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Trendy v podnikání
Business Trends

▶ Business Administration ▶ Management ▶ Marketing
▶ Finance and Accounting

POSLÁNÍ

Časopis „Trendy v podnikání“ je vědeckým recenzovaným periodikem vydávaným Fakultou ekonomickou Západočeské univerzity v Plzni.

Posláním časopisu je publikovat původní teoretické i aplikační výstupy výzkumu českých i zahraničních autorů zejména v zaměření na podnikovou ekonomiku a management. Časopis je ale také otevřen příspěvkům orientovaným mezioborově, protože často jen takto široce lze jak teoreticky, tak i aplikovaně řešit problémy současné hospodářské praxe a přinášet poznatky o nových a inovativních postupech. Časopis je orientován především na témata zahrnující vývoj nových metod, inovace aplikačních postupů a poslední trendy v podnikové ekonomice, managementu, marketingu a ve financích a účetnictví.

Časopis je určen odborné veřejnosti zahrnující:
- odborné a vědecké pracovníky vzdělávacích institucí zaměřených do oblasti působnosti časopisu;
- manažery a pracovníky s rozhodovací pravomocí především v podnikové sféře;
- studenty navazujících magisterských a doktorských studií v oblasti podnikového managementu.

Trendy v podnikání jsou metodologicky pluralistickým časopisem. Publikovány jsou výsledky založené na kvantitativním, kvalitativním i smíšeném výzkumu jakož i konceptuální příspěvky a články rozvíjející teoretické poznání, prezentující testování empirických hypotéz i statě obsahující případové studie.

Každý článek je anonymně recenzován dvěma recenzenty. Recenze zajišťuje redakční rada časopisu. V časopise není možné publikovat článek, který byl uveřejněn nebo nabídnut k uveřejnění v jiném časopise či knižní publikaci.

AIMS & SCOPE

The journal ”Business Trends“ is a scientific, reviewed periodical published by the Faculty of Economics, University of West Bohemia in Pilsen, the Czech Republic.

The aim of the journal is to publish original theoretical and application outputs of the Czech and foreign authors, mainly focusing on business economics and management. The journal is also open to contributions dealing with interdisciplinary topics because only this way the issues of the current economic practice can be solved both theoretically and also by means of applied procedures, and like this, the findings concerning new and innovative methods can be disseminated. The journal aims mainly at topics including the development of new methods, innovations of applied procedures and the latest trends in business economics, management, marketing, finance and accounting.

The journal is meant for professional audience, including:
- professional and scientific workers of educational institutions specializing in the fields within the scope of the journal;
- managers and executives especially in the business sector;
- students of the follow up master and doctoral studies in the field of business management.

Business trends is a methodologically pluralistic journal. It provides results based on quantitative, qualitative and mixed research as well as conceptual contributions and articles developing theoretical cognition. Tests of empirical hypotheses and treatises containing case studies are also frequently published.

Each article is reviewed by two reviewers anonymously. The reviews are provided by the editorial board of the journal. The journal cannot publish any articles that were published or offered for publication in another journal or a book.

TRENDY V PODNIKÁNÍ
BUSINESS TRENDS

Obsah – Content

Zveřejněné příspěvky byly recenzovány. Příspěvky neprocházejí jazykovou redakcí. / Contributions in the journal have been reviewed but not edited.

Klíčová slova – Keywords:
Podniková ekonomika – Business Economics
Management – Management
Marketing – Marketing
Finance a účetnictví – Finance and Accounting

Editorial

Dear readers,
This special issue of the journal Trendy v podnikání (Business Trends) is associated with the international conference held in Pilsen in November 2024. The section of this conference, „Applications of AI in Organizational Settings and in Higher Education“, was supported by the Visegrad Fund project 22410207.
The aim of this project is not only to contribute to the innovation of higher education in the V4 countries in connection with the advent of AI but also to link the education process with innovations in organizational practice. This connection seeks to support the development of new competency among university graduates. Consequently, this special issue contains contributions both from corporate practice and the educational process at universities regarding AI implementation in 2024.
Among the contributions addressing this issue in greater depth are the papers by Havlas and Novotná, as well as by Daněk and Pospíšil.
Author Knihová focuses on the pedagogical approaches to innovating tertiary education in the context of AI's emergence. This is complemented by an experiment conducted by Kincl, Gunina, Novák, and Pospíšil, which evaluates the potential use of AI in the assessment of the educational process. The education-focused section is further enriched by case studies and practical experiences regarding the application of AI tools in educational processes, contributed by Eger and Turčáni. All of these papers highlight both the potential benefits and certain limitations of employing AI in higher education.
Another area of focus in this issue is the implementation of new technologies, particularly AI, in organizational practice. The paper by Velnerová and Poulová examines the effective use of open data, while Michelini presents the application of AI tools in financial consulting.
Finally, in this issue, you can find a research study by Mikulcová, Medeková, Lančarič, and Savov, who present a pilot study based on a questionnaire survey exploring the implementation of AI in university environments in Slovakia. Their research is a pilot study. The international team of V4 project prepares further research using quantitative and qualitative methods to examine the topic at selected universities in the V4 countries. The quantitative part, using a questionnaire survey, will map students' competency and facilitate comparisons among participants from the four EU countries. Meanwhile, using focus groups, the qualitative part will provide deeper insight into this issue.
In conclusion, it is worth noting that the section on November 21, 2024 also featured contributions from other speakers, particularly from corporate practice. For instance, Kristl Volfová presented the use of virtual reality in employee development, while Svoboda provided insights into the development of AI applications for business entities.
The opening keynote was given by Professor Lukasz Tomczyk, who discussed contemporary approaches to the construct of digital competency concerning AI. He emphasized that this is an emerging issue characterized by multiple and sometimes divergent approaches and ways of solution.

Ludvík Eger.

Visegrad Fund

ABOUT PROJECT

Visegrad Fund:
Innovation of the education process towards implementing AI tools. Project: 22410207

Applicant:
- **University of West Bohemia**

Project partners:
- **Slovak University of Agriculture in Nitra**
- **Eötvös Loránd University**
- **Jagiellonian University in Kraków**
- **Prague University of Economics and Business**

Short description of the project:
Artificial Intelligence is becoming an increasingly important. There is a lack of information on suitable AI applications, a lack of AI skills in academics and students. Universities face several challenges associated with incorporating AI into the education process. The project will help to implement innovative solutions, which has not yet been adequately implemented in the current curricula.

