized enterprises in Bulgaria is stagnating. The share of ICT specialists is below the EU average. At the same time, according to the European Union (data not specified, b), Bulgaria lags behind in research and development.

The share of ICT specialists in Romania is lower than average. According to the European Union (2024b), the number of ICT specialists in Romania was below the EU average in 2023 and decreased further in 2024. Digitalization in Romania is at a low level. Digital public services are also not widely used. At the same time, there are frequent changes of government in the country. This makes the situation even worse.

Both countries are characterized by a below-average share of ICT specialists. At the same time, training focused on digital skills for employees in enterprises is not widespread. In both countries, there are frequent changes of government. Political instability worsens the situation in the country. Improving political stability would contribute to improving Bulgaria and Romania in the development of digitalization and in the readiness of the population in cities for the introduction of digital services. In both countries, improving research and development would be a great positive.

Why is the situation more positive in the Slovak Republic? We consider the growing share of young people with digital skills and the increasing share of ICT specialists (European Union, data not specified, c) to be positive. It is important for the Slovak Republic to maintain the growing trend in both above indicators. Research and development also need to be improved. The political stability of the country is also important for further positive development.

Our study has several limitations. The first limitation is the disadvantage of the internet usage indicator. Hernandez and Faith (2023) state that during the Covid pandemic, it turned out that the databases on internet users in Eurostat databases did not fully reflect people's ability to use the internet connection. Users who are below certain thresholds (for example, in terms of frequency of use) are also included in the group of "internet users". The authors point out the need to supplement the published data with, for example, new categories. However, Eurostat databases are currently the most comprehensive databases allowing for comparison of internet usage in EU cities. The second limitation is the use of secondary data. Obtaining primary data from all EU countries using the same methodology would be very demanding in terms of financial resources and time. The secondary data used come from a trusted source. Therefore, we consider their use to be correct.

In further ongoing research, it is important to monitor groups of residents in cities who may be disadvantaged in using digital services. These are mostly disadvantaged groups, whose further disadvantage could be further exacerbated. At the same time, we consider it important to monitor progress in digitalization in all EU countries in connection with building a smart city. After all, building a smart city is not possible without the development of digitalization.

CONCLUSION

People in cities who do not have the opportunity to use established digital services are disadvantaged. Therefore, access to the internet by city dwellers is important in the digitalisation of services in cities, and the digital skills of city dwellers are important.

The aim of our study was to determine, based on an analysis, the specificities of EU countries in the readiness of city dwellers to use digital services when building a smart city in terms of using the internet for basic activities and in terms of basic digital skills.

The aim of the study was to point out which EU countries have the weakest readiness of city dwellers, based on selected perspectives. Building smart cities can be more challenging in these countries, and taking measures to improve the readiness of city dwellers to introduce digital services is most urgent within the EU. At the same time, we tried to obtain findings on approaches that are important in terms of the readiness of city dwellers to use digital services.

We used the following indicators in the analysis: 1/ Percentage of individuals who used internet in the last 3 months. Individuals living in cities. Internet use: sending/receiving e-mails, 2/ Individuals living in cities. Individuals with no overall digital skills.

The analysis included the following research questions: Which countries lag behind others in digital skills? Which countries lag behind others in internet use in cities? In which countries does the indicator have a negative trend? What measures can be implemented in lagging countries or in countries with an unsatisfactory trend of the indicator?

In the study, we focused on comparing countries and analyzing the trend of the indicator characterizing internet use. We used regression analysis and verified the quality of the model. We used the Breusch-Godfrey test to determine autocorrelation.

Based on our criteria, we consider Romania and Bulgaria to be the countries within the EU where the readiness of urban residents to implement digital services is the weakest. It is important that changes occur in both countries that would lead to a turnaround in development. Both countries are characterized by a below-average share of ICT specialists. Both countries experience frequent changes of government. Political instability worsens the situation in the country. Improving political stability would contribute to Bulgaria and Romania's progress in digitalisation and the readiness of urban populations to adopt digital services. In both countries, improving training in digitalisation and improving research and development would be key positives.

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ENGLISH COURSE DESIGN FOR UNDERGRADUATE STUDENTS IN MANAGEMENT IN TOURISM PROGRAMME OF STUDY AT A. DUBČEK UNIVERSITY IN SLOVAKIA: BRIDGING THE B1-B2 PROFICIENCY GAP

Monika GULLEROVÁ

Abstract

The paper proposes a specialized English for Specific Purposes (ESP) curriculum for students in the Management in Tourism programme at Alexander Dubček University of Trenčín. The need arises from a mismatch between students' incoming CEFR B1 proficiency and the B2–C1 linguistic requirements of tourism management positions aligned with SKKR level 6. The review of literature identified major pedagogical innovations including task-based language teaching, corpus-informed vocabulary instruction, gamification, and virtual reality simulations. Using target-situation analysis of programme documents, the study outlines a two-year course titled Strategic Communication and Management in Tourism. Four thematic modules address HR communication, digital storytelling, sustainable tourism discourse, and intercultural crisis management. The blended-learning format includes Moodle, VR and mobile applications to increase engagement and reduce speaking anxiety. The course integrates Green Tourism lexical bundles absent from current ESP textbooks. Findings demonstrate that performance-based simulation tasks foster communicative self-efficacy and bridge the B1–B2 proficiency gap. The proposed curriculum represents an evidence-based response to post-2020 digitalization and sustainability demand in the tourism sector.

Key words:
Management in Tourism, English for Special Purposes, Task-Based Language Teaching, Blended Learning, Virtual Reality, Green Tourism vocabulary, Intercultural Communicative Competence

JEL Classification I23, I25, Z32, M53, J24 https://doi.org/10.52665/ser20250203

INTRODUCTION

The contemporary tourism industry operates within a globalized context in which English is not simply a professional competence, but a core component of its operational infrastructure. For higher education institutions in non-English-speaking countries, this situation requires a pedagogical transition from General English toward more highly specialized forms of English for Specific Purposes (ESP). The paper examines this imperative within the institutional context of Alexander Dubček University of Trenčín, Faculty of Social and Economic Relations, with particular focus on the undergraduate Management in Tourism programme of study. The current job market requires that graduates in tourism management programmes possess more than basic transactional language skills; they require the linguistic agility to handle difficult management situations, evaluate socio-economic patterns and trends, and implement sustainable development strategies. According to the study programme's profile, graduates are expected to fill middle and top management positions such as Tourist Information Centre Managers, Tourism Quality Managers, and Process Optimisation Specialists (TnUAD, 2025). These roles are in line with the Slovak Qualifications Framework (SKKR) level 6, requiring a high degree of autonomy and communicative competence. However, entering students often display a proficiency level at CEFR B1, which is insufficient for the nuance required in professional negotiation, crisis management, and strategic planning (Council of Europe, 2020). Moreover, the tourism sector in the post-2020 period has been profoundly transformed by the digitalization of destination management and the pressing sustainability demand. Recent research indicates that traditional ESP curricula often fail to adequately address these emerging sectors, leaving graduates with a "lexical gap" regarding green tourism and digital marketing strategies (Veerachaisantikul et al., 2025; Oktavianti et al., 2025). Additionally, the psychological dimension of language use, especially Communication Self-Efficacy (CSE) and Intercultural Communicative Competence (ICC), has been identified as a stronger predictor of service performance than grammatical accuracy alone (Rachim & Salam, 2025). The paper proposes a design for a specialized ESP course with a title "Strategic Communication and Management in Tourism" (SCMT). The design is based on a systematic review of the latest Scopus and Web of Science literature, ensuring that the pedagogical strategies employed, from Task-Based Language Teaching (TBLT) to Virtual Reality (VR) simulations, are evidence-based and in line with recent industry standards. The main goal is to facilitate a structured and systematic progression from B1 to B2 proficiency, equipping students with the professional competencies necessary to thrive in the modern tourism economy.

1. LITERATURE OVERVIEW

A literature review was to identify effective pedagogical interventions in ESP for tourism. The review was focused on key notions such as "ESP tourism curriculum," "Task-Based Language Teaching," "Intercultural Communicative Competence," "Green Tourism vocabulary," and "Gamification in higher education." The review synthesized findings on linguistic needs, specifically the gap between general English and the specific lexical bundles required for sustainable tourism (Oktavianti et al., 2025), technological interventions regarding the efficacy of virtual reality (VR) in reducing physiological stress during English speaking tasks (Takada et al., 2023) and the role of gamification in maintaining motivation (Shortt et al., 2021), and pedagogical frameworks focusing on the shift from presentation-practice-production (PPP) to task-based language teaching (TBLT) as the superior method for professional fluency (Purwanto et al., 2024).

This methodological triangulation guarantees that the proposed course extends beyond a purely theoretical construct, constituting a methodologically sound solution reflecting both the specific TnUAD context and the global standards of the tourism industry.

2. GOAL AND METHODOLOGY

The primary goal of the paper is to design a comprehensive, needs-based English for Specific Purposes (ESP) curriculum tailored for undergraduate students in the Management in Tourism programme of study at Alexander Dubček University of Trenčín, Faculty of Social and Economic Relations. The primary pedagogical objective is to advance students' proficiency from CEFR level B1 to B2, while ensuring the development of both linguistic competence and the pragmatic strategies necessary for effective performance in managerial positions. Partial objectives include: to design tasks that transition students from concrete, descriptive language (B1) to abstract, argumentative, and strategic discourse (B2), to integrate corpus-informed vocabulary related to Green Tourism and Digital Storytelling, addressing gaps in current coursebooks, and to propose a blended learning model utilizing Moodle and Virtual Reality (VR) to increase engagement and reduce anxiety in foreign language. A multi-layered methodological framework was used to design the course using the target situation analysis (TSA) based on the relevant literature. An analysis of the specific study programme documents and graduate profiles of the Faculty of Social and Economic Relations at TnUAD was conducted, including reviewing the Management in Tourism accreditation documents and study plans to identify the specific hard skills that the English course must support (TnUAD, 2025). The analysis confirmed that graduates are expected to perform high-level tasks, such as creating concepts for the promotion of tourism and managing regional tourism organizations, which require B2+ competency (TnUAD, 2025).

3. FINDINGS

The analysis of the requirements of the Management in Tourism programme of study, combined with the relevant literature review, resulted in the development of a clearly defined course design. The proposed course titled Strategic Communication and Management in Tourism is designed as a two-semester compulsory module, replacing or augmenting existing General English provisions. The target situation analysis showed a significant discrepancy between the B1 skills typically held by incoming students and the B2/C1 demands of the target jobs, such as for instance Tourism Quality Manager. At current B1 level, students can maintain interaction and get across what they want to, in a range of contexts. They can cope flexibly with problems in everyday life, e.g. public transport, standard hotel check-in (Council of Europe, 2020). In the target level of B2, students must understand the main ideas of complex text on both concrete and abstract topics, including technical discussions in their field of study. They must interact with a degree of fluency and spontaneity that makes regular interaction with native speakers quite possible without strain (Council of Europe, 2020).

Table 1: Competency Gap and Curricular Solutions

Target Job Role (TnUAD Profile)	Required Competency (SKKR 6/7)	Linguistic Gap (B1 to B2)	Proposed Curricular Module
Tourist Information Centre Manager	Managing staff, handling complex complaints, interpreting regional data.	B1 students lack diplomatic language for conflict resolution and specific HR vocabulary.	Module 1: HR and Management (Role-play: Hiring and Firing)
Marketing Manager	Promoting destinations, creating digital content, managing social media crises.	B1 students struggle with persuasive writing, nuancing "toxicity" in reviews, and narrative flow.	Module 2: Digital Storytelling/ Marketing
Process Optimisation Specialist	Analysing workflows, implementing sustainable practices, reporting.	Lack of specialized "Green Tourism" vocabulary, such as for instance carbon footprint, ethical sourcing.	Module 3: Sustainability/Green Ethics
Front Office Manager	Operational crisis management (overbooking, health emergencies).	High anxiety in spontaneous speaking; inability to use conditionals for negotiation.	Module 4: Operational Crisis Simulation (VR)

Source: TnUAD. (2025). *Study Programmes: Management in Tourism*. Faculty of Social and Economic Relations, Alexander Dubček University of Trenčín.

The syllabus is structured around thematic modules using a Task-Based Language Teaching (TBLT) framework. In TBLT, the task is the primary unit of instruction, and language form is analysed retrospectively (Purwanto et al., 2024).

Module 1: The Modern Tourism Manager (week 1-4)

Learning objective: To develop the linguistic skills necessary for Human Resource Management and professional self-presentation.

Input materials: Authentic job advertisements for Tourism Quality Managers and Destination Specialists; video interviews with industry leaders.

Language Focus: Action verbs for CVs; behavioural interview questions; language of evaluation and assessment.

Core Task: The Recruitment Simulation. Students work in groups. Group A writes a job description and interview protocol for a managerial position. Group B prepares CVs and cover letters. Then, they conduct live interviews.

Assessment: Portfolio submission of the CV/Cover Letter and a reflective report on the interview performance.

Module 2: Destination Management through Digital Storytelling (weeks 5-8)

Learning objective: To master persuasive language and digital literacy for destination marketing.

Input Materials: Analysis of successful travel blogs, Instagram reels, and promotional videos.

Language Focus: Adjectives of degree; narrative tenses for storytelling; evaluative language; toxicity analysis in social media comments (Almeida & Pereira, 2024).

Core Task: The "Hidden Gem" Campaign, utilizing the "Shutterbug" method (Fonseca et al., 2024), students take original photographs of a local Slovak destination. They are to create a digital narrative, such as video or blog post, promoting this destination to an international audience, focusing on unique selling points.

Assessment: Presentation of the digital campaign; peer review of the narrative structure.

Module 3: Sustainable Tourism and Green Ethics (weeks 9-12)

Learning objective: To equip students with the specialized vocabulary of environmental sustainability and corporate social responsibility (CSR).

Input Materials: UN Sustainable Development Goals (SDGs); Green Tourism certification criteria; corpus-based word lists featuring collocations such as sustainable consumption, community-based tourism, and eco-friendly infrastructure (Oktavianti et al., 2025).

Language Focus: Cause and effect (connectors); speculating about the future (future continuous/perfect); corpus-informed lexical bundles.

Core Task: The Green Audit. Students are given a case study of a non-sustainable hotel. They must audit the hotel against Green Tourism criteria and present a Transition Strategy Proposal to a board of investors.

Assessment: Written proposal and oral defence of the strategy.

Module 4: Intercultural Crisis Management (2nd year of study)

Learning objective: To develop Intercultural Communicative Competence and crisis resolution skills.

Input Materials: Critical incidents involving cultural misunderstandings; case studies of service failures.

Language Focus: Diplomatic language (modals of politeness); passive voice for depersonalizing conflict; conditionals for negotiation.

Core Task: The VR Crisis Simulation. Using Virtual Reality tools, students face high-pressure scenarios, such as a guest refusing to pay due to cultural offense, a medical emergency, or a double-booking.

Assessment: Real-time performance assessment based on a rubric evaluating linguistic accuracy, empathy, and strategic resolution (Takada et al., 2023).

To support learners of 21st-century, the course utilizes a Blended Learning environment (Liu et al., 2024), such as Moodle platform, gamification and virtual reality. Moodle Platform shall be used for asynchronous delivery of reading materials, grammar drills, and peer-review forums dedicated to communicative tasks. Next, implementation of game mechanics, such as leaderboards, badges for "vocabulary master" are utilized to enhance motivation. Apps like Duolingo or Quizizz are integrated for spaced repetition of terminology (Shortt et al., 2021).

4. DISCUSSION

The proposed English course for undergraduate students in Management in Tourism programme of study is designed to move beyond the intermediate level with task-based language teaching. The transition from B1 to B2 is often the most difficult for students, characterized by a plateau where progress slows. Traditional methods that focus on grammar rules often fail to provide the procedural knowledge required for spontaneous fluency. By adopting task-based language teaching, this course aligns with findings by Purwanto et al. (2024), who demonstrated that TBLT in hospitality training significantly improves speaking confidence because the focus shifts from avoiding mistakes to completing the job. The course design also has the component of intercultural communicative competence since globalization has made it a non-negotiable skill for tourism managers. A major innovative component of this course is the integration of a Corpus-Informed Green Tourism Module. Recent bibliometric analyses and corpus studies (Oktavianti et al., 2025; Veerachaisantikul et al., 2025) highlight that general tourism textbooks often lack the specific collocations required to discuss sustainability. By utilizing a Green Tourism vocabulary list generated from authentic industry texts, the course ensures students are learning the language of the future economy. This directly supports the FSEV's mission to prepare graduates for the national economy and public sector, where sustainable development is a policy priority. In addition, the inclusion of Digital Storytelling and VR addresses the affective dimension of learning. Almeida and Pereira (2024) found that learner-generated content (photography and storytelling) significantly boosts engagement by making the learning personal and creative. Furthermore, Takada et al. (2023) provided physiological evidence, such as monitoring brain hemoglobine and heart rates that VR training reduces the anxiety associated with speaking English in high-pressure hospitality scenarios. For students at A. Dubcek University of Trenčín, who may lack opportunities for real-world immersion, VR provides a safe proxy for experience, lowering the affective filter and building the confidence or self-efficacy necessary for B2 performance. With the sound theoretical framework, implementation at FSEV, TnUAD requires addressing practical issues. The Administration in Tourism in Management programme of study must ensure that English teachers are coordinated with the core departments to ensure the ESP tasks reflect the content being taught in Slovak. Thus, the content and language integrated learning synergy would maximize the relevance of the course.

CONCLUSION

The proposed course titled Strategic Communication and Management in Tourism, responds directly to the documented gap between students' incoming B1 proficiency and the B2/C1 communicative demands embedded in SKKR level 6 professional roles. By grounding its structure in target situation analysis and aligning its learning tasks with real managerial communication scenarios, the course shifts ESP instruction away from general linguistic knowledge toward professional communicative competence. The findings confirm that traditional grammar-focused ESP courses lack the lexical depth, pragmatic flexibility, and intercultural sensitivity demanded by the post-2020 tourism landscape, particularly in the domains of sustainability and digital destination management. The modular design presented in this paper addresses these deficits through a principled integration of task-based language teaching, corpus-informed vocabulary instruction, digital storytelling, and Virtual Reality simulations. These strategies support not only linguistic development, but also learner agency, communication self-efficacy, and intercultural communicative competence, which all are the factors increasingly correlated with workplace performance. The proposed blended learning environment, incorporating Moodle-mediated asynchronous tasks and gamification elements, further strengthens the learning experience by enabling personalized practice and encouraging autonomous vocabulary development. Successful implementation will require adequate technical resources and teacher training, along with ongoing coordination between language and content instructors to ensure cross-curricular coherence. To summarize, the course design presented in the paper establishes a systematic pathway for developing the communicative and strategic competencies required of future managers in tourism. It seeks to equip graduates not merely to participate in professional discourse, but to make informed, ethical, and responsive managerial decisions in an evolving global tourism industry. Future research should focus on piloting the course, evaluating learning outcomes longitudinally, and further refining the integration of VR and corpus-based materials, thereby contributing to evidence-based ESP pedagogy for tourism and related fields.

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THE USE OF INTELLIGENT TECHNOLOGIES IN HUMAN RESOURCE MANAGEMENT AND THEIR RELATIONSHIP WITH HRM FUNCTIONS

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Abstract

The digitalization and development of intelligent technologies increasingly affect human resource management, yet empirical evidence on how specific technologies relate to individual HRM functions remains limited, particularly in Central and Eastern Europe. This study aimed to examine relationships between the use of selected intelligent technologies (artificial intelligence, Big Data, the Internet of Things, and virtual reality) and the level of HRM functions in organizations. Data were collected through a questionnaire survey of 150 HR managers from medium-sized and large enterprises operating in Slovakia, using a five-point Likert scale. Relationships were analyzed using Spearman's correlation coefficient with Benjamini–Hochberg (FDR) correction; statistical analyses were conducted in SPSS and visualized via correlation heatmaps in R. The results revealed statistically significant positive relationships between all examined technologies and HRM functions, with the strongest associations for Big Data and weaker but consistent relationships for virtual reality. The study contributes by identifying technological areas most closely linked to HRM functions in Slovak enterprises, while its limitations include the cross-sectional design, national focus, and the inability to infer causality.

Key words:
functions of human resource management, HR managers, AI, BD, IOT, VR

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INTRODUCTION

Rapid technological progress and the increasing deployment of intelligent technologies are fundamentally transforming organizational operations and management practices. In an environment characterized by technological change, globalization, and intensified competition, effective human resource management (HRM) plays an increasingly important role in supporting organizational performance and long term sustainability (Body et al., 2024). Digital transformation, commonly associated with the Fourth Industrial Revolution, has been identified as a key driver of changes in HRM, prompting organizations to reconsider how HR activities are designed and delivered (Van den Berg et al., 2020). Digital technologies influence multiple HR related processes across the employee lifecycle, including recruitment, training, performance management, and workforce planning. The adoption of tools such as artificial intelligence, Big Data analytics, and other digital solutions enables organizations to enhance efficiency, improve decision making, and strengthen their competitive position (Kholod et al., 2021). At the same time, the extent and nature of technology adoption in HRM vary across organizational and national contexts. Empirical evidence indicates that while digital HR tools are widely implemented in many organizations, differences exist in the pace and depth of adoption, often shaped by external conditions and contextual factors (Ulatowska et al., 2023). Although the importance of intelligent technologies for HRM is widely acknowledged, their integration into HR processes remains uneven, and organizations differ in how they leverage specific technologies to support HRM activities. Understanding these patterns is essential for advancing knowledge on digital HRM and for supporting informed managerial decision making in organizations operating in increasingly digital environments.

1. LITERATURE OVERVIEW

Human resource management is commonly defined as a systematic approach to managing and developing people in organizations, based on the assumption that HR practices significantly influence organizational performance (Armstrong & Taylor, 2014). In the literature, HRM is frequently conceptualized through HRM functions, which translate HRM principles into structured areas of organizational practice and enable the assessment of HRM activities in a consistent manner (Patrick & Mazhar, 2019). HRM functions cover core activities across the employee lifecycle, including planning, staffing, performance management, employee experience, well-being, rewards, development, internal mobility, job design, and HR administration (Alkalha et al., 2012; Koopmans et al., 2014; Havenga et al., 2013; Weziak-Bialowolska et al., 2022). A comprehensive functional framework comprising twelve HRM functions has been proposed by Deepa et al. (2024)

Artificial intelligence is frequently discussed as a technology capable of supporting automation and decision-making in HR processes. Existing literature highlights the potential of AI to improve HR efficiency and contribute to organizational productivity. However, research also points to a lack of comprehensive frameworks guiding the strategic adoption of AI in HRM (Malik et al., 2023). In addition, ethical considerations related to transparency, data privacy, and fairness remain prominent concerns in the application of AI within HR contexts (Varma et al., 2023). These aspects suggest that AI may be associated with various HRM functions, particularly those involving evaluation and decision support.

Big Data has emerged as a core element of data driven management and is often regarded as a critical investment for maintaining organizational competitiveness. Prior research indicates that Big Data analytics can enhance organizational and HR performance when analytical capabilities are aligned with appropriate organizational conditions (Mikalef et al., 2019). Empirical studies also demonstrate the applicability of advanced analytics and machine learning in HR related decisions, such as promotion modelling and leadership identification (Gülten & Baraçlı, 2024). These findings suggest a strong link between Big Data utilization and the perceived effectiveness of HRM functions.

The Internet of Things enables continuous data collection through interconnected devices and systems and has been associated with process optimization in organizational environments. In HRM contexts, IoT applications may support workplace monitoring, compliance, and risk management, while also introducing new challenges related to data governance and integration (Abdussamad et al., 2022). Research further suggests that linking IoT data with HR analytics can contribute to improved resource utilization and working conditions (Podder et al., 2024), indicating potential connections between IoT usage and HRM function performance.

Virtual reality has gained attention as a technology applicable to HRM activities such as recruitment, onboarding, training, and the communication of organizational culture. Several studies argue that VR can support the transition toward digital HRM by offering immersive and interactive solutions (Svatiuk et al., 2022; Lai et al., 2023). Research in training contexts reports positive effects on motivation and engagement, although findings also suggest that the benefits of VR are not always consistent across applications and settings (Yudintseva, 2023). This positions VR as a developing technology with varying relevance across HRM functions.

The reviewed literature demonstrates that intelligent technologies including AI, BD, IoT, and VR are increasingly integrated into HRM and may support a wide range of HR related activities. However, existing studies often focus on individual technologies or specific HR applications and provide limited empirical evidence on how the utilization of particular technologies relates to the perceived level of specific HRM functions. Moreover, research examining these relationships in the context of Slovak medium-sized and large organizations remains scarce. Therefore, the objective of this study is to identify relationships between the use of selected intelligent technologies and the level of individual human resource management (HRM) functions in organizations. Specifically to identify relationships between the use of selected intelligent technologies (AI, Big Data, IoT, and VR) and the level of HRM functions as perceived by HR managers in medium-sized and large enterprises operating in Slovakia. By applying correlation analysis, the study aims to determine which technologies are most strongly associated with HRM function levels.

2. GOAL AND METHODOLOGY

The main objective of the research was to examine relationships between the use of selected intelligent technologies and the level of individual human resource management (HRM) functions in organizations. The research focuses on identifying specific intelligent technologies in relation to HRM functions, rather than examining causal effects. Based on the gap and the aim of the study, a research question was set. RQ: What relationships exist between the use of selected intelligent technologies and the level of HRM functions in organizations?

Data were collected through a questionnaire survey conducted among HR managers working in medium-sized and large enterprises operating in Slovakia. A total of 150 valid questionnaires were obtained and included in the analysis. The respondents were HR managers responsible for human resource management functions within their organizations, which ensured the relevance and reliability of the collected data.

Respondents assessed the extent of use of intelligent technologies in the field of human resource management, namely artificial intelligence (AI), big data (BD), Internet of Things (IoT) and virtual reality (VR), as well as the level of performance of twelve selected HRM functions. All items were measured using a five-point Likert scale, where higher values indicated a higher degree of use of technologies or a higher level of perceived performance of the HRM function. Table 1 presents the variable codes used in the study and their corresponding descriptions.

Table 1: Codes of variables

Code	Variable description
AI	Artificial intelligence
IOT	Internet of Things
BD	Big Data
VR	Virtual reality
HRMF1	Workforce planning
HRMF2	Recruitment
HRMF3	Employee selection
HRMF4	Performance appraisal
HRMF5	Employee experience management
HRMF6	Employee engagement support
HRMF7	Employee health and well-being support
HRMF8	Compensation management
HRMF9	Training and development
HRMF10	Internal mobility and career progression
HRMF11	Job design
HRMF12	Employee self-service management

Source: author's processing

Data analysis was conducted using both SPSS and R software. Descriptive statistics, including mean values and standard deviations, were used to describe the basic characteristics of the research variables. Given the ordinal nature of the Likert-scale data, Spearman's rank correlation coefficient (ρ) was applied to analyze the relationships between the use of intelligent technologies and the level of HRM functions. The strength of Spearman's rank correlation coefficients was interpreted based on absolute values, with coefficients below 0.10 considered negligible, values between 0.10 and 0.39 weak, 0.40 to 0.69 moderate, 0.70 to 0.89 strong, and values of 0.90 or higher indicating very strong correlations (Schober, et al. 2018).

To control for the increased risk of false-positive results due to multiple testing, the Benjamini–Hochberg procedure for controlling the false discovery rate (FDR) was applied. The results of the correlation analysis were visualized using a correlation heatmap created in the R environment, which enabled a clear and comprehensive presentation of the strength and direction of the identified relationships.

Participation in the survey was voluntary and anonymous. The study is subject to certain limitations. The research focuses exclusively on organizations operating in Slovakia, which may limit the generalizability of the findings. Furthermore, the cross-sectional nature of the study and the use of self reported data allow for the identification of relationships between variables, but not for the determination of causal effects.

3. FINDINGS

This section presents the empirical findings of the study based on the analysis of data collected from HR managers in medium-sized and large organizations operating in Slovakia. The results include descriptive statistics of the analyzed variables and the outcomes of the correlation analysis examining relationships between the use of selected intelligent technologies and the level of HRM functions. Spearman's rank correlation coefficients were applied to identify the strength and direction of associations between variables. The findings are presented in tabular form and supported by graphical visualization using a correlation heatmap.

3. 1 Descriptive statistics

Table 2 presents the descriptive statistics of the analyzed variables. The sample consisted of 150 respondents for all variables.

Table 2: Descriptive statistics of the analyzed variables

	N	Minimum	Maximum	Mean	Std. Deviation
AI	150	1	5	3.30	.911
IOT	150	1	5	3.39	1.008
BD	150	1	5	3.61	.952
VR	150	1	5	3.19	1.139
HRMF1	150	1	5	3.80	.801
HRMF2	150	1	5	3.81	.906
HRMF3	150	1	5	3.77	.878
HRMF4	150	1	5	3.79	.835
HRMF5	150	1	5	3.88	.802
HRMF6	150	1	5	3.88	.850
HRMF7	150	1	5	3.83	.943
HRMF8	150	1	5	3.72	.996
HRMF9	150	1	5	3.79	.880
HRMF10	150	1	5	3.73	.879
HRMF11	150	1	5	3.67	.830
HRMF12	150	1	5	3.77	.785

Source: author's processing (SPSS)

The mean values for the use of intelligent technologies ranged from 3.19 to 3.61 on a five-point Likert scale. Among the analyzed technologies, Big Data showed the highest mean value (M = 3.61; SD = 0.952), followed by Internet of Things (M = 3.39; SD = 1.008) and artificial intelligence (M = 3.30; SD = 0.911). Virtual reality achieved the lowest mean value (M = 3.19; SD = 1.139), indicating a comparatively lower level of utilization.

The mean values of HRM functions ranged from 3.67 to 3.88, suggesting a generally high perceived level of HRM function performance across the analyzed organizations. The highest mean values were observed for HRMF5 and HRMF6 (both M = 3.88), while the lowest mean value was recorded for HRMF11 (M = 3.67). Standard deviations indicate moderate variability in respondents' assessments.

3. 2 Correlation analysis of intelligent technologies and HRM functions

Spearman's rank correlation coefficient was used to examine the relationships between the use of intelligent technologies and the level of HRM functions. The results of the correlation analysis are presented in Table 3. Statistical significance was evaluated using p-values, with results considered statistically significant at $p < 0.05$. All identified correlations were positive and statistically significant at the 0.001 significance level ($p < 0.001$). The results remained statistically significant after applying the Benjamini–Hochberg correction for multiple testing.

Table 3: Spearman's rank correlation

		AI	IOT	BD	VR
HRMF1	Correlation Coefficient	.407***	.477***	.561***	.375***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF2	Correlation Coefficient	.444***	.412***	.535***	.375***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF3	Correlation Coefficient	.412***	.351***	.512***	.400***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF4	Correlation Coefficient	.478***	.435***	.540***	.409***
		<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF5	Correlation Coefficient	.303***	.353***	.499***	.295***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF6	Correlation Coefficient	.357***	.421***	.498***	.331***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF7	Correlation Coefficient	.339***	.407***	.481***	.378***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF8	Correlation Coefficient	.381***	.416***	.504***	.348***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF9	Correlation Coefficient	.404***	.395***	.517***	.309***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF10	Correlation Coefficient	.478***	.500***	.580***	.412***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF11	Correlation Coefficient	.413***	.397***	.483***	.420***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
HRMF12	Correlation Coefficient	.392***	.439***	.541***	.363***
	Sig. (2-tailed)	<.001	<.001	<.001	<.001
	N	150	150	150	150
*** Correlation is significant at the 0.001 level (2-tailed).					

Source: author's processing (SPSS)

Artificial intelligence exhibited predominantly weak to moderate positive correlations with HRM functions. Weak correlations were observed for several HRM functions (e.g., HRMF5, $\rho = 0.303$), while moderate correlations were identified for HRMF4 and HRMF10 (both $\rho = 0.478$).

Similarly, the Internet of Things demonstrated weak to moderate positive relationships with HRM functions, with correlation coefficients ranging from weak associations ($\rho = 0.351$ for HRMF3) to moderate associations ($\rho = 0.500$ for HRMF10).

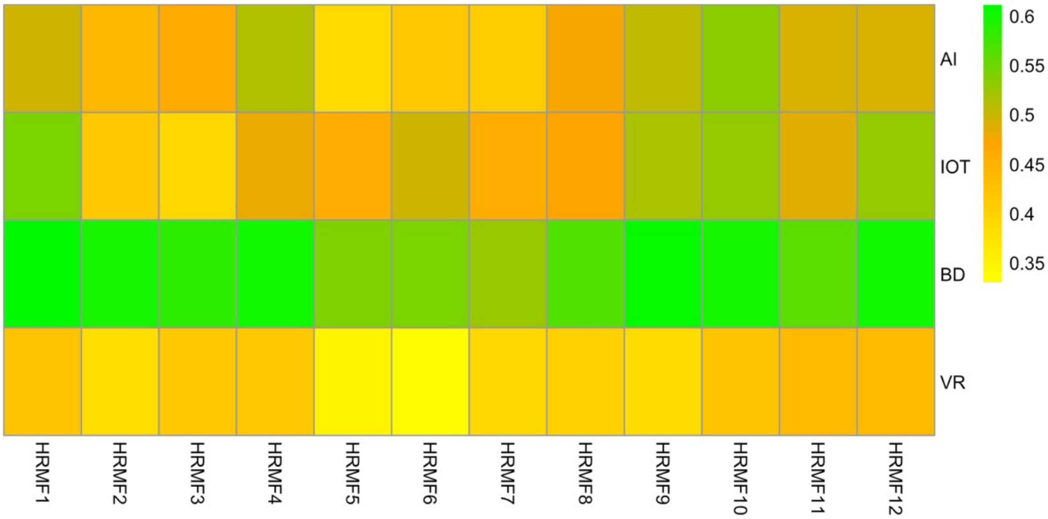
Virtual reality showed mainly weak positive correlations across HRM functions, with correlation coefficients ranging from $\rho = 0.295$ (HRMF5) to $\rho = 0.420$ (HRMF11). Only a limited number of relationships reached the moderate correlation level.