Conference Business Trends, section focused on AI tools
21st – 22nd November 2024, Pilsen, Czech Republic

https://www.tvp.zcu.cz/indexen.php

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APPLICATION OF AI IN ORGANIZATIONAL PRACTICE AND HIGHER EDUCATION

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Abstract: AI is one of the fastest rising technologies today. Industry is tackling implementation in strategic areas, while education must respond by changing teaching methods The objective of this paper is to provide a comprehensive overview of AI implementation in industry and education, identify synergistic opportunities between these sectors, and explore future trends that foster innovation and competitiveness. The author focuses on the analysis and comparison of different approaches and methodologies, examining specific use cases of AI and their impact on transforming educational practices and industrial processes. This thesis is based on a literature search that summarizes current knowledge and practices of AI implementation. The author analyses existing studies and use cases to identify key trends and approaches in industry and education. The findings show that industry is actively integrating AI into strategic areas, leading to improvements in process automation, predictive maintenance and product innovation. Higher education is adapting to these changes and transforming its teaching methods and curricula to prepare students to work with AI. In conclusion, effective implementation of AI requires close collaboration between industry and education. Limitations include the rapidly changing technological environment and the need for continuous adaptation.

Keywords: Artificial intelligence, Literature research, Industry, Higher Education, Implementation

JEL Classification: L63, I23, C63

INTRODUCTION

Artificial Intelligence (AI) has quickly become one of the most transformative technologies of the 21st century, revolutionizing many fields, including industry and education. While AI is becoming increasingly established in strategic industries such as manufacturing, telecommunications and healthcare, its benefits go hand in hand with radical changes in automation, predictive maintenance and product and service innovation. These technologies enable companies to optimize their processes and respond more effectively to market demands, thereby increasing their competitiveness. It is the implementation of AI that is one of the key factors driving the evolution of Industry 4.0, which focuses on digitalization and the integration of smart technologies, and paves the way for Industry 5.0, where human collaboration with artificial intelligence and other advanced technologies will be a key element to make systems more efficient, sustainable and adaptable. However, at this stage of development, we face challenges around transparency, ethics and the readiness of organizations to implement AI, raising questions about the accountability and reliability of these technologies.

Higher education is evolving alongside industry to meet new labour market demands and technological advancements. Institutions are rethinking traditional methods to equip students with skills for the digital age. AI in education offers personalized learning, boosting student engagement and fostering creative and critical

thinking. It also enables the development of innovative tools to prepare future professionals for a rapidly changing job market. Additionally, AI can transform pedagogy through intelligent assessment, automated feedback, and performance analysis, enhancing the efficiency and quality of education.
This dual approach - industry and education - reveals a synergy between these fields, where effective implementation of AI in both spheres can bring not only technological but also societal benefits. Industry and academia should work together to share knowledge and experience to ensure that education is prepared for the dynamics of technological innovation and that industry benefits from a trained workforce capable of working with advanced technologies, therefor fostering long-term competitiveness and innovation at a global level.
The objective of this paper is to provide a comprehensive overview of AI implementation in industry and education, identify synergistic opportunities between these sectors, and explore future trends that foster competitiveness and innovation.

1. LITERATURE RESEARCH

The following table presents the key studies that were subjected to detailed literature review.

Tab. 1: Resource list

Source		
Author(s)	**Title**	**Key words**
Nolle, Lars; Stahl, Frederic; El-Mihoub, Tarek	On Explanations for Hybrid Artificial Intelligence	Hybrid Artificial Intelligence, Trust, Blackboard Systems, Neural-networks, Models
Kose, Utku; Vasant, Pandian	Fading Intelligence Theory: A Theory on Keeping Artificial Intelligence Safety for the Future	Fading intelligence theory, artificial intelligence safety, future of artificial intelligence, artificial intelligence
Kumpulainen, Samu; Terziyan, Vagan	Artificial General Intelligence vs. Industry 4.0: Do They Need Each Other?	Artificial general intelligence, Industry 4.0, systematic mapping study, google distance
Ahmed, Imran; Jeon, Gwanggil; Piccialli, Francesco	From Artificial Intelligence to Explainable Artificial Intelligence in Industry 4.0: A Survey on What, How, and Where	Artificial intelligence, Industries, Manufacturing, Artificial intelligence (AI), explainable artificial intelligence (XAI), Industry 4.0
Ameen, Linda Talib; Yousif, Maysam Raad; Alnoori, Najwa Abdulmunem Jasim; Majeed, Ban Hassan	The Impact of Artificial Intelligence on Computational Thinking in Education at University	Artificial intelligence (AI), ChatGPT, computational thinking, education, university, chemistry, computer science
Joehnk, Jan; Weissert, Malte; Wyrtki, Katrin	Ready or Not, AI Comes- An Interview Study of Organizational AI Readiness Factors	Artificial intelligence, AI adoption, AI readiness, Organizational readiness assessment, Interview study

Source: Own Processing

Resources were selected according to the established methodology, with their relevance determined by how they contribute to the paper's overall objectives.

2. METHODOLOGY

The methodology of this paper is based on a systematic literature search covering scholarly articles, publications and research studies in the fields of industry, education and innovation implementation over the last ten years. A structured approach was used to select relevant sources, including databases such as Scopus, Web of Science and Google Scholar. The search was conducted using keywords related to the topics of industrial development, education systems and different strategies for implementing technological innovation.

The search included studies published in peer-reviewed scientific journals, conference proceedings and grey literature that met predetermined quality and timeliness criteria. Each article was evaluated based on relevance, methodological quality and contribution to the field under study. Articles containing at least one of the keywords: Artificial Intelligence, Study, Education, Future, Industry, Framework were included in the search. Emphasis was placed on identifying trends, challenges and best practices in the studied sectors to gain a comprehensive overview of the current state of development and applications in industry, education and their interactions.

3. RESULTS

Using the methodology provided, our literature research presents results that offer a comprehensive overview of AI implementation in industry and education, identify synergistic opportunities between these sectors, and explore future trends that foster innovation and competitiveness.

3.1. Preparatory phase of using AI

If an organization or educational institution decides to implement artificial intelligence (AI), it is essential to first assess its readiness for the move. Jöhnk et al. (2021) study defines the key factors that an institution must consider before starting an AI implementation. These factors include:

- Strategic direction of the company - Before the actual implementation of AI, it is crucial that AI use cases are aligned with the strategic direction of the organization. The institution should identify areas where AI can bring improvements, such as processes where automation or more efficient resource management is possible (Hofmann, P. et al. 2020). It is also important to identify new opportunities that could bring innovative solutions and strengthen the organization's competitiveness (Pumplun, L. et al. 2019).
- Resources - Implementing AI is challenging not only from a technological but also financial perspective. Organizations must consider not only the cost of the implementation itself, but also the cost of operating, maintaining, and continuously optimizing the solutions (Pumplun, L. et al. 2019). At the same time, they need to invest in building the know-how for long-term sustainability so that the organisation can effectively manage and develop AI systems (Agrawal, A. et al.2018).
- Knowledge - Ensuring sufficient expertise is essential for successful implementation, especially in the early stages of a project. The organization must identify key roles and experts who will be responsible for leading and implementing the AI project. At the same time, it is important that employees perceive AI as a tool to make their work easier and more efficient, which can increase their willingness and readiness to use new technologies (Davenport, T. 2018).
- Culture - Innovation in an organization depends on its ability to adapt to new technologies. The organisation needs to examine the current level of knowledge of employees and encourage further training in AI. At the same time, it is important to establish an ethical framework for the use

of AI to ensure that AI is used responsibly and in accordance with the company's values and policies (Davenport, T. 2018).