In contrast, Big Data displayed consistently moderate positive correlations with all analyzed HRM functions. Correlation coefficients ranged from ρ = 0.481 (HRMF7) to ρ = 0.580 (HRMF10), indicating stable and comparatively stronger associations than those observed for the other technologies. Moderate correlations were identified across all HRM functions, with higher values particularly evident for HRMF1, HRMF4, HRMF9, HRMF10, and HRMF12.

3. 3 Correlation heatmap of intelligent technologies and HRM functions

To facilitate a comprehensive overview of the identified relationships, the correlation matrix was visualized using a correlation heatmap (Figure 1), which was created in the R software environment.

Figure 1 Heatmap of correlations



Source: author's processing

The heatmap illustrates clear differences in the strength of associations across technologies, with Big Data displaying consistently higher correlation values across all HRM functions. Artificial intelligence and Internet of Things show moderate patterns of association, while virtual reality demonstrates comparatively lower correlation intensities. The visualization supports the numerical results presented in Table 3 and highlights the relative dominance of Big Data in relation to HRM functions.

4. DISCUSSION

The aim of the paper was to examine relationships between the use of selected intelligent technologies and the level of individual human resource management (HRM) functions in organizations. In line with the RQ1 "What relationships exist between the use of selected intelligent technologies and the level of HRM functions in organizations?", the findings confirm that statistically significant positive associations exist between all analyzed intelligent technologies and HRM functions, although the strength of these relationships differs across technologies.

The strongest and most consistent relationships were observed for Big Data across nearly all HRM functions. Moderate associations were identified particularly for workforce planning (HRMF1), recruitment (HRMF2), performance appraisal (HRMF4), internal mobility and career progression (HRMF10), and employee self-service management (HRMF12). These functions are inherently data intensive and rely on systematic information processing, which aligns with existing literature emphasizing the role of Big Data analytics in supporting evidence based HR decision making and HR process optimization (Mikalef et al., 2019; Verma et al., 2021). Prior studies demonstrating the applicability of analytics and machine learning in promotion decisions and workforce evaluation further support the observed associations with performance appraisal and career related HRM functions (Gülten & Baraçlı, 2024).

Artificial intelligence exhibited weaker to moderate relationships with HRM functions, with relatively stronger associations identified for recruitment (HRMF2), performance appraisal (HRMF4), training and development (HRMF9), internal mobility and career progression (HRMF10), and job design (HRMF11). These findings correspond with prior research describing AI in HRM as a technology primarily applied in selected HR areas, particularly those involving automation, screening, and decision support, rather than across all HRM functions uniformly (Malik et al., 2023). Ethical and implementation related concerns discussed in the literature may partially explain why AI adoption remains uneven across HRM functions, especially those requiring human judgment and interpersonal interaction (Varma et al., 2023).

The Internet of Things demonstrated predominantly weak to moderate associations with HRM functions, with comparatively higher correlations observed for workforce planning (HRMF1), employee health and well-being (HRMF7), internal mobility and career development (HRMF10), job design (HRMF11), and employee self-service management (HRMF12). These results align with studies highlighting IoT applications in workplace monitoring, environmental optimization, and support of employee related administrative processes (Abdussamad et al., 2022; Podder et al., 2024). The findings suggest that IoT technologies may be more closely linked to HRM functions associated with the work environment and operational support rather than strategic HR activities.

Virtual reality showed the weakest, though still statistically significant, associations across HRM functions. Slightly stronger relationships were observed for employee selection (HRMF3), performance appraisal (HRMF4), internal mobility and career progression (HRMF10) and job design (HRMF11). This pattern is consistent with previous research indicating that VR is mainly utilized in specific HR contexts, such as recruitment, onboarding, and training, where immersive technologies can enhance engagement and experiential learning (Svatiuk et al., 2022; Lai et al., 2023; Yudintseva, 2023). The relatively low correlation values suggest that VR remains a complementary rather than a core technology within HRM practices in the analyzed organizations.

However, several findings of this study diverge from conclusions emphasized in existing literature. While prior studies frequently portray artificial intelligence and virtual reality as strategically transformative technologies for HRM, the present results indicate only weak to moderate associations between AI and most HRM functions and comparatively weaker associations for VR across the analyzed functions. This contrasts with research highlighting the central role of AI in enhancing HR productivity and decision making and the growing importance of VR in recruitment, training, and organizational culture development (Malik et al., 2023; Svatiuk et al., 2022; Lai et al., 2023). The weaker relationships observed in this study suggest that, within the Slovak medium-sized and large enterprise context, these technologies may still be implemented selectively rather than systematically across HRM functions. In contrast to conceptual and future oriented studies, the findings indicate that data driven technologies such as Big Data currently play a more prominent and consistently embedded role in HRM practice, whereas immersive and AI based solutions remain at an earlier stage of integration.

Overall, the findings demonstrate that intelligent technologies are not uniformly associated with all HRM functions. Data driven technologies, particularly Big Data, show stronger and more consistent relationships with HRM functions compared to emerging and immersive technologies such as VR. This supports the view that digital HRM development is incremental and function specific, reflecting differences in technological maturity, applicability, and organizational readiness. From a practical perspective, the results suggest that organizations aiming to strengthen HRM functions may benefit from prioritizing analytics oriented technologies while adopting other intelligent technologies selectively based on functional relevance.

CONCLUSION

This study addressed the growing relevance of intelligent technologies in human resource management by examining relationships between selected technologies and HRM functions. The objective was to examine associations between intelligent technologies and the level of HRM functions using data collected from 150 HR managers in medium-sized and large organizations in Slovakia. Spearman's rank correlation analysis revealed statistically significant positive relationships across all technologies, with Big Data showing the strongest and most consistent associations with HRM functions, particularly those related to planning, recruitment, development, and career progression. The findings indicate that data driven technologies are currently more closely aligned with HRM function maturity than emerging and immersive technologies such as AI and VR, which appear to be applied more selectively. The study is limited by its cross-sectional design and national scope and by the use of correlation analysis, which does not allow causal inference. Despite these limitations, the results contribute empirical evidence to the digital HRM literature and provide practical insights for organizations seeking to prioritize technology adoption in HRM. Future research should focus on longitudinal analyses, cross country comparisons, and function specific investigations to further explore technology and HRM relationships.

ACKNOWLEDGMENTS

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REVOLUTION IN LEARNING: INTEGRATION OF AI TOOLS INTO HIGHER EDUCATION — BIBLIOGRAPHICAL ANALYSIS

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Abstract

The rapid development of artificial intelligence, particularly generative AI tools, has significantly influenced higher education systems worldwide. In recent years, scholarly attention has increasingly focused on the educational potential of these technologies as well as on their ethical, institutional, and pedagogical implications. The aim of this paper is to identify key research trends and thematic areas related to the integration of artificial intelligence tools in higher education through a bibliometric analysis. The study is based on a dataset of 51 empirical articles indexed in the Web of Science database and published between 2021 and 2025. Data analysis and visualization were conducted using the VOSviewer software. The results reveal a substantial increase in research output after 2023, largely driven by the widespread adoption of generative AI tools such as ChatGPT. Major research themes include personalized learning, student performance and motivation, as well as issues related to academic integrity and critical thinking. The findings confirm the interdisciplinary nature of the research and indicate a shift from initial scholarly discussions to a more systematic examination of the impacts of artificial intelligence on the quality of higher education.

Key words:
artificial intelligence; generative artificial intelligence; higher education; bibliometric analysis; ChatGPT; academic integrity

JEL Classification I23, O33, C88 https://doi.org/10.52665/ser20250205

INTRODUCTION

Artificial intelligence refers to the ability of a digital machine to perform tasks commonly associated with intelligent beings. The development of artificial intelligence is significantly changing the ways in which people interact, communicate, live, learn and work. Artificial intelligence is currently becoming one of the main factors in the transformation of the modern education system, affecting not only teaching methods, but also the organization and management of educational institutions. Artificial intelligence systems are gradually becoming key in the individualization of teaching, automation of administrative tasks, or expanding access to education. Educational platforms are increasingly using artificial intelligence tools to support individualization of learning, automate selected pedagogical and administrative processes, and thus increase the efficiency of the higher education environment. Students no longer have access only to static learning materials, but are able to use intelligent tutoring systems that adapt to their individual pace and preferences.

1 LITERATURE OVERVIEW

Higher education has undergone significant changes in recent decades, primarily due to rapid technological advances that have disrupted conventional models of teaching and learning (Qolamani & Mohammed, 2023). The development of digital tools and innovations has also significantly impacted school teaching practices and administrative functions. In particular, artificial intelligence has become a transformative force in education. At its core, artificial intelligence refers to the development of computer systems capable of performing tasks that simulate human intelligence (Du-Harpur et al., 2020). The literature has confirmed the fact that systems that are based on artificial intelligence can adapt to the specific requirements and competencies of each student, thereby providing personalized feedback and assistance to the student. Adaptive learning personalizes education by continuously evaluating each student's performance in real time and creating an ever-changing individualized learning path guided by artificial intelligence and machine learning, thereby increasing the quality of education and student satisfaction (Taylor et al., 2021). This integration of personalized and adaptive learning leads to more effective, efficient, and engaging learning experiences, and learning itself is tailored to the individual needs of students (Du Plooy et al., 2024). Empirical studies also indicate that students who use AI technologies as part of the learning process achieve, on average, better academic results than those students who rely exclusively on traditional teaching methods and procedures. This in turn confirms the fact that educational systems supported by AI tools can adapt content based on student performance and provide exactly what the student needs to improve their skills. In higher education, AI tools manifest themselves in various forms, such as tutoring systems, personalized learning platforms, adaptive assessment tools, and more (Bhutoria, 2022). Personalized education supported by AI tools can also help eliminate learning difficulties for marginalized students, students with special needs, etc. (Yonezawa et al., 2012). Generative AI refers to a type of AI that is capable of creating human-like content (e.g. text, narratives, visual artwork). This advanced system works by interpreting specific instructions or prompts to generate original and contextually relevant output, mimicking the creative processes observed in human cognition (Lim et al., 2023). Generative AI has gained a lot of attention from people from different backgrounds and professional fields after the launch of ChatGPT in November 2022 (Chavez et al., 2023). The launch of ChatGPT on the market and in practice has sparked many discussions about its potential application and use in education (Baabdullah, 2024). Educational institutions and researchers have presented many arguments from different perspectives, highlighting a number of advantages, but also expressing concerns related to the use of generative AI, e.g. in the form of ChatGPT (Ali et al., 2024a). Some studies suggest that one of the significant benefits of generative AI is related to personalized learning, accessibility, or even support for students with special needs (Korneeva et al., 2023; Lo, 2023; Yonezawa et al., 2012). Equally important, however, there have been legitimate concerns regarding, for example, the ethical implications of using AI tools. Because AI systems require vast amounts of data, including confidential information about students and faculty, this raises serious questions about privacy and data protection (Korneeva et al., 2023; Zawacki-Richter et al., 2019) and also, for example, plagiarism (Ali et al., 2024b; Tlili et al., 2023). Despite the significant potential of AI in supporting teaching and learning, its implementation in higher education also brings new ethical, pedagogical, and institutional risks that require systematic professional reflection. For example, in times of budget cuts, administrators may be tempted to replace teaching with profitable automated AI solutions. Faculty members, teaching assistants, student advisors, and administrative staff may fear that intelligent tutors, expert systems, and chatbots will take their jobs away (Zawacki-Richter et al., 2019). AI also plays a key role in the area of access to information. With advanced algorithms, it is possible to quickly analyze large amounts of data and identify relevant information, streamlining the way that scientific communities and individuals access new information in their fields. Digitization and artificial learning thus ensure that information is not only accessible but also tailored to the specific needs of users.

2 GOAL AND METHODOLOGY

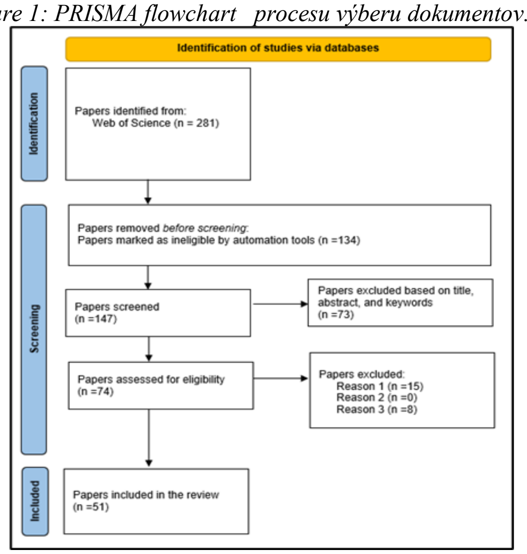
The aim of our paper is to analyze the use of AI tools in the educational environment of universities and to identify factors that influence their implementation in higher education. That is, to answer the question: "What are the main topics (areas) of research on the use of AI tools in higher education and their key findings?" The search for relevant studies was carried out in the Web of Science database. The Web of Science (WoS) database was used to compile an initial set of articles due to its broad coverage of high-quality, peer-reviewed literature in the fields of education, technology and interdisciplinary areas, thus ensuring the search for relevant empirical studies. The WoS database is a commonly used resource for systematic or bibliographic reviews of the literature. In November 2025, we conducted a search in the WoS database to find English publications that contain the terms artificial intelligence, higher education and empirical studies in the title, abstract or keywords. We used the search string listed in Table 1. Because many surveys show a rapid increase in publications focused on artificial intelligence (e.g., ChatGPT) since 2022, our review included studies from 2021 to 2025 to ensure a focus on the current state of the art in the field.

Table 1: Search string for identifying relevant studies in the WoS database

TITLE-ABS-KEY ("artificial intelligence")
AND
TITLE-ABS-KEY ("higher education ")
AND
TITLE-ABS-KEY ("empirical study" OR "empirical research" OR "experimental study" OR "case study")

As recommended by Chiu et al. (Chiu et al., 2023), we limited the search to categories related to AI research in higher education. This process was completed on November 30, 2025, resulting in 281 potential studies. We retained only full-text papers for further analysis, leaving us with 147 articles. We then performed manual screening using inclusion or exclusion criteria (Table 2) to assess the relevance of these articles to our focus. We screened the remaining studies based on their titles, abstracts, and keywords, and excluded studies that were not related to higher education, not related to artificial intelligence, not empirical, were conference papers, work in progress, reviews, meta-analyses, or had not been peer-reviewed. All publications that were considered irrelevant or lacking substantial content on AI in higher education were removed from our dataset. The selection process took place in several stages (Figure 1).

Figure 1: PRISMA flowchart procesu výberu dokumentov.



Source: Page MJ, et al. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. This work is licensed under CC BY 4.0. To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/

The final database contained 51 articles. We then performed a bibliometric analysis on these 51 articles. Bibliometric analysis involves quantitatively summarizing the metadata of large-scale research articles, including year of publication, title, abstract, citations, authors, and institutions. It serves as an effective method for understanding the state of a research field, especially when the scope of the review is broad and the dataset is too large to be manually reviewed (Donthu et al., 2021). The analysis was performed using VOSviewer software.

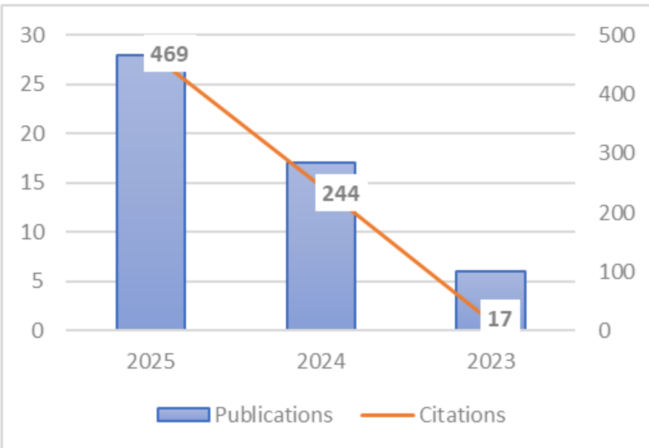
Table 2: Inclusion/exclusion criteria.

Reason	Studies were included if:	Studies were excluded if:
1.	Focused on the application, integration, or impact of artificial intelligence in higher education contexts.	It did not explicitly address artificial intelligence or its applications in education.
2.	Was the research empirical, using experimental, quasi-experimental, or other data-driven research methods?	They were secondary sources (e.g., reviews, opinion articles, meta-analyses).
3.	They have been published in peer-reviewed journals.	These were conference papers, theses, dissertations, or works in progress.

3 FINDINGS

Identifying research trends helps us understand the current state of AI in higher education and reveals where scholarly and institutional attention is most focused. We examined the following key dimensions: year of publication, country of study, citation analysis, keyword analysis.

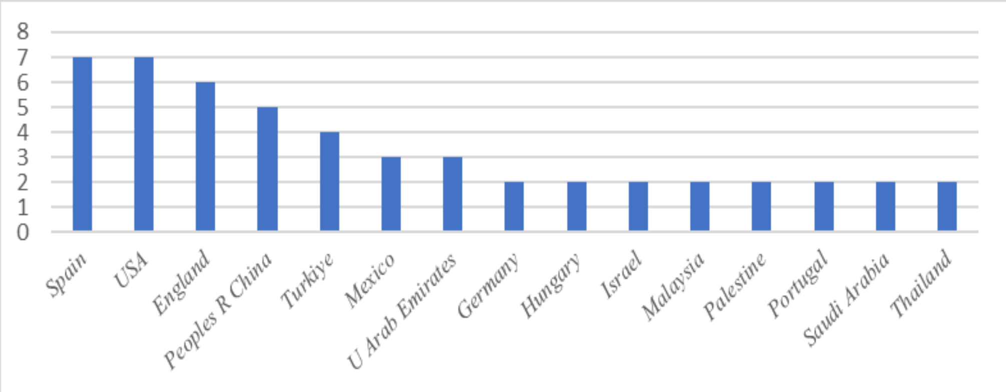
Figure 2: Development of the number of publications and citations depending on the year of publication



Source: Web of Science

The data shown in Figure 1 shows a significant time trend in the number of published articles in individual years focused on the integration of artificial intelligence tools into higher education. The lowest number of identified articles was recorded in 2023 (6 articles). In the following year, 2024, there was a 284% increase in scientific production to 17 articles, which is evidence of the growing research interest in this topic in the academic community. The highest number of publications was recorded in 2025, namely 28 articles, which represents a more than fourfold increase compared to 2023.

Figure 3: Number of publications by country



Source: Web of Science

Among the 48 countries identified, Spain and the USA show the highest production of scholarly articles focused on the use of AI tools in higher education in our analysis. Such high publication activity in these countries may be related to their long-term focus on research into educational activities as well as the rapid adoption of generative AI tools in their academic environment. The following countries, such as England and the People's Republic of China, show a slightly lower, but still significant number of publications. Most other countries are represented by only one or two articles, which points to the geographically dispersed nature of research and the absence of dominant national research centers in this area. At the same time, there is no significant author dominance, since the maximum number of published articles per author is one, which may indicate the initial phase of the formation of the research community and the high degree of interdisciplinarity of the research area under study.

Citation analysis identified six highly cited articles in the analyzed set. The most cited publication was published in the journal Education Sciences and accumulated 309 citations, corresponding to an average of 77.25 citations per year. Other highly cited articles were published in the journals Cogent Education (120 citations), Computers and Education Open (53 citations), International Journal of Educational Technology in Higher Education (46 citations), Smart Learning Environments (32 citations), and Education and Information Technologies (30 citations). All journals in which the most cited articles were published are indexed in the Web of Science Core Collection. The articles appeared predominantly in journals ranked in the first quartile (Q1) of the Education & Educational Research category with journal impact factors ranging from approximately 5 to more than 16, while Cogent Education had a journal citation indicator close to the disciplinary average (JCI ≈ 0.97).

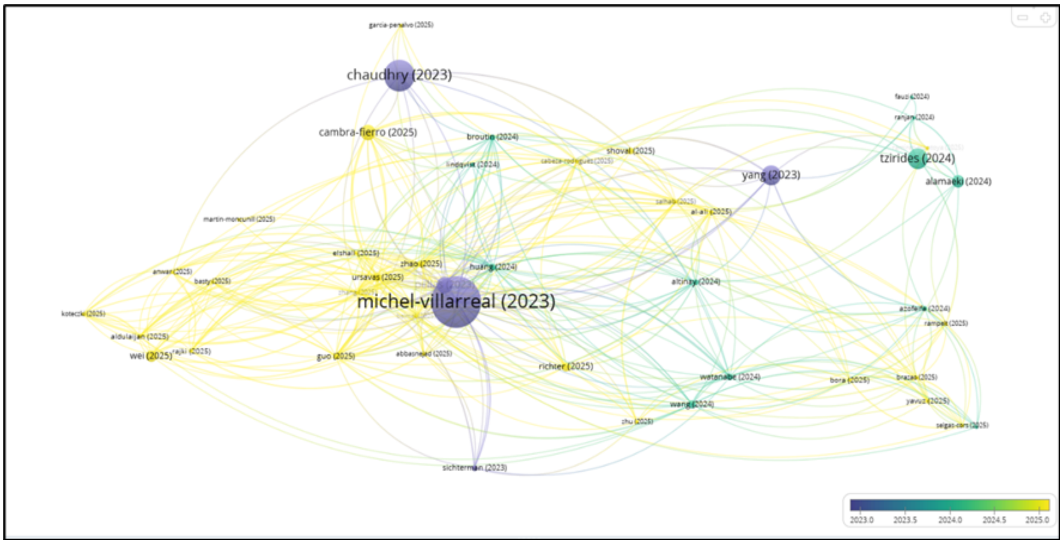
Table 3: Most cited publications and author

Publications	citations		magazín
	average per year	total	country
Michel-Villarreal, R. ; Vilalta-Perdomo, E ; (...); Gerardou, FS: ***Challenges and Opportunities of Generative AI for Higher Education as Explained by ChatGPT*** (2023)	77,25	309	EDUCATION SCIENCES England
Chaudhry, IS ; Sarwary, SAM ; (...); Chabchoub, H.: ***Time to Revisit Existing Student's Performance Evaluation Approach in Higher Education Sector in a New Era of ChatGPT — A Case Study*** (2023)	30	120	COGENT EDUCATION Spojené arabské emiráty
Tzirides, AO ; Zapata, G. ; (...); Kalantzis, M.: ***Combining human and artificial intelligence for enhanced AI literacy in higher education*** (2024)	17,67	53	COMPUTERS AND EDUCATION OPEN USA
Yang, Qifan ; Lian, LW a Zhao, JH: ***Developing a gamified artificial intelligence educational robot to promote learning effectiveness and behavior in laboratory safety courses for undergraduate students*** (2023)	11,75	46	INTERNATIONAL JOURNAL OF EDUCATIONAL TECHNOLOGY IN HIGHER EDUCATION China
Pellas, Nikolaos: ***The influence of sociodemographic factors on students' attitudes toward AI-generated video content creation*** (2023)	8	32	SMART LEARNING ENVIRONMENTS Grécko
Cambra-Fierro, JJ ; Blasco, MF ; (...); Trifu, A. **ChatGPT adoption and its influence on faculty well-being: An empirical research in higher education** (2025)	10	30	EDUCATION AND INFORMATION TECHNOLOGIES Spain

Source: https://www.webofscience.com/wos/woscc/citation-report/c0b67784-d6ef-4392-9eb2-9ac63ee364c3-01957e0582

The temporal visualization of the most cited authors provides insight into the dynamics of research development in the field of integrating AI tools into higher education in the monitored period. The color spectrum of the nodes reflects the chronological aspect of publication activity, with older works shown in cooler shades and newer publications in warmer colors. It is clear from the visualization that a significant increase in publication and citation activity occurs after 2023, which corresponds to the spread of generative AI tools and their rapid adoption in the academic environment. Authors publishing in 2024 and 2025 create denser connections, which indicates the growing intensity of scientific discussion and the gradual consolidation of the research field. Older works from 2023 and earlier periods fulfill the function of theoretical starting points in the network, which are followed by newer empirical and application-oriented studies.

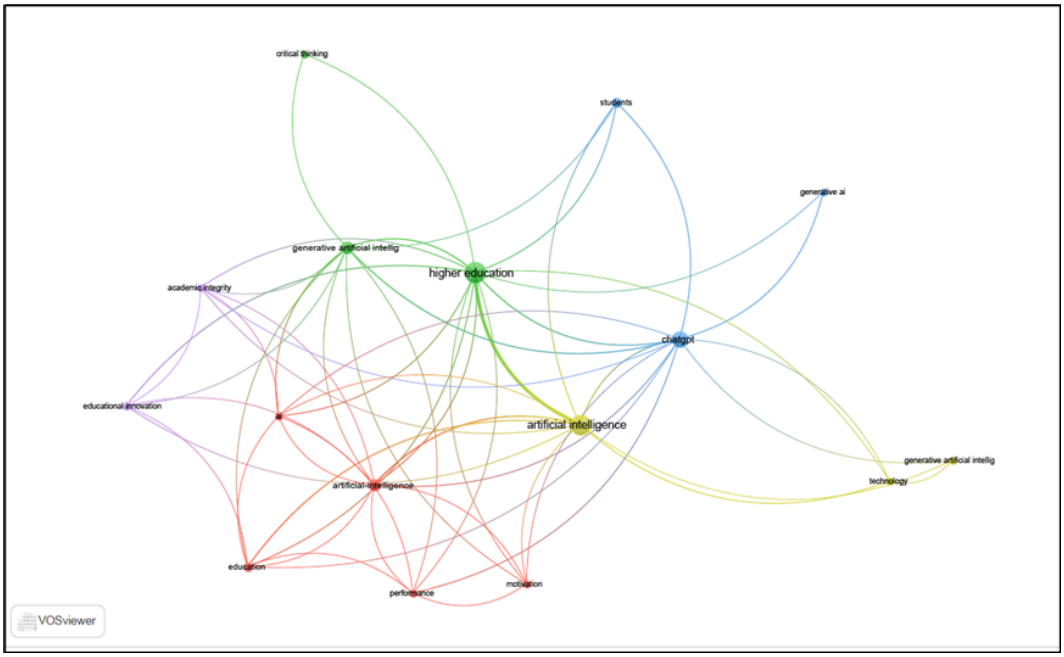
Figure 4: Visualization, ktorá znázorňuje sieť najcitovanejších autorov v čase



Source: processed using the VOSviewer software tool

Figure 3 shows a network visualization of the co-occurrence of keywords in the field of integrating artificial intelligence tools into higher education, created using the VOSviewer software. The size of the nodes represents the frequency of occurrence of individual keywords, while the thickness of the links reflects the strength of their mutual relationships. The color distinction of the nodes points to thematic clusters within the analyzed research field.

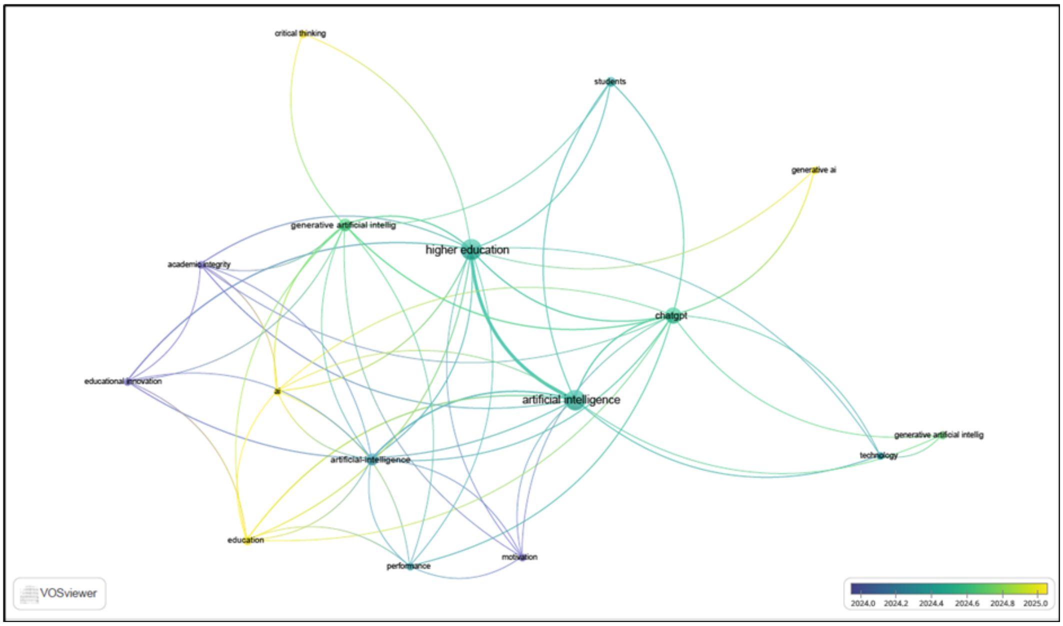
Figure 5: Visualization of relationships between keywords - thematic areas of research



Source: processed using the VOSviewer software tool

Figure 4 shows us a temporal visualization of keywords in the analyzed set. Through this analysis, we can identify how research content changes over time.

Figure 6: Visualization of network relationships between keywords with timeline



Source: processed using the VOSviewer software tool

4 DISCUSSION

The results of the bibliographic analysis point to a significant acceleration of research aimed at integrating artificial intelligence tools into higher education, which is closely related to the rapid development of generative artificial intelligence in recent years. In particular, the emergence of large-scale language models, such as ChatGPT, has fundamentally influenced the direction of research discourse and initiated an intensive professional discussion about their pedagogical potential, as well as the risks associated with their use in an academic environment. The wide availability of these tools creates increased pressure to address ethical, didactic and institutional issues, which is also reflected in the growing number of scientific outputs in this area. The findings indicate that this is a dynamically developing research area, in which a further increase in publication activity can be expected in the near future. The distribution of highly cited publications in internationally recognized journals (Cogent Education, Computers and Education Open, Education Sciences...) and across multiple geographical regions points to the strong global visibility and interdisciplinary nature of research focused on artificial intelligence in higher education. The most frequently cited works focus primarily on the analysis of the impacts of generative artificial intelligence on the process of learning, teaching and student assessment. The authors identify several potential benefits, including personalization of learning, continuous support for students, relieving teachers of routine tasks, and creating innovative educational experiences. At the same time, however, they point out significant risks, especially in the areas of academic integrity, ethics, security, quality and reliability of the information generated, as well as possible implementation barriers and the risk of overreliance on artificial intelligence tools (Michel-Villarreal et al., 2023). Particular attention is paid to the question of the extent to which current assessment approaches are able to adequately capture the development of key student competencies in an environment where generative AI tools are readily available.

Research in this area reflects the need to reconsider traditional forms of assessment and emphasizes the importance of developing critical thinking, problem-solving, communication and ethical skills. At the same time, it is shown that a suitably designed combination of human intelligence and artificial intelligence can support the development of students' AI literacy, especially through collaborative and participatory teaching strategies that lead to the conscious, critical and ethical use of AI tools in learning (Tzirides et al., 2024). The results also point to the expanding research interest in innovative didactic approaches, such as the use of gamified educational robots or intelligent systems, which can positively affect learning outcomes, student motivation and reducing cognitive load (Yang et al., 2023). At the same time, it is confirmed that the acceptance of AI tools by students is influenced by several factors, such as age, previous technological experience or participation in AI education. Although the overall attitude of students towards AI is largely positive, research points to ongoing ethical challenges, issues of inclusion and the need for systematic integration of AI education into higher education curricula (Pellas, 2023). An interesting finding is also the impact of the use of generative AI on the well-being of university educators, as the results indicate the potential of AI tools to contribute to reducing stress and increasing work well-being (Cambra-Fierro et al., 2025). Citation analysis indicates a shift in research interest from initial conceptual and exploratory approaches to more systematic exploration of the effectiveness, ethical implications and long-term sustainability of integrating AI into higher education. This trend confirms that the field is maturing and gradually moving towards a deeper reflection on the impacts of AI on the quality of education and academic values.

The results of the keyword analysis support these findings. The dominant position of the terms artificial intelligence, higher education and ChatGPT in the network indicates a strong orientation of current research on generative AI in the academic context. Links with terms such as students, performance and motivation reflect the growing interest in empirically assessing the impacts of AI tools on student outcomes and engagement. A separate thematic cluster focused on academic integrity and critical thinking highlights the ethical and pedagogical challenges that accompany the implementation of generative AI, and points to the need for systematic development of critical thinking as a key competence in the era of artificial intelligence. At the same time, the cluster focused on educational innovation and technology indicates that AI is perceived not only as a technological tool, but also as a significant catalyst for pedagogical innovation. The temporal analysis of keywords shows that research has evolved from general topics related to education and technology to a more detailed examination of specific aspects of the educational process. The latest publications reflect the rapid response of the academic community to the advent of generative artificial intelligence and at the same time point to a shift from technological enthusiasm to a deeper analysis of the pedagogical, evaluative and ethical implications of its use. This development confirms that research on the integration of artificial intelligence into higher education is in a transitional phase towards a systematic and critically reflected examination of its impacts on the quality of learning, student assessment and the preservation of academic values.

This study contributes to the theoretical discourse on artificial intelligence in higher education by systematizing existing empirical evidence into a coherent thematic structure. By identifying dominant and emerging research clusters, the paper provides a conceptual map that supports theory-building in AI-supported learning, academic integrity, and institutional adaptation.

This study has several limitations. First, the analysis was limited to the Web of Science database, which may exclude relevant studies indexed elsewhere. Second, bibliometric methods capture research trends but do not assess the pedagogical effectiveness of AI tools. Future research should therefore combine bibliometric approaches with qualitative and longitudinal empirical studies.

CONCLUSION

The presented bibliometric analysis confirms that research on the integration of artificial intelligence tools into higher education is a dynamically developing and interdisciplinary field. The results of our analysis point to a significant increase in research activity after 2023, which is closely related mainly to the spread of generative AI tools, especially ChatGPT, in the academic environment. The dominant research topics focus on personalized learning, academic performance and student motivation, with increasing emphasis also on issues of academic integrity and the development of critical thinking. From a practical point of view, the findings have significant practical implications for colleges and universities. They point to the need for systematic and pedagogically sound integration of artificial intelligence tools into the educational process, as well as the necessity of creating institutional strategies and ethical frameworks that will reflect the new challenges associated with their use. The development of teachers' and students' competencies in the area of critical and responsible use of generative artificial intelligence requires special attention. In terms of future research, empirical and comparative studies focusing on the long-term pedagogical impacts of the use of AI tools, as well as research on their impact on student assessment, academic integrity and equality of access to education, seem promising. Further research should also focus on the institutional and organizational aspects of the implementation of artificial intelligence tools in higher education, in order to support their meaningful and sustainable use in academic practice. Overall, the results point to the strongly interdisciplinary nature of the research area.

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PSYCHOMETRIC VALIDATION OF THE SLOVAK VERSION OF THE JOB CRAFTING SCALE

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Abstract

In occupational psychology, there is growing interest in the active shaping of work by employees, with job crafting representing a key mechanism for supporting work engagement, well-being, and adaptability in a changing work environment. Despite growing research interest, however, there remains insufficient verification of job crafting measurement tools in the Slovak cultural context. The research gap lies in the absence of empirical evidence on the factor structure and validity of the Slovak translation of the job crafting scale, which limits the reliable measurement of this construct. The study is based on the job demands-resources (JD-R) model, which conceptualizes job crafting as a process of actively adjusting job demands and resources through approach and avoidance strategies with different consequences for work outcomes and employee health.The psychometric properties of the Slovak version of the scale were verified using confirmatory factor analysis on a sample of 500 respondents from various industries who evaluated 21 items of the tool. The translation and adaptation of the scale were carried out using standardized procedures, including back-translation and content validation.The results confirmed the original four-factor structure of the scale and supported a two-factor model distinguishing between approach and avoidance job crafting, with the model showing good fit, high reliability, and convergent validity. The study provides a robust validation framework for measuring job crafting in the Slovak context, extends the empirical support for the JD-R model in the Central European environment, and creates a solid foundation for internationally comparable research and evidence-based interventions in the field of work engagement and well-being.

Key words:
Job crafting, Psychometric validation, JD-R model, Factor structure, Work psychology

JEL Classification M54, J2, J23 https://doi.org/10.52665/ser20250206

INTRODUCTION

In recent decades, research in occupational psychology has shifted its focus from a static understanding of work to the dynamic processes through which employees actively shape their work environment (Wrzesniewski & Dutton, 2001; Wiesman; Nissinen et al., 2024). One of the key concepts in this regard is job crafting, which refers to a set of self-initiated changes through which individuals modify their work tasks, relationships, and demands to better match their abilities, needs, and values (Lanke et al., 2024). This approach reflects a shift from the traditional way of managing work, which focused on optimizing tasks and work systems without emphasizing individual influences (Dhanpat, 2025). Supporting proactive employee behavior in the workplace is considered a key factor in increasing their engagement, satisfaction, and performance, which also has a significant impact on the overall sustainability of the work environment (Irfan et al., 2023).

At the same time, however, there is ongoing debate about the extent to which the approach-avoidance dichotomy is sufficient to capture the measurement structure of job crafting (Lopper et al., 2024). Several studies point out that individual forms of approach job crafting, increasing structural job resources, increasing social job resources, and increasing demanding job requirements may represent qualitatively different strategies that are related but do not necessarily form a single latent construct (Holman et al., 2024). Accurate verification of the factor structure is therefore crucial not only from a theoretical but also from a methodological point of view (Chan et al., 2025).

Valid and culturally adapted measurement tools are a prerequisite for the further development of job crafting research (Lanke et al., 2024). Despite growing interest in this construct, however, there has been a lack of systematic verification of the factor structure of the frequently used job crafting scale in the Slovak context (Tims et al., 2012). The adaptation and validation of the translation thus represent an important step towards expanding empirical research in this cultural environment (Mukherjee & Dhar, 2023).

The aim of this study is therefore to verify the factor structure of the Slovak version of the job crafting scale using confirmatory factor analysis. Specifically, two competing models were compared: a simplified 2-factor model distinguishing between approach and avoidance job crafting and a more detailed 4-factor model corresponding to the original theoretical arrangement of individual dimensions. The study aimed to assess which of these models provides a more appropriate description of the data and better captures the latent structure of job crafting in the Slovak context.

The structure of the article is divided into the following sections: the introduction presents the theoretical basis of the job crafting construct and its significance in the context of occupational psychology. This is followed by a presentation of the research methodology, including the adaptation and validation of the Slovak version of the job crafting scale, which involves the translation process, verification of the factor structure through confirmatory factor analysis, and evaluation of the psychometric properties of the tool. This section is followed by the results, which present comparisons of different models of factor structure, factor loadings, reliability, and validity, along with a discussion of their suitability. The conclusion summarizes the main findings of the research and recommendations for future studies, including suggestions for verifying the measurement invariance and longitudinal stability of the scale. The entire article thus provides a comprehensive view of the psychometric validation of the job crafting measurement tool in the Slovak environment.

1. LITERATURE REVIEW

The concept of job crafting emerged as a direct response to the limitations of traditional job design, which was based on a "one size fits all" approach and focused primarily on efficiency through task simplification. Classic job design viewed the employee as a reactive element of the system, while job crafting emphasizes individual differences and the need for self-actualization (Lanke et al., 2024). Its theoretical basis is based on the assumption that employee motivation to actively shape their work stems from three basic psychological needs: the need for personal control over work, the need to maintain a positive self-image, and the need for social connection with others (Dhanpat, 2025; Chan et al., 2025). In the context of today's digital environment, where job roles are constantly changing in collaboration with algorithms and artificial intelligence, job crafting is becoming even more important (Chan et al., 2025).

The concept of job crafting represents a fundamental shift in the field of work design, as it transfers the initiative from the organization directly to the individual (Wrzesniewski & Dutton, 2001; Chan et al., 2025). The work environment is characterized by rapid technological changes, digitization of work processes, and increasing complexity of work tasks, suggesting that traditional top-down models of work design are no longer sufficient (Nissinen et al., 2024). These approaches were based on the assumption that job roles and tasks are stable, universally defined by management, and that employees act primarily as passive performers of assigned activities (Bakker & Demerouti, 2017; Mousa & Chaouali, 2023). In response to these limitations, the concept of job crafting began to take shape in organizational psychology, representing a significant shift from static job design to a dynamic, employee-initiated approach (Wrzesniewski & Dutton, 2001; Chan et al., 2025). Job crafting changes the paradigm of the employee from a passive performer of predefined tasks to an active co-creator and "architect" of their own work, who continuously adapts their job content to better match their abilities, preferences, and psychological needs (Wrzesniewski & Dutton, 2001; Güner et al., 2023; Dhanpat, 2025).

The basic theoretical framework for job crafting was laid down by Wrzesniewski and Dutton (2001), who defined this construct as the physical and cognitive changes that individuals actively make within the boundaries of their job tasks or relationships (Costantini, 2024; Chan et al., 2025; Nissinen et al., 2024). In this conception, employees are understood not as "pieces of clay" shaped by the organization, but as active job crafters who adapt their job content to better match their abilities, values, and needs (Dhanpat, 2025; Mousa & Chaouali, 2023). Job crafting is therefore a bottom-up process initiated by the employee themselves and often takes place without direct instruction or control from management (Tims & Bakker, 2010; Zhang et al., 2025).

The original concept of job crafting distinguishes three basic areas (Wrzesniewski & Dutton, 2001) in which employees implement these active changes (Geldenhuys et al., 2021; Lopper et al., 2024).

1. The first is **task crafting**, which involves changes in the number, scope, or nature of work activities. For example, an employee may expand their job description to include tasks that better utilize their strengths or change the way tasks are performed through new technological tools to increase efficiency (Zhang et al., 2021; Chan et al., 2025).
2. The second area is **relational crafting**, which refers to adjustments in the quality and quantity of social interactions in the workplace. Employees can choose with whom they will collaborate, build support networks, or modify relationships with colleagues, supervisors, or clients (Geldenhuys et al., 2021; Harju et al., 2024). Through these changes, employees create a social environment that better supports their well-being and performance at work (Guo & Hou, 2022; Mousa & Chaouali, 2023; Zhang et al., 2025).
3. The third area is **cognitive crafting**, which represents a change in how employees interpret the meaning and purpose of their work. Work is no longer perceived as just a set of duties but takes on a broader meaning and mission, leading to a greater sense of purpose and intrinsic motivation (Geldenhuys et al., 2021; Yang et al., 2022; Lopper et al., 2024).

Development of the concept and connection to the JD-R model

Although the original understanding of job crafting provided an important qualitative framework for understanding the active role of employees, the gradual development of the concept led to its integration into broader theoretical models of work motivation and well-being. The most significant step in this direction was the linking of job crafting to the JD-R (Job Demands-Resources) model (Tims & Bakker, 2010; Dhanpat, 2025; Irfan et al., 2023). This model is based on the assumption that every work environment can be described using two basic categories: job demands and job resources (Bakker & Demerouti, 2014, 2017; Irfan et al., 2023; Lopper et al., 2025). Job demands are the physical, psychological, or social aspects of work that require sustained effort and are associated with certain costs, such as fatigue or stress (e.g., time pressure or emotionally demanding clients). In contrast, job resources are factors that help achieve work goals, reduce the negative impact of demands, and promote learning, growth, and motivation (e.g., autonomy, feedback, social support) (Bakker & Demerouti, 2017; Costantini, 2024; Irfan et al., 2023; Nissinen et al., 2024)

From the perspective of the JD-R model, employees are not just passive recipients of these characteristics of the work environment, but active actors who seek to regulate the balance between demands and resources (Bakker & Demerouti, 2017; Dhanpat, 2025; Lopper et al., 2024). In this context, Tims and Bakker (2010) redefined job crafting as a set of changes that employees make to better align their job demands and resources with their own abilities and needs (Holman et al., 2024; Tims et al., 2012). Job crafting thus ceased to be understood merely as a change in the "boundaries" of work and began to be perceived as an active mechanism for regulating the energy and motivational characteristics of a job (Irfan et al., 2023; Zhang & Parker, 2019). Within the JD-R model, job crafting plays a dual role: it supports the motivational process leading to higher work engagement and at the same time helps prevent the health-damaging process associated with excessive demands and the risk of burnout (Bakker & Demerouti, 2017; Nissinen et al., 2024).

The methodological operationalization of the concept within the JD-R model was provided by Tims et al. (2012), who developed a job crafting scale. The original assumption of a three-factor structure was verified on the basis of factor analysis and modified to a four-dimensional model. These dimensions allow for the quantitative measurement of the frequency of crafting among employees in various professions (Tims et al., 2012; Irfan et al., 2023).

The four dimensions according to Tims et al. (2012) are:

1. **Increasing structural job resources**, which includes activities aimed at developing skills, learning new things, and increasing autonomy. An example is an employee's effort to learn new technologies or change the process of performing a task to make it more meaningful (Zhang et al., 2021).
2. **Increasing social job resources**: this refers to proactively seeking feedback, coaching from superiors, or support from colleagues. Employees actively ask about their performance or seek inspiration from more experienced colleagues (Tims et al., 2012; Nissinen et al., 2024).
3. **Increasing challenging job demands**: This refers to behavior in which employees take on new tasks, assume more responsibility, or voluntarily participate in projects. These challenges are perceived as positive stressors that stimulate personal development and a sense of achievement (Wang et al., 2024).
4. **Decreasing hindering job demands**: This involves efforts to minimize aspects of work that are perceived as hindering performance or mentally exhausting. It involves avoiding emotionally demanding interactions or simplifying unnecessarily complex processes (Tims et al., 2012; Lopper et al., 2024).

This shift has enabled more accurate quantitative measurement of job crafting and a deeper understanding of its implications for engagement, performance, and well-being (Holman et al., 2024). Research shows that strategies aimed at increasing resources and challenges are generally associated with higher engagement, while excessive reduction of demands can have negative consequences for performance if it turns into passive avoidance of work (Lichtenthaler & Fischbach, 2019; Laguía et al., 2024; Lopper et al., 2025).

APPROACH AND AVOIDANCE CRAFTING

Based on empirical findings on the different consequences of individual dimensions of job crafting, current literature distinguishes between two basic behavioral orientations, namely approach and avoidance job crafting (Bruning & Campion, 2022; Lopper et al., 2024; Zhang & Parker, 2019). This conceptual framework provides an even deeper division of these dimensions based on employee orientation, namely approach and avoidance job crafting (Costantini, 2024; Zhang et al., 2025; Zhang & Parker, 2019).

Approach job crafting involves active efforts focused on growth, development, goal achievement, and enhancing the positive aspects of work, as well as seeking out more challenging tasks and challenges (Costantini, 2024; Lopper et al., 2024). In the context of the job demands-resources (JD-R) model, it involves increasing structural resources (e.g., competence development, autonomy) and social resources (e.g., feedback, support) (Tims et al., 2012; Nissinen et al., 2024; Kooij et al., 2022). Approach crafting-oriented employees actively seek out new projects, initiate change, and perceive job demands as learning opportunities rather than threats (Wang et al., 2024). This type of crafting is consistently associated with positive outcomes such as higher work engagement, greater job satisfaction, and higher performance (Holman et al., 2024; Laguía et al., 2024).

Conversely, avoidance job crafting focuses on protecting against stress and escaping negative states by eliminating or reducing undesirable job characteristics (Zhang & Parker, 2019). This strategy corresponds primarily with the dimension of reducing hindering demands and reflects the preventive orientation of the employee (Lichtenthaler & Fischbach, 2019; Laguía et al., 2024). It is motivated by the desire to "avoid something bad" and manifests itself primarily by reducing obstructive work demands, for example by limiting emotionally demanding interactions, avoiding conflict situations, or simplifying cognitively demanding tasks (Bruning & Campion, 2022; Lopper et al., 2025). This type of crafting corresponds to a preventive, often reactive motivational orientation aimed at conserving existing energy resources (Bruning & Campion, 2018; Lu et al., 2022; Wang et al., 2024). However, avoidance crafting is viewed ambivalently in the literature, as its excessive or exclusive use can lead to passivity, social withdrawal, and a long-term decline in motivation or performance (Hu et al., 2020; Petrou & Xanthopoulou, 2021; Zhang et al., 2025).

The key difference between approach and avoidance job crafting lies in their functional impact on employee well-being and performance. While approach orientation mobilizes energy and generates new resources that support growth and engagement, avoidance orientation focuses on minimizing losses without creating new developmental impulses (Lichtenthaler & Fischbach, 2019; Lopper et al., 2024). Meta-analytic findings show that approach job crafting is consistently associated with positive work outcomes, while avoidance job crafting shows rather weak, insignificant, or negative relationships with these indicators (Demerouti et al., 2021; Kooij et al., 2022; Holman et al., 2024). At the same time, some studies point to the existence of different job crafter profiles that reflect combinations of these strategies. For example, Nissinen et al. (2024) identify passive, average, and active crafters, with active crafters showing the highest levels of engagement and learning in the workplace. At the same time, however, newer person-centered approaches suggest that these two orientations are not mutually exclusive. The most adaptive employee profiles combine a high level of approach crafting with selective and appropriate use of avoidance strategies, which serve as a protective mechanism during periods of increased stress (Demerouti et al., 2021; Zhang et al., 2025).

From a methodological point of view, this framework is operationalized through the Approach–Avoidance Job Crafting Scale, which confirms the existence of two independent higher-order factors and emphasizes that job crafting is not a uniform construct but a hierarchically organized system of dimensions (Lopper et al., 2024) . For organizations, this implies that job crafting is not a universally beneficial phenomenon. Supporting approach-oriented forms of crafting can stimulate innovation, engagement, and sustainable performance, while excessive dominance of avoidance strategies may signal low identification with work or early stages of burnout (Demerouti et al., 2021; Dhanpat, 2025; Wang et al., 2024). Research shows that while approach crafting leads to resource expansion, avoidance crafting can be dysfunctional in the long term because it reduces proactivity and can lead to alienation from work (Laguía et al., 2024; Petrou & Xanthopoulou, 2021). Nevertheless, it appears that avoidance crafting may be a necessary survival strategy in extremely demanding conditions, where it serves as a last line of defense against burnout (Harju et al., 2024; Holman et al., 2024).

In the context of constant technological change, digitalization, and the implementation of artificial intelligence, job crafting is increasingly understood as a key adaptive skill that enables employees to maintain their mental well-being and stable employment (Chan et al., 2025; Kooij et al., 2022). Employees with high levels of job crafting agility are able to quickly and effectively adapt their demands and resources in response to unexpected disruptions, such as the COVID-19 pandemic (Dhanpat, 2025). This agility allows them not only to cope with stress, but also to actively seek new opportunities for learning and professional growth. The link between job crafting and the JD-R model also shows that managerial support and autonomy at work are key prerequisites that enable employees to effectively shape their work (Irfan et al., 2023; Zhang et al., 2025). When employees feel psychologically empowered, they are more likely to leverage their strengths and interests through crafting, leading to their sustainable employability and overall well-being (Kooij et al., 2022). Job crafting is therefore not just an individual effort, but the result of an interaction between personal characteristics and the design of the work environment (Laguía et al., 2024).

2. GOAL AND METHODOLOGY

The research was conducted as a quantitative questionnaire study. The research sample consisted of 500 working respondents with no missing values in the analyzed variables (Table 1). Most respondents worked in non-managerial positions, with the sample being relatively evenly represented across company size categories. Respondents with secondary education with a high school diploma and university education dominated, with the generational structure of the sample reflecting the predominance of younger and middle-aged cohorts in the current labor market.

Table 1: Sociodemographic and occupational characteristics of the sample (N = 500)

Job position	Frequency	Percent
I work in a management position (I lead a team of people)	155	31.0
I work in a non-managerial position	345	69.0
Type of company	Frequency	Percent
Microenterprise (1 – 9 employees)	69	13.8
Small enterprise (10 – 49 employees)	135	27.0
Medium-sized enterprise (50 – 249 employees)	152	30.4
Large enterprise (250 or more employees)	144	28.8
Education	Frequency	Percent
Secondary education without high school diploma	24	4.8
Secondary education with diploma	166	33.2
Bachelor's degree	74	14.8
Master's degree or combined bachelor's and master's degree	224	44.8
Doctorate	12	2.4
Generation	Frequency	Percent
1945 or earlier	5	1.0
1946 - 1964	16	3.2
1965 - 1980	95	19.0
1981 - 1996	285	57.0
1997 or later	99	19.8

Source: author's processing

Measuring tool. Job crafting was measured using the Slovak version of the job crafting scale based on the original tool by Tims et al. (2012). The scale consists of 21 items, which are divided into four dimensions within the original four-factor model: Increasing structural job resources (IStJR; 5 items), Increasing social job resources (ISoJR; 5 items), Increasing challenging job demands (ICHJD; 5 items), and Decreasing hindering job demands (DHJD; 6 items) (Tims et al., 2012).

Within the two-factor model (Lopper et al., 2024), the items of the IStJR, ISoJR, and ICHJD dimensions are grouped into the approach job crafting factor (15 items), while the items of the DHJD dimension form the avoidance job crafting factor factor (6 items).

Respondents rated individual statements on a 5-point Likert scale.

Translation of the scale. The translation of the job crafting scale into Slovak was carried out in accordance with standard recommendations for the adaptation of psychological measurement tools. The original English version was first independently translated by two bilingual experts with knowledge of occupational and organizational psychology. A consensus Slovak version was created based on a comparison of both translations.

Subsequently, a back-translation into English was carried out by an independent person who was not familiar with the original version of the scale. The back-translation was compared with the original wording of the items, and no significant differences in meaning were identified. The final version of the scale was revised in terms of language and content to ensure comprehensibility and conceptual equivalence of the items in the Slovak context.

Psychometric validation procedure. The validation of the Slovak version of the job crafting scale was carried out in accordance with standard recommendations for the psychometric evaluation of measurement tools. The factor structure of the scale was verified using confirmatory factor analysis (CFA) with the maximum likelihood (ML) method, which is suitable for testing hypothetical measurement models within structural modeling (Hair et al., 2019). The two-factor model of approach and avoidance job crafting was tested in several specifications as part of the validation process; further analyses present the final version of the model used for comparison with the original four-factor solution.

The quality of the model fit was assessed based on several fit indices, specifically the χ^2/df ratio, CFI and TLI indices, and the RMSEA approximation measure. When interpreting these indicators, the recommended threshold values for acceptable and good model fit were taken into account, as well as their joint interpretative significance, rather than the isolated fulfillment of individual criteria (Hu & Bentler, 1999).

The reliability of latent constructs was assessed using composite reliability (CR), which provides a more accurate estimate of internal consistency compared to traditional item-based coefficients (Hair et al., 2019). Convergent validity was assessed using average extracted variability (AVE), with AVE values interpreted in the context of the simultaneously achieved level of composite reliability (Fornell & Larcker, 1981).

The discriminant validity of the constructs was verified using the Fornell–Larcker criterion, according to which the square root of the AVE of each construct should be higher than its correlations with other latent variables (Fornell & Larcker, 1981). This procedure allows for the assessment of the degree of empirical distinctiveness of the individual dimensions of the measured construct.

3. FINDINGS

Data normality. Before performing confirmatory factor analysis, data normality was assessed. Univariate distributions of several items showed mild to moderate skewness and kurtosis. The multivariate normality test indicated a violation of normality (Mardia's coefficient = 196.75). However, given the size of the sample, the maximum likelihood (ML) method was considered appropriate for parameter estimation.

Comparison of models. To verify the factor structure of the Slovak version of the job crafting scale, two competing models were tested: (a) a 2-factor model distinguishing between approach and avoidance job crafting, and (b) a 4-factor model corresponding to the original theoretical structure.

As shown in Table 2, the 2-factor model showed an unacceptable level of fit with the data (CFI = .77, TLI = .75, RMSEA = .106). In contrast, the 4-factor model achieved acceptable to good fit indices (CFI = .91, TLI = .89, RMSEA = .069). The differences in fit indices indicate that the 4-factor model represents not only a statistically but also a practically significantly better solution than the simplified 2-factor model and was therefore chosen as the final measurement model.

Table 2: Comparison of model fit

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA
2-factor	1240.51	188	6.60	.77	.75	.106
4-factor	618.34	183	3.38	.91	.89	.069

Source: author's processing

Factor loadings. All items had statistically significant standardized factor loadings ($p < .001$) in both models. However, compared to the 2-factor model, the 4-factor model showed consistently higher and more balanced factor loadings across the dimensions of approach job crafting (see Table 3). This pattern suggests a more accurate distinction between different types of job crafting behavior within a more detailed factor structure.

Table 3: Standardized factor loadings in the 2-factor and 4-factor models

Dimension	**2-factor model (λ)**	**4-factor model (λ)**
Increasing Structural Job Resources (IStJR)	.43 – .74	.51 – .79
Increasing Social Job Resources (ISoJR)	.46 – .76	.58 – .77
Increasing Challenging Job Demands (ICHJD)	.55 – .78	.73 – .77
Decreasing Hindering Job Demands (DHJD)	.61 – .81	.61 – .76

Source: author's processing

Note: The ranges of standardized factor loadings are reported. All loadings were statistically significant ($p < .001$).

Reliability and convergent validity. The reliability of the constructs was assessed using composite reliability (CR) and convergent validity using average extracted variability (AVE) (Table 4). In both models, CR values reached the recommended minimum of .70, indicating good internal consistency of the constructs. In the 2-factor model, approach job crafting showed high composite reliability (CR = .90), but its AVE value was just below the recommended threshold of .50. In the 4-factor model, the AVE values were in most cases at or close to this limit, which, in combination with sufficiently high CR values, supports the convergent validity of the individual dimensions.

Table 4: Reliability and convergent validity (CR and AVE)

	Factor	**CR**	**AVE**
2- factor	Approach job crafting (APJC)	.90	.49
	Avoidance job crafting (AVJC)	.85	.49
4- factor	Increasing Structural Job Resources (IStJR)	.81	.46
	Increasing Social Job Resources (ISoJR)	.83	.50
	Increasing Challenging Job Demands (ICHJD)	.85	.54
	Decreasing Hindering Job Demands (DHJD)	.85	.49

Source: author's processing

Note: CR = composite reliability; AVE = average extracted variability.

Discriminant validity. Discriminant validity was assessed using the Fornell–Larcker criterion. In the 2-factor model, discriminant validity was confirmed, as the square roots of the AVE of both constructs exceeded their mutual correlation (Table 5), indicating that approach (APJC) and avoidance (AVJC) job crafting are empirically distinguishable constructs.

Table 5: Discriminant validity – Fornell–Larcker criterion (2-factor model)

Factor	**APJC**	**AVJC**
APJC	**.70**	.41
AVJC	.41	**.70**

Source: author's processing

Note: The diagonal contains the square roots of AVE (√AVE). APJC = approach job crafting, AVJC = avoidance job crafting.

In the 4-factor model, most constructs met the Fornell–Larcker criterion, as the AVE square roots were higher than their correlations with other factors (Table 6). The exception was the stronger correlation between increasing social work resources and increasing demanding work requirements. However, this correlation did not exceed the critical value of .85 and is consistent with their common orientation towards active, development-oriented forms of job crafting.

Table 6: Discriminant validity – Fornell–Larcker criterion (4-factor model)

Factor	**IStJR**	**ISoJR**	**ICHJD**	**DHJD**
IStJR	**.68**	.48	.58	.21
ISoJR	.48	**.71**	.81	.39
ICHJD	.58	.81	**.73**	.38
DHJD	.21	.39	.38	**.70**

Source: author's processing

The results of confirmatory factor analysis support the 4-factor structure of the Slovak version of the job crafting scale. Although the simplified 2-factor model achieved high internal consistency and basic discriminant validity, the 4-factor model provides a more accurate and psychometrically appropriate capture of the latent structure of job crafting. These findings support the understanding of approach job crafting as a heterogeneous construct consisting of several qualitatively distinct strategies.

4. DISCUSSION

The aim of this study was to verify the factor structure of the Slovak version of the job crafting scale using confirmatory factor analysis (Chan et al., 2025). The results supported the original four-factor structure of the construct and also pointed to the limitations of its simplified division into approach and avoidance job crafting (Lopper et al., 2024).

The findings suggest that approach job crafting is not a homogeneous construct but consists of several qualitatively different strategies aimed at actively changing work (Holman et al., 2024). Although increasing structural job resources, increasing social job resources, and increasing challenging job demands show moderate to strong mutual correlations, their separate modeling allows for a more accurate capture of the latent structure of job crafting. This result is consistent with the theoretical understanding of job crafting as a set of different ways in which employees actively shape their work environment (Wrzesniewski & Dutton, 2001, Wiesman).

Although the 2-factor model distinguishing between approach and avoidance job crafting achieved high internal consistency and met the basic criteria for discriminant validity, its overall model fit was significantly weaker compared to the 4-factor model. This suggests that the approach–avoidance dichotomy may have heuristic or descriptive value, but may not be sufficient to accurately capture the measurement structure of the construct. In the context of adapting the measurement tool, it therefore seems more appropriate to retain a more detailed factor structure (Zhang & Parker, 2019; Lopper et al., 2024; Nissinen et al., 2024).

From a methodological point of view, the results point to the importance of systematically comparing alternative measurement models when validating translations of psychological scales (Chan et al., 2025). Although some dimensions of approach job crafting showed AVE values just below the recommended threshold, their high composite reliability values support the convergent validity of the constructs. At the same time, stronger correlations between some dimensions do not necessarily pose a problem of discriminant validity as long as they remain below critical thresholds and are theoretically interpretable.

The study contributes to job crafting research primarily by providing a psychometrically validated Slovak version of a frequently used measurement tool, thereby expanding the possibilities for empirical research on job crafting in the Central European cultural context. The results also support the understanding of job crafting as a multidimensional construct and point to the limits of its simplified classification in measurement models.

From a practical point of view, the validated four-factor structure allows for flexible use of the scale depending on the objectives of research or practice. The limitations of the study include the use of self-assessment data and a cross-sectional research design, which does not allow for assessing the stability of the factor structure over time. Future research should focus on verifying the measurement invariance of the scale across different groups of respondents and on longitudinally verifying the stability of the identified structure.

CONCLUSION

This study successfully confirmed the factor structure of the Slovak version of the job crafting scale, comparing two models: a simpler two-factor model and a more detailed four-factor model. The results of the confirmatory factor analysis showed that both models are appropriately structured, but the more complex four-factor model better reflects the theoretical dimensions of work and provides a more detailed view of the forms of job crafting in the Slovak context. The objectives of the study, focused on verifying the factor structure and validity of the instrument, were thus fulfilled, and the study contributes to the development of empirical instruments for measuring job crafting in the Slovak population.

The contribution of the study is not only the confirmation of the validity of the adapted measurement tool, but also a better understanding of the structural aspects of job crafting in the cultural environment of Slovakia, which is important for further research and practical implementation in the work environment. The limitations of the study include the possible incompleteness of the representation of various occupational sectors and the limited longitudinal perspective, so it is advisable to extend the research to include analyses of measurement invariance across different groups of respondents and time periods.

For future research, it is recommended to examine how the structural and approach-avoidance structure of job crafting changes in long-term studies, or what factors influence its development, including the influence of the organizational environment and individual characteristics of employees. From a practical perspective, it is necessary to raise awareness of the possibilities of promoting forms of job crafting among employees and managers so that they can effectively implement changes in the workplace in line with individual needs and thus improve well-being at work and the organization as a whole.

At the same time, it is important to emphasize that the availability of relevant and valid tools for measuring job crafting has the potential to promote a better understanding of these dynamics in practice, which can lead to better adaptation of personnel strategy and development of the work environment. This study thus serves as a springboard for further research and practical applications in the field of occupational psychology and human resource management, and its results can help in the development of policies and interventions to support activities that increase job satisfaction and performance. The results can also serve as inspiration for organizations to implement a strategy aimed at expanding awareness, while also monitoring the potential risks associated with the excessive dominance of avoidance strategies, which is key to maintaining a balance between employee development and protection.

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Appendix

Approach job crafting	Zvýšenie štrukturálnych pracovných zdrojov (IStJR) Increasing Structural Job Resources	Snažím sa rozvíjať svoje schopnosti.	I try to develop my capabilities
		Pracujem na svojom profesionálnom rozvoji.	I try to develop myself professionally
		V práci sa snažím učiť nové veci.	I try to learn new things at work
		Dbám na to, aby som svoje schopnosti využíval / využívala naplno.	I make sure that I use my capacities to the fullest
		Sám / sama sa rozhodujem o tom, ako budem svoju prácu vykonávať.	I decide on my own how I do things
	Zvýšenie sociálnych pracovných zdrojov (ISoJR) Increasing Social Job Resources	Žiadam svojho nadriadeného, aby ma mentoroval alebo koučoval.	I ask my supervisor to coach me
		Overujem si u svojho nadriadeného, či je spokojný s mojou prácou.	I ask whether my supervisor is satisfied with my work
		Môj nadriadený je pre mňa zdrojom inšpirácie.	I look to my supervisor for inspiration
		Pýtam sa ostatných kolegov na spätnú väzbu k môjmu pracovnému výkonu.	I ask others for feedback on my job performance
		Žiadam ostatných kolegov o radu.	I ask colleagues for advice

	Rastúce náročné pracovné požiadavky (ICHJD) Increasing Challenging Job Demands	Keď sa objaví zaujímavý projekt, proaktívne sa ponúknem ako spolupracovník.	When an interesting project becomes available, I proactively offer to participate.
		Ak sa objavia nové trendy alebo zmeny, som medzi prvými, ktorí sa o nich dozvedia a vyskúšajú ich.	When new developments or changes emerge, I am among the first to learn about them and try them out.
		V prípade, keď v práci nemám veľa povinností, vnímam to ako príležitosť začať niečo nové.	When my workload is low, I see it as an opportunity to initiate new tasks or projects.
		Pravidelne si beriem úlohy naviac, aj keď za to nedostávam peniaze.	I regularly take on additional tasks, even when they are not financially rewarded.
		Snažím sa svoju prácu urobiť podnetnejšou tým, že sa vystavujem novým výzvam.	I try to make my work more challenging by exploring new ways of connecting different aspects of my job.
Avoidance job crafting	Znižovanie prekážajúcich pracovných požiadaviek (DHJD) Decreasing Hindering Job Demands	Dbám na to, aby moja práca nevyžadovala príliš veľa sústredenia a premýšľania.	I make sure that my work is mentally less intense
		Snažím sa zabezpečiť, aby moja práca bola emocionálne menej náročná.	I try to ensure that my work is emotionally less intense
		Organizujem si svoju prácu tak, aby môj kontakt s ľuďmi, ktorých problémy ma emocionálne ovplyvňujú, bol minimálny.	I manage my work so that I try to minimize contact with people whose problems affect me emotionally
		Organizujem si svoju prácu tak, aby môj kontakt s ľuďmi, ktorých očakávania sú nereálne, bol minimálny.	I organize my work so as to minimize contact with people whose expectations are unrealistic
		Snažím sa zabezpečiť, aby som v práci nemusel / nemusela robiť veľa náročných rozhodnutí.	I try to ensure that I do not have to make many difficult decisions at work
		Organizujem si prácu tak, aby som nemusel / nemusela sústrediť pozornosť príliš dlho a naraz.	I organize my work in such a way to make sure that I do not have to concentrate for too long a period at once

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CLUSTER ANALYSIS OF THE EU REGIONAL COMPETITIVENESS INDEX OF NUTS-2 REGIONS

Pavol ORŠANSKÝ

Abstract

This research investigates the complex dynamics of regional development within the European Union by performing a cluster analysis of the EU Regional Competitiveness Index (RCI 2.0) across 234 NUTS-2 regions. The central issue addressed is the "Capital City Bias" and the challenge of balancing industrial productivity with the quality of life for residents. Furthermore, the study explores the "middle-income trap," a problematic state where regions transitioning through developmental stages may face a policy vacuum if basic infrastructure is neglected before innovation ecosystems are fully mature. The primary objective is to identify hidden patterns and specific similarities within regional groupings to move beyond simple rankings and better understand the unique developmental needs of different clusters. To achieve this, the study utilizes the k-means++ clustering algorithm, an advanced iteration of Lloyd's algorithm that employs a heuristic for more effective centroid seeding to improve both running time and solution quality. The research focuses on the three core sub-indices of the RCI: Basic (including institutions and infrastructure), Efficiency (labor market and higher education), and Innovation (technological readiness and business sophistication). To determine the optimal number of clusters for each sub-index, the Calinski-Harabasz criterion (variance ratio criterion) is applied, ensuring that the resulting data partitions are both dense and well-separated. Furthermore, Non-negative Matrix Factorization (NNMF) is employed as a sophisticated visualization tool, allowing for the transformation of multidimensional regional data into a two-dimensional plane while preserving essential Euclidean norms. The results demonstrate a persistent geographical divide in Europe, characterized by a stark "elitism" in capital cities compared to their stagnating peripheries, providing critical insights for the tailoring of future Cohesion Policies.