- Data - For a successful AI deployment, it is essential to have enough quality data to train the models. The organization must identify the key data types and sources that will be needed for the specific purpose and use case of AI. In this way, the right AI model that will reflect the nature and needs of the organization can be selected (Jöhnk et al. 2021).

These factors serve as a basis for assessing an organization's readiness to implement AI and help identify areas that require improvement or preparation before the technology can be put into practice.

3.2. Possibilities of applying different types of AI

Commonly available AI tools that are gaining considerable popularity are the AI-based chatbots. These tools use advanced language models trained on large datasets and offer users support in a variety of areas such as text generation, data analysis or automation of repetitive tasks. Interaction with them takes the form of a conversation, with the user interacting with the tool via prompts in chat (Rossettini, G. et al., 2024). In addition to well-known chatbot AI tools such as Copilot, ChatGPT or Gemini, the potential of Hybrid AI is increasingly being explored in the industry. Hybrid AI combines the benefits of several types of AI, in particular machine learning (ML), symbolic AI and knowledge-based systems, to enable better decision making and complex problem solving.

In the industrial sector, hybrid AI is being used to solve challenges where traditional machine learning approaches have hit their limitations.

Nolle Lars' (2023) paper explored implementations of hybrid artificial intelligence (AI) models that represent pioneering approaches in improving the efficiency and trustworthiness of AI systems. The first model is a hybrid system that consists of multiple types of AI, with the individual components communicating and collaborating with each other (Jordan, M.I. & Mitchell, T.M, 2015). This model allows the benefits of different AI technologies such as machine learning, symbolic AI and neural networks to be combined, leading to more advanced solutions in complex fields such as medicine. In this field, hybrid systems are used for diagnosis, personalised treatment and analysis of large amounts of health data, increasing the accuracy and speed of medical decisions (Nolle, L. et al., 2002).

The second system is XAI (Explainable AI), whose main goal is to increase trust between users and AI systems (Bielecki, A. & Wójcik, M., 2021). XAI focuses on transparency by being able to explain to users how it concluded its decisions and outputs. This capability reduces the risk of "AI hallucinations" - situations where AI generates incorrect or illogical results for no apparent reason. XAI increases clarity for users by providing accessible explanations, which is especially key in sensitive areas such as medicine or law, where a wrong decision can lead to serious consequences (El-Mihoub, T. et al., 2006).

Both systems can be integrated into the so-called Blackboard system, which is a platform for linking various AI modules with large knowledge bases. The Blackboard system allows combining multiple types of data records such as text, images, audio or video to support complex analysis and decision making based on multimodal data (Rudin, C. et al., 2021). This system finds applications in medicine, for example, where it can combine image data from X-rays, textual descriptions of medical records and other diagnostic information, leading to more accurate diagnosis and a better understanding of a patient's medical condition (Buhrmester, V. et al., 2021).

The results of the I. Ahmed, G. Jeon and F. Piccialli (2022) survey on the use of Artificial Intelligence (AI) and Explainable Artificial Intelligence (XAI) in Industry 4.0 show that classical AI is most applicable in the field of Machine Learning. In this case, AI learns directly from data, rather than using prompts from users, giving it the ability to automate and optimise various processes based on historical data and patterns (Bougdira, A. et al., 2019).

Another important application is Deep Learning, which, unlike classical machine learning, processes data through multiple contextual layers, making it capable of capturing even complex relationships and abstractions in data (Soto, J. C. et al., 2019). This approach is used in cases where complex analyses is needed, for example in image or audio processing (Villalba-Diez, J. et al., 2019).
Natural Language Processing (NLP) is another key use case for AI in Industry 4.0. NLP allows users to interact with computers using natural language, eliminating the need for programming skills and opening new possibilities for people without a technical background. This makes interacting with AI systems more accessible and easier for a wider range of users, supporting innovation and technology implementation across industries (Li, L. et al., 2018).
Computer Vision is another form of application that allows artificial intelligence systems to recognize and analyse images and videos (Gunning, D. et al., 2021). This approach improves the perception of context based on visual information and finds application in areas where it is difficult to describe the problem verbally, such as detecting defects in a production line or analysing medical images.
There are three key stages in the processing and learning of AI models within XAI:

- **Pre-model – At this stage, we focus on minimizing the dimensionality of the data while preserving its variability, thus simplifying the work of the model and increasing efficiency**
- In-model – In this step, we try to identify rules and patterns among the data that the model can use for learning and prediction.
- Post-model – This stage focuses on interpreting what the AI model has learned and evaluating its ability to apply what it has learned in real-world situations.

In the field of Explainable Artificial Intelligence (XAI), research has identified various approaches and models to enhance the trustworthiness of AI systems. In terms of implementation, we distinguish two main approaches: the Model Specific and the Model Agnostic. The Model Specific approach focuses on specific, predefined AI models and their internal structure, while trying to explain the functioning of these models (Arrieta, A. B. et al., 2020). In contrast, the Model Agnostic approach focuses on explaining the results, independent of the internal structure of the model, allowing for greater flexibility in interpreting different AI systems (Carletti, M. et al., 2019).
Another important aspect of XAI are the local and global approaches to explaining results. The local approach explains how the model arrived at a particular decision for a particular input, while the global approach describes the overall behaviour of the model in a broader context. This differentiation is useful when analysing the performance of AI systems at different levels and allows for a better understanding of their operation (Arya, V. et al., 2019).
These results show that proper integration and explanation of AI is essential to ensure reliability and trustworthiness in Industry 4.0.

3.3. Using ai in education

Freely available AI tools such as ChatGPT, Google Bard or Copilot are being increasingly integrated into education systems. Research of Ameen, L.T., Yousif, M.R., Jasim Alnoori, N.A., Majeed, B.H. (2024) at the Faculty of Chemistry at Baghdad University has focused on exploring the ways in which students and educators use these AI models. The research identified several specific use cases, including automated responses to frequently asked questions, which greatly facilitated the teaching process and improved access to quick and relevant information for both parties.
The study primarily focused on the phenomenon of Computational Thinking, which focuses on systematic problem solving using computational tools and techniques (Ban Hassan, M. et al., 2022). The research, which was conducted between 2023 and 2024 on a sample of 146 respondents, included students from two different disciplines - computer science and chemistry. The groups were subjected to two tests designed to test both their academic knowledge and their ability to apply computational thinking to problem solving.

Each group was divided into two subgroups - a control group, which did not use any AI tools, and an experimental group, which was allowed to use AI tools. The results showed that students in the experimental group who had AI tools available performed better than the control group. This trend was particularly pronounced for students in computer science, where artificial intelligence was shown to be particularly effective in solving tasks related to information technology.