Key words:
cluster analysis, Regional Competitiveness Index, k-means++ clustering

JEL Classification M12, M54, O32 https://doi.org/10.52665/ser20250207

INTRODUCTION

Since 2010, the EU Regional Competitiveness Index (RCI) has been measuring the major factors of competitiveness for all the NUTS-2 level regions across the European Union. The Index measures, with a rich set of indicators, the ability of a region to offer an attractive environment for firms and residents to live and work. Since the 2022 edition of the RCI uses an updated methodological framework, to facilitate comparison over time. In addition, starting from the original data used in 2016 and 2019, the scores have been re-calculated using the new methodology, labelled as RCI 2.0, 2016 edition, and RCI 2.0, 2019 edition. The resulting rankings do not replace the RCI rankings published in 2016 and 2019, produced with the old methodology. The RCI is composed of three sub-indices: **Basic**, **Efficiency** and **Innovation**, and of 11 pillars that describe the different aspects of competitiveness.

The **Basic sub-index** refers to the key basic drivers of all types of economies. It identifies the main issues that are necessary to develop regional competitiveness and includes five pillars: (1) *The Institutions*, (2) *The Macroeconomic Stability*, (3) *The Infrastructures*, (4) *The Health* and (5) *The Basic Education*. The **Efficiency sub-index** includes three pillars: (6) *Higher education, training and lifelong learning*, (7) *Labor market efficiency* and (8) *Market size*. Lastly, the **Innovation sub-index** includes the three pillars that are the drivers of improvement at the most advanced stage of economic development: (9) *Technological readiness*, (10) *Business sophistication* and (11) *Innovation*. The final

RCI 2.0 is weighted arithmetic mean of these three sub-indices, which are weighed differently per development stage (gross domestic product (GDP) per head in purchasing power standards (PPS) expressed as an index with the EU-27 average set to 100), as shown in Table 1. For more details of each pillar or others information about the methodology see (Dijkstra 2023).

Table 1: Table of sub-indexes weights of the RCI

Stage of Development	Sub-index weight		
	Basic	Efficiency	Innovation
GDP index[1] < 75	30%	50%	20%
GDP index[1] ∈ [75,100]	25%	50%	25%
GDP index[1] > 75	20%	50%	30%

Source: author's processing

[1] GDP/ head (PPS), Index EU-27 = 100.

In our work we try to find some specific similarities in each type of sub-index which are other than those in other groups. In other words, we do **cluster analysis** of every sub-index in relation to NUTS-2 regions of the EU. Cluster analysis involves applying clustering algorithms with the goal of finding hidden patterns or groupings in a data set. It is therefore used frequently in exploration data analysis but is also used for anomaly detection and preprocessing for supervised learning. Clustering algorithms form groupings in such a way that data within a group (or cluster) has a higher measure of similarity than data in any other cluster. Various similarity measures can be used, including Euclidean, probabilistic, cosine distance, and correlation. Most unsupervised learning methods are a form of cluster analysis. Clustering algorithms fall into two broad groups: (1) *Hard clustering*, where each data point belongs to only one cluster, such as the popular k-means method and (2) *Soft clustering*, where each data point can belong to more than one cluster, such as in Gaussian mixture models. Examples include phonemes in speech, which can be modeled as a combination of multiple base sounds, and genes that can be involved in multiple biological processes. We use **k-means clustering**, or Lloyd's algorithm (Lloyd 1982), which is an iterative, data-partitioning algorithm that assigns n observations to exactly one of k clusters defined by centroids, where k is chosen before the algorithm starts. We use an improved version of this algorithm called the **k-means++ algorithm**. The k-means++ algorithm uses a heuristic to find centroid seeds for k-means clustering. According to Arthur and Vassilvitskii (Arthur and Vassilvitskii 2007), k-means++ improves the running time of Lloyd's algorithm, and the quality of the final solution.

1 LITERATURE OVERVIEW

The literature on the EU Regional Competitiveness Index (RCI) reveals a central "problematic": the challenge of reconciling administrative boundaries with functional economic realities while balancing social well-being against industrial productivity. Academic debate in this area is primarily structured around three core tensions.

A recurring theme in the literature is the dual nature of regional competitiveness. While traditional indices (like the WEF's Global Competitiveness Index) focus on business productivity, the RCI problem lies in its attempt to measure a region's attractiveness for both firms and residents (Annoni & Dijkstra, 2019). This creates a theoretical friction: policies that benefit firms (e.g., lower corporate taxes or flexible labor markets) may sometimes conflict with the "quality of life" metrics (e.g., high social protection and environmental standards) that make a region attractive to residents.

Scholars frequently highlight the "Modifiable Areal Unit Problem" (MAUP) as a significant hurdle in RCI research. The index utilizes NUTS 2 administrative regions, which are often criticized for being "artificial" constructions that do not reflect actual labor markets or commuting patterns. Literature points out that this can lead to the "Capital City Bias", where a capital's high performance masks deep-seated stagnation in its immediate rural periphery, complicating the delivery of effective Cohesion Policy.

The RCI employs a unique methodology where pillars are weighed differently based on a region's stage of development (GDP per capita). The problematic identified here is the potential for a "middle-income trap." Literature (Dijkstra et al., 2023) suggests that as regions transition from "Basic" to "Efficiency" and "Innovation" stages, the shift in priorities can lead to a policy vacuum where basic infrastructure is neglected before innovation ecosystems are fully mature.

2 METHODOLOGY

The main method used in our work is cluster analysis which refers to a family of algorithms and tasks rather than one specific algorithm. It can be achieved by various algorithms that differ significantly in their understanding of what constitutes a cluster and how to efficiently find them. Popular notions of clusters include groups with small distances between cluster members, dense areas of the data space, intervals or particular statistical distributions. Clustering can therefore be formulated as a multi-objective optimization problem. The appropriate clustering algorithm and parameter settings (including parameters such as the distance function to use, a density threshold or the number of expected clusters) depend on the individual data set and intended use of the results. It is an iterative process of knowledge discovery or interactive multi-objective optimization that involves trial and failure. There is a common denominator: a group of data objects, which is one of the reasons why there are so many clustering algorithms.

k-means clustering is a method of vector quantization, originally from signal processing, that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid), serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells (partition of a plane into regions close to each of a given set of objects). k-means clustering minimizes within-cluster variances (squared Euclidean distances), but not regular Euclidean distances, which would be the more difficult Weber problem: the mean optimizes squared errors, whereas only the geometric median minimizes Euclidean distances. For instance, better Euclidean solutions can be found using k-medians and k-medoids. The problem is computationally difficult (nondeterministic polynomial - hard); however, efficient heuristic algorithms converge quickly to a local optimum.

Given a set of observations $(\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n)$, where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k ($\leq n$) sets $\boldsymbol{S} = (S_1, S_2, \dots, S_k)$ so as to minimize the within-cluster sum of squares (WCSS) (i.e. variance). Formally, the objective is to find

$$\operatorname{argmin}_{\boldsymbol{S}} \sum_{i=1}^{k} \sum_{\boldsymbol{x} \in S_i} \|\boldsymbol{x} - \boldsymbol{C}_i\|^2 = \operatorname{argmin}_{\boldsymbol{S}} \sum_{i=1}^{k} |S_i| \operatorname{Var} S_i \quad (1)$$

where $\|\dots\|$ is the L^2 norm (Euclidean distance) between the two vectors and $\boldsymbol{C}_i$ is the mean (also called centroid) of points in S_i, i.e.

$$\boldsymbol{C}_i = \frac{1}{|S_i|} \sum_{\boldsymbol{x} \in S_i} \boldsymbol{x}, \quad (2)$$

where $|S_i|$ is the size of S_i. This is equivalent to minimizing the pairwise squared deviations of points in the same cluster

$$\operatorname{argmin}_{\boldsymbol{S}} \sum_{\boldsymbol{x}, \boldsymbol{y} \in S_i} \|\boldsymbol{x} - \boldsymbol{y}\|^2 \quad (3)$$

The equivalence can be deduced from identity

$$|S_i| \sum_{\boldsymbol{x} \in S_i} \|\boldsymbol{x} - \boldsymbol{C}_i\|^2 = \frac{1}{2} \sum_{\boldsymbol{x}, \boldsymbol{y} \in S_i} \|\boldsymbol{x} - \boldsymbol{y}\|^2 \quad (4)$$

Since the total variance is constant, this is equivalent to maximizing the sum of squared deviations between points in different clusters (between-cluster sum of squares, BCSS) (Kriegel 2017).

k-means clustering, or Lloyd’s algorithm, is an iterative, data-partitioning algorithm that assigns n observations to exactly one of k clusters defined by centroids, where k is chosen before the algorithm starts. The algorithm proceeds as follows:

- Choose k initial cluster centers (centroid). For example, choose k observations at random or use the k-means ++ algorithm for cluster center initialization (the default).

- Compute point-to-cluster-centroid distances of all observations to each centroid
- There are two ways to proceed: (1) *Batch update* - assign each observation to the cluster with the closest centroid, (2) *Online update* - individually assign observations to a different centroid if the reassignment decreases the sum of the within-cluster, sum-of-squares point-to-cluster-centroid distances.
- Compute the average of the observations in each cluster to obtain k new centroid locations.
- Repeat steps 2 through 4 until cluster assignments do not change, or the maximum number of iterations is reached.

k-means++ improves the running time of Lloyd's algorithm, and the quality of the final solution. The k-means++ algorithm chooses seeds as follows, assuming the number of clusters is k.

- Select an observation uniformly at random from the data set, x. The chosen observation is the first centroid and is denoted C_1.

- Compute distances from each observation to C_1. Denote the distance between C_1 and the observation m as $d\left(x_m, C_j\right)$.
- Select the next centroid, C_2 at random from x with probability

$$P = \frac{d^2(x_m, C_1)}{\sum_{j=1}^{n} d^2(x_j, C_1)}. \quad (5)$$

- To choose center j, we compute the distances from each observation to each centroid and assign each observation to its closest centroid. For each $m = 1, \ldots, n$ and $p = 1, \ldots, j-1$, select centroid j at random from x with probability

$$P = \frac{d^2(x_m, C_p)}{\sum_{x_h \in C_p} d^2(x_h, C_p)}, \quad (6)$$

where C_p is the set of all observations closest to centroid C_p and x_m belongs to C_p.

- Repeat step 4 until k centroids are chosen.

The algorithms use a two-phase iterative algorithm to minimize the sum of point-to-centroid distances, summed over all k clusters. I. This first phase uses batch updates, where each iteration consists of reassigning points to their nearest cluster centroid, all at once, followed by recalculation of cluster centroids. This phase occasionally does not converge with a solution that is a local minimum. That is, a partition of the data where moving any single point to a different cluster increases the total sum of distances. This is more likely for small data sets. The batch phase is fast, but potentially only approximates a solution as a starting point for the second phase. This second phase uses online updates, where points are individually reassigned if doing so reduces the sum of distances, and cluster centroids are recomputed after each reassignment. Each iteration during this phase consists of one passing through all the points. This phase converges to a local minimum, although there might be other local minimums with lower total sum of distances. In general, finding the global minimum is solved by an exhaustive choice of starting points, but using several replicates with random starting points typically results in a solution that is a global minimum

An important task in clustering is the correct determination of the number of clusters. This ensures that the data is properly and efficiently divided. The correct choice of k is often ambiguous, with interpretations depending on the shape and scale of the distribution of points in a data set and the desired clustering resolution of the user. In addition, increasing k without penalty will always reduce the amount of error in the resulting clustering, to the extreme case of zero error if each data point is considered its own cluster (i.e., when k equals the number of data points, n). Intuitively then, the optimal choice of k will strike a balance between maximum compression of the data using a single cluster, and maximum accuracy by assigning each data point to its own cluster. If an appropriate value of k is not apparent from prior knowledge of the properties of the data set, it must be chosen somehow. There are several categories of methods for making this decision. We use the Caliński-Harabasz criterion. This criterion is sometimes called the variance ratio criterion

(VRC). The Caliński-Harabasz index is defined as

$$VRC_k = \frac{SS_B}{SS_W} \cdot \frac{n-k}{k-1}, \qquad (7)$$

where SS_B is the overall between-cluster variance, SS_W is the overall within-cluster variance k is the number of clusters, and n is the number of observations. The overall between-cluster variance SS_B is defined as

$$SS_B = \sum_{i=1}^{k} n_i \|m_i - m\|^2, \qquad (8)$$

where k is the number of clusters, n_i is the number of observations in i-th cluster, m_i is the centroid of i-th cluster, m is the overall mean of the sample data. The overall within-cluster variance SS_W is defined

$$SS_W = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - m_i\|^2, \qquad (9)$$

where k is the number of clusters, x is a data point, C_i is the i-th cluster, m_i is the centroid of i-th cluster. Well-defined clusters have a large between-cluster variance (SS_B) and a small within-cluster variance (SS_W). The larger the VRC_k ratio, the better the data partition. To determine the optimal number of clusters, maximize VRC_k with respect to k. The optimal number of clusters corresponds to the solution with the highest Caliński-Harabasz index value (Caliński & Harabasz 1974).

Non-negative matrix factorization (NNMF), also non-negative matrix approximation is a group of algorithms in multivariate analysis and linear algebra where a matrix V is factorized into (usually) two matrices W and H, with the property that all three matrices have no negative elements. This non-negativity makes the resulting matrices easier to inspect. The factorization uses an iterative algorithm starting with random initial values for W and H. Because the root means square residual D might have local minima, repeated factorizations might yield different W and H. Sometimes the algorithm converges to a solution of lower rank than k, which can indicate that the result is not optimal. More detailed information can be seen in (Michael 2007).

3 FINDINGS

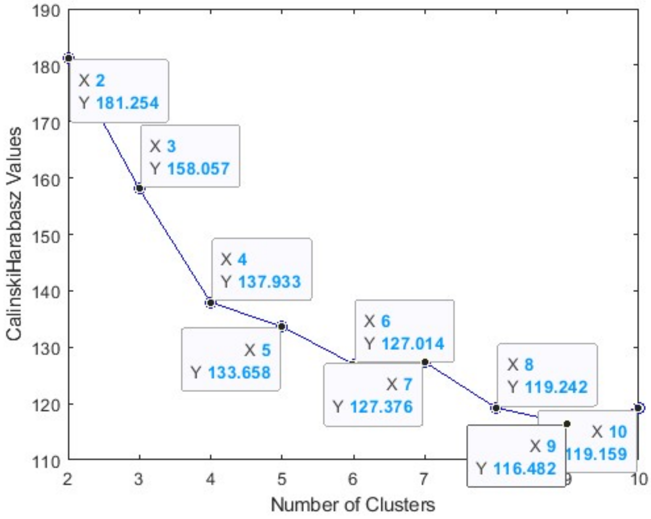
The results of the cluster analysis are divided into three subcategories according to individual subindexes, i.e. Basic, Efficiency and Innovation according to NUTS-2 regions.

Basic sub-index cluster analysis of EU countries

The Basic sub-index includes five pillars: the institutions, the macroeconomic stability, the infrastructures, the health and the basic education. That means we must analyse 234 vectors (number NUTS-2 regions) of dimension 5 (number of Basic sub-index pillars). First, we must find the best number of clusters for this analysis. Using MatLab function *evalclusters*, which creates a clustering evaluation object containing data used to evaluate the optimal number of data clusters, we find that the best number of clusters is 2 (see Figure 1). Higher value of Caliński-Harabasz index means the clusters are dense and well separated, although there is no "acceptable" cut-off value. We need to choose that solution which gives a peak or at least an abrupt elbow on the line plot of Caliński-Harabasz indices. The choice of only two clusters is also suitable considering the dendrogram (see Figure 2) where we can see intermixture of clusters. In the next step (using MatLab function *kmeans*), we sorted the data into these two clusters and found their centroids.

The centroids characterizing the values of institutions, macroeconomic stability, infrastructures, health and basic education are this four points $C_1 = [68.88, 81.26, 62.51, 87.93, 85.16]$ and $C_2 = [134.50, 120.62, 107.96, 105.71, 111.45]$. For better further visualization, we chose Nonnegative matrix factorization (NNMF) to display the 5-dimensional space in the plane (see Figure 3.). We see at least a separation of clusters, but a clear division into two groups with better and worse ratings is evident. This division is also visually obvious at map of EU (Figure 4), where we can see division of the NUTS-2 regions of EU with dividing Europe by diagonal running from south-west to north-east. Except for the region of Central Bohemia and Prague itself, the entire eastern block is part of the cluster together with Greece and Italy, part of the Iberian Peninsula.

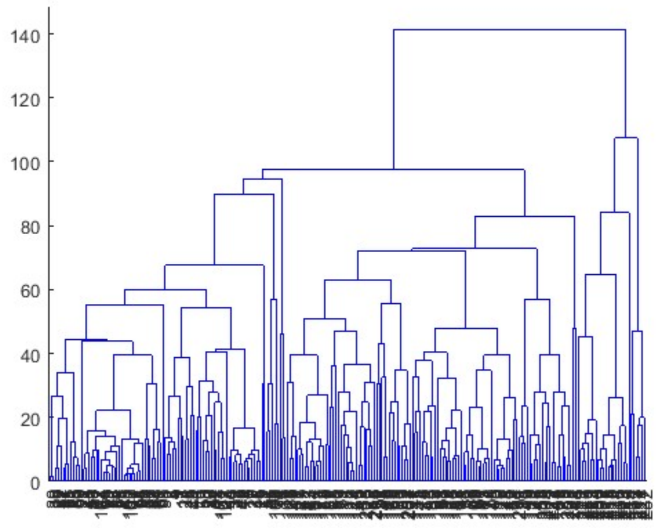
Figure 1: Line-plot of Caliński-Harabasz values vs number of clusters for the Basic sub-index dataset of NUTS-2 regions



1 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

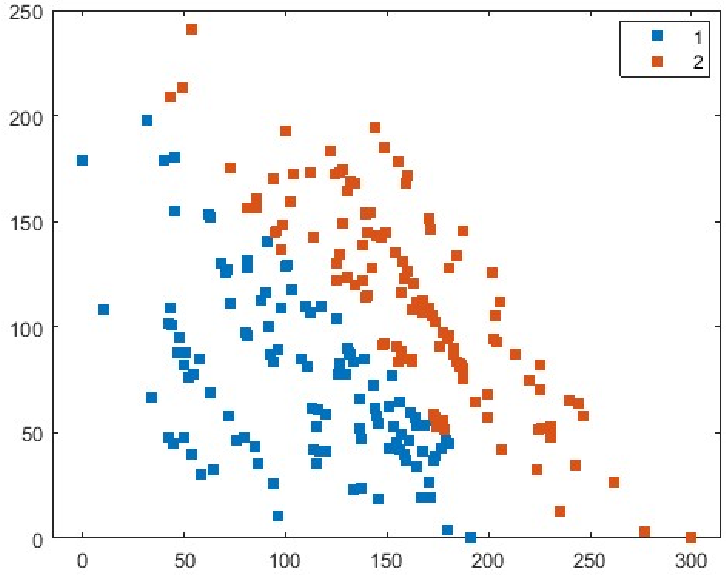
2

3 Figure 2: Dendrogram for the Basic sub-index dataset of NUTS-2 regions



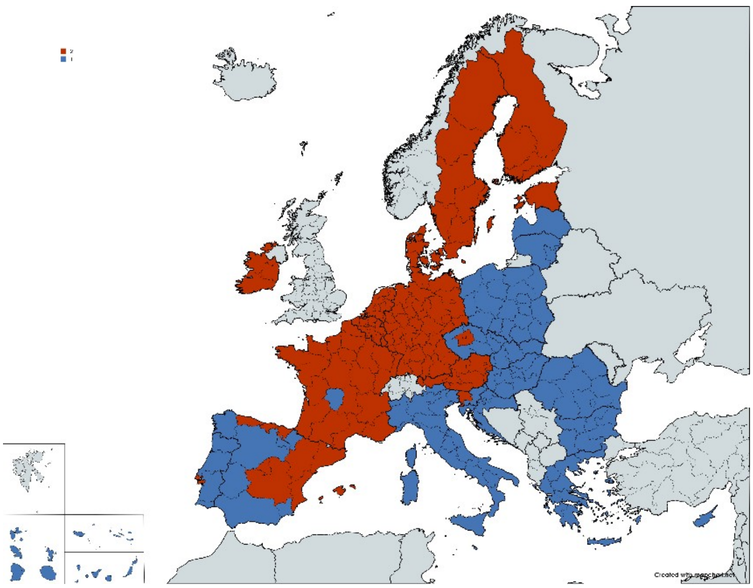
4 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

Figure 3: NNMF visualization for the Basic sub-index dataset of NUTS-2 regions



5 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

Figure 4: The NUTS-2 maps of the Basic sub-index dataset for two clusters

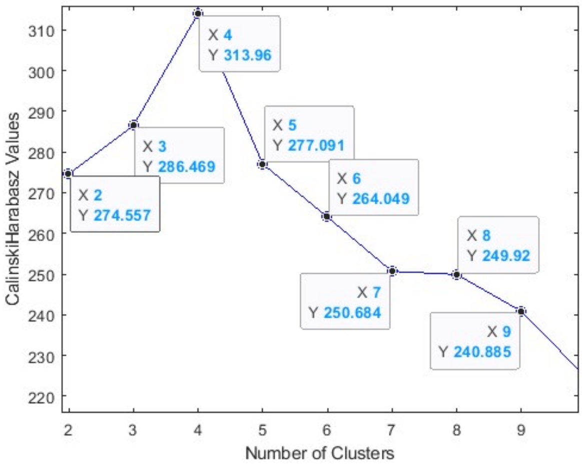


6 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

Efficiency sub-index cluster analysis of EU countries

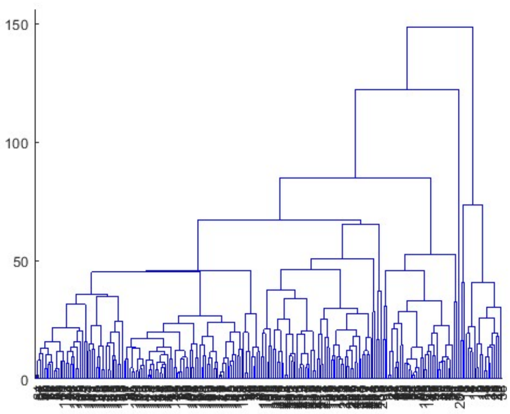
The Efficiency sub-index includes three pillars: higher education, training and lifelong learning, the labor market efficiency and the market size. So, we have 234 vectors of dimension 3. If we evaluate the number of clusters, we obtain the number of 4 clusters (see Figure 5 also Figure 6).

Figure 5: Line-plot of Caliński-Harabasz values vs number of clusters for the Efficiency sub-index dataset of NUTS-2 regions



7 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

Figure 6: Dendrogram for the Efficiency sub-index dataset of NUTS-2 regions

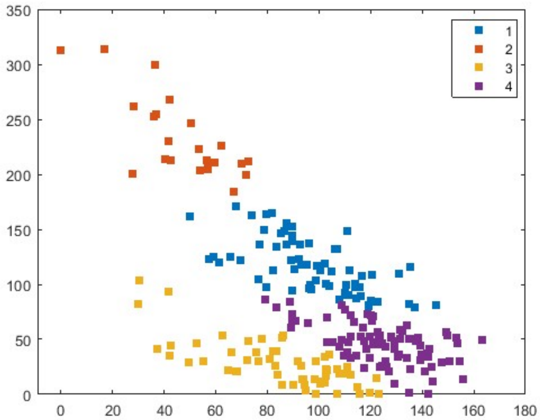


8 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

The centroids of these four clusters, which represent lifelong learning, the labor market and the market size, are $C_1 = [107.95, 111.89, 111.54]$, $C_2 = [114.03, 116.10, 207.33]$, $C_3 = [69.33, 70.17, 33.60]$ and

$C_4 = [103.99, 103.14, 54.23]$. If we transform the obtained clusters into two-dimensional vectors, the visualization can be seen on the NNMF visualization (Figure 7).

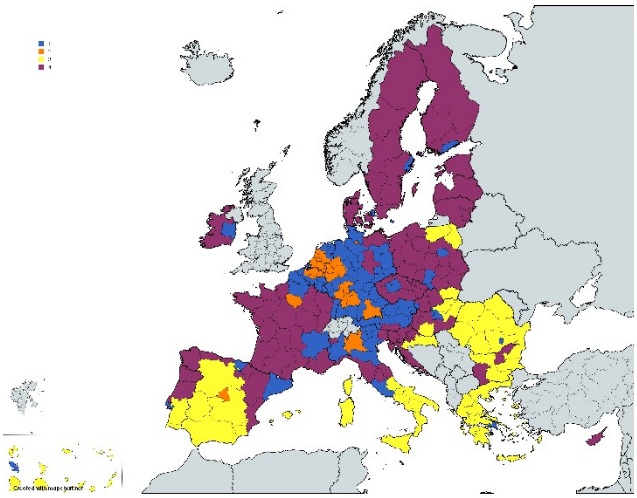
Figure 7: NNMF visualization for the Efficiency sub-index dataset of NUTS-2 regions



9 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)).*

After drawing the clusters on the geographical map, the categorization according to the regional development in the north-south and east-west direction is obvious. And there is also a strong elitism around the developed capital cities and their agglomerations, or cen-ters such as the Ruhr, northern Italy, or the BENELUX countries (Figure 8).

Figure 8: The NUTS-2 maps of the Efficiency sub-index dataset for four clusters

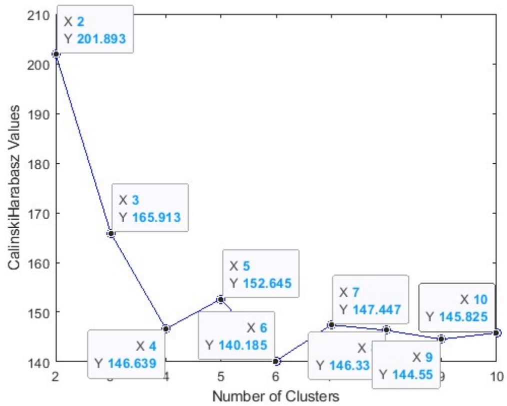


10 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

Innovation sub-index cluster analysis of EU countries

Innovation sub-index includes the three pillars that are the drivers of improvement at the most advanced stage of economic development: technological readiness, business sophistication and innovation. That means we have also 234 vectors of dimension 3. If we draw the dependence between the Caliński-Harabasz values and the number of clusters, we see that the highest value is for the basic division into two clusters, but considering the elbow rule, we can also choose the number of clusters 4 (see Figure 9).

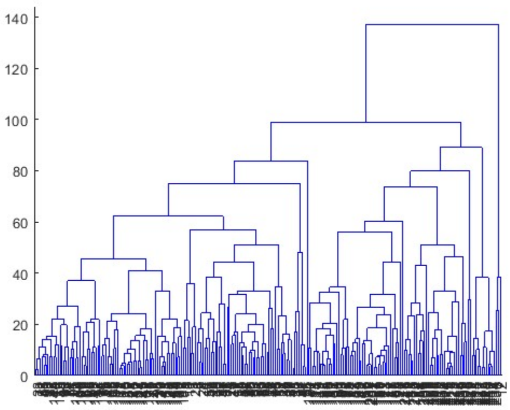
Figure 9: Line-plot of Caliński-Harabasz values vs number of clusters for the Innovation sub-index dataset of NUTS-2 regions



11 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)).*

From the dendrogram also can be also seen that the best way to analyze this dataset is for number of clusters 2 or 4 (see Figure 10).

Figure 10: Dendrogram for the Innovation sub-index dataset of NUTS-2 regions

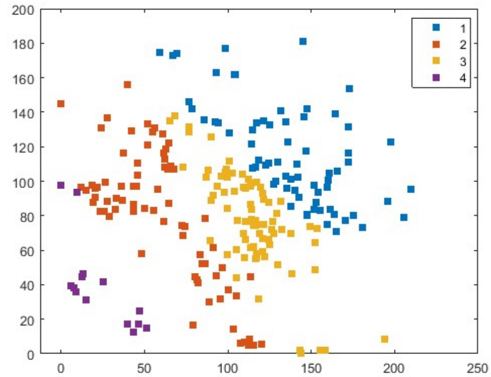


12 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

Using the MatLab function *kmeans* we get four clusters with their centroids (representing technological readiness, business sophistication and innovation) $C_1 = [130.11,\ 127.75, 131.84]$

$C_2 = [88.18, 66.31, 60.00]$, $C_3 = [93.65, 105.73, 97.14]$ and $C_4 = [35.89, 20.95, 39.03]$. Using the Nonnegative matrix factorization, we can visualize the resulted clustering in two-dimensional way (Figure 11). And now it is clear that the choice of four clusters is better way than only dividing the dataset into two clusters.

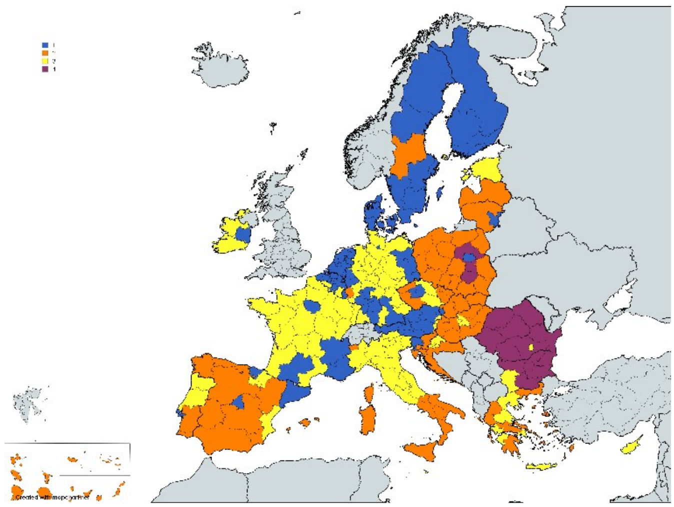
Figure 11: NNMF visualization for the Innovation sub-index dataset of NUTS-2 regions



13 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

The map of NUTS-2 region according to our obtained clustering indexation for Innovation pillars is very similar to the previous one for Efficiency pillars. It means there can been seen all the stereotypes about the rate of innovativeness, e.g. more innovativeness western Europe in contrast to the east Europe (Romania, Bulgaria and easter regions of Poland), typical centers of innovations as (BENELUX, Ruhr, the capitals with their surroundings). Also, the difference between the south and north of Europe can be seen.

Figure 12: The NUTS-2 maps of the Innovations sub-index dataset for four clusters



14 *Source: author's processing from data of the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO)*

4 DISCUSSION

In our article, we analyzed individual assessments of the level of competitiveness of EU regions (NUTS-2) according to three basic sub-indexes (Basic, Efficiency, Innovation). As a starting point, we use the EU Regional Competitiveness Index (RCI), whose individual components (evaluation indices) we evaluated using cluster analysis. We com-pared the obtained categorizations with the regional characteristics of the given regional territorial unit.

The cluster analysis was conducted within the MATLAB environment, utilizing the advanced **k-means++** algorithm. In addition to standard clustering techniques, a notable feature of this study is the application of Non-negative Matrix Factorization (NNMF) for data visualization. This method facilitates the transformation of multidimensional matrices into a two-dimensional space while preserving the structural relationships between entities, thereby significantly enhancing the clarity of the results.

CONCLUSION

This study successfully applied advanced cluster analysis to the EU Regional Competitiveness Index (RCI 2.0) to identify patterns of economic development across 234 NUTS-2 regions. By employing the k-means++ algorithm and validating results through the Caliński-Harabasz criterion, the research moved beyond simple rankings to reveal distinct regional groupings based on the three core sub-indices: Basic, Efficiency, and Innovation.

The analysis of the Basic sub-index revealed a fundamental geographical divide in Europe, separating more developed regions from an "eastern bloc" that includes Greece, Italy, and parts of the Iberian Peninsula. In contrast, the Efficiency and Innovation sub-indices highlighted a more complex four-cluster structure. These findings underscore a significant "elitism" surrounding capital cities and major industrial hubs like the Ruhr and BENELUX countries, which consistently outperform their peripheries.

Methodologically, the use of Non-negative Matrix Factorization (NNMF) proved to be a highly effective tool for visualizing multidimensional competitiveness data in a two-dimensional space while preserving essential Euclidean norms. Ultimately, these results confirm that regional competitiveness in the EU remains characterized by persistent north-south and east-west disparities, as well as a stark contrast between innovative urban centers and stagnant rural regions. These insights are critical for tailoring future Cohesion Policies to the specific developmental needs of each identified regional cluster.

ACKNOWLEDGMENTS

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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON CONTEMPORARY HUMAN RESOURCE MANAGEMENT

Jana ŠPANKOVÁ, Jana SOCHUĽÁKOVÁ

Abstract

At present, the impact of artificial intelligence (AI) is increasingly evident across various fields, including human resource management. Artificial intelligence supports the management of work processes and enhances productivity. It has the potential to transform HR activities through relevant and in-depth analyses of individual functions. However, AI also entails several risks, such as increased stress and psychosocial risks. For this reason, it is essential to consider the responsible and transparent use of AI. Employees require adequate support to build a sufficient level of trust in AI and to understand how to use its tools responsibly.
The presented study examines the impact of artificial intelligence on contemporary human resource management and the labour market. The main thematic areas within this issue were identified through a systematic literature review based on bibliometric analysis using data from the Web of Science and Scopus databases. The analysed period covers the years 2015–2025.

Key words:
artificial intelligence, labour market, human resource management, literature review, WOS

JEL Classification J21, J24, O33 https://doi.org/10.52665/ser20250208

INTRODUCTION

Artificial intelligence (AI) is a key technological tool that significantly influences the way we work, communicate, and make decisions. It represents a field of computer science focused on the development of machines capable of mimicking human thinking, decision-making, and behaviour based on algorithms stored in their memory (Bhbosale, 2020).

Artificial intelligence can be classified into several levels according to their complexity:

- Artificial Narrow Intelligence (ANI): AI focused on a limited set of specific capabilities.
- Artificial General Intelligence (AGI): AI possessing cognitive abilities comparable to those of humans.
- Artificial Superintelligence (ASI): AI that surpasses human intelligence.

ANI is highly specialized and is commonly used for specific tasks such as speech recognition, facial identification, or data prediction. Narrow AI is not capable of learning independently beyond its original purpose; it must be designed for a specific function and trained on data that are relevant to a particular problem or domain.

AGI refers to the ability of computer systems to replicate the cognitive functions of the human brain. ASI is capable of understanding and, in theory, should be able to learn and perform any intellectual task that a human can accomplish. However, unlike general AI, it can surpass human capacities and abilities by multiple orders of magnitude (Schweighofer, 2023).

The rapid development of artificial intelligence and automation represents one of the most significant and irreversible trends in contemporary society, directly affecting the labour market and human resource management. The implementation of artificial intelligence in HR activities brings not only benefits but also several risks and disadvantages that require careful attention. According to Gašparík (2025), the main challenges include a reduction in the number of jobs, particularly in administrative and junior HR positions, which are the most susceptible to automation. This development is closely linked to the need for reskilling, as HR professionals must develop technological, analytical, and strategic skills in order to remain relevant in a changing work environment.

A major risk is algorithmic bias, which may lead to unintended discrimination against candidates if AI systems are inadequately designed. Another significant challenge concerns data protection, as the processing of sensitive employee data requires full compliance with legislation such as the General Data Protection Regulation (GDPR). Finally, excessive reliance on technology may result in the dehumanisation of HR processes, manifested in the loss of personal interaction, empathy, and trust between employees and employers.

1. LITERATURE OVERVIEW

Artificial intelligence represents one of the most significant technological innovations of the contemporary era. Although the concept of artificial intelligence emerged as early as the 1950s, its practical application in the business environment has only begun to develop extensively over the past two decades. Today, AI is no longer merely a set of algorithms but a complex system capable of autonomous learning, adaptation, and decision-making based on input data. These capabilities make AI particularly suitable for deployment across numerous areas of corporate management, where it can replace or complement human activities.

The reason artificial intelligence has attracted such considerable attention in recent years lies in the fact that advances in computing power and data availability, together with theoretical knowledge, have reached a level that has enabled this remarkable technological progress (Spano, 2019).

At present, we are witnessing the intensive deployment of artificial intelligence systems that are penetrating not only the fields of science, research, and strategic sectors, but also everyday life through consumer electronics and commonly used systems. Their use has become so natural that it often goes unnoticed; however, we increasingly rely on these systems and expect the benefits they provide, which add value to various aspects of our lives.

Similarly to the field of cybersecurity, the development and use of artificial intelligence are often characterised by a tendency to prioritise convenience and technological benefits, frequently at the expense of caution and adherence to security principles (Šantavý, 2023).

In his book, Spano (2019) states: "What is artificial intelligence? In short, it is intelligence demonstrated by machines, as opposed to that displayed by humans. It is a field of study within computer science that seeks to reproduce what the human brain does. This means perceiving the world through the senses, understanding and responding to speech, learning, planning, and solving problems. Since this reproduction is carried out by a computer, it is software that provides this intelligence."

Over the years, a significant increase in interest in the topic of artificial intelligence can be observed, with the year 2023 proving to be a turning point. As Komárek and Ryšavá (2024) note, "AI may become a key driver of economic development and a catalyst for changes in the way people live and work."

The significance of artificial intelligence lies in its potential to revolutionise various aspects of our lives and to bring substantial progress across multiple fields. When used responsibly, AI can lead to innovative solutions, increased efficiency, and an improved quality of life (Rudrawar, 2023). Zhang and Lu (2021) state that artificial intelligence is the science of enabling computers to perform tasks that, in the past, could only be carried out by humans.

The impact of artificial intelligence is evident across all industries. Fossen and Sorgner (2019) suggest that the areas in which AI is currently achieving the greatest progress are associated with non-routine cognitive tasks, which are often performed by medium- to highly skilled workers. These workers tend to adapt more easily to new technologies, as there is a high likelihood that they already work with digital technologies. More highly educated workers are also more likely to possess task-specific human capital, which may make adaptation more costly for them.

In order to enhance the efficiency of human resource management processes and improve performance, organisations have begun to adopt disruptive technological innovations in this area. The concept of digitalisation of human resource management refers to the transformation of HR activities through their automation using various software solutions and technological tools (Malik et al., 2022).

The issue of artificial intelligence and its impact on the labour market and society is not a phenomenon of recent years. In the past, technological progress has led to the loss of numerous jobs. Many authors focus on examining the impact of AI on unemployment (Virgili, 2024; Dall'Anese, 2020; Makridakis, 2017; Kudoh, 2025). As a result, some scholars adopt a pessimistic perspective on the implementation of AI. In 2019, Andrea Renda addressed this issue in his publication Artificial Intelligence, emphasising that AI would take over human jobs.

On the other hand, many authors argue that the use of AI technologies does not automatically lead to an increase in unemployment (Mutascu, 2021; Gries and Naudé, 2018). Instead, the changes brought about by the digital age compel the workforce to adapt to a new working environment influenced by the use of AI technologies (Abdeldayem and Aldulaimi, 2020). Meister (2019) predicted that artificial intelligence would create more jobs than it would eliminate.

As noted by Sanyaolu and Atsaboghena (2022), functions such as recruitment and selection, onboarding, performance management, employee engagement, and retention are currently carried out with the support of virtual assistants. The development of human resource information systems (HRIS) has provided a foundation for the application of artificial intelligence in human resource management.

The topic of artificial intelligence has become the subject of discussion in academic circles, as evidenced by the growing number of publications indexed in the Web of Science and Scopus databases. The first contribution recorded in Scopus dates to 1966 under the title Artificial Intelligence in Automated Design (Jirauch, 1966). The author notes that new techniques in the field of artificial intelligence are continuously being developed yet are "too distant" to be considered practical at that time.

In the Web of Science database, the first article addressing artificial intelligence in relation to the labour market and human resource management appeared in 1994. The authors emphasised the use of artificial intelligence in the automation of production within changing manufacturing environments (Yazici et al., 1994).

2. GOAL AND METHODOLOGY

The study focuses on analysing the impact of artificial intelligence on the labour market and human resource management. The aim of the study is to identify and analyse the research directions of authors whose work includes keywords related to artificial intelligence, human resource management, and the labour market, and whose studies are available in the Web of Science and Scopus databases based on predefined criteria.

To select relevant literature, the Web of Science and Scopus databases were chosen, and the analysed period was limited to the years 2015–2025. This period represents a phase of intensive technological development across various sectors, including the labour market and human resource management, making it a relevant timeframe for analysing current trends and impacts. In selecting relevant studies, a search string consisting of the keywords "AI", "labour market", and "human resource management" was applied.

3. FINDINGS AND DISCUSSION

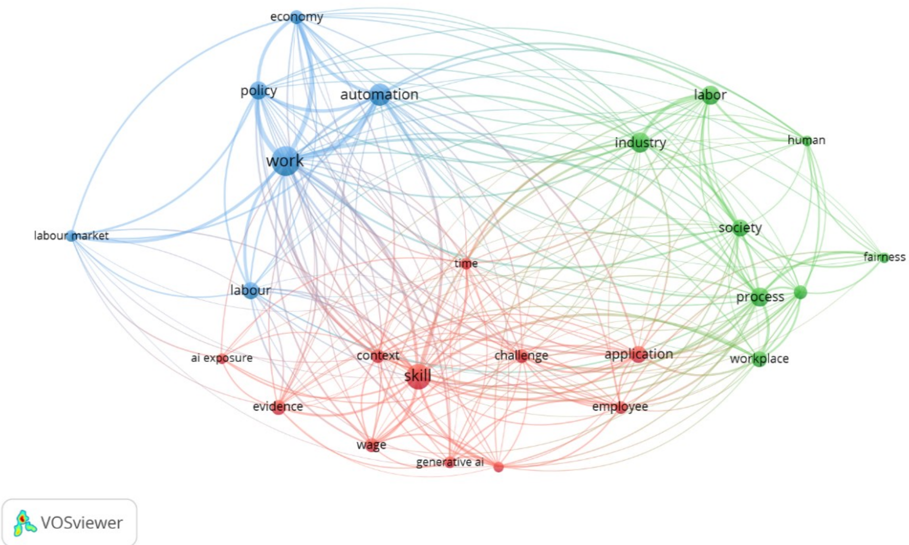
Figure 1 illustrates a network visualization of keywords related to artificial intelligence, work, and business management, created using the VOSviewer tool based on an analysis of term occurrences in the academic literature. Individual nodes represent dominant concepts, with their size reflecting the frequency of occurrence, while the distance between nodes indicates the degree of thematic relatedness. Coloured clusters identify the main thematic areas of research.

The blue cluster is centred around the concepts of work, automation, policy, economy, and labour market. The dominance of these terms indicates a strong focus in the literature on the systemic impacts of AI on work, the labour market, and economic policy. This thematic area highlights the macroeconomic and regulatory dimensions of AI implementation, in which artificial intelligence is perceived as a driving force behind structural changes in the labour market. From a business management perspective, this cluster reflects the need for organisations to strategically adapt to process automation, as well as to align corporate strategies with public policies and prevailing economic conditions.

The green cluster includes words such as industry, process, workplace, employee, society, and fairness. This cluster represents the organisational and socio-ethical dimensions of AI application. From a business management perspective, particular emphasis is placed on the transformation of work processes, changes in the workplace environment, and the relationship between technology and employees. The occurrence of terms such as fairness and human indicates the growing importance of ethical considerations, justice, and social responsibility in the implementation of AI within organisational systems.

The red cluster is oriented towards the micro-level and the development of human capital, with dominant concepts including skill, generative AI, wage, evidence, challenge, and context. This cluster reflects intensive research into changes in skills, remuneration, and the challenges that AI poses for human resource management. It highlights evolving skill requirements for employees and the impact of AI on productivity, wages, and competency profiles. From a managerial perspective, this represents an area of strategic importance, as skill development, reskilling, and talent management are becoming key instruments of organisational competitiveness.

Figure 1: Keyword co-occurrence map



Source: own elaboration

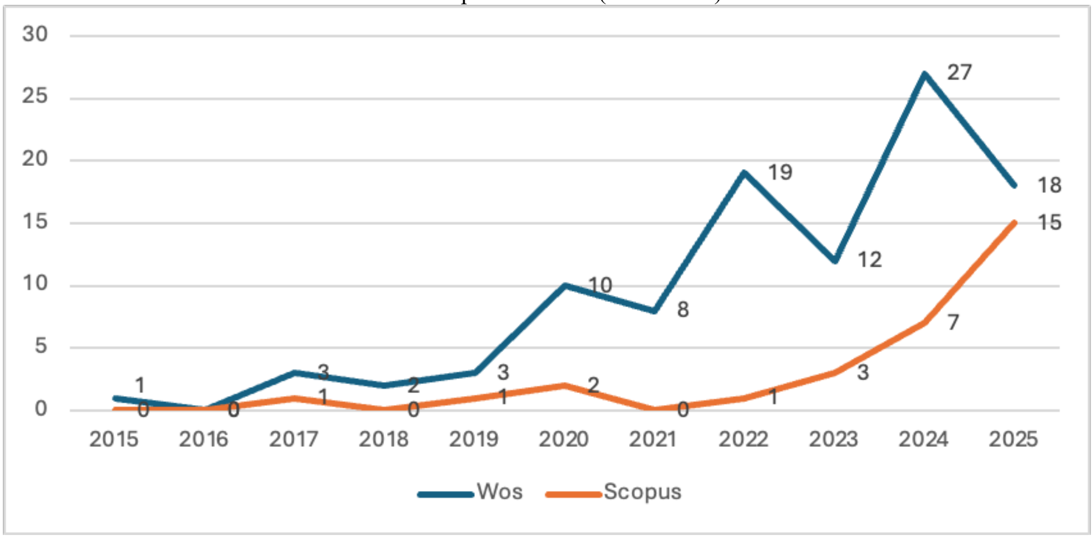
A significant feature of the visualisation is the high degree of interconnection between clusters, which highlights the interdisciplinary nature of AI research in the context of work and business management. Concepts such as *application*, *time*, and *challenge* function as bridging nodes between the macro-, meso-, and micro-levels of analysis, emphasising that the implementation of AI in organisations is a dynamic process influenced by technological, organisational, and societal factors.

Overall, the visualisation confirms that artificial intelligence in business management represents not merely a technological innovation, but a complex transformative force that affects organisational strategy, processes, human resources, and ethical frameworks.

The graph in Figure 2 illustrates the development in the number of publications using the keywords "AI", "labour market", and "human resource management" in the Web of Science and Scopus databases over the period 2015–2025. The results indicate a significant increase in scholarly interest in this topic, particularly after 2020, reflecting the growing importance of artificial intelligence in the fields of work and human resource management.

The lower number of records in 2025 is likely due to data incompleteness, as not all publications from that year had been indexed in the databases at the time of analysis. In addition, temporal delays between article publication and database indexing, as well as differences in authors' use of keywords, may also play a role.

Figure 2: Use of the keywords "AI", "labour market", and "human resource management" in the Web of Science and Scopus databases (2015–2025).



Source: own elaboration

The content of the analysed publications points to three main analytical levels. The first is the macro level, which addresses the economic and institutional consequences of AI implementation, including changes in the labour market, productivity, and the role of public policies. The second level comprises the organisational perspective, focusing on the implementation of AI in business processes, the transformation of jobs, decision-making mechanisms, and managerial functions. The third level, the micro level, concentrates on individuals, particularly on changes in required skills, impacts on wages, job satisfaction, and the human–technology relationship.

A significant characteristic of the analysed body of literature is the growing attention paid to the ethical and social aspects of AI, such as algorithmic transparency, fairness in decision-making, and managerial responsibility in the deployment of intelligent systems. These themes are particularly relevant for contemporary business management, as they indicate a shift from purely technical optimisation towards sustainable and socially responsible management.

Overall, the analysed body of literature provides a robust theoretical and empirical foundation for examining artificial intelligence as a strategic factor in business management. The conclusions of individual studies support the assertion that the successful integration of AI requires not only technological investments, but also the adaptation of organisational structures, the development of human capital, and well-considered managerial decision-making.

One of the earliest authors to address this issue—and also the most cited in the Web of Science database, with 325 citations—is Frank et al. (2019). The study analyses the potential impacts of artificial intelligence and automation on the labour market, with a particular focus on methodological barriers that hinder accurate measurement and prediction. The authors highlight that AI can both substitute for and complement human labour, with its effects manifesting primarily at the level of specific tasks and skills rather than entire occupations.

A key challenge identified is the lack of detailed, dynamic, and spatially sensitive data on job-related skills, which would enable the empirical capture of processes of substitution and complementarity between humans and technologies. The article emphasises the need for new data sources, particularly from online job postings and résumés, as well as the use of machine learning methods to monitor changes in skill demand. In conclusion, the authors recommend that research and policy-making focus on building labour market resilience in light of the uncertainty surrounding technological development.

Another notable contribution in this field, with 294 citations in the Web of Science database, is the study by Agrawal, Gans, and Goldfarb (2019). The authors analyse the impact of artificial intelligence on the labour market through a task-based framework in which AI reduces the cost of prediction as an input into decision-making processes. They identify four channels through which cheaper and more accurate prediction affects labour demand: the direct substitution of labour in prediction tasks, the subsequent automation of complementary decision-making tasks, productivity-enhancing complementarities between labour and decision-making, and the creation of new tasks.

This framework implies that the overall effect of AI on employment and wages is *a priori* ambiguous and depends on the relative returns to labour and capital in complementary tasks. The article thus provides a theoretical explanation for why empirical estimates of the impacts of AI often yield weak or inconclusive effects.

Among the most cited articles is the study by Acemoglu et al. (2022), with 280 citations. The authors examine the impact of artificial intelligence (AI) on the labour market using data from online job postings in the United States since 2010. The study focuses on the growth of AI-related jobs, documenting a rapid increase in AI-intensive positions between 2010 and 2018, particularly in firms where employees perform tasks compatible with current AI capabilities.

The authors also investigate employment effects, showing that the adoption of AI within firms leads to reduced hiring for non-AI-related positions, alongside changes in the skill requirements of remaining job postings. In addition, the study examines macroeconomic effects; although these changes are clearly observable at the firm level, the aggregate impact of AI on employment and wage growth in the most exposed industries and occupations remains too small to be statistically detectable.

Overall, the article demonstrates that AI has local and structural effects on the labour market by reshaping job types and required skills, while its aggregate effect on employment and wages remains limited at present.

In their earlier study, Acemoglu and Restrepo (2020), which has received 259 citations in the Web of Science database, argue that the current development of artificial intelligence is disproportionately oriented towards the automation of existing job tasks rather than the creation of new tasks in which labour could be productively employed. This "misdirected" path of technological progress contributes to stagnating labour demand, a declining labour share of national income, and rising inequality, while simultaneously weakening productivity. The authors emphasise that the economic consequences of AI are not technologically determined but rather depend on innovation choices and institutional arrangements.

The main difference between Acemoglu and Restrepo (2020) and Acemoglu et al. (2022) lies in the type of approach and level of analysis. The 2020 article is predominantly conceptual and normative in nature; it analyses the direction of technological progress in AI and argues that its current focus on automation leads to adverse macroeconomic outcomes, such as stagnating labour demand, a declining labour share of income, and increasing inequality. In contrast, the 2022 study is empirical and descriptive, relying on micro-level data from online job postings to identify the specific mechanisms through which AI adoption alters firms' hiring behaviour and skill requirements.

While the former article evaluates which type of AI development should be socially preferred, the latter documents the effects of the current diffusion of AI as observed in empirical data. As a result, whereas the normative conclusions of the 2020 study anticipate potentially strong long-term impacts of AI on the labour market, the empirical findings from 2022 point to effects that remain weak at the aggregate level but are clearly observable at the micro level of firms.

The divergence between the normative conclusions of Acemoglu and Restrepo (2020) and the weak aggregate effects identified by Acemoglu et al. (2022) is largely attributable to the time lag between AI adoption at the firm level and its macroeconomic consequences. During the observed period (2010–2018), artificial intelligence was at a relatively early stage of diffusion, with its use concentrated in a limited number of firms and in tasks compatible with the technical capabilities of AI at that time.

At this stage, the effects primarily manifest in changes to hiring strategies, skill requirements, and internal work reorganisation, which are readily identifiable in micro-level data but are not yet sufficient to generate substantial shifts in aggregate employment or wages. Macroeconomic effects—such as persistent changes in labour demand or wage structures—typically materialise only after broader technology adoption, sectoral reallocation, and adjustments in labour market institutions, which explains their currently limited empirical detectability.

CONCLUSION

The impact of artificial intelligence on the labour market and human resource management is complex and multifaceted. While there is considerable potential for increased productivity (Ključnikov, 2023), economic growth (Batabyal, 2024), and the creation of new jobs, existing risks related to labour substitution, widening inequalities, and the need for skill adaptation cannot be overlooked. Labour market policies, the education system, and the capacity of organisations and individuals to adapt to these changes play a crucial role in shaping outcomes.

Looking ahead, a significant development of human resource information systems can be expected, with process simplification emerging as a key trend and a fundamental element of future HR system evolution. The implementation of artificial intelligence in human resource management brings both challenges and opportunities. The effective and appropriate use of AI in HR management requires consideration not only of technological aspects but also of the human factor and the individual needs of employees when implementing new technologies.

For this reason, responsible and transparent use of AI is essential. Employees require adequate support to develop a sufficient level of trust in AI and to understand how to use its tools responsibly.

In his work, Lang (2025) formulates seven recommendations for organisational leaders:

- Invest in increasing AI literacy in order to strengthen collaboration among employees and foster the development of critical thinking.
- Establish clear rules and act as a role model for the responsible use of AI.
- Promote continuous dialogue about AI—where it creates value, where it poses risks, and what kind of support employees need.
- Build a safe environment that facilitates the transparent use of AI.
- Invest in strategic planning and reskilling to prepare employees for forthcoming changes in the work environment.
- Seek a balance between innovation and risk management—enable experimentation while ensuring compliance with organisational policies.

- Monitor trends and developments in artificial intelligence and emerging technologies.

Artificial intelligence tools enable versatile applications and, in the field of human resource management, help perform a wide range of tasks more quickly and more effectively.

The issue of applying artificial intelligence in human resource management and the labour market is highly extensive, thereby opening further avenues for future research in this area.

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LEGAL, ECONOMIC AND ETHICAL LIMITS AND CHALLENGES OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT

Petra BOBÍKOVÁ, Patrik BŘEČKA, František BABIČ

Abstract

The rapid development of artificial intelligence (AI) is fundamentally transforming human resource management processes, creating new opportunities while also introducing complex legal, economic, and ethical challenges. This article focuses on analysing the limits and possibilities of AI implementation in various areas of human resource management from the employer's perspective, with particular emphasis on the protection of employees' rights as the weaker party in employment relationships. Special attention is devoted to the pre-contractual phase of employment, especially the recruitment process, where the deployment of AI tools raises critical issues related to compliance with the principle of equal treatment and the prohibition of discrimination. The article further examines the processing of personal data in the context of automated decision-making and explores the key questions employers must address to properly design internal policies and procedures. Finally, it offers a technological perspective, highlighting the dynamic development of AI capabilities and their potential impact on the legal, ethical, and organisational frameworks of human resource management. The aim of the article is to contribute to the academic discourse on the legally compliant and sustainable use of AI in the employment context.

Key words:
artificial intelligence (AI), human resource management, labour law, personal data protection, discrimination and equal treatment

JEL Classification K2, M5,O33 https://doi.org/10.52665/ser20250209

INTRODUCTION

In recent years, artificial intelligence (AI) has become one of the most widely discussed topics across various industries. Its rapid development and ability to extend beyond purely technical environments into everyday life have opened new possibilities, but also new challenges. One area where these changes are becoming increasingly evident is human resource management (HR). This discipline—primarily concerned with recruiting new employees, helping them adapt to the work environment, and managing employee relations—already employs AI systems to automate processes, support decision-making, and analyse data.

Various AI tools can be used at different stages of the recruitment process: outreach (e.g. drafting gender-neutral job advertisements), sorting (e.g. searching through CVs for the purpose of evaluating and ranking candidates), assessment (e.g. analysis of video interviews, including voice or face recognition) and facilitation (e.g. communicating with applicants and answering questions via chatbots) (Gupta et al., 2024, pp. 30–34).

However, with the rise of these technologies, not only do practical questions of efficiency and effectiveness arise, but so too do fundamental legal and ethical dilemmas. How can we ensure that algorithms make decisions fairly and transparently? What factors must organisations consider when implementing them? And where should the line be drawn between innovation and the protection of employees' fundamental rights?

This article will address these questions, focusing on the legal status of artificial intelligence in human resources in terms of specific methods of deployment.

LABOUR LAW RELATIONSHIPS

When evaluating the deployment of artificial intelligence in human resources, it is essential to adopt a perspective that emphasises the most important element of this process – the employee themselves. The legal status of employees in Slovakia is governed primarily by Act No. 311/2001 Coll., the Labour Code, as amended (hereinafter referred to as the "Labour Code"), which constitutes the fundamental legal framework for labour relations. Under this Act, employees are regarded as the weaker contracting party and are therefore afforded enhanced protection by law. This includes the right to fair and equal treatment, protection against discrimination, the right to safe and healthy working conditions, and the right to fair remuneration for work performed. The consistent application of the basic principles of labour relations is crucial when deploying artificial intelligence, as neglecting them may give rise to legal risks.

The responsibility for protecting employee rights lies primarily with the employer, who is obliged to respect and observe these rights at all stages of the employment relationship – from recruitment and hiring, through adaptation and performance evaluation, to termination of employment. At the same time, it is usually the employer who initiates the introduction of artificial intelligence systems, as their intention is to increase efficiency, reduce administrative burdens and improve overall management and decision-making processes (Du, 2024, pp. 71–77).

In this context, however, it is essential that the deployment of AI tools is not seen merely as a technological innovation, but also as a process that must comply with legal regulations, the principles of equal treatment and personal data protection, while ensuring adequate oversight and transparency of the decisions made by these systems, which is primarily required by new European legislation.

In the context of employees' legal status, employers can be said to find themselves in a relatively challenging position when seeking to ensure effective solutions and their subsequent implementation in the field of human resource management.

Employers can basically proceed in two ways. The first is to develop their own solution, which gives them greater control over the process itself and, in theory, over the development of the artificial intelligence tool, especially in terms of risks associated with bias or other undesirable parameters. However, this alternative is only really feasible for software companies with sufficient economic and human resources. The effectiveness of such an approach remains questionable, as there are already commercially available software solutions with implemented artificial intelligence functionalities on the market .[1]

Their use therefore represents the second approach that an employer can choose. Alternatively, they can opt for a combination of both options – for example, ordering their own tailor-made solution on a custom-made basis, in which case the key factor is the selection of a supplier capable of guaranteeing compliance with legislative requirements during development.

Regardless of the solution chosen, the issue of data remains a key concern. If the tool is available, there is a need to adapt it to the specifics of the employer. A typical example is the recruitment process, where each employer applies different criteria when assessing the suitability of candidates, which is conditioned by the diversity of job positions. In such a case, it is necessary to use historical data from recruitment processes to train existing artificial intelligence models. However, this approach raises several problematic questions: how to process data so that bias is not reproduced in the generated outputs (an example known from Amazon (Li, 2022, pp. 187–192)) and, at the same time, how to ensure legislative compliance, especially in terms of personal data protection.

PRE-CONTRACTUAL RELATIONSHIPS AND THE PRINCIPLE OF EQUAL TREATMENT

The recruitment process is regulated by Section 41 of the Labour Code, which applies to precontractual relationships and defines the rights and obligations of employers towards job applicants. From a data processing perspective, these provisions also set limits on the scope of

[1] This is the presumed choice of contract type regulated in Section 91 of Act No. 185/2015 Coll. Copyright Act, as amended.

information that an employer is entitled to request from a potential employee.

However, the restrictions are not limited to the scope of data. The provisions of Section 41 of the Labour Code must be interpreted in conjunction with other legislative requirements, in particular Article 1 of the Labour Code in conjunction with Section 13 of the Labour Code, which enshrines the principle of equal treatment. This section also explicitly refers to Act No. 365/2004 Coll. on equal treatment in certain areas and protection against discrimination, as amended (hereinafter referred to as the "Anti-Discrimination Act"). The above provisions therefore clearly establish the employer's obligation to ensure that the entire process of selecting and recruiting employees is carried out in a non-discriminatory manner. This obligation also applies if the recruitment process involves the use of artificial intelligence tools, with the employer always being responsible for complying with the principle of equal treatment.

It follows from the above that the issue of potential bias in artificial intelligence systems is an important aspect for employers when using them in the recruitment process. Potential bias does not arise primarily from the technology itself, but from the nature and processing of the input data provided to the system. This factor is key in assessing the reliability and legality of the results generated by AI tools. There are numerous articles and studies in the professional literature and publications that systematically address the issue of bias in the context of artificial intelligence and provide a basis for identifying and minimising the risks associated with discriminatory or other undesirable effects (Kolaříková & Horák, 2020, p. 107). Specifically, however, we can mention a study on discrimination (Zuiderveen Borgesius, 2018), which explains the reasons why artificial intelligence tools may be biased. It specifically defines problems related to (i) the method of defining the "target variable" and "class labels"; (ii) labelling training data; (iii) collecting training data; (iv) selecting features; and (v) proxy functions. It also specifically identifies the possibility that (vi) artificial intelligence systems may be deliberately used for discriminatory purposes.

The relevance of the issues defined in this way is also applicable to the recruitment process. Looking at them specifically, in the case of the first (i), this could be a situation where, for example, "successful employee" is set as the target, with success measured only on the basis of speed of advancement in the career ladder or job retention, the system may favour profiles that correspond to historical patterns – for example, younger men rather than women or people from other social groups who have had fewer opportunities in the past. In the case of training data labelling (ii) itself, this may be the case if CVs or applicants have been subjectively evaluated by HR staff in the past and these evaluations are used as inputs for AI training, the system will simply learn their biases. This means that if HR managers have indirectly preferred a certain type of candidate in the past, the algorithm will adapt to this. Regarding the collection of training data (iii), there may be situations where the data is incomplete, unrepresentative or comes only from a limited group of applicants (e.g. from certain universities or regions), and the system will not be able to fairly assess candidates from different backgrounds. The issue of feature selection (iv), i.e. the characteristics of candidates that the algorithm considers, may mean that even seemingly neutral features, such as postcode or type of school, may indirectly serve as indicators of socio-economic status, gender or ethnic origin, thereby introducing indirect bias into the decision-making process. The proxy function (v) may mean that the system assumes that the length of previous employment is a good indicator, thereby discriminating against people who have had career breaks due to parental leave or health problems. Finally, there is also the possibility of deliberate misuse of artificial intelligence in the recruitment process. An employer could deliberately set up the system to discriminate against a particular group – for example, indirectly restricting the recruitment of older workers, people with foreign-sounding names or women for certain positions. In such cases, AI becomes a tool that not only reflects existing inequalities but actively reproduces and reinforces them.

In this context, it should be emphasised that even the application of the principle of equal treatment has its limits and specificities, which must be interpreted in conjunction with other principles applied in labour relations. In this context, particular reference can be made to the special protection of young employees and pregnant women, which is enshrined in Articles 6 and 7 of the Labour Code. For this reason, a situation may arise in practice that outwardly appears to be unequal treatment, but in reality, is a consequence of the employer's obligation to ensure increased protection of the rights of these specially protected groups of employees, which is ultimately also permitted by the provisions of Section 8 of the Anti-Discrimination Act.

Transparency is ultimately an essential aspect of legislative compliance, also on the basis of Regulation (EU) No (EU) 2024/1689 of 13 June 2024, which lays down harmonised rules in the field of artificial intelligence and amends Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act) (hereinafter referred to as the "AI Regulation"), which will be discussed in the last part of this article.

The AI Regulation is the first comprehensive and harmonised framework of rules governing the use of artificial intelligence within the European Union. Its structure is based on the categorisation of artificial intelligence systems according to their level of risk, with each category associated with a different range of rights and obligations for entities operating in the supply chain. First and foremost, it is important to note that, according to Annex III of the AI Regulation, "AI systems intended to be used for the recruitment or selection of natural persons, in particular for the placement of targeted job advertisements, analysing and filtering job applications and evaluating candidates" are classified as high-risk systems. In the context of the above, one of the obligations of the deploying entity is the obligation of transparency, within the meaning of Article 13 of the AI Regulation. Explicitly stated, "high-risk AI systems must be designed and developed in such a way as to ensure that their operation is sufficiently transparent to enable deploying entities to interpret the system's outputs and use them appropriately." For an employer planning to deploy an existing artificial intelligence tool, this means in practice that they must require the supplier to demonstrate compliance with this obligation.

When using an artificial intelligence tool in the recruitment process, it is necessary to demonstrate compliance with the above-mentioned legislation, specifically the Labour Code and the Anti-Discrimination Act, to fulfil the transparency obligation. In the event of an anti-discrimination lawsuit, the burden of proof lies with the defendant, i.e. in this case the employer, who will have to prove that there has been no violation of the principle of equal treatment in connection with the use of artificial intelligence tools.