There was also a positive impact of using AI tools in chemistry, but the results were not as significant as for computer science students. This difference may be explained by the fact that artificial intelligence is directly linked to techniques used in IT, whereas in chemistry disciplines, problem solving often requires more complex applications of theoretical knowledge that may be less directly supported by AI tools (Abdulsalam, W. H. et al., 2018).

The research findings confirm that artificial intelligence can increase the effectiveness of students and educators, with its greatest benefits observed in areas where computational thinking is a key element of success.

3.4. AI limitations

When working with artificial intelligence, a lot of emphasis is placed on user trust. In their paper, Utku Kose and Padian Vasant (2017) addressed the issue of a phenomenon called "Fading AI". This phenomenon is based on the premise that if artificial intelligence is trained on a specific dataset and then new data is gradually added to that dataset, the accuracy and efficiency of the model may decrease. In other words, the performance of an AI model may fade when it is confronted with new or expanding data that may not be consistent with the original training dataset (Mitchell, T.M., 1997).

Kose and Vasant point out that this phenomenon can have serious consequences, especially in systems that require high reliability and accuracy, such as medical diagnostic systems, financial prediction or autonomous driving (Bostrom N. & Yudkowsky E., 2014). If the datasets used to train AI are constantly changing or expanding without simultaneously optimising the training algorithms, the model may lose the ability to correctly interpret new information, leading to a degradation in its performance.

In their study, they propose several approaches to mitigate this problem, including continuous model retraining, adaptive algorithms, and hybrid solutions that combine traditional machine learning methods with advanced techniques such as deep learning (Trabulsi, A. 2015). They also stress the importance of carefully managing and updating datasets to avoid unnecessary errors and preserve the credibility of AI systems.

The topic of "fading AI" is also significant from the perspective of trust between users and AI, as a reduction in the accuracy of systems can lead to a reduction in the credibility and acceptability of these technologies in critical areas where errors are unacceptable (Yampolskiy, R. V. 2013).

4. DISCUSSION

In the discussion section, it is important to reflect on the key findings of these studies and their relevance to the practical implementation of artificial intelligence (AI) in various fields. As Jan Johnk's (2020) study demonstrates, prior to the actual implementation of AI, an organisation or educational institution needs to thoroughly assess its readiness, with key factors including strategic direction, resources, expertise, organisational culture and access to data. These factors are key to the successful implementation of AI in practice, and identifying opportunities and appropriate use cases allows organisations to effectively direct their resources and maximise the benefits of AI technologies.

For AI applications in Industry 4.0, as shown by research by Nolle Lars (2023), it is interesting to see advances in hybrid AI and Explainable AI (XAI). Hybrid AI, which combines machine learning, symbolic AI, and knowledge-based systems, has emerged as a key tool in solving complex problems, especially in medical applications where accuracy and reliability of decision makers are crucial. XAI, in turn, opens the door to more transparent and understandable use of AI, which is important for building trust between users and AI systems.

In terms of education, research at the Faculty of Chemistry at Baghdad University (2023-2024) has yielded valuable insights into the positive impact of AI tools such as ChatGPT and Google Bard on improving students' academic performance and computational thinking. In the IT field, these tools have been shown to increase student efficiency, suggesting that implementing AI in the educational process has significant potential not only for facilitating learning, but also for preparing students to work with modern technologies in the future.
The topic of "fading AI" brought up by Kose and Vasant (2017) brings another important aspect to the discussion. Their warning about the risk of decreasing the accuracy of AI systems as datasets proliferate points to the need for regular updating and optimization of AI models. This phenomenon has a major impact on maintaining the credibility of AI systems, especially in critical domains such as healthcare or financial systems, where errors caused by inconsistent data can have serious consequences.
Based on this knowledge, successful AI implementation depends on many factors, including deploying the technology correctly, understanding its limitations, and ensuring credibility through transparency and continuous optimization.

CONCLUSION

Artificial intelligence has a huge number of applications in both organisations and education. The main questions that institutions need to ask themselves is what to implement, how to implement it and where to implement. The answer to these questions is the need to implement technologies that solve current organizational problems or provide opportunities for new challenges and innovations.
Artificial intelligence can be implemented either as a simple tool to automate monotonous and repetitive tasks, or as a complex system composed of multiple models that cover a wider range of activities and decision-making processes. The scope of implementation depends on the culture of the organisation, its financial and technological resources, and the nature of the data it works with. Organisations need to focus on the long-term goals they are pursuing and implement AI in a way that directly contributes to their strategy and development.
A key intersection between organisations and educational institutions is computational thinking, which is changing the way people think about problem solving. This approach promotes logical and systematic reasoning, which is essential for the effective use of AI tools. The ability to master artificial intelligence is becoming critical for future job seekers as the industry increasingly moves towards hybrid artificial intelligence and explainable artificial intelligence (XAI).
Natural Language Processing (NLP) represents a significant area that allows students and future employees to use AI without the need for extensive programming knowledge. This technology allows direct interaction with computers using natural language, breaking down technological barriers and making AI widely available to a variety of professions.
When implementing AI, organizations must also be mindful of the sustainability of the technology, which will lead to the creation of new jobs focused on the management and development of AI systems. This aspect of sustainability means that AI solutions must be designed with long-term operation and adaptation to new challenges and requirements in mind.
Based on his analysis, the author concludes that AI will not replace humans in employment, but workers who are unable to operate AI tools or do not have developed computational thinking skills can be replaced by those who do. This trend underlines the importance of continuous learning and development of the skills needed to work in a dynamic, technologically advanced environment.

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AI-POWERED IMMERSIVE LEARNING: TRANSFORMING TERTIARY EDUCATION

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Abstract: We live in a world where human attention is exposed to thousands of stimuli shorter than the proverbial attention span of a goldfish in a fishbowl. A famous Microsoft study found that since 2000, the average human attention span has dropped from 12 seconds to 8 seconds. It also applies to Gen Z and the ALPHA generation members, often called the "second-screen generation" since it is their nature to use multiple screens simultaneously. These young people find it challenging to filter out irrelevant stimuli - and their inability to concentrate fully impairs their study and work performance. Therefore, educators are looking for ways to engage their students and help them learn more efficiently. Nowadays, a promising trend is AI-powered immersive learning, which is enabled by New Age Technologies (NATs). This conceptual study explores how immersive learning powered by NATs can address the challenges posed by diminishing attention spans and multitasking behaviors among Gen Z and Generation Alpha students. The study examines the potential of immersive learning environments to create engaging, interactive, and personalized educational experiences that capture attention and improve focus. Immersive learning can transform abstract concepts into hands-on experiences by integrating NATs, fostering more profound understanding and long-term retention. The paper proposes an Imersive Learning Framework for designing and implementing immersive learning experiences in educational settings. It discusses the benefits and challenges of this approach, ultimately aiming to inspire new pedagogical strategies aligning with the needs of a digitally native generation.

Keywords: AI, generative multimodal models, engagement, AI-powered immersive learning, New Age Technologies, tertiary education

JEL Classification: I23, M3

INTRODUCTION

In recent years, the way younger generations consume information has undergone a significant transformation. A Microsoft study from 2015 revealed that the average attention span of Generation Z is just eight seconds—four seconds shorter than that of millennials—largely due to their constant exposure to digital content and the simultaneous use of multiple screens (McSpadden, 2015, Hooton, 2015)). The diminishing attention spans and pervasive multitasking behavior among Gen Z and ALPHA generation students pose significant challenges, particularly in educational contexts. These generations, often called the "second-screen generation", increasingly demand information that is fast, accessible, and authentic, often favoring user-generated content created by peers, end-users, or even anonymous contributors on social media over professionally produced materials. Generative artificial intelligence (Gen AI) applications, such as ChatGPT, now deliver instant, complex answers at unprecedented speeds, reshaping the expectations of immediacy across all generations, particularly Gen Z and Generation ALPHA. Higher education institutions must adapt swiftly to meet these evolving demands. It is worth mentioning that the rise of AI has been enabled by exceptional scientific breakthroughs recognized by the Royal Swedish Academy of Sciences. The 2024 Nobel Prize in Physics, awarded to two university professors, John J. Hopfield and Geoffrey E. Hinton, for their revolutionary work on neural networks, highlights the transformative role of artificial intelligence (AI) in modern society.

University course designers are aware of the potential of innovative AI-driven applications. They recognize that integrating New Age Technologies (NATs), i.e., technologies with AI at their core, represents a unique opportunity to address the challenges universities face. Designing courses that tackle the issues of fleeting attention spans and multitasking, which undeniably contribute to diminished focus, is of utmost importance and it is an essential starting point. By creating immersive and engaging learning environments that align with the digital-first behaviors of Gen Z and Generation ALPHA, modern university courses can foster deeper understanding and support long-term knowledge retention. Through innovative course design that keeps students engaged, university educators can equip students with the skills and creativity necessary to thrive in an increasingly dynamic and technology-driven world.

The purpose of this study is to explore how immersive learning, enabled by NATs, can create engaging and effective educational environments tailored to the needs of digitally native students. As the demands and behaviors of Gen Z and Generation ALPHA evolve, university teachers face the challenge of staying at the forefront of innovation, helping students achieve their life success by fostering creativity, critical thinking, and adaptability. To remain leaders in education, teachers must design learning environments that not only engage students but also deliver measurable results. This study proposes a framework for immersive learning with three key components: *engagement strategies* to capture and sustain attention, *interactivity* to promote active participation, and *hyper-personalization* through AI-driven adaptive learning paths. Additionally, it outlines practical implementation strategies using tools such as generative multimodal models, VR/AR/XR platforms, and AI-based analytics, as well as illustrative scenarios to demonstrate their application.

Immersive learning resonates with the idea expressed by Philip Kotler and his co-authors, who aptly titled one of their latest works, Marketing 6.0, with the subtitle "The Future is Immersive." This thoughtful statement, although rooted in the marketing domain, translates seamlessly to the field of education, where immersive experiences hold equally significant relevance for preparing students to thrive in a dynamic and rapidly changing world.

This paper is divided into five main sections. The Introduction presents the challenges posed by changing attention spans and multitasking behaviors observable among digitally native students. Aiming at addressing these issues efficiently, the potential of New Age Technologies (NATs) and immersive learning are suggested alongside a proposed framework for implementing immersive learning in educational settings.

The *Literature Review and Theoretical Background* examine foundational theories such as constructivism, experiential learning, and Flow Theory and explore the role of NATs, including AI and VR/AR/XR, in creating engaging educational experiences. The proposed *Immersive Learning Framework* introduces three key components—*engagement, interactivity*, and *hyper-personalization*—and outlines implementation strategies and illustrative scenarios. The *Benefits and Challenges* section evaluates the advantages of immersive learning, such as enhanced focus and retention, while addressing obstacles like infrastructure and ethical concerns. Finally, the sub-chapter *Discussion* and Implications considers the pedagogical, research, and broader implications of adopting immersive learning practices, concluding with actionable insights for educators and educational institutions.

The author of this article is deeply concerned about the future of tertiary education, being fully aware of the pros and cons of the coming period which will be influenced by AI at all levels of the educational process. The rapid advancement of AI and NATs have the potential to change education fundamentally. However, apart from promising opportunities, we can identify many challenges, e.g., the risk of widening the digital divide between individuals and educational institutions because of their differing access to resources. These are complex issues which demand a proactive, thoughtful, and sensitive approach. Therefore, the key questions this article aims to address are:

- **RQ1:** “What are the key components of AI-driven immersive learning that enhance student engagement and understanding in tertiary education?”
- **RQ2:** “How can tertiary education institutions design and implement immersive learning environments using New Age Technologies?”

By exploring these questions, the article seeks to provide actionable insights and strategies for leveraging AI to transform tertiary education while addressing its challenges responsibly.

1. LITERATURE REVIEW AND THEORETICAL BACKGROUND

This chapter examines the attention spans and multitasking behaviors of digital natives, particularly Gen Z, along with immersive learning as a method of instruction, the role of New Age Technologies (NATs), and the relevance of these issues to tertiary education.

1.1. Attention Span and Multitasking of Digital Natives

In an effort to overcome the extremely *short human attention span*, educators attempt to use various methods of instruction, particularly the method of *immersive learning.* The relatively easy access to New Age Technologies (NATs), lead by AI, is a promising field helping educators design the learning experience anew. Researchers in methods of instruction have long relied on the widely adopted theoretical foundations of *constructivism* (Jean Piaget, Lev Vygotsky), *enquiry-based learning* (John Dewey), and *experiential learning* (David A. Kolb), which represent the cornerstone for the further development of learning theories. Further, it is important to notice gamification and *Flow Theory* (Mihaly Csikszentmihalyi) and *social learning* (Lev Vygotsky and Albert Bandura). Among the newest concepts, *immersive learning* (helps better focus and retention) and *adaptive learning* (enables personalization) emerge.

Multitasking is another defining characteristic typical of Gen Z and Gen ALPHA behavior. Both educators and medical professionals have expressed concern about its consequences, noting that "the concurrent consumption of multiple media forms is increasingly prevalent in today’s society and has been associated with negative psychosocial and cognitive impacts" (Loh & Kanai, 2014). Hand in hand with the widespread availability of smartphones, offering ever more advanced functions, distraction and multitasking have become global phenomena and are among the most critical issues at the intersection of technology and education (Deng et al., 2024). Another study, framed within the self-determination theory, advanced the understanding of problematic smartphone use in university classrooms by demonstrating its linkage to academic motivation and mental health outcomes, such as anxiety and insomnia (Tamayo et al., 2024). Addressing controlled motivation in academic settings requires creating environments that reduce external pressures and foster intrinsic interest and self-driven goals.

Moreover, an increasing body of research highlights the potential negative effects of excessive social media use among college students. A survey involving 523 college students revealed that the fear of missing out (FOMO), particularly regarding events on social media, was positively associated with social media multitasking. This multitasking, in turn, was positively related to cognitive distraction, ultimately resulting in a measurable decline in academic performance (Zhao, 2023).