The aim of pointing out these issues is to demonstrate the importance of the correct approach to data when using artificial intelligence systems in the recruitment process, because only consistent data processing will make it possible to remove or at least eliminate the risk of bias and ensure that the system deployed in this way supports fair and transparent employee selection in accordance with the defined legislative requirements. Finally, it should be noted that the number of complaints of discrimination in employment relationships is already showing an upward trend (Informative report on discrimination and gender equality in labour relations, 2024). It is therefore reasonable to assume that the implementation of artificial intelligence tools may further intensify this phenomenon.

PROCESSING OF PERSONAL DATA

In the context of collecting data on job applicants, it is particularly important to address the issue of personal data protection, as the vast majority of the information provided and evaluated in this way is personal data.[2] The processing of personal data is a broad issue, the basic legal framework for which is provided by Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016

[2] The term is defined in Article 4(1) of Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data

on the protection of natural persons with regard to the processing of personal data and on the free movement of such data (hereinafter referred to as the "GDPR"), supplemented by national legislation, in particular Act No. 18/2018 Coll. on the protection of personal data, as amended.

According to Article 6(1) of the GDPR, the existence of a legal basis is a fundamental condition for the lawfulness of processing, and this list is exhaustive. At the same time, it is necessary to respect the principles of processing set out in Article 5 of the GDPR, such as lawfulness, transparency, data minimisation and purpose limitation.

In pre-contractual employment relationships, i.e. particularly in the process of selecting a suitable candidate, the personal data of applicants is processed primarily for the purpose of taking steps prior to entering an employment contract within the meaning of Article 6(1)(b) of the GDPR (Valentová et al., 2020, p. 97). At the same time, in certain cases, the legal basis for processing may also be derived from the fulfilment of the employer's legal obligation under Article 6(1)(c) of the GDPR, in particular regarding obligations arising from the Labour Code or specific regulations (e.g. proof of qualifications, keeping mandatory documentation).

It follows from the above that the processing of personal data of job applicants is generally based on a combination of legal bases under Article 6(1)(b) and (c) of the GDPR, with the use of the applicant's consent being of limited significance in this context and generally not constituting the primary legal basis.

However, the assessment of the situation in question changes somewhat when artificial intelligence tools are used in the processing of job applicants' data. From the point of view of personal data processing, it is not so much the technology itself that is important, but the purpose of the processing. If the artificial intelligence tool serves exclusively as a means of processing data for the same purpose (selecting a suitable candidate), the legal basis remains unchanged (Article 6(1)(b) and (c) of the GDPR). However, a problem may arise in two situations, namely in the event of a change in the purpose of processing, i.e. if the personal data of job applicants is also used for purposes other than the selection process itself, e.g. for artificial intelligence training purposes. In such a case, it is necessary to assess the compatibility of the purposes under Article 6(4) of the GDPR or to obtain a new legal basis, most often in the form of the applicant's consent. The second aspect of the assessment is automated individual decision-making, which is regulated in Article 22 of the GDPR and grants a natural person the right not to be subject to a decision based solely on automated processing, including profiling, if it has legal effects or significantly affects them. Therefore, if the decision to accept or reject a candidate were solely the result of an artificial intelligence tool, the employer would have to ensure an exception under Article 22(2) of the GDPR, the most relevant being obtaining the explicit consent of the data subject or taking measures to ensure human intervention in the decision-making process.

It follows from the above that the use of artificial intelligence in the processing of job applicants' personal data is possible, but it must be set up in such a way that the purpose of the processing is clearly defined and legally justified, there is no change of purpose without a new legal basis, and that the rights of applicants under Article 22 of the GDPR are respected in automated decision-making.

The employer is therefore obliged not only to determine the appropriate legal basis for processing, but also to ensure compliance with the key principles of the GDPR. This is particularly the principle of transparency, which requires job applicants to be clearly and comprehensively informed about the use of AI tools, including the purpose and basic principles of data processing. Furthermore, the principle of data minimisation must be observed, which means that only data that is necessary for assessing the applicant's qualifications and is proportionate to the purpose pursued may be processed. In cases where the use of AI poses a high risk to the rights and freedoms of the persons concerned, the employer is obliged to carry out a data protection impact assessment in accordance with Article 35 of the GDPR. It is also recommended to maintain appropriate human intervention in the decision-making process so that decisions with a significant impact on candidates are not left solely to the algorithm. The area of cybersecurity also requires special attention, but this goes beyond the scope of this analysis.

If the processing of job applicants' personal data is based on the legal basis of consent pursuant to Article 6(1)(a) of the GDPR, its revocability within the meaning of Article 7(3) of the GDPR must be considered. Consent must be as easy to withdraw as it was to give, and the employer is obliged to immediately stop processing or ensure the deletion of personal data. However, in the context of the use of artificial intelligence, this requirement poses problems. If applicants' data is used for training or profiling within AI systems, its subsequent deletion from the model can be technically very complicated or even impossible without a fundamental modification of the algorithm. This situation leads to the risk that the artificial intelligence system will continue to contain data that, after withdrawal of consent, may no longer be processed in accordance with the law. For this reason, it can be concluded that consent as a legal basis is not an appropriate legal basis in relation to the application of artificial intelligence in the processing of personal data of job applicants.

TECHNOLOGICAL PERSPECTIVE

Based on a simple analysis of the current situation, we can identify several challenges from a technological perspective in the use of AI in the recruitment process and in personnel procedures (Aguinis et al., 2024), (Madanchian et al., 2023, pp. 367–377), (Nejad et al., 2025, pp. 1203–1218), (Tambe et al., 2019, pp. 15–42), (Ore et al., 2022, pp. 1771–1782), (Hunkenschroer et al., 2022, pp. 977–1007):

- The effectiveness of AI use depends significantly on the quality and complexity of the input data. Decision-making processes can be influenced by inaccurate or incomplete data. At the same time, a significant amount of data (e.g. texts, websites, images, videos, etc.) is required to train large language models or artificial neural networks. These models learn from data, and the training itself can reinforce existing biases or prejudices contained in the input data (e.g. Amazon's unsuccessful deployment of a recruitment tool (Drage et al., 2022, pp.1-25)). A typical problem with AI models is their "black box" nature, i.e. their non-transparent internal functioning, decision-making and selection of alternatives. This lack of transparency raises concerns about accountability, fairness and overall trust in AI (Varma et al., 2023, pp.1-11).
- Deploying and integrating new AI tools into existing software in an organisation, especially in human resources departments, is a technical challenge. The older the existing software, the more complicated the integration and the lower the effectiveness of the new solutions. Data protection and privacy are also important factors, as the processing of sensitive personal data must be secure and comply with legislation (Yam et al., 2021, pp. 611–623). Another obstacle may be problems in human-computer interaction, which lead to resistance to change and distrust of technology. HR professionals will therefore need to acquire new skills and adapt their working methods (Arora et al., 2021, pp. 288–293).
- The relatively high initial costs of the necessary infrastructure (setup, administration, development, maintenance, updates and data management) can be partially eliminated by outsourcing, i.e. using the services of third parties providing AI tools in a cloud environment. This can be particularly advantageous for companies with a lower number of recruitments per year (Sharma et al., 2024, pp. 219-213). However, it is essential to thoroughly analyse the requirements at the outset and compare the costs with the potential benefits. Another interesting aspect is the perspective of job seekers who interact with the AI tool from an external environment, considering different platforms, device types, internet connection quality, etc.
  - The complexity of HR phenomena makes it difficult to create data-driven decision-making models. Employee motivation, behaviour and emotions are dynamic, complex and change over time. It is often difficult to separate individual performance from teamwork, and

objective performance measurement has many dimensions (Kotlyar et al., 2023, pp. 955–991), (Park et al., 2021, pp. 1–15). In addition, traditional recruitment practices often use outdated methods, such as a limited set of keywords when sorting CVs.

- A lack of technical expertise and know-how is another obstacle, as AI tools are currently being implemented primarily in other areas of business. However, investing in the education and development of employees with a relevant portfolio of knowledge and practical skills contributes to building the organisation's high-quality intellectual capital (Salmelin, 2025, pp. 187–200).

CONCLUSION

In conclusion, it can be summarised that when implementing AI in the field of human resource management, it is essential that employers approach this process with the utmost caution and responsibility. First and foremost, it is necessary to ensure compliance with the basic principles of the Labour Code and the Anti-Discrimination Act, and these principles must also be considered when selecting and setting up the AI tool itself. Equally important is compliance with the personal data protection rules, with particular attention being paid to the choice of the legal basis for processing, which minimises risks and does not create legal or technical obstacles in the future.

Each deployment of an artificial intelligence tool must be assessed individually, not only in terms of its purpose, but also regarding its potential impact on the rights and obligations of all parties involved. It is therefore advisable to prepare documentation that will enable the employer to identify risks in a timely manner and prevent possible violations of legislation, while maintaining the transparency of the entire process.

Employers should also consider introducing mechanisms for ongoing monitoring and auditing of AI tools so that they can respond flexibly to changes in the legal framework or technical aspects of the tools' operation. Only such an approach can create the conditions for the reliable deployment of artificial intelligence tools and, at the same time, increase the efficiency of human resource management. At the same time, it will ensure that the implementation complies with the applicable legislative framework and respects the protection of the fundamental rights of subjects of labour relations.

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VALUE CHAINS AND INNOVATION ECOSYSTEMS: HOW DIGITALIZATION SHAPES COMPETITIVENESS AND SUSTAINABILITY IN THE WOOD-PROCESSING SECTOR

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Abstract

The growing pressure for sustainability, decarbonization, and digitalization is reshaping how Slovak enterprises in the wood-processing industry build competitiveness. The paper examines how digital technologies, sustainable innovations, and value chains drive the transition toward a circular and climate-neutral economy. It focuses on Smart Industry, the Internet of Things (IoT), and Artificial Intelligence (AI), which enhance resource efficiency, reduce environmental impact, and enable transparent supply-chain management. Emphasis is placed on innovation ecosystems—cooperation among firms, start-ups, and regional actors—in applying ESG principles. The findings underline the need for digitally driven and sustainability-oriented supplier–customer integration that generates synergies within smart, green regions of Slovakia, while noting barriers such as low investment in green innovation, limited technological readiness, and insufficient green skills. Positive examples, such as the SmartHead platform, show that linking technology with sustainability enables transparent ESG reporting, builds trust, and creates value for people, the planet, and business.

Key words:
sustainability, value chains, digitalization, green innovation

JEL Classification M21, L73, O31, O33, Q56 https://doi.org/10.52665/ser2020210

INTRODUCTION

The growing convergence of sustainability, digitalization, and climate neutrality represents a defining transformation of European industry, often described as the “twin transition” (Elavarasan et al., 2022). Within this dynamic context, Slovakia’s wood-processing sector occupies a strategic position as a pillar of the national bioeconomy and regional development, contributing significantly to employment, value creation, and the circular use of renewable resources (Kristakova et al., 2021; Paluš et al., 2020). Increasing regulatory and societal pressures, driven by the European Green Deal and climate-neutrality objectives, have accelerated the demand for sustainable innovation and green transformation in resource-intensive industries (Carmona-Martínez et al., 2024; Sikora, 2020).

Digitalization—encompassing Smart Industry, IoT, and Artificial Intelligence—has emerged as a key enabler of this transformation, improving energy efficiency, transparency, and traceability across value chains (Ferreira et al., 2023). However, its diffusion remains uneven among Slovak enterprises due to high investment costs, skill shortages, and limited technological readiness (Maksymova & Nastase, 2024). Integrating digital and sustainable practices across the entire value chain is therefore essential for strengthening competitiveness and fostering regional innovation ecosystems that align with ESG principles (Stroumpoulis & Kopanaki, 2022).

Against this background, the present study investigates how digital technologies, sustainable innovations, and value-chain integration jointly enhance the competitiveness and climate performance of Slovak wood-processing enterprises. It contributes to the discourse on circular and climate-neutral economies by identifying both enabling mechanisms and structural barriers that shape the sector’s twin transition.

2. PROBLEM FORMULATION AND METHODOLOGY

2.1 Problem Formulation

The accelerating convergence of sustainability imperatives, digital transformation, and innovation ecosystems is reshaping the competitive landscape of the Slovak wood-processing industry. This sector, a strategic pillar of the national bioeconomy, has become a testbed for implementing the European Union's "twin transition" — the simultaneous shift toward digitalization and climate neutrality (Elavarasan et al., 2022; Kristakova et al., 2021;). The integration of environmental, social, and governance (ESG) principles into industrial value chains reflects an emerging paradigm in which economic efficiency, ecological responsibility, and technological sophistication reinforce one another (Sikora, 2020).

Digital technologies are key enablers of this transformation. Tools such as artificial intelligence (AI), the Internet of Things (IoT), and cyber-physical systems (CPS) enhance transparency, optimize material flows, and facilitate predictive maintenance in manufacturing (Singh et al., 2022). In wood-processing enterprises, the use of smart sensors, digital twins, and blockchain-based traceability systems supports real-time resource monitoring, thereby reducing waste and carbon emissions while improving process efficiency (Liu et al., 2023). These technologies also foster new business models, including servitization and digital platforms, which strengthen the integration of suppliers, producers, and customers along sustainable value chains (Stroumpoulis et al., 2024).

The role of innovation ecosystems in this context is pivotal. The wood-processing industry increasingly depends on networks of enterprises, start-ups, and research institutions that co-create technological and ecological value (Vostriakova et al., 2023). Such ecosystems promote open innovation, cross-sectoral collaboration, and the exchange of green knowledge, leading to the diffusion of advanced materials such as bio-based composites and non-wood biomaterials (Antov et al., 2023). These developments illustrate the systemic shift toward circularity — where value creation is decoupled from resource depletion through recycling, reuse, and renewable feedstocks (Osvaldová & Potkány, 2024; Huber et al., 2023).

At the macroeconomic level, this transformation aligns with the European Green Deal's objectives for climate neutrality by 2050, demanding decarbonization across all industrial sectors (Carmona-Martínez et al., 2024). However, barriers such as low investment in green innovation, limited digital readiness, and insufficient green skills persist, particularly among small and medium-sized enterprises (Maksymova & Nastase, 2024; Chatzistamoulou, 2023). In Slovakia, regional disparities and structural weaknesses may hinder the diffusion of digital and sustainable technologies. Nonetheless, successful examples—such as the SmartHead platform integrating ESG data management—demonstrate that combining transparency with technology enhances trust, stakeholder engagement, and long-term competitiveness (Šulyová et al., 2020).

Thus, the theoretical foundations of this study rest upon three interlinked pillars: 1. the digital transformation of production systems through Smart Industry and IoT, 2. the sustainability transition driven by ESG and circular economy principles, and 3. the formation of innovation ecosystems that mediate these processes within regional and national value chains. Together, these dimensions form a comprehensive framework for understanding how Slovak wood-processing enterprises can leverage digital and sustainable innovation to achieve competitiveness in a climate-neutral economy (Paluš et al., 2020; Stroumpoulis et al., 2024).

2.1 Research Aim and Questions

The primary aim of this research is to analyze the interrelationship between digitalization, innovation, and ESG (Environmental, Social, and Governance) performance in the Slovak wood-processing industry, with a particular focus on how digital technologies and innovation ecosystems support the transition towards a circular and climate-neutral bioeconomy. The study seeks to identify how tools such as IoT, AI, and data-driven management enhance operational efficiency, transparency, and environmental sustainability while simultaneously strengthening governance and stakeholder engagement along value chains. Furthermore, it aims to examine the barriers and enabling factors influencing the adoption of ESG-oriented digital transformation and to propose recommendations for building innovation ecosystems that integrate economic competitiveness with sustainable and responsible business practices.

Research Questions:

1. How does digital transformation enhance ESG (Environmental, Social, and Governance) performance in the Slovak wood processing industry?
2. What role do innovation ecosystems and digital technologies (IoT, AI, data analytics) play in promoting sustainability, transparency, and competitiveness along the wood value chain?
3. What key barriers and enabling factors influence the integration of digitalization, innovation, and ESG principles in Slovak wood-processing enterprises?

2.3 Methodology

The study employs a qualitative secondary analysis, exploratory research design aimed at understanding how Slovak wood-processing enterprises integrate digital technologies, sustainable innovations, and value-chain collaboration in pursuit of competitiveness and climate neutrality. The empirical analysis is based on secondary data collected from peer-reviewed academic literature, national strategic documents, and corporate case evidence (e.g., SmartHead, Bučina DDD).

A thematic content analysis approach was applied to identify patterns and relationships among digital transformation, ESG implementation, and innovation ecosystems. Themes were developed inductively from data and validated through iterative comparison across sources. Triangulation of information from academic, policy, and industry perspectives ensured analytical rigor and credibility.

Data interpretation followed an ESG-based competitiveness framework, which integrates environmental performance (resource efficiency and carbon reduction), social performance (stakeholder trust and employee skills), and governance performance (transparency, reporting, and innovation management). This approach allows for a multidimensional understanding of how digital transformation contributes to sustainable competitiveness within the Slovak wood-processing industry.

3. PRACTICAL PART: DIGITALIZATION, INNOVATION, AND ESG IN THE SLOVAK WOOD PROCESSING INDUSTRY

The growing interdependence of digitalization, innovation, and sustainability is profoundly transforming the Slovak wood processing industry. In recent years, a new paradigm has emerged in which digital transformation and green innovation act as key drivers of improved ESG (Environmental, Social, and Governance) performance, resource efficiency, and long-term competitiveness. Empirical research from the last decade confirms that the integration of digital technologies, ecological solutions, and value-chain collaboration represents a critical mechanism for enhancing both environmental and economic performance (Loučanová et al., 2020; Su et al., 2023; Feng & Nie, 2024; Sang et al., 2025).

3.1 Innovation Orientation and ESG Integration in Slovak Enterprises

According to Loučanová et al. (2017), innovations in Slovak wood-processing enterprises are primarily oriented toward modernization of production technologies and optimization of raw material processing to improve efficiency and product quality. Larger enterprises increasingly invest in digital transformation, while small and medium-sized enterprises (SMEs) focus mainly on incremental innovations driven by regulatory compliance.

A later study by Loučanová et al. (2020) revealed that experts and entrepreneurs in the sector prioritize environmental and process innovations, such as material efficiency, waste recycling, and low-emission production processes. These directions align with the principles of the circular economy and the ESG framework, in which digital tools support transparency, accountability, and environmental monitoring (Chen & Wang, 2024; Yang et al., 2023). However, innovation strategies in practice often remain narrowly technological, lacking a holistic ESG integration that connects innovation with social responsibility, governance quality, and long-term sustainability goals.

The main obstacles to this alignment include financial constraints, low digital maturity, and insufficient green skills, which limit the sector's capacity to implement comprehensive ESG-oriented innovations (Melichová et al., 2021; Maksymova & Nastase, 2024).

3.2 IoT, Supply Chains, and ESG Transparency

A significant shift towards digitalization has been documented by Šulyová and Koman (2020), who analyzed the adoption of Internet of Things (IoT) technologies in logistics within Slovak wood-processing enterprises. Their findings demonstrate that IoT implementation can reduce operational costs by up to 20%, improve supply-chain traceability, and enable real-time data analytics—a foundation for stronger governance and ESG reporting.

Compared to global leaders such as West Fraser Timber (Canada) or Weyerhaeuser (USA), Slovak enterprises currently employ mostly basic IoT applications—moisture sensors, RFID tagging of raw material, and GPS-based transport monitoring. International best practices, however, indicate that integrating IoT with blockchain and cloud-based systems achieves full supply-chain transparency, enabling immutable audit trails and green logistics certification (Wei & Zheng, 2024; Yu et al., 2024).

Šulyová and Koman (2020) proposed a three-phase logistics audit model to guide digital transformation:

1. Descriptive phase – collection of process data;
2. Diagnostic phase – identification of inefficiencies and bottlenecks;
3. Recommendation phase – formulation of IoT-based improvement strategies.

Such audits support the implementation of Industry 4.0 principles by integrating AI-driven decision support, automated guided vehicles (AGV), augmented reality (AR) scanning, and digital twins for predictive maintenance. These technologies jointly enhance energy efficiency, occupational safety, and ESG governance, providing verifiable data for sustainability reporting.

3.3 Artificial Intelligence and Green Innovation in Wood Processing

Recent advances in artificial intelligence (AI) further illustrate how digitalization supports ESG outcomes. Vacek et al. (2024) applied AI for defect detection in roundwood using CT scanning, leveraging 3D scanning and neural networks to identify wood species, knots, and pith with over 95% accuracy. This data-driven optimization minimizes waste, reduces energy intensity, and contributes directly to climate neutrality and environmental efficiency, reinforcing the *Environmental* dimension of ESG.

From the *Governance* perspective, AI enhances internal control and data-driven decision-making, thereby improving transparency and accountability. Such technologies exemplify how green innovation and digital capability building serve as mediating mechanisms between digital transformation and ESG performance (Wu & Li, 2023; Wei & Zheng, 2024).

3.4 Bioinnovations, Value Chains, and Stakeholder Integration

As Martínková et al. (2019) note, bio-based innovations—including bio-adhesives, biocomposites, and nanocellulose—create higher added value while supporting eco-efficiency. Integrating these innovations within digital value chains fosters a shift toward the circular bioeconomy, characterized by resource recirculation, renewable inputs, and reduced environmental impact.

In this context, digital stakeholder integration has emerged as a critical governance instrument. Real-time data exchange between suppliers and customers enhances trust, transparency, and ESG disclosure (Mohiuddin et al., 2024). Empirical evidence from Central Europe confirms that joint transport planning and logistics optimization can reduce procurement costs by 24–40% (Kogler et al., 2021), while simultaneously contributing to social and environmental performance.

Table 1: ESG-oriented digital strategies for sustainable logistics and supply chain integration.

Strategy	ESG Impact	Effect / Benefit	Source
Joint transport planning	E, G	Reduced logistics emissions and costs (up to 24%)	Kogler et al. (2021)
Higher transport utilization	E	Fuel savings up to 40%	Kogler et al. (2021)
IoT-enabled logistics	E, G	20% cost reduction; real-time traceability	Šulyová & Koman (2020); Yu et al. (2024)
Real-time data sharing	S, G	Improved collaboration and transparency	Mohiuddin et al. (2024)

Source: Kogler et al. (2021); Šulyová & Koman (2020); Yu et al. (2024) ; Mohiuddin et al. (2024)

Digitalization thus functions as a multi-dimensional ESG enabler: improving operational efficiency (*Governance*), reducing environmental impact (*Environment*), and strengthening collaboration and social responsibility (*Social*). The convergence of digital and sustainable processes generates a synergistic ESG effect, supporting Slovakia's transition to a climate-neutral bioeconomy.

3.5 Barriers, Recommendations, and Innovation Ecosystems

Despite visible progress, the digital-ESG transformation of the Slovak wood processing sector faces structural barriers: high investment costs, limited financing, insufficient coordination between research and industry, and an underdeveloped ecosystem for ESG-driven innovation (Loučanová et al., 2020; Melichová et al., 2021).

Table 2: Typology of Barriers

Type of Barrier	ESG Dimension Affected	Description	Sources
Financial	E, G	Insufficient capital for green and digital transformation in SMEs	Loučanová et al. (2017); Melichová et al. (2021)
Informationa	G	Weak awareness of innovation and ESG funding opportunities	Štěrbová et al. (2016)
Managerial	G	Lack of coordination between innovation and ESG policies	Beckmann et al. (2020)
Market	S, G	Low competitiveness against innovative foreign producers	Kaputa et al. (2015)
Skills-related	S	Deficiency in digital and green skills	Maksymova & Nastase (2024); Chatzistamoulou (2023)

Source: Loučanová et al. (2017); Melichová et al. (2021)); Štěrbová et al. (2016)); Beckmann et al. (2020); Kaputa et al. (2015)); Maksymova & Nastase (2024); Chatzistamoulou (2023)

4. DISCUSSION

The study confirms that digitalization and sustainability form a mutually reinforcing foundation of competitiveness in the Slovak wood-processing industry, consistent with international findings (Su et al., 2023; Chen & Wang, 2024; Wei & Zheng, 2024). Similar to observations by Konovalova and Burtsev (2024), a digital divide persists between larger enterprises and SMEs: while leading firms invest in smart technologies and ESG reporting, smaller ones remain in the early stages of transformation. This gap limits the diffusion of green innovation, reduces transparency, and slows progress toward circular and climate-neutral objectives.

Our findings align with Zhang et al. (2022) and Kumar et al. (2022), who emphasize that limited financing, low technological readiness, and weak cooperation with research institutions are primary barriers for SMEs. In Slovakia, these constraints are further reinforced by regional disparities and skill shortages, confirming that the twin transition requires not only capital investment but also systemic capacity building and governance reform.

At the same time, the Slovak experience mirrors global evidence that digitalization and innovation enhance ESG performance through improved efficiency, resource allocation, and stakeholder transparency (Wu & Li, 2023; Yang et al., 2023). As in other manufacturing sectors, the Slovak wood industry demonstrates that the integration of AI, IoT, and data analytics directly supports the Environmental and Governance dimensions of ESG by enabling real-time monitoring and data-driven decision-making.

However, the current innovation ecosystem in Slovakia remains fragmented. Compared with best practices in Western Europe and Asia (Li et al., 2025; Yu et al., 2024), cooperation between enterprises, research institutions, and start-ups is still limited. This weakens the diffusion of bio-based innovations, such as composites and nanocellulose, and delays the transition to a circular bioeconomy (Osvaldová & Potkány, 2024; Beckmann et al., 2020).

In this regard, our observations correspond with recent studies on the circular and climate-neutral economy in Slovakia (Paluš et al., 2020; Kristakova et al., 2021; Korneliuk, 2024), which stress that despite high potential for sustainable growth, the sector faces barriers in governance, financing, and innovation diffusion. Addressing these will require strengthening regional innovation ecosystems, developing green and digital skills, and fostering cross-sectoral cooperation to balance efficiency, biodiversity, and climate goals.

In summary, the Slovak wood-processing industry reflects broader international trends: while digitalization and innovation clearly improve ESG performance and competitiveness, progress remains uneven. Bridging the digital divide—especially for SMEs—and linking technology with sustainability through collaborative innovation ecosystems are essential steps toward a resilient, circular, and climate-neutral bioeconomy.

CONCLUSION

Digitalization, sustainability, and innovation ecosystems have become key drivers of competitiveness in the Slovak wood-processing industry. The ongoing twin transition—linking digital and green transformation—enhances efficiency, transparency, and ESG performance across value chains. Technologies such as IoT and AI improve resource use, reduce emissions, and strengthen governance through data-driven decision-making and reporting.

Despite progress, barriers remain: high investment costs, low digital maturity, and a lack of green skills limit the sector’s transformation, especially among SMEs. To overcome these challenges, stronger cooperation between business, government, and academia is essential. Targeted investment support, skill development, and innovation networks can accelerate digital and sustainable change.

In sum, connecting technology with sustainability turns traditional wood value chains into smart, transparent, and climate-responsible ecosystems. Such integration not only boosts competitiveness but also creates long-term value for people, the planet, and business.

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BUILDING ENGAGED HUMAN CAPITAL: THE MEDIATING ROLE OF JOB CRAFTING IN THE SERVANT LEADERSHIP–WORK ENGAGEMENT RELATIONSHIP

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Abstract

Human capital constitutes a key pillar of the competitiveness of small and medium-sized enterprises (SMEs). To strengthen this pillar, SMEs increasingly develop strategies aimed at enhancing Work Engagement (WE) and adopt contemporary approaches to human capital management, such as Servant Leadership (SL). These practices promote proactive employee behaviors, including Job Crafting (JC). Although prior research has established a positive relationship between Servant Leadership and work engagement, the mediating role of Job Crafting in this relationship remains insufficiently explored. Grounded in Self-Determination Theory (SDT), this study examines the effect of Servant Leadership on Work Engagement, with Job Crafting serving as a mediating mechanism. Using the partial least squares structural equation modeling (PLS-SEM) approach, we analyzed data from 342 employees in small and medium-sized enterprises. The findings reveal that Job Crafting (JC) significantly mediates the relationship between Servant Leadership (SL) and Work Engagement (WE). This study advances the theoretical understanding of Job Crafting (JC) and Work Engagement (WE), while offering practical insights into how Servant Leadership (SL) can enhance the engagement and vitality of human capital within SMEs.

Key words:
Job Crafting, Servant Leadership, Work Engagement, SMEs, Human Capital

JEL Classification M10, M12, M14 https://doi.org/10.52665/ser20250211

INTRODUCTION

In today's business environment, human capital is one of the most important factors for the success of small and medium-sized enterprises (SMEs). SMEs face many challenges, such as limited resources and a lack of expertise (Badri et al., 2025; Prokop et al., 2025) . Therefore, these enterprises are intensively developing strategies to promote work engagement (WE), which is defined as a positive, fulfilling state of mind associated with work, represented by vitality, dedication and absorption (Gürbüz et al., 2024; Zeshan et al., 2025) . One of the current and effective approaches to human capital management is servant leadership (SL), which focuses on meeting the needs of employees, developing their abilities and promoting their well-being (Ghlichlee & Motaghed Larijani, 2024; Quan & Van Dierendonck, 2025). According to self-determination theory, servant leadership (SL) involves creating a supportive work environment that fulfils basic psychological needs (autonomy, competence and relatedness). This significantly increases intrinsic motivation and work engagement (Altuniji et al., 2025; Costantini et al., 2025). In addition, it encourages proactive employee behaviour, such as job crafting (JC), i.e. reshaping work to better align tasks with individual needs and preferences (Badri et al., 2025; Clinton et al., 2025) .

Despite an extensive number of studies, there remains a significant gap in understanding the role of job crafting (JC) as a mediator between Servant Leadership (SL) and Work Engagement (WE), especially in the context of small and medium-sized enterprises, which have different structural and cultural conditions compared to large companies. Most research to date has focused on large or listed companies, while SMEs face highly specific organisational constraints and challenges. Therefore, the mechanisms that apply within large organisations may not be directly transferable to SMEs (Quan & Van Dierendonck, 2025). Furthermore, it is unclear to what extent job crafting (JC) actually mediates the link between servant leadership (SL) and work engagement (WE) in this context, as current studies often examine only the direct relationship or other mediating mechanisms (Jehanzeb & Mushtaq, 2025; Mostafa et al., 2025). These ambiguities pose a challenge for research, which should clarify how servant leadership (SL) stimulates proactive employee behaviour (JC) and how this behaviour subsequently influences their work engagement (WE), thereby expanding knowledge about the dynamics of human capital in SMEs.

The research therefore examines the mediating role of Job Crafting (JC) in the relationship between servant leadership (SL) and work engagement (WE). The empirical part is based on a questionnaire survey of 342 SME employees, with data analysis performed using Partial Least Squares Structural Equation Modelling (PLS-SEM), which allows for the testing of complex mediating relationships. This approach makes it possible to capture the complex interrelationships between organisational resources, individual proactive behaviour and work outcomes (Gürbüz et al., 2025; Zeshan et al., 2025) .

This study expands our knowledge of how servant-oriented leadership (SL) encourages proactive employee behaviour and work engagement (WE). The results show that job crafting (JC) plays a significant mediating role in the relationship between servant leadership (SL) and work engagement (WE), confirming its position as a key mechanism for activating intrinsic motivation and meaningfulness of work. Practical recommendations are based on detailed evidence of how servant leadership (SL) can increase employee engagement (WE) by promoting proactive behaviour, which is key to effective human capital management in an SME environment.

1.1 Core constructs and theoretical foundations

In current research on organisational behaviour, attention is increasingly shifting from pathological phenomena to positive work states and the contextual factors that support them. Among the most significant outcome variables is work engagement (WE), which is defined as a positive, fulfilling state of mind related to work, characterised by vitality, dedication and absorption (Gürbüz et al., 2025; Zeshan et al., 2025) . Work engagement (WE) is considered a key indicator of employees' psychological well-being and a significant predictor of performance, innovative behaviour and organisational success (Jehanzeb & Mushtaq, 2025).

In terms of antecedents of work engagement, job resources, including leadership quality, play a crucial role. Servant leadership (SL) is an ethically oriented leadership style in which leaders prioritise the needs, development and well-being of employees over their own interests (Ghlichlee & Motaghed Larijani, 2024; Quan & Van Dierendonck, 2025). Serving leadership (SL) is perceived as an important job resource as it provides employees with support, autonomy and opportunities for personal growth, thereby creating a supportive work environment conducive to positive work attitudes (Fröhlich et al., 2025; Mostafa et al., 2025).

However, in addition to contextual resources, work engagement (WE) is also influenced by the active role of the employees themselves. One of the key proactive behaviours is job crafting (JC), which refers to the deliberate modification of work tasks, relationships and cognitive perceptions of work in order to achieve a better fit between work and individual needs, abilities and values (Clinton et al., 2025; Olya et al., 2024). In particular, approach-oriented job crafting (JC), focused on seeking resources and challenges, is associated with positive work outcomes (Manzanares et al., 2024; Xu et al., 2024).

The theoretical framework that integrates the influence of leadership resources, proactive behaviour and work engagement is self-determination theory (SDT). SDT's requirement is that intrinsic motivation and positive work states arise when basic psychological needs for autonomy, competence, and relatedness are satisfied (Altuniji et al., 2025; Costantini et al., 2025). This framework allows us to explain how the organisational context and individual proactivity together shape employee engagement.

1.2 Servant leadership as a contextual resource

Servant leadership (SL) is considered in the literature to be one of the most important contextual resources at work, as it combines ethical leadership, support for development and empowerment of employees (Quan & Van Dierendonck, 2025). Leaders who apply servant leadership (SL) approach, create an environment of psychological safety and trust that supports the autonomous functioning of employees and their intrinsic motivation (Ruiz-Palomino et al., 2025).