1.2. Immersive Learning Experience and NATs

This study aims to investigate how immersive learning, facilitated by New Age Technologies (NATs), can foster engaging and effective educational environments tailored to the needs of digitally native learners. To achieve this, it is essential to examine recent advancements in immersive learning, particularly focusing on its definition and the principles of immersive learning experience design. A comprehensive pilot study introduced an innovative architecture combining Artificial Intelligence (AI) and Virtual Reality (VR) to develop a highly immersive and efficient learning environment utilizing avatars. This approach enabled researchers to evaluate interpersonal effectiveness in individuals interacting with avatars. The key findings demonstrated that avatars could significantly enhance interpersonal effectiveness, providing a robust framework for measuring, predicting, and improving these skills. The authors concluded that avatars represent a valuable tool for assessing and enhancing interpersonal competencies (Nagendran et al., 2022).

A recent study focused on immersive learning experience, specifically on the design and development of an immersive escape room game in VR to teach building energy simulation topics. In the game, players must solve puzzles like, for instance, assembling walls using different materials. The players are carefully guided through the tutorial system that combines educational content, puzzles, and different types of hints to educate the players about parameters that influence energy efficiency, structural resistance, and costs. Consequently, they completed two sets of post-questionnaires, one after the tutorial and one after the puzzle level. The results indicated that the onboarding level successfully provided good usability while maintaining a low task load. It means that the onboarding level was designed to be easy to use, requiring minimal mental effort from participants. On the other hand, the escape room level provided an engaging, visually appealing, and usable learning environment by arousing players' curiosity through the gameplay. The immersive environment of this type can be designed for different educational contents from various fields (Arbesser-Rastburg et al., 2024).

Drawing on this and other relevant insights, it is also essential to examine the transition from university education to corporate training and, subsequently, to continuous learning, which aligns with the integration of immersive learning experiences and advanced technologies in corporate settings. Companies such as UPS, Volvo Group, and Walmart have adopted immersive technologies for employee training. For instance, UPS utilizes virtual reality (VR) to train drivers in tasks such as package stacking and handling real-world scenarios, including encounters with dogs. Walmart employs VR for soft skills training, including managing interactions with frustrated customers and leveraging data-driven insights to enhance employee performance. Similarly, Volvo Group uses VR to train employees in procedures such as replacing batteries on electric trucks, thereby improving practical skills in a controlled environment (Bousquette, 2024). Hilton has also embraced VR training to enhance corporate team members' understanding of hotel operations. This initiative reduced in-class training time from four hours to just 20 minutes and resulted in behavioral changes in 87% of participants (Dilmegani, 2024). Corporate training is already taking the lead; however, educational institutions, particularly universities, should spearhead this shift by integrating theoretical foundations with practical applications to set exemplary standards for immersive learning.

1.3. AI's Role in Tertiary Education

To delve deeply and effectively into the complexities of AI's role in education, it is essential to address the mixed messages that have both inspired and alarmed educators, policymakers, and the public. In a comprehensive study examining AI-powered systems designed to make online learning in higher education more accessible, affordable, and achievable, Goel (2020) investigates the promising potential of AI in enhancing learning experiences. Specifically, he highlights AI's capacity for large-scale personalization, while also addressing concerns about its ethical implications and its transformative impact on human cognitive and socio-emotional functioning. Goel argues that innovative AI-driven technologies enhance online education by increasing accessibility (through readily available materials), affordability (by reducing teacher workloads), and achievability (by offering personalized learning assistance and fostering student engagement).

Building on these advancements, we observe a continuation of AI's transformative potential through personalized and adaptive learning. Personalized learning, enabled by AI, tailors educational content and pacing to meet individual learner needs, while adaptive learning systems dynamically modify instructional methods to support knowledge and skill acquisition based on real-time assessments of student performance and progress.

Soon, digital native learners of Gen Z will gradually enter their first employment, and thus it is essential to examine the challenges of this transition. In their study, Stepher and Majchrzak, after discussing the range

of business opportunities that experts suggest will prevail in the economy with omnipresent AI, focus on how entrepreneurs can use AI as a tool to help them increase their chances of entrepreneurial success. Advancing research at the AI-entrepreneurship nexus can enable scholars to support entrepreneurs in leveraging AI to enhance their decision-making and actions for productive outcomes while mitigating some of AI's darker aspects within the entrepreneurial context (Shepherd & Majchrzak, 2022).
Building on Gray Scott's idea that "technology is natural" (ModernMind Publications, 2023), this study views the incorporation of AI in education as a logical progression in teaching and learning. Much like the natural processes of adaptation and evolution, AI provides tools that enable educators to tailor lessons to individual students' needs, enhance teaching methods, and has great potential to improve learning outcomes. By embracing this perspective, educators can reimagine traditional approaches and effectively address the unique challenges posed by digitally native students.

This study examines the potential of immersive learning environments to create engaging, interactive, and personalized educational experiences that capture attention and improve focus. By integrating NATs, immersive learning can transform abstract concepts into hands-on experiences, fostering deeper understanding and long-term retention.

2. METHODOLOGY

This study employs a conceptual research approach to explore the potential of AI-powered immersive learning in helping educators address the challenges of teaching digitally native students. The methodology includes a literature review of foundational theories such as constructivism, experiential learning, and Flow Theory, as well as recent advancements in immersive learning technologies, including VR/AR and and AI-powered applications. Comparative analysis was conducted to examine existing immersive learning frameworks and their applications, primarily in corporate training environments such as those used by UPS, Walmart, and Volvo. These corporate case studies provided real-world insights into the integration of New Age Technologies (NATs), offering transferable lessons for tertiary education. The proposed Immersive Learning Framework was developed through synthesis, combining theoretical insights with practical examples to ensure its relevance and applicability. This multidisciplinary approach bridges gaps between theory and practice, offering actionable strategies for educators and educational institutions.

3. IMMERSIVE LEARNING FRAMEWORK PROPOSAL

Benefiting from her extensive teaching experience, as well as insights from prior research and practical applications, the author of this study designed an Immersive Learning Framework. It is aimed at integrating immersive learning experiences into modern educational settings. Having discussed and addressed both the benefits and challenges of immersive learning, the framework aims to inspire innovative pedagogical strategies that align with the evolving needs and behaviors of digitally native generations. The proposed Immersive Learning Framework can help instructional designers prepare their higher education courses, not omitting important areas. Let us start with the three most relevant components of the learning process, i.e., engagement, interactivity, and hyper-personalization.

3.1. Immersive Learning Framework – Key Components

The most relevant key components of the proposed Immersive Learning Framework are:

- Engagement: It is to be understood as strategies aimed at capturing and sustaining students' attention.
- Interactivity: Tools and techniques designed to foster active student participation in the learning process.

- Hyper-personalization: Due to the concurrent analysis of an LMS users/students, AI-driven adaptive learning paths can be suggested to optimize the individual learning process.

The proposed Immersive Learning Framework further focuses on the following aspects:

- Definition/Context: Provides a clear explanation of each component to contextualize its role in the framework.
- Strategies/Tools: Highlights key methods and technologies for implementing the component.
- Examples in Tertiary Education: Offers practical examples to illustrate real-world application.
- Expected Outcomes: Summarizes the intended benefits and results for students and educators.

The proposed structure balances theoretical depth with practical insights, making it easy for educators to understand and apply the Immersive Learning Framework in educational settings (see Tab. 1).

Tab. 1: Immersive Learning Framework

Component	Definition/Context	Strategies/Tools	Examples in Tertiary Education	Expected Outcomes
Engagement	Capturing and sustaining students' attention.	- Gamified content - VR/AR/XR immersive storytelling - AI-based nudges	- Virtual reality labs for engineering courses - Gamified quizzes in LMS	**- Increased focus and participation - Reduced dropout rates**
Interactivity	Encouraging active participation and collaboration.	- Collaborative VR spaces - Simulations - Real-time polling tools	- VR-based case studies for business courses - Simulation of debates in political science	**- Improved critical thinking - Enhanced teamwork and collaboration**
Hyper-personalization	Adapting learning pathways based on individual needs and preferences.	- AI-driven learning analytics - Adaptive learning platforms - Chatbots for support	- Personalized study plans for language learners - AI-generated feedback on writing assignments	**- Enhanced student satisfaction - Improved knowledge retention**

Source: own elaboration

3.2. Implementation Strategies

Effective design and implementation of *immersive learning strategies* in tertiary education requires a strategic approach that integrates innovative technologies with pedagogical practices tailored to the current needs of digitally native students. The following steps exemplify *a systematic method for embedding immersive learning into higher education curricula* and highlight the most critical areas of the implementation process.

1. Assess Institutional Readiness

- Conduct an audit of the available technological infrastructure and resources. This includes hardware (e.g., VR headsets, AR-enabled devices) and software (e.g., AI-based learning platforms, generative multimodal models and related applications).
- Evaluate your faculty preparedness through surveys or workshops. Your aim is to gauge precisely familiarity with immersive learning tools. If the findings do not meet the expectation, more training is the first remedy to think of.

2. Define Learning Objectives and Outcomes

- Clearly articulate the learning objectives that immersive learning experiences will support. It may encompass fostering critical thinking, enhancing engagement, or improving retention.
- Align these objectives with specific course outcomes to ensure relevance and integration into the curriculum.

3. Select Appropriate Technologies

- Identify tools and platforms that align with course objectives. Simultaneously, budgetary constraints should be taken into consideration. Tools and platforms to consider:
    - **Generative Multimodal Models**: Use AI-driven tools like ChatGPT for content generation, language practice, or real-time feedback.
    - **VR/AR Platforms**: Integrate virtual simulations for hands-on experiments (e.g., VR anatomy for medical students) or AR-enhanced fieldwork in disciplines like archaeology and others.
    - **Integrate virtual business simulations** where students can manage a virtual company, practice decision-making in real-time scenarios, and experience the consequences of their choices in areas such as marketing, operations, and finance. For example:
        - A **VR-based supply chain simulation** where students oversee production, logistics, and inventory management, making decisions under time and resource constraints.
        - An **AR-enhanced case study** on leadership and crisis management, where students interact with virtual team members to resolve conflicts or manage a product recall in a realistic environment.
    - **AI-Based Analytics**: Leverage AI-driven analytics for personalized learning pathways, identifying struggling students, and tailoring content delivery.

4. Develop Immersive Learning Content

- Collaborate with the best subject matter experts in the field to create VR/AR/XR simulations, gamified activities, or AI-enabled adaptive quizzes.
- Ensure content diversity to address various learning styles and inclusivity needs. Remember that no student should be left behind.

5. Pilot and Test the Program

- Introduce immersive learning in selected courses as a pilot program to test its effectiveness and gather feedback from both students and faculty.
- Use data analytics and qualitative surveys to refine the approach based on user experience and outcomes.

6. Train and Support Educators

- Offer workshops at varying levels of difficulty and provide ongoing support for faculty to ensure confident adoption of new tools and methods. Familiarity reduces fear and resistance to change.

- Provide access to technical support and resources, such as user guides and troubleshooting assistance. The integration of on-demand educational videos is highly recommended to enhance accessibility and self-paced learning.

7. Monitor, Evaluate, and Scale

- Continuously assess the impact of immersive learning through metrics like student performance, engagement levels, and satisfaction surveys.
- Scale successful implementations across additional courses and departments while addressing challenges identified during the pilot phase.

Implementation strategies outlined in this chapter encompass the necessary areas for integrating immersive learning experiences; however, it is evident that individual implementations will vary depending on the specific field of study and the budgets allocated in different tertiary educational institutions, colleges, and universities. Grant agencies in individual countries should actively collaborate to support high-quality educational strategies, as this is in the interest of society as a whole and crucial for shaping the future.

4. BENEFITS AND CHALLENGES OF IMMERSIVE LEARNING SCENARIOS

4.1. Benefits

Immersive learning scenarios offer educators and learners numerous advantages. They include enhanced engagement, deeper understanding, and improved knowledge retention. Let us explore these three points in more detail.

Improved Engagement

One of the primary benefits of immersive learning scenarios is their ability to foster heightened engagement. By fully immersing students in a specific topic and related activities, these scenarios are so engaging that they create an environment which helps students filter out distractions and intrusive stimuli, allowing them to focus entirely on the task at hand. The immersive nature of the particular learning scenario encourages active participation, as students interact with the learning environment and take on various roles or tasks. This focused engagement enhances their overall learning experience.

Deeper Understanding

The focused engagement facilitated by immersive learning scenarios leads students to a more profound understanding of the subject matter. When students are actively involved and fully present in the learning process, they can grasp complex concepts and ideas more effectively. Immersive scenarios typically simulate real-life contexts, enabling students to connect theoretical knowledge with practical application. As a result, learning materials become more meaningful and memorable.

Improved Knowledge Retention

In immersive learning environments, a deep understanding naturally leads to significantly enhanced knowledge retention. When students thoroughly understand the study materials and their implications, they are more likely to retain them over the long term. Integrating active participation, real-world context, and emotional engagement in an immersive learning experience fosters strong cognitive and emotional connections. This synergetic interplay amplifies the learning process, making the experience impactful and enduring.

Addressing Attention Span Challenges Through Immersive Learning

Immersive learning and thoughtful design of immersive learning experiences can address attention span challenges. Drawing upon their own experience, educators know well that traditional teaching methods often struggle to compete with the multitude of stimuli vying for learners' attention. The levels of disengagement and superficial understanding are critical.