In accordance with SDT, servant leadership (SL) contributes to the satisfaction of all three basic psychological needs. Support for autonomy is manifested in the delegation of authority and trust in employee decision-making, competence development through coaching and feedback, and relationality through quality interpersonal relationships (Fröhlich et al., 2025). Fulfilling these needs leads to higher intrinsic motivation, which is a direct predictor of work engagement (Clinton et al., 2025). Based on this theoretical framework, the following hypothesis is formulated:

H1: Servant Leadership (SL) has a positive direct effect on Work Engagement (WE).

1.3 Job crafting as an agentic mechanism

Job crafting (JC) represents the active role of employees in shaping their own work experience and is considered a key mechanism through which employees utilise available work resources (Manzanares et al., 2024). Job crafting (JC) involves seeking out structural and social resources and taking on new challenges that increase the meaningfulness of work and promote personal growth (Xu et al., 2024).

From the perspective of Conservation of Resources Theory (COR), Job Crafting (JC) is a resource gain strategy that leads to the accumulation of psychological resources such as self-confidence, a sense of competence, and meaningfulness of work (Badri et al., 2025). These resources subsequently support the emergence of a positive spiral of resource acquisition, which manifests itself in higher levels of work engagement (WE).

While at the same time, job crafting is closely linked to SDT, as it allows employees to actively satisfy their needs for autonomy, competence and relatedness (Costantini et al., 2025). Employees who have the opportunity to reshape their work show higher intrinsic motivation and engagement. On this basis, the following hypotheses are formulated:

H2: Servant Leadership (SL) has a positive direct effect on Job Crafting (JC).

H3: Job Crafting (JC) has a positive direct effect on Work Engagement (WE).

1.4 Job crafting as a mediator between servant leadership and work engagement

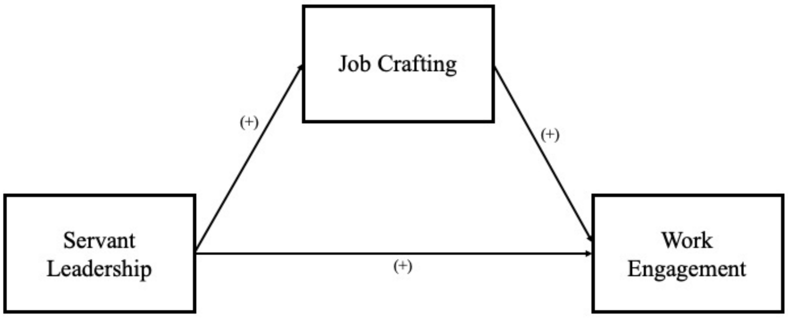
Although servant leadership (SL) provides employees with significant work resources, the mere existence of a supportive context does not automatically lead to higher work engagement (WE). Current research indicates that individual proactivity plays a key role in transforming organisational resources into positive work outcomes (Gürbüz et al., 2025; Zeshan et al., 2025).

In this context, job crafting (JC) represents a behavioural path through which employees actively use the resources provided by servant leadership (SL). Servant leadership (SL) creates motivational conditions in line with SDT that encourage engagement in job crafting (JC), and this process subsequently leads to higher work engagement (WE). Empirical studies confirm that job crafting (JC) mediates the relationship between various organisational antecedents and Work Engagement (WE), which supports its theoretical relevance in the context of servant leadership (SL). Based on these arguments, the following hypothesis is formulated:

H4: Servant Leadership (SL) has a positive indirect effect on Work Engagement (WE) through Job Crafting (JC).

The comprehensive hypothetical model can be expressed in the diagram shown in Figure 1.

15 Figure 13: Hypothetical model



16 *Source: Processed by the authors*

2. PROBLEM FORMULATION AND METHODOLOGY

2.1 Participants and data collection

We conducted our research among employees of small and medium-sized enterprises (SMEs) who are facing the challenge of transitioning to modern technologies that are shaping and will increasingly shape work design and work practices. We collected 342 responses from respondents in Central Europe who are employed on a permanent basis in small and medium-sized enterprises (SMEs). These employees originate from Austria, the Czech Republic, Poland and Slovakia. Data collection took place in two waves. In the first wave, we collected data from Austria, the Czech Republic and Poland through the MNForce research agency. In the second wave, we collected data through the Survio.com platform in Slovakia. We compiled the distributed questionnaire based on the adopted methods of measuring the individual variables that make up our hypothetical model. These adopted measurement methods were verified through numerous studies(e.g.: Geldenhuys et al., 2021; Kolářová et al., 2016; Moreira et al., 2020; Navarro-Abal et al., 2023).

To determine the minimum sample size, we used the results of **F tests** - Linear multiple regression: fixed model, R^2 deviation from zero in the G*Power programme. The input data consisted of the effect size f^2 , which was equal to 15, the probability of error $\alpha = 0.05$, and the number of predictors = 2.

Analysis: A priori: Compute required sample size

Input: Effect size $f^2=0.15$

A err prob=0.05

Power(1-β err prob)=0.95

Number of predictors = 2

Output: Noncentrality parameter $\lambda = 16.050000$

Critical F=3.0837059

Numerator df=2

Denominator df=104

Total sample size=107

Actual power=0.9518556

The results revealed that at least 107 measurements are required to achieve a 95% confidence level. In this case, the type of test used to calculate the minimum sample size depended on the method used to test our hypothetical model.

2.2 Variables and how they were measured

Scales taken from verified and renowned studies were used to measure individual variables. This procedure ensures the necessary reliability and confidence that the constructs have undergone a critical process of verification and renovation.

We measured **Servant Leadership (SL)** using a 28-item scale validated in research by Grobler & Flotman, (2020) and Kolářová et al., (2016). An example item reads as follows: "My supervisor sets aside time for personal conversations." Respondents had the option of responding using a five-point Likert scale, where 1 indicates "strongly disagree" and 5 indicates "strongly agree."

Job Crafting (JC) was measured using a 15-item scale that was tested in studies by Geldenhuys et al., (2021) and Slemp & Vella-Brodrick,(2013). An example item reads as follows: "I introduce new approaches to improve my work." Respondents had the option to respond using a five-point Likert scale, where 1 indicates the response "almost never" and 5 indicates "very often."

We measured **Work Engagement (WE)** using the 17-item UWES-17 scale. This is a unified and general tool for measuring employee engagement. It has been used in research by, for example, Moreira et al., (2020), Navarro-Abal et al., (2023) and Wojcik-Karpacz, (2018). An example item reads as follows: "I feel happy when I work intensively." Respondents were able to respond using a five-point Likert scale, where 1 indicates "almost never" and 5 indicates "very often".

We evaluated the internal consistency of the items selected for measurement using Cronbach's alpha. The results of the internal consistency measurement of the selected items achieved an excellent level, which ultimately represents the reliability of the measured variables. Servant Leadership (SL) Cronbach α = 0.964. Work Engagement (WE) Cronbach α = 0.962. Job Crafting (JC) Cronbach α = 0.929. Specific questionnaire questions are listed in the appendix.

2.3 Statistical analyses

The data obtained from the questionnaire survey were analysed using the partial least squares structural equation modelling (PLS-SEM) method. The method was chosen based on its ability to estimate models in terms of understanding individual hypothetical relationships (Ringle et al., 2023). In addition, the method was chosen because the theoretical model we proposed is complex, robust, and proposes a higher-order construct (J. Hair et al., 2023). The SmartPLS 4 statistical software was used to perform the method (Sarstedt et al., 2024). The PLS-SEM implementation process itself consists of two basic steps. The first is the measurement model and the second is the path model, which expresses the resulting relationships and compares them with the bootstrapping results (Sarstedt et al., 2024).

The reliability of the model was verified using Cronbach's alpha and composite reliability (rho_a, rho_c), with the value having to exceed 0.700. Validity was tested in terms of convergent and discriminant validity (J. F. Hair et al., 2024). Convergent validity was confirmed by the AVE test (>0.500). Discriminant validity was verified by the HTMT test (<0.85), the Fornell-Larcker criterion (FL < √AVE) and cross-loadings, where each indicator had a higher loading in its own variable than in others (Sarstedt et al., 2021).

The second step was bootstrapping testing within the path model. When testing five variables, we used 5,000 bootstrapping samples (Magno et al., 2024). The PLS-SEM method works with confidence intervals at $p<0.05$ and T-statistics <1.64. We further examined the coefficient of determination R^2 and the predictive power of the model Q^2 predict. A value of $Q^2 > 0$ confirms the predictive ability of the model. Comparison of prediction errors (RMSE, MAE) with a naive model (LM_RMSE, LM_MAE), where it is necessary that the RMSE and MAE values do not exceed the values of the naive model LM_RMSE and LM_MAE in most cases.

3. RESULTS

3.1 Measurement model

The reliability test results indicate reliable internal consistency of the data obtained using validated variable measurement scales. Specifically, in Cronbach's alpha test, the results reached levels >0.700. Composite reliability tests (rho_a, rho_c) also achieved values >0.700. Convergent validity was tested using the AVE test, where individual variables achieved the required level of >0.500. An overview of the results is provided in Table 1.

17 Table 7: Reliability and convergent validity

	Cronbach's alpha	(rho_a)	(rho_c)	(AVE)
JC	0.928	0.930	0.938	0.518
SL	0.964	0.965	0.966	0.508
WE	0.962	0.965	0.966	0.627

18 Source: Processed by the authors using SmartPLS 4

In addition to convergent validity, we also verified divergent validity, which we tested using the Heterotrait-monotrait test (HTMT) and the Fornell-Larcer criterion test. The results of the HTMT test revealed that all items examined did not exceed the threshold value of >0.85, thus meeting the necessary criteria that reject internal correlation between individual variables. The test results are shown in Table 2.

19 Table 8: Heterotrait-monotrait ratio test

	JC	SL	WE
JC			
SL	0.628		
WE	0.666	0.671	

20 Source: Processed by the authors using SmartPLS 4

To verify divergent validity, we also performed the Fornell-Larcer criterion test. The results are verified using correlation analyte values, which must not exceed the square root of the AVE test for individual variables. In our case, the results reject a high internal correlation between the variables under investigation, thus meeting the criteria for the second step within PLS-SEM, namely the path analysis test. The results of the FL test are shown in Table 3.

21 Table 9: Fornell-Larcer criterion test

	JC	SL	WE
JC	0.720		
SL	0.604	0.712	
WE	0.633	0.654	0.792

22 Source: Processed by the authors using SmartPLS 4

3.2 Path Model

The second step in PLS-SEM is the analysis of the Path Model, which we use to test the support for the established hypotheses. In connection with the testing itself, we compared the results with the results of bootstrapping samples, which were performed in the body of n = 5,000. The results of the Path coefficient testing are shown in Table 4.

23 Table 10: Path coefficient and hypothesis testing

	Original sample	**Sample mean**	**Standard deviation**	**T statistics**	**P values**	**Supported/Not Supported**
H1: SL -> WE	0.428	0.427	0.051	8.425	0.000	Supported
H2: SL -> JC	0.604	0.607	0.044	13.652	0.000	Supported
H3: JC -> WE	0.375	0.377	0.054	6.896	0.000	Supported
H4: SL -> JC -> WE	0.226	0.229	0.037	6.137	0.000	Supported

24 Source: Processed by the authors using SmartPLS 4

The results of path coefficient testing revealed support for the established hypotheses. Specifically, we found that servant leadership has a direct positive impact on job crafting, with a path coefficient of 0.604. The results of bootstrapping testing showed a value of 0.607, which indicates a robust construct of the given relationship. The significance level p = 0.000 demonstrates the statistical significance of the tested relationship and supports H2. Furthermore, the results showed a positive direct effect of servant leadership on employee engagement, with a path coefficient of 0.428. The bootstrapping result was 0.427, which also demonstrates the robustness of this relationship. The significance level reached a value of p = 0.000, which proves statistical significance and thus supports H1. Furthermore, the results revealed that job crafting has a direct positive impact on employee engagement. Specifically, the path coefficient result reached a value of 0.375 and the bootstrapping result 0.377, confirming the robustness of the construct. Furthermore, the significance level reached a value of p = 0.000, confirming statistical significance and thus supporting H3. Finally, we tested the mediating role of job crafting in the relationship between servant leadership and employee engagement. The results showed that servant leadership has a specifically indirect positive effect on employee engagement through job crafting. Specifically, the result of the specifically indirect effect showed that the path coefficient reached a value of 0.226. The bootstrapping result reached a value of 0.229, which demonstrably proves the robustness of the given construct. This relationship is also supported by the value p = 0.000, which confirms statistical significance and thus supports H4.

In addition to the path coefficient, we also verified the predictive power of the model within the sample under study. We verified this power using the coefficient of determination R^2. The results revealed that servant leadership (SL) explains 36.5% of the total variability of job crafting (JC R^2= 0.365). This result points to the mediating effect of job crafting (JC) in the examined construct. On the other hand, job crafting (JC) explains up to 51.7% of the total variability of work engagement (WE R^2= 0.517). These results point to the predictive power within the sample under study. The results are shown in Table 5.

25 Table 11: Predictive power of the model within the sample

	R-square
JC	0.365
WE	0.517

26 *Source: Processed by the authors using SmartPLS 4*

In addition to the predictive power within the sample, we also tested the predictive power outside the sample using the Q^2predict test. As part of the test, we compared the RMSE and MAE model values with the values of the naive LM_RMSE and LM_MAE models. The test results are shown in Table 6.

27 Table 12: Predictive power of the model outside the sample

	Q²predict	RMSE	MAE	LM_RM	LM_MA
CC_2	0.201	1.090	0.872	1.137	0.893
CC_3	0.197	1.110	0.897	1.111	0.887
CC_4	0.163	1.069	0.851	1.090	0.868
CC_5	0.155	1.036	0.828	1.007	0.802
SC_1	0.188	1.035	0.821	1.009	0.784
SC_2	0.173	1.244	1.025	1.273	1.028
SC_3	0.201	1,196	0.992	1.248	1.017
SC_4	0.185	1,176	0.967	1.234	1.002
SC_5	0.170	1.091	0.899	1.103	0.878
TC_1	0.252	1.056	0.865	1.060	0.853
TC_2	0.151	1.109	0.899	1.114	0.898
TC_3	0.194	1.137	0.923	1.154	0.908
TC_4	0.232	1.112	0.917	1.146	0.918
TC_5	0.092	1.110	0.897	1.120	0.906
EE_1	0.350	0.952	0.745	0.987	0.760
EE_10	0.240	1.134	0.915	1.185	0.953
EE_11	0.240	1.045	0.813	1.054	0.801
EE_12	0.255	1.026	0.805	1.052	0.819
EE_13	0.247	1.001	0.788	1.043	0.806
EE_14	0.182	1.110	0.902	1.089	0.848
EE_15	0.199	1.034	0.789	0.992	0.758
EE_16	0.356	0.968	0.755	0.999	0.758
EE_17	0.257	1.080	0.827	1.099	0.848
EE_2	0.291	1.013	0.775	0.990	0.743
EE_3	0.156	1.092	0.862	1.085	0.851
EE_4	0.315	0.973	0.754	1.013	0.780
EE_5	0.246	1.043	0.783	1.083	0.832
EE_6	0.216	1.079	0.865	1.115	0.888
EE_7	0.372	0.989	0.815	1.008	0.803
EE_8	0.293	1.069	0.851	1.085	0.850
EE_9	0.230	1.057	0.819	1.097	0.851

28 *Source: Processed by the authors using SmartPLS 4*

The results of testing the predictive power within the sample revealed that approximately half of the values of the tested items of individual variables do not exceed the values of the naive LM_RMSE and LM_MAE models. These results indicate the moderate to moderately strong predictive power of the hypothetical model.

CONCLUSION

The aim of this study was to examine the effect of servant leadership (SL) on work engagement (WE), with job crafting (JC) serving as a mediating mechanism. The results provided clear support for all tested hypotheses. Servant leadership (SL) showed a strong and statistically significant positive effect on job crafting (JC), suggesting that leaders oriented towards serving others create conditions that support proactive employee behaviour. At the same time, a direct positive effect of servant leadership (SL) on work engagement (WE) was also confirmed, highlighting its importance as a contextual work resource. The results further showed that job crafting (JC) has an positive and significant impact on work engagement (WE), confirming its role as a key behavioural mechanism supporting positive work states.

A key finding of the research is the confirmation of the mediating role of job crafting (JC) in the relationship between servant leadership (SL) and work engagement (WE). The indirect effect was statistically significant and robust, suggesting that servant leadership (SL) increases employee engagement (WE) not only directly but also indirectly by supporting their proactive job crafting (JC). The predictive power of the model was rated as moderate to strong, with servant leadership (SL) explaining a significant portion of the variability in job crafting (JC) and the combination of servant leadership (SL) and job crafting explaining (JC) more than half of the variability in work engagement (WE).

The results support the basic requirements of self-determination theory (SDT), according to which a work environment that supports autonomy, competence, and relatedness is associated with higher intrinsic motivation and positive work states. The findings suggest, while at the same time, that job crafting (JC) is a behavioural mechanism through which employees actively respond to supportive leadership behaviour and use it to optimise their work experience. The contribution of the study thus lies in confirming the suitability of SDT as a theoretical framework for examining the relationships between leadership style, proactive behaviour and work engagement (WE), without the ambition to conceptually expand this theory.

From a practical standpoint, the results imply that organisations can encourage their employees to be more engaged at work by creating an environment that aligns with the principles of Self-Determination Theory (SDT). Servant leadership (SL) is a leadership style that can increase employees' intrinsic motivation and their willingness to engage in job crafting (JC) by promoting autonomy, competence and quality interpersonal relationships. The practical implications of these findings are the need to give employees room for initiative, encourage their active participation in shaping work tasks, and create conditions that legitimise proactive behaviour. Such an approach allows organisations not only to increase work engagement (WE), but also to use limited resources more effectively by activating employees' intrinsic motivation.

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DATA-DRIVEN MARKETING AND DIGITAL INTELLIGENCE: MEASURING MATURITY IN SLOVAK ORGANIZATIONS

Miroslav REITER

Abstract

This paper examines the level of data-driven marketing maturity and the use of digital intelligence tools among Slovak organizations. Based on a quantitative survey (n = 124) covering three key dimensions: marketing automation tools, customer lifecycle data management, and social media analytics, the study identifies how organizations integrate data into their strategic and operational marketing processes. The results show that while most respondents actively use online tools such as newsletters, chatbots, and AI systems, data management often remains fragmented across multiple platforms. A significant portion of organizations collect customer data throughout the entire lifecycle, but analytical utilization is still limited. Furthermore, only half of the surveyed organizations systematically analyze social media data, indicating a gap between digital infrastructure and strategic data application. The findings highlight the need for comprehensive CRM integration, advanced data analytics, and a stronger alignment between marketing intelligence and digital maturity development.

Key words:
customer relationship management, data-driven marketing, digital intelligence, digital maturity, social media analytics

JEL Classification M31, M15, O33, L86

INTRODUCTION

The rapid digitalization of marketing processes has shifted organizational priorities from technology adoption toward data-driven decision-making and knowledge-based performance. In this new paradigm, digital intelligence serves as a critical enabler of marketing effectiveness, integrating customer insights, automation, and analytics across multiple channels. Empirical studies confirm that modern marketing organizations increasingly rely on analytics, machine learning, and artificial intelligence to enhance personalization and strategic responsiveness, yet the gap between adoption and strategic use persists in practice.

Recent literature conceptualizes data-driven marketing maturity as a multidimensional and staged capability encompassing strategy, data integration, technology, processes, skills, culture, and measurement. The most influential works, such as Cao et al. (2019) and Johnson et al. (2019, 2021), propose either formative higher-order constructs or staged assimilation models explaining how firms evolve from initial adoption to routinized, data-driven operations. Empirical validation through structural equation modeling has established that data-driven use depends on sensemaking mechanisms such as external knowledge acquisition, data quality improvement, experimentation, and information dissemination. These findings emphasize that marketing maturity cannot be captured by tool presence alone but must reflect the integration and regular use of analytics in decision-making.

In the Slovak and Central European context, organizations face persistent barriers that limit this transition. Studies from Slovakia, Poland, and the Czech Republic show that while awareness and perceived usefulness of analytical and automation tools are high, their systematic application remains limited due to deficits in data quality, analytical competence, and digital culture. Evidence from the DACH region complements these findings by identifying similar inhibitors, suggesting a regional pattern of underutilization relative to technological adoption.

The purpose of this paper is to analyze data-driven marketing maturity among Slovak organizations and to identify key factors that influence the integration of digital intelligence into marketing practice. The study examines three focal domains: marketing automation, customer lifecycle data management, and social media analytics. The research contributes to understanding how organizations can bridge the gap between adoption and strategic use of digital tools and develop a culture of evidence-based marketing management.

2. PROBLEM FORMULATION AND METHODOLOGY

The development of data-driven marketing capabilities is one of the key conditions for achieving competitiveness and sustainable growth in the digital economy. Although organizations increasingly recognize the importance of customer data, analytics, and automation, many of them remain at the initial stages of digital maturity. The central research problem addressed in this paper is how Slovak organizations utilize digital intelligence tools to manage marketing communication, collect and process customer data, and analyze information from social media channels.

The paper formulates its main research question as follows: What is the level of data-driven marketing maturity among Slovak organizations, and which factors influence their ability to transform collected data into actionable marketing intelligence? The study focuses on three specific dimensions of digital maturity:

(1) the use of online marketing communication tools such as newsletters, chatbots, and AI-based systems;
(2) customer lifecycle data management and the integration of information across CRM systems;
(3) the analytical use of social media data for decision-making and marketing optimization.

The research methodology is based on a quantitative survey conducted among Slovak organizations from various sectors in 2024. The questionnaire contained 14 questions, out of which three (C12–C14) are analyzed in this paper. These questions explore the extent of digital tool adoption, the systematic collection of customer data, and the use of social media analytics. The total sample consisted of 124 valid responses obtained from representatives of small, medium, and large enterprises.

The empirical basis of the research was a structured online questionnaire conducted throughout 2024. Its design followed the methodological standards of quantitative survey research, drawing conceptual inspiration from international studies on digital readiness, particularly those by ADMA and Deloitte (2018), and complemented by the OECD (2024) indicators of digital economy performance. The questionnaire focused on identifying strategic, financial, and operational aspects of digital transformation within marketing practice. The data collection was implemented electronically via e-mail invitations and targeted social media communication, addressing a broad range of Slovak organizations across multiple sectors. A total of 152 complete responses were obtained, corresponding to a 16 percent response rate from the original sample of 937 contacted entities.

The collected responses were evaluated using descriptive and comparative statistical procedures. Frequency and percentage analyses were supported by visual representations to interpret major patterns in digital strategy implementation, technological adoption, and marketing resource allocation. The analytical process was performed using Microsoft Excel in combination with Python-based tools, notably the Pandas and Matplotlib libraries, within a Jupyter Notebook environment. This combination ensured both methodological transparency and the reproducibility of analytical steps.

The overall methodological framework thus provided a reliable empirical foundation for assessing the degree of digital maturity and the integration of data-driven approaches in Slovak marketing organizations.

Collected data were processed using descriptive and comparative statistical methods to identify patterns and relationships between the adoption of marketing technologies and the level of data utilization. The results were interpreted in the context of established maturity models of data-driven marketing (Cao et al., 2019; Johnson et al., 2019; Johnson et al., 2021) and empirical evidence from European studies on digital analytics and automation (Zumstein et al., 2022;

Semerádová & Weinlich, 2020; Rostek & Zawistowska, 2019).

The methodological approach combines the analysis of frequency distributions, cross-tabulations, and qualitative interpretation of open-ended responses. This triangulated perspective allows the identification of adoption–use gaps, the assessment of digital intelligence maturity, and the formulation of recommendations for improving the integration of CRM, automation, and analytics into marketing management. The findings contribute to the understanding of how Slovak organizations can progress from fragmented data management toward fully data-driven marketing strategies supported by continuous learning and evidence-based decision-making.

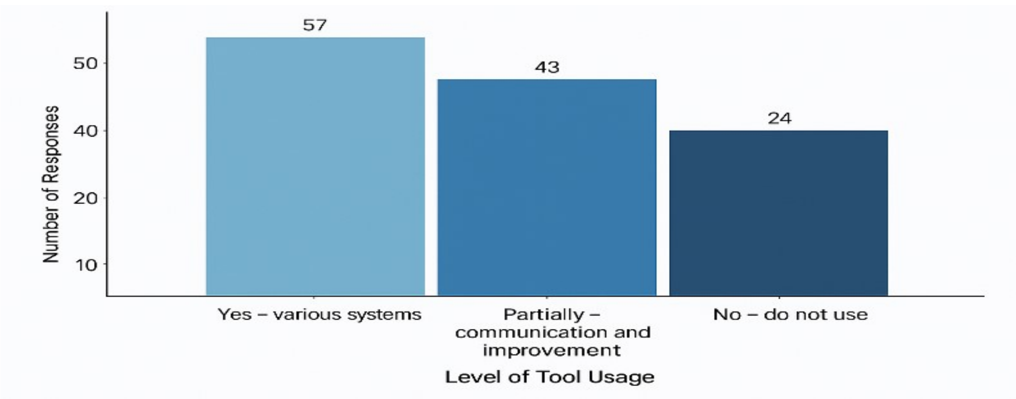
3. PROBLEM SOLUTION

The analysis of survey results provides a comprehensive view of how Slovak organizations apply digital intelligence in their marketing activities. The examined questions focus on the use of online communication tools, the management of customer lifecycle data, and the analytical processing of information from social media platforms. Together, these areas represent the key indicators of data-driven marketing maturity.

Use of online communication tools

The first evaluated indicator (Question C12) examined whether organizations use online tools such as newsletters, social networks, chatbots, or AI systems to attract and retain customers. The majority of respondents confirmed active use of these tools, which suggests that Slovak organizations recognize the potential of digital marketing for client acquisition and relationship management. However, many respondents reported that their current use is limited to operational functions without advanced automation or data integration. This indicates that digital tools are often used as communication channels rather than as sources of structured analytical insight. Similar findings were reported by Johnson, Muzellec and Zahay (2021), who highlight that marketing departments often adopt big data tools but fail to achieve routinized analytical use. These results indicate that while organizations understand the strategic importance of digital communication, the analytical feedback loop between marketing activities and customer insights remains weak. The implementation of marketing automation and CRM-linked content tools could enhance personalization and measurement of campaign effectiveness. Organizations that integrate communication data with analytical dashboards can achieve better targeting precision and optimize customer engagement. Therefore, improving automation maturity should be considered a priority area of digital transformation in Slovak marketing practice.

Figure 14: Use of online tools for marketing communication and client acquisition

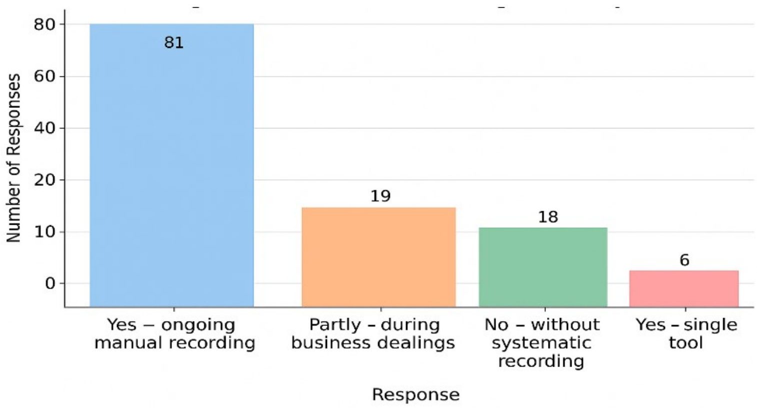


Source: own work

Customer lifecycle data management

The second focus area (Question C13) explored how organizations collect and manage customer data throughout the entire lifecycle. A significant portion of respondents confirmed that data are gathered continuously through CRM, ERP, or other databases, which demonstrates a relatively high degree of digitization. Nevertheless, the integration and analytical use of these data remain limited. Only a smaller group of organizations declared that they maintain a unified customer view accessible across departments. This confirms the conclusions of Cao, Duan and El Banna (2019), who emphasize that the real maturity of marketing analytics depends not only on the existence of systems but also on the organization's ability to integrate data and apply them in strategic decisions. In Slovakia, fragmented databases and manual data processing are still common, which reduces the efficiency of data-driven marketing processes. The findings also suggest that organizations often underestimate the value of continuous customer data enrichment and cleansing. Establishing unified data governance frameworks could help reduce duplication and inconsistencies across systems. Furthermore, integrating transactional and behavioral data would enable a more holistic understanding of customer journeys and lifetime value. Achieving such integration represents a critical step toward the creation of adaptive and intelligence-driven marketing ecosystems.

Figure 15: Recording customer data across the entire lifecycle

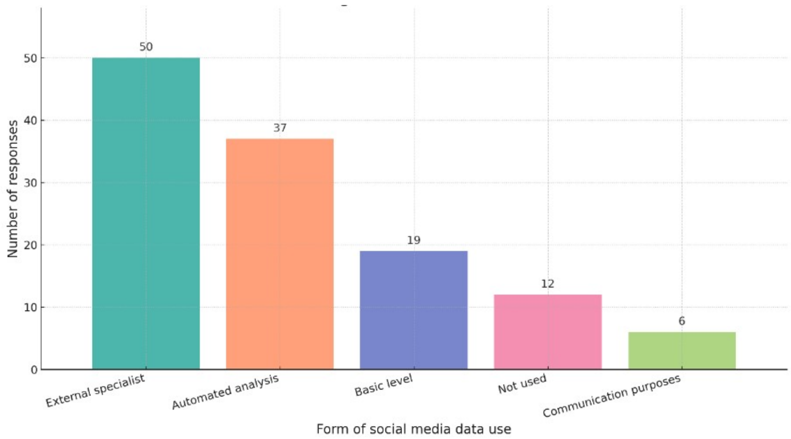


Source: own work

Use of social media analytics

The third analyzed indicator (Question C14) measured the extent to which organizations work with data from social media. More than half of the surveyed organizations stated that they actively monitor and evaluate social data, while the rest either plan to use them in the future or employ social networks primarily for basic communication purposes. This finding is consistent with the study of Zumstein, Jörger and Zelic (2022), which demonstrated that European companies often perceive the value of social data but lack the analytical frameworks and skills required for effective utilization. In the Slovak context, the challenge lies in transforming large volumes of social interactions into actionable insights that can guide marketing strategies and customer engagement initiatives. Despite the growing use of social networks, the majority of organizations still rely on manual or basic monitoring rather than automated analytics platforms. Investing in social listening tools and sentiment analysis could significantly improve market understanding and brand perception tracking. Moreover, integrating social analytics with CRM systems would allow the measurement of customer sentiment in real time, supporting proactive communication and reputation management. Developing analytical competencies in this area could therefore become a major competitive advantage for Slovak organizations.

Figure 16: Working with data from social networks



Source: own work

DISCUSSION

The combined interpretation of these results shows that Slovak organizations are at an intermediate stage of data-driven marketing maturity. The adoption of digital tools is relatively widespread, but their strategic integration into analytical and decision-making processes is limited. The findings confirm the existence of an adoption–use gap, as described in international research by Johnson, Friend and Lee (2019) and Semerádová and Weinlich (2020). The main barriers to achieving full maturity include insufficient analytical competence, fragmented data infrastructures, and the lack of a consistent data culture that supports evidence-based management.

To overcome these challenges, organizations need to focus on developing analytical skills, improving data quality, and implementing governance frameworks that ensure systematic data utilization. Advanced CRM integration, automation of reporting, and the implementation of social analytics tools could significantly enhance marketing performance. Furthermore, cross-functional cooperation and continuous learning are essential for embedding data-driven decision-making into the organizational culture.

Overall, the empirical evidence confirms that the transformation toward data-driven marketing in Slovakia is progressing but remains uneven across sectors. The results highlight the need for a comprehensive digital strategy that links technology, data, and human capabilities into a coherent system of digital intelligence, enabling organizations to achieve higher levels of competitiveness and sustainable growth in the digital economy.

CONCLUSION

The presented study examined the level of data-driven marketing maturity in Slovak organizations through three key dimensions: the use of online communication tools, customer lifecycle data management, and the application of social media analytics. The results confirm that the adoption of digital tools is relatively high, but their strategic use and analytical integration remain limited. Organizations in Slovakia are gradually transitioning from operational digitalization to more advanced forms of digital intelligence, yet they face persistent barriers related to analytical skills, data quality, and technological integration (Cao et al., 2019).

The findings reveal that many organizations still rely on fragmented information systems and isolated marketing activities, which hinders the effective transformation of data into actionable insights. The research identified a clear adoption–use gap, where the presence of digital tools does not automatically lead to their full analytical utilization. This aligns with previous studies emphasizing that data quality, culture, and competence are the main determinants of marketing maturity (Johnson et al., 2021).

To achieve sustainable progress, organizations should focus on the systematic integration of CRM, automation, and social analytics platforms into unified data ecosystems. Building a data-oriented culture supported by training and analytical competence development is equally essential. Public institutions and professional associations can play a significant role by promoting digital literacy programs and encouraging collaboration between academia and industry.

Future research should extend the current analysis by applying longitudinal data and structural equation modeling to evaluate causal relationships between technology adoption, data integration, and marketing performance. Expanding the sample and including comparative studies with neighboring Central European countries would also provide valuable insights into regional dynamics of digital intelligence development.

The study contributes to the growing body of knowledge on digital transformation and marketing maturity by providing empirical evidence from Slovakia and outlining practical steps that can help organizations bridge the gap between digital adoption and strategic data-driven marketing.

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HARMONISATION OF THE LEGAL FRAMEWORK AND THE ETHICAL PRINCIPLES UNTHE FIELD ARTIFICIAL INTELLIGENCE

Daniela NOVÁČKOVÁ

Abstrakt

Jednou z priorít Európskej únie je aj technologická transformácia a budovanie jednotného digitálneho trhu.V danej súvislosti musíme brať na zreteľ, že digitálne technológie, medzi ktoré patrí aj umelá inteligencia významným spôsobom podporujú dosahovanie cieľov Európskej zelenej dohody. Vo vedeckej štúdii metódou systémovej analýzy objasňujeme súčasnú harmonizáciu právneho rámca Európskej únie týkajúceho sa umelej inteligencie s poukázaním na využívanie umelej inteligencie v oblasti ľudských zdrojov a ochrany práv občanov. Prínosom štúdie je poukázať na implementáciu umelej inteligencie v oblasti ľudských zdrojov a na etické princípy, aby sa systémy umelej inteligencie vyvíjali, zavádzali a používali dôveryhodným spôsobom.

Kľúčové slová: *harmonizácia,ochrana práv občana, umelá inteligencia*

Abstract

One of the priorities of the European Union is technological transformation and the creation of a single digital market.. In this context, we must take into account that digital technologies, including artificial intelligence, significantly support the achievement of the objectives of the European Green Deal.In a scientific study using the method of system analysis, we clarify the current harmonization of the European Union's legal framework on artificial intelligence, with reference to the use of artificial intelligence in the field of human resources and the protection of citizens' rights. The study highlights the implementation of artificial intelligence in human resources and ethical principles to ensure that artificial intelligence systems are developed, deployed, and used in a trustworthy manner.

Key words: *harmonization, protection of citizens' rights, artificial intelligence*

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ÚVOD

Umelú inteligenciu považujeme dnes za strategickú technológiu, ktorá má pozitívne dopady na život občanov, podnikov, pričom musí byť zákonná, etická a rešpektovať základné práva a hodnoty. Umelá inteligencia ponúka významné zvýšenie efektívnosti a produktivity, ktoré môžu posilniť konkurencieschopnosť európskeho priemyslu a zlepšiť životné podmienky občanov. Umelá inteligencia je súčasťou života občanov a jej vplyv badať vo všetkých oblastiach hospodárstva, ale aj v oblasti sociálneho a kultúrneho života. Umelá inteligencia sa neustále vyvíja, avšak technológie umelej inteligencie môžu pre používateľov predstavovať nové bezpečnostné riziká. Európska únia (EÚ) sa snaží o koordinovaný prístup a investičný prístup, ktorý má dvojaký cieľ: nabádať k využívaniu umelej inteligencie a zároveň riešiť riziká spojené s využívaním tejto novej technológie. (EK Biela kniha o umelej inteligencii,2020)

Biela kniha o umelej inteligencii z roku 2020 uvádza, že: *„Európska únia musí konať jednotne a pri podpore vývoja a zavádzania umelej inteligencie si musí vymedziť vlastnú cestu založenú na európskych hodnotách."* (Brusel COM(2020) 65 final) Regulačný rámec EÚ v oblasti umelej inteligencie je zameraný z tohto dôvodu na ochranu práv občanov, na rozvoj podnikania a na rozvoj služieb verejného záujmu (doprava, vzdelávanie, energetika a nakladanie s odpadom). V danej súvislosti zdieľame názor, že umelá inteligencia by mala mať vhodnú právnu reguláciu a mala by byť etická, čím sa zabezpečí súlad s etickými princípmi a hodnotami. Aj napriek tomu, že umelá inteligencia ponúka významné zvýšenie efektívnosti a produktivity v rôznych oblastiach, existujú aj riziká najmä z hľadiska ochrany bezpečnosti, práv spotrebiteľov a základných práv občanov.

Aplikácia umelej inteligencie vzhľadom na jej osobitné vlastnosti (napr. zložitosť, závislosť od údajov, autonómne správanie sa) môže mať okrem iného aj vplyv na základné práva človeka ustanovené v Charte základných práv Európskej únie. Kľúčovou prioritou Európskej únie je, aby právo na súkromie a na ochranu osobných údajov bolo zaručené počas celého životného cyklu systému umelej inteligencie. Umelú inteligenciu je možné využívať aj v oblasti ľudských zdrojov, analytika riadená umelou inteligenciou môže optimalizovať plánovanie pracovnej sily, získavanie talentov a riadenie výkonnosti – to všetko s cieľom zlepšovania kvality starostlivosti poskytovanej zamestnancom a zároveň znižovania prevádzkových nákladov v tomto procese v podniku.

2. CIEĽ A METODOLÓGIA

Cieľom vedeckej štúdie je skúmanie využívania umelej inteligencie ((articial intelligence, AI)) v oblasti ľudských zdrojov, analýza aktuálneho právneho rámca Európskej únie, ako aj objasnenie univerzálnych etických zásad umelej inteligencie. V záujme dosiahnutia cieľa vedeckej štúdie sme aplikovali metódu rešerše pri objasnení pojmu umelá inteligencia, pričom sme analyzovali dokumenty Európskej únie a stanovili sme systémové znaky pojmu umelá inteligencia. Zároveň sme poukázali aj na definície pojmu umelá inteligencia niektorých významných autorov. Metódou generalizácie sme identifikovali vysokorizikové systémy umelej inteligencie v kontexte právnej úpravy. Zároveň sme poukázali na harmonizáciu slovenskej právnej úpravy v oblasti umelej inteligencie s platným právnym rámcom Európskej únie (EÚ).

3. RIEŠENIE PROBLÉMU

3.1Pojem umelá inteligencia

K problematike umelej inteligencie existuje viacero definícií a názorov autorov. My sme sa zamerali na definície pojmu umelá inteligencia významných medzinárodných organizácií, ktorých je Slovenská republika členským štátom a na definície viacerých autorov.

Podľa odborníkov, ktorí pracovali na Bielej knihe o umelej inteligencii (2020) "*umelá inteligencia je skupina technológií, ktoré kombinujú údaje, algoritmy a výpočtovú kapacitu.*" (Brusel,COM(2020) 65 final)

Oznámenie Komisie Európskemu parlamentu, Európskej rade, Rade, Európskemu hospodárskemu a sociálnemu výboru a Výboru regiónov s názvom Umelá inteligencia pre Európu uvádza, že:„*Umelá inteligencia sú systémy, ktoré vykazujú inteligentné správanie tým, že analyzujú okolité prostredie a podnikajú kroky – s istou mierou samostatnosti – na dosiahnutie konkrétnych cieľov. Systémy umelej inteligencie môžu byť založené výlučne na softvéri a pôsobiť vo virtuálnom svete (napr. hlasoví asistenti, softvér na analýzu fotografií, vyhľadávače, systémy rozpoznávania hlasu a tváre), ale umelá inteligencia môže byť aj súčasťou hardvérových zariadení (napr. vyspelé roboty, autonómne vozidlá, bezpilotné vzdušné prostriedky alebo aplikácie internetu vecí).*"(Oznámenie Komisie. Umelá inteligencia pre Európu. COM/2018/237)

Nariadenie EÚ 2024/1689 v článku 3 uvádza, že: „*systém AI je strojový systém, ktorý je dizajnovaný na prevádzku s rôznymi úrovňami autonómnosti, ktorý môže po nasadení prejavovať adaptabilitu a ktorý pre explicitné alebo implicitné ciele odvodzuje zo vstupov, ktoré dostáva, spôsob generovania výstupov, ako sú predpovede, obsah, odporúčania alebo rozhodnutia, ktoré môžu ovplyvniť fyzické alebo virtuálne prostredie.*" (Ú. v. EÚ L, 2024/1689) Recitál 12 predmetného nariadenia pojem strojový vykladá ako fakt, že systémy umelej inteligencie fungujú na strojoch, pričom výstupy generované systémom AI odrážajú rôzne funkcie vykonávané systémami AI a zahŕňajú predpovede, obsah, odporúčania alebo rozhodnutia. (Ú. v. EÚ L, 2024/1689)

Systémy umelej inteligencie sú softvérové (a prípadne aj hardvérové) systémy navrhnuté ľuďmi, ktoré vzhľadom na komplexný cieľ konajú vo fyzickom alebo digitálnom rozmere tak, že vnímajú svoje prostredie prostredníctvom získavania údajov, interpretácie zhromaždených štruktúrovaných alebo neštruktúrovaných údajov, odvodzovania poznatkov alebo spracúvania informácií odvodených z týchto údajov a že rozhodujú o najlepších krokoch, ktoré sa majú vykonať na dosiahnutie daného cieľa. Systémy umelej inteligencie môžu buď používať symbolické pravidlá, alebo sa naučiť numerický model, a takisto môžu upraviť svoje správanie na základe analýzy vplyvu, aký malo ich predchádzajúce konanie na ich prostredie.

(Etické usmernenia pre dôveryhodnú umelú inteligenciu, 2019) Podľa členov Expertnej skupiny na vysokej úrovni pre umelú inteligenciu.“ *umelá inteligencia ako vedecká disciplína obsahuje niekoľko prístupov a techník, ako je strojové učenie (ktorého konkrétnymi príkladmi sú hĺbkové učenie a učenie posilňovaním), strojové odvodzovanie (ktorého súčasťou je plánovanie, programovanie, reprezentácia a odvodzovanie poznatkov, vyhľadávanie a optimalizácia) a robotika (do ktorej patrí kontrola, percepcia, senzory a ovládače, ako aj začlenenie všetkých ostatných techník do kyberneticko-fyzických systémov*). (Etické usmernenia pre dôveryhodnú umelú inteligenciu,2019)

Organizácia pre hospodársku spoluprácu a rozvoj – OECD (Council (2021, s. 3) umelú inteligenciu definuje ako „*univerzálnu technológiu, ktorá má potenciál zlepšovať blaho byt ľudí, prispievať k pozitívnej udržateľnej globálnej hospodárskej činnosti, zvyšovať inovácie a produktivitu a pomáhať reagovať na kľúčové globálne výzvy*.“

V danej súvislosti môžeme konštatovať, že umelá inteligencia je technológia budúcnosti, zahŕňajúca softvér využívajúci strojové učenie a iné nástroje na spracúvanie informácií. Strojové učenie je podoblasť, ktorá skúma schopnosť systémov zlepšovať svoj výkon na základe skúseností (Russell & Norvig, 2021, s. 1).

Daná skutočnosť nasvedčuje tomu, že definícia umelej inteligencie zohľadňuje skôr technologickú stránku fungovania umelej inteligencie a nie je zameraná na správanie sa človeka, ale na samotnú technológiu, prevádzku a na informačné systémy (napr. strojové odvodzovanie, robotika a pod.) Nariadenie EÚ 2024/1689 ustanovuje okrem iného aj pravidlá a sankčný režim za nedodržiavanie predpisov, čím sa zabezpečuje, že vývojári a používatelia nesú zodpovednosť za svoje konanie. Na základe uvedeného možno konštatovať, že viaceré medzinárodné organizácie majú vo svojom programe umelú inteligenciu a venujú jej aj náležitú pozornosť. V danej súvislosti sa stotožňujeme s názorom Pintérovej (2014), že: „*hlavným prostriedkom na dosiahnutie rovnováhy a vytvorenie súdržného a účinného právneho rámca pre AI je medzinárodná spolupráca a neustály dialóg medzi zainteresovanými stranami.*“ V praxi to bude znamenať, že adresáti noriem (štáty) by mali vytvoriť spoločný právny rámec v záujme správneho zavádzania a fungovania umelej inteligencie.

Pre ilustráciu uvádzame aj názor slovenského autora I.Farkaša (2024), podľa ktorého:”*Umelá inteligencia je vedecká disciplína, ktorej cieľom je riešiť po mocou výpočtových nástrojov rôzne problémy podobným spôsobom ako človek alebo aj inak a lepšie, v ideálnom prípade optimálne. Inšpiráciou tu môže byť kognitívna veda, ktorá skúma ľudské myslenie, ale aj všeobecne samotná matematika, ktorá je univerzálnym nástrojom na opis sveta a dá sa využiť na hľadanie optimálnych ciest.*” Vedecká komunita si osvojila teóriu, že umelá inteligencia nie je len vedeckou dsciplnínou, ale je to súbor strojových hardvérových a softvérových technológií, ktoré sa správajú inteligentne vo virtuálnom svete, pričom urýchľujú, rozhodujú, škálujú určité schopnosti s mierou autonómie na dosiahnutie konkrétnych cieľov.

De-Lima-Santos & Ceron (2022) sú toho názoru, že: „*umelá inteligencia vychádza zo siedmych hlavných podoblastí: strojové učenie, počítačové videnie, rozpoznávanie reči, spracovanie prirodzeného jazyka, plánovanie, rozvrhovanie a optimalizácia, expertné systémy a robotika.*” V zásade ide o využívanie digitálnych technológií v rôznych oblastiach, aby vykonávali veci dané veci lepšie alebo robili rozhodnutia na vyššej úrovni, pri ktorých je obvykle potrebná ľudská inteligencia.

3.2 Právny rámec Európskej únie

Na úrovni Európskej únie bolo prijaté nariadenie 2024/1689 ustanovujúce zavádzanie dôveryhodnej umelej inteligencie sústredenej na človeka, a pritom zabezpečiť vysokú úroveň ochrany zdravia, bezpečnosti, základných práv zakotvených v Charte základných práv EÚ vrátane demokracie, právneho štátu a ochrany životného prostredia. (čl. 1 nariadenia) Predmetné nariadenie okrem iného presne ustanovuje aj vysokorizikové systémy (čl. 6 ods. 2), medzi ktoré patria:

a) biometria
b) kritická infraštruktúra
c) vzdelávanie a odborná príprava
d) zamestnanosť, riadenie pracovníkov a prístup k samostatnej zárobkovej činnosti
e) prístup k základným súkromným službám a základným verejným službám a dávkam a ich využívanie
f) presadzovanie práva
g) migrácia, azyl a riadenie kontroly hraníc
h) výkon spravodlivosti a demokratické procesy (Príloha III nariadenia 2024/1689)

Z uvedeného je zrejmé, že identifikácia rizikových systémov využívania AI je pomerne rozsiahla a ovplyvňuje rôzne oblasti.

3.3 Zložky umelej inteligencie

Expertná skupina na vysokej úrovni pre umelú inteligenciu Európskej únie (2019), zdieľa názor, že: „*dôveryhodná umelá inteligencia má tri zložky, ktorých sa treba pridržiavať počas celého životného cyklu systému:*

1. Zákonnosť: zabezpečenie dodržiavanie celého platného práva a právnych predpisov.

2. Etickosť: zabezpečenie súladu s etickými zásadami a hodnotami.

3. Odolnosť: z technického aj sociálneho hľadiska, keďže systémy umelej inteligencie môžu aj pri dobrých úmysloch spôsobiť neúmyselnú ujmu."

V danej súvislosti musíme zdôrazniť, že súčasťou zložiek dôveryhodnej umelej inteligencie by mala byť aj zodpovednosť a kontrola.

Pojem zákonnosť alebo aj princíp viazanosti právom možno chápať ako povinnosť dodržiavať platný právny rámec subjektami, ktorým je právny predpis adresovaný. Právne predpisy prijímané inštitúciami sú záväzné pre adresátov, ktorým sú určené. Európska únia prijíma právne predpisy rôznej právnej sily s cieľom ustanoviť jednotné pravidlá pre členské štáty v záujme dosahovania cieľov EÚ. Členské štáty sú povinné dané akty rešpektovať, v prípade transponovať do národných právnych poriadkov. Dôveryhodný systém umelej inteligencie nemôže správne fungovať bez právnych predpisov.

Na umelú inteligenciu, jej zavádzanie a používanie bolo inštitúciami EÚ prijatých viacero právne záväzných pravidiel (Charta základných práv EÚ), sekundárne akty EÚ (napríklad všeobecné nariadenie o ochrane údajov, smernica o strojových zariadeniach a pod.)

Vzhľadom na ciele Európskej únie a správnu aplikáciu práva Európskej únie v oblasti umelej inteligencie bol zriadený Úrad pre umelú inteligenciu v rámci Európskej komisie ako centrum odborných znalostí v oblasti umelej inteligencie, ktorý tvorí základ jednotného európskeho systému riadenia umelej inteligencie.

Základným právnym rámcom umelej inteligencie je primárna právna úprava Európskej únie, ustanovenie článku 4 ods. 2 písm. a) Zmluvy o Európskej únii a články 26, 27, 114 a 115 Zmluvy o fungovaní Európskej únie a Charta základných práv EÚ. (Ú. v. EÚ C 202, 7.6.2016)
Primárna práva úprava je doplnená širokým spektrom sekundátnych aktov a inými nástrojmi typu Biela kniha o umelej inteligencii a pod. Spomedzi širokého spektra sekundárnej legislatívy Európskej únie je významné Nariadenie Európskeho parlamentu a Rady (EÚ) 2024/1689 z 13. júna 2024, ktorým sa stanovujú harmonizované pravidlá v oblasti umelej inteligencie. V zmysle ustanovenia článku 1 nariadenia 2024/1689 „*účelom nariadenia je zlepšiť fungovanie vnútorného trhu a podporiť*

zavádzanie dôveryhodnej umelej inteligencie sústredenej na človeka, a pritom zabezpečiť vysokú úroveň ochrany zdravia, bezpečnosti, základných práv zakotvených v charte vrátane demokracie, právneho štátu a ochrany životného prostredia pred škodlivými účinkami systémov AI v Únii a podporovať inovácie.“ (Ú. v. EÚ L, 2024/1689, 12.7.2024) Z uvedeného je zrejmé, že Európska únia zaviedla jednotnú a vysokú úroveň ochrany verejných záujmov, pokiaľ ide o zdravie, bezpečnosť a základné práva, a najmä stanovuje spoločné pravidlá pre vysokorizikové systémy umelej inteligencie. Predmetné nariadenie sa nazýva aj akt o umelej inteligencii, ustanovuje jednotné pravidlá pre vývoj a využívanie AI technológií v rámci Európskej únie. Nariadenie sa zameriava na identifikáciu a reguláciu AI systémov podľa ich rizikovosti a stanovuje povinnosti pre poskytovateľov, distribútorov a používateľov AI systémov. Vzťahuje sa na na verejné aj súkromné subjekty pôsobiace v rámci členských štátov Európskej únie.

Etika aj napriek tomu, že je filozofickou disciplínou je okrem zákonnosti ďalšou významnou zložkou umelej inteligencie, ktorej objektom je mravnosť. Etika umelej inteligencie predstavuje systém pravidiel a noriem, ktoré určujú správanie a konanie ľudí k mravnej dokonalosti. Etika umelej inteligencie je zameraná na zodpovedné správanie sa, avšak nemôže poskytnúť definitívne odpovede a riešenia sporných problémov. Etický spôsob konania je determinovaný tradíciou, spočívajúci na slobodnom rozhodnutí. Dominantným cieľom etiky umelej inteligencie je rozlíšiť dobro od zla, morálne od nemorálneho a správne od nesprávneho.

Etické usmernenie pre umelú inteligenciu (2019) uvádza, že: „pojem *etická umelá inteligencia sa používa na označenie vývoja, zavádzania a používania umelej inteligencie, ktorou sa zabezpečuje súlad s etickými normami vrátane základných práv, ako osobitných morálnych nárokov, etických zásad a súvisiacich základných hodnôt*.” Ide o systém aplikovanej etiky, ktorá sa zameriava na používanie a zavádzanie umelej inteligencie so zreteľom na zabezpečenie dodržiavania základných práv vrátane práv stanovených v Charte základných práv Európskej únie, vrátane úcty k ľudskej dôstojnosti.

Inštitút odolnosti umelej inteligencii musí spĺňať viacero kritérií. Musí mať právny rámec, musí byť v súlade s etickými požiadavkami so zámerom chrániť verejné záujmy a individuálne práva a zároveň budovať dôveru v technológie AI a podporovať inovácie. Musí byť odolný voči nepriateľským útokom, napadnutiam a proti zneužitiu systému umelej inteligencie škodlivými aktérmi. Technická odolnosť musí byť na takej úrovni, aby bola zabezpečená telesná a duševná nedotknuteľnosť ľudí.

3.4.Etické zásady umelej inteligencie

Expertná skupina na vysokej úrovni pre umelú inteligenciu identifikovala etické zásady umelej inteligencie:

a) rešpektovanie ľudskej autonómie
b) prevencia ujmy
c) spravodlivosť
d) vysvetliteľnosť. (Expertná skupina na vysokej úrovni pre umelú inteligenciu, 2019)

Etické zásady, zakotvené v základných právach majú svoj pôvod v primárnej právnej úprave Európskej únie, ktoré sa musia dodržiavať s cieľom zabezpečiť, aby sa systémy umelej inteligencie zavádzali a používali dôveryhodným spôsobom. Stanovenie eticky správneho postupu pri používaní nástrojov založených na umelej inteligencii je subjektívne a môže sa líšiť v rôznych kultúrach a spoločnostiach.

Rešpektovanie ľudskej autonómie je výrazne spojené s právom na ľudskú dôstojnosť a slobodu (články 1 a 6 Charty základných práv EÚ). Prevencia ujmy úzko súvisí s ochranou telesnej alebo duševnej nedotknuteľnosti (článok 3 Charty základných práv EÚ). Inštitút spravodlivosti je úzko prepojený s právami na nediskrimináciu, solidaritu a spravodlivosť (článok 21 a iné články Charty základných práv EÚ). Vysvetliteľnosť a zodpovednosť úzko súvisia s právami, ktoré sa týkajú spravodlivosti (článok 47 Charty základných práv EÚ)

Pričom etické princípy chápeme ako „*fundamentálne štandardy správania sa , od ktorých závisia mnohé iné štandardy a súdy. Princíp je nevyhnutnou normou v myšlienkovom systéme, ktorý utvára základ pre morálne uvažovanie v tomto systéme*“(Beauchamp 1996,

s. 80-81) V danej súvislosti musíme brať na zreteľ, že systémy umelej inteligencie sú zamerané na jednotlivca, smerujú k zabezpečeniu rešpektovania slobody a autonómie ľudí, čo v praxi znamená, že musia byť fokusované pozitívne so zámerom zlepšiť jeho životné podmienky.

Rešpektovanie ľudskej autonómie možno chápať ako právo jedinca, človeka mať moc a kontrolu nad vlastným životom, pričom systémy umelej inteligencie by mali navrhovať riešenie, aby dopĺňali a posilňovali ľudské kognitívne a sociálne zručnosti. Rešpektovanie ľudskej autonómie súvisí s právom na ľudskú dôstojnosť, teda na rešpektovanie seba ako jedinečného nositeľa ľudských hodnôt. Na základe svojej dôstojnosti je človek sám osebe a sám pre seba vždy hodnotou. (Mačkinová) Ochrana ľudskej dôstojnosti vyplýva zo samotnej podstaty ľudského bytia a je základným ľudským právom. (článok 1 Charty základných práv EÚ).

Pri objasnení pojmu prevencia ujmy musíme brať do úvahy, že ide o ochranu predchádzania pred niečím nežiadúcim, resp. o opatrenie na ochranu predchádzania niečomu nežiadúcemu.

V danej súvislosti ide o elimináciu možných príčin a o bezpečnosť jednotlivca, pretože systémy umelej inteligencie môžu spôsobiť ujmu a môžu aj nepriaznivo pôsobiť na ľudí. Z tohto dôvodu systémy umelej inteligencie musia byť bezpečné a chrániť ľudskú dôstojnosť človeka.Zásadný význam má prevencia v oblasti dostupnosti informácií, najmä so zreteľom vo vzťahy medzi zamestnávateľmi a zamestnancami, alebo aj medzi subjektami ponúkajúcimi služby a spotrebiteľmi medzi vládami a občanmi. V rámci zásady prevencie ujmy sa musí brať zreteľ, že prevencia má zabrániť nepriaznivému javu a má eliminovať tento nepriaznivý jav už v počiatočnom štádiu prostredníctvom opatrení, ktoré by zamedzili jeho ďalšiemu prehlbovaniu a šíreniu.Vývoj, zavádzanie a používanie systémov umelej inteligencie musia byť spravodlivé a transparentné.

Súčasťou zásady vysvetľovania je poskytovanie pravdivých a dôveryhodných informácií. Daný výklad musí byť založený na dôveryhodnosti všetkých procesov a subjektov, ktoré sú súčasťou životného cyklu systému. Aj napriek tomu, že dané etické zásady nie sú právne záväzné, a rešpektovanie uvedených pravidiel spočíva na dobrovoľnom prístupe, vo všeobecnosti majú zásadný význam.

3.5 Dôveryhodná umelá inteligencia

Dôveryhodnosť umelej inteligencie je determinovaná dôsledným dodržiavaním kľúčových zásad, medzi ktoré ktoré zaraďujeme ľudský faktor a dohľad, technická spoľahlivosť a bezpečnosť, súkromie a správa údajov, transparentnosť, rozmanitosť, nediskriminácia a spravodlivosť, spoločenský a environmentálny blahobyt ako aj zodpovednosť. Uvedené zásady boli identifikované Expertnou skupinou na vysokej úrovni pre umelú inteligenciu (EK,2019). V danej súvislosti by bolo na mieste, keby sme do skupiny kľúčových zásad zaradili aj inštitút kontroly a monitorovania, aby sa predišlo zneužívaniu umelej inteligencie. Súšasťou týchto zásad by mal byť aj efektívny mechanizmus nápravy pre obete v prípade škôd, ktorý by prispel k budovaniu dôvery používateľov. Slovenská právna úprava je koncipovaná už tak, že boli ustanovené aj vnútroštátne orgány pre výkon dohľadu nad trhom pri využívaní najmä vysokorizikových systémov umelej inteligencie.

Podľa nášho názoru dôveryhodná inteligencia by mala byť:

a) legálna (rešpektovať daný platný právny stav)
b) etická (rešpektovať etické zásady a hodnoty)

Pri vývoji a zavádzaní umelenej inteligencie by mal byť kladnený dôraz na zaručenie ochrany slobody, dôstojnosti a bezpečnosti človeka, ako aj celej spoločnosti.Akékoľvek používanie technológii umelej inteligencie by malo byť prospešné pre človeka a spoločnosť a malo by prispievať k spoločnému blahu. Technológie umelej inteligencie musia byť pod kontrolou a musia byť ovládané človekom.

3.6 Využívanie AI v oblasti ľudských zdrojov

Umelá inteligencia môže značne prispieť k efektivite, presnosti, automatizácie administratívnych procesov v oblasti personalistiky každej organizácie. Súčasťou procesov je napríklad správa údajov o zamestnancoch, správa dochádzky, spracovanie platov, a širšie spektrum úloh spojených s ľudskými zdrojmi. Využívanie umelej inteligencie v oblasti ľudských zdrojov prináša aj možné riziká týkajúce sa zaujatosti, ochrany súkromia a ochrany osobných údajov. Modely umelej inteligencie v oblasti ľudských zdrojov musia byť koncipované tak, aby boli bezpečné, pretože existuje tu vysoké riziko ublíženia.

Podľa súčasnej platnej právnej úpravy – nariadenia 2024/1689 Príloha III explicitne ustanovuje využívanie AI (ods.4) s názvom Zamestnanosť, riadenie pracovníkov a prístup k samostatnej zárobkovej činnosti:

a) „systémy AI, ktoré sa majú používať na nábor alebo výber fyzických osôb, najmä na umiestňovanie cielených inzerátov na pracovné miesta, na analýzu a filtrovanie žiadostí o zamestnanie a na hodnotenie uchádzačov;

b) systémy AI, ktoré sa majú používať pri rozhodovaní o podmienkach pracovnoprávnych vzťahov, o kariérnom postupe v zamestnaní alebo ukončení zmluvných pracovnoprávnych vzťahov, pri prideľovaní úloh na základe individuálneho správania alebo osobných čŕt alebo charakteristických znakov alebo pri monitorovaní a hodnotení výkonnosti a správania osôb v rámci takýchto vzťahov.“ (Ú.v.EÚ L 2024/1689)

Využívanie umelej inteligencie v oblasti ľudských zdrojov je determinované zavedením náborového softvéru AI, ktorý obsahuje najmä :

a) presný popis práce týkajúci sa pracovnej pozície
b) presný popis vzdelania
c) presný popis praktických skúseností
d) presný popis zručností a jazykových kompetencií
e) testy odbornej spôsobilosti, za účelom správneho výberu potenciálnych pracovníkov podľa vhodnosti pracovného miesta.

Správne nastavené algoritmy dokážu predpovedať potreby personálneho obsadenia, identifikovať výber nových zamestnancov a optimalizovať úsilie o udržanie zamestnancov. Nástroje umelej inteligencie môžu pomocou prediktívnej analýzy identifikovať najlepších kandidátov (analýza životopisov, vyhodnotenie zručností a pod.)

Očakáva sa, že organizácie a podnikateľské subjekty prijmú aj Kódexy správania sa a riadenia na podporu dobrovoľného uplatňovania niektorých alebo všetkých požiadaviek týkajúce sa vysokorizikových systémov AI. Asociácia pre umelú inteligenciu (ASAI) predstavila prvý Etický kódex pre vývoj, implementáciu a používanie umelej inteligencie (AI) na Slovensku. Dokument ponúka základný rámec pravidiel, ktoré by mali dodržiavať vývojári, podniky aj používatelia systémov umelej inteligencie.

3.7 Slovenská právna úprava

V súčasnosti je v procese schvaľovania aj návrh zákona o organizácii štátnej správy v oblasti umelej inteligencie a o zmene a doplnení niektorých zákonov, ktorým sa implementujú ustanovenia nariadenia Európskeho Parlamentu a Rady (EÚ) 2024/1689 z 13. júna 2024. Predmetný návrh zákona ustanovuje inštitucionálne zabezpečenie dohľadu nad trhom v oblasti umelej inteligencie. Inými slovami povedané, pripravovaná právna úprava ustanovuje príslušné vnútroštátne orgány pre výkon dohľadu nad trhom pri využívaní najmä vysokorizikových systémov umelej inteligencie a ich kompetencie, jednotné kontaktné miesto a pod. (Návrh zákona 2025 MIRRISR) Účinnosť navrhnutého zákona je ustanovená od 1. januára 2026.Problematika ochrany základných práv v súvislosti s využívaním systémov umelej inteligencie podľa čl. 77 nariadenia EÚ 2024/1689 nie je predmetom úpravy predkladaného návrhu zákona. Tieto kompetencie majú v pôsobnosti Úrad na ochranu osobných údajov a Úrad verejného ochrancu práv. Zákonodárcovia zároveň v § 6 návrhu zákona ustanovili povinnosti prevádzkovateľov vysokorizikového systému umelej inteligencie.

4. VÝSLEDKY

Umelá inteligencia sa stáva súčasťou hospodárskych, sociálnych, kultúrnych vzťahov, prináša výhody a má aj negatívnu stránku a sú spojené s ňou aj riziká. Európska únia, ktorá je lídrom v zavádzaní opatrení pre správne fungujúci digitálny trh a podporuje etický a spravodlivý rozvoj umelej inteligencie, pričom kladie dôraz na dôveryhodnosť. Pri zavádzaní harmonizačných pravidiel a etických zásad v praxi je potrebné:

a) zabezpečiť, aby systémy umelej inteligencie boli bezpečné a spoľahlivé
b) zabezpečiť ochranu základných práv občanov
c) zabezpečiť ochranu súkromia
d) zabezpečiť správne uplatňovanie inštitútu zákazu diskriminácie
e) zabezpečiť výkon dohľadu nad trhom pri využívaní najmä vysokorizikových systémov umelej inteligencie
f) odstraňovať technologické riziká
g) zabezpečiť, aby algoritmy a výsledky činnosti systémov umelej inteligencie boli ovládateľné človekom.

ZÁVER

Európska únia v rámci svojich cieľov vybudovať dobre fungujúci digitálny trh iniciuje prijímanie opatrení prehlbujúce proces európskej ekonomickej integrácie, medzi ktoré bezpochyby môžeme zaradiť aj nariadenie o umelej inteligencii. Vedecký článok obsahuje analýzu aktuálnej sekundárnej právnej úpravy EÚ v danej oblasti a poukazuje na ochranu práv občana v kontexte Charty základných práv EÚ. Identifikovali sme riziká spojené s používaním umelej inteligencie, ktoré ohrozujú bezpečnosť a život občanov. Umelá inteligencia mení hospodárske, sociálne a kultúrne vzťahy, ako aj obchodné modely. V strede záujmu je predovšetkým zavádzanie dôveryhodnej umelej inteligencie a vysoká ochrana digitálneho súkromia občanov. Identifikovali sme konkrétne oblasti umelej inteligencie, ktorá môže byť využívaná v oblasti ľudských zdrojov v rôznych organizáciách. Zároveň sme poukázali aj pripravovaný slovenský právny predpis týkajúci sa umelej inteligencie. Objasnili sme skutočnosť, že na úrovni Európskej únie je nevyhnutná harmonizácia právnych predpisov, ktoré zabezpečia rovnaké podmienky a účinnú ochranu práv a slobôd občanov vo všetkých členských štátoch EÚ. Záverom možno konštatovať, že umelá inteligencia prináša viacero otázok týkajúce sa zodpovednosti, rozhodovania a etiky, udržateľnosti a pod. V danej súvislosti je potrené brať na zreteľ, že významnú úlohu bude zohrávať nielen globálny kontext, ale aj aj kultúrny, sociálny,právny a regionálny kontext, čo zdôrazňuje potrebu diferencovaného prístupu k implementácii umelej inteligencie v štátoch sveta.

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