Immersive learning environments, however, create a focused and interactive context that minimizes external distractions. By fully engaging learners in realistic scenarios and tasks, immersive learning holds their attention through active participation and emotional involvement. The sense of presence in these environments not only captures their focus but also sustains it over longer periods, counteracting the tendency for attention to waver. This heightened engagement allows learners to concentrate intensely on the subject matter, fostering better understanding and retention of knowledge. As a result, immersive learning directly addresses the challenges posed by short attention spans, offering a powerful tool to maintain learners' focus and improve overall educational outcomes.

Abadia et al. (2024), in their study on the challenges of adopting immersive virtual reality (IVR) in online learning, support the previously mentioned findings on immersive learning. Moreover, their research underscores the critical role of educators, as their data demonstrate that while IVR enhances online engagement and social skills, it is limited by the absence of guiding learning theories.

4.2. Challenges

Despite its advantages, immersive learning faces several challenges. Among these, you will encounter with high costs of implementation, the need for advanced technological infrastructure, and gaps in digital literacy on the side of educators as well as students. All these aspects can create significant barriers, particularly in under-resourced settings. Ethical concerns also arise, including data privacy risks and potential biases in AI-driven systems. It may impact equitable access and fair outcomes. Addressing these issues is essential to fully realize the potential of immersive learning.

5. DISCUSSION AND IMPLICATIONS

5.1. Pedagogical Implications

Educators play a crucial role in effectively incorporating immersive learning techniques into their teaching practices and learning scenarios. To succeed, they must redesign study materials to suit immersive learning environments, embrace innovation with confidence, and critically evaluate the advantages and disadvantages of these approaches. Additionally, it is essential for educators to take timely corrective actions to address any emerging challenges. A comprehensive, step-by-step framework for adopting immersive learning techniques is outlined in Chapter 2 of this article.

5.2. Future Research Directions

The conceptual study presented here highlights the need for future research to explore the long-term impacts of immersive learning on educational outcomes, including knowledge retention, skill development, and learner motivation. Additionally, studies assessing the effectiveness of specific immersive technologies, such as virtual reality or augmented reality, across diverse educational contexts would also provide valuable insights. Another related research area involves investigating how NATs can be customized to address individual learning needs and foster inclusivity, making it a critical topic for further exploration.

5.3. Broader Implications

Immersive learning significantly enhances university students' outcomes by equipping them with practical skills and fostering their adaptability in dynamic work environments through immersive learning scenarios. By bridging the gap between theoretical knowledge and real-world application, they have a much better chance to prepare learners to handle complex tasks with confidence, compared to traditional teaching methods. Additionally, immersive learning fosters lifelong learning by cultivating a positive attitude toward learning itself. It conveys a clear message that learning can be engaging, personalized, adaptable to diverse preferences, and supportive of continuous skill development. All these aspects are crucial for a rapidly evolving global knowledge economy.

Beyond education, immersive learning reduces geographical and accessibility barriers, promoting equitable opportunities worldwide. It also transforms corporate training by emphasizing experiential methods to boost performance and satisfaction. Furthermore, its adoption drives innovation in educational technology, inspiring educators to use advanced tools to enhance learning across sectors.

CONCLUSION

This study aimed to explore how AI-driven immersive learning can help educators address the challenges arising from teaching digitally native students while simultaneously proposing educational strategies for tertiary education institutions, specifically colleges and universities. By integrating theoretical insights with practical frameworks, the findings provide a comprehensive roadmap for advancing education to meet contemporary challenges

This study explored two central research questions. In response to RQ1—*'What are the key components of AI-driven immersive learning that enhance student engagement and understanding in tertiary education?'*—the study identified three pivotal components: *engagement, interactivity, and hyper-personalization,* as outlined in the proposed Immersive Learning Framework. Each of these components fosters improved focus and retention by leveraging tools such as gamification, AI-based adaptive learning, and collaborative VR spaces.

Addressing RQ2—*'How can tertiary education institutions design and implement immersive learning environments using New Age Technologies?'*—the study proposed a systematic guidance with steps including readiness assessment, objective alignment, technology selection, and iterative evaluation. By following this approach, institutions can effectively integrate NATs into their curricula.

Without profound changes in instructional design and teaching methods, the appeal of traditional university education may continue to decline, as specialized micro-certificates increasingly offer young people the opportunity to acquire targeted skills and knowledge in a shorter time frame, leading to equally well-paid jobs and interesting careers. As preferences shift, higher education must adapt to remain relevant in a rapidly evolving world.

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COMPARING HUMAN AND AI-BASED ESSAY EVALUATION IN THE CZECH HIGHER EDUCATION: CHALLENGES AND LIMITATIONS

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Abstract: Generative artificial intelligence (GenAI) tools offer innovative capabilities for addressing a wide array of tasks involving extensive datasets, both textual and non-textual. These tools have shown remarkable potential in the field of education, where their functionalities are increasingly leveraged not only by students but also by educators. This study investigates the extent to which human evaluator assessments align with automated evaluations conducted by large language models, with a focus on a) the complexity of the evaluated texts (academic essays that encompass literature reviews, critical assessments of sources, and reflective insights within the context of societal or economic practices) and b) the unique challenges posed by the Czech language, in which the evaluated works are submitted. The research adopts a quantitative (cross-sectional) approach, analysing 30 essays submitted as an assignment for a foundational theoretical course at the master's level. These essays were evaluated by a human evaluator and subsequently by virtual assistants utilizing large language models, specifically ChatGPT (paid version 4.0) and Claude (paid version Sonet 3.5). Statistical analysis revealed that there is a significant statistical difference between human evaluator and both automated systems. Moreover, the evaluations were not consistent when distinguishing between good and less good essays. We also discussed challenges and limitations of using GenAI tools for evaluating submitted text assignments in the context of tertiary education.

Keywords: Automated essay evaluation, generative AI, ChatGPT, tertiary education

JEL Classification: I23

INTRODUCTION

In recent years, advancements in machine learning, natural language processing, and image recognition (often confused with developments in artificial intelligence) have increasingly impacted various human activities, with the potential to fundamentally transform or even render certain tasks obsolete. This trend has not bypassed the domain of (tertiary) education (Lodge et al., 2023; Lye & Lim, 2024). Tools based on large language models (LLMs) are employed (with varying outcomes and ethical implications) not only by students in completing their assignments (Nugroho et al., 2024; Sweeney, 2023; Tossell et al., 2024) but also by educators. For teachers, these tools offer significant assistance in course design, enhancing learning experiences, predicting performance or satisfaction, recommending resources, and more (An et al., 2023; Ouyang et al., 2022). Moreover, these tools play a crucial role in automated scoring (Barrot, 2024; Xu et al., 2024), even in the context of international large-scale assessments involving multilingual student responses (Jung et al., 2024). Automated evaluation can then be a response to the differing results of evaluators with varying levels of experience (Powers et al., 2015). However, the efficacy and reliability of automated evaluation, especially in the assessment of complex works such as academic essays — where even human evaluators often disagree — remain subjects of ongoing debate (Bui & Barrot, 2024; Vo et al., 2023).

Automated scoring systems, despite significant recent advancements, still face considerable challenges. These systems tend to focus more on formal attributes of the assessed text such as grammar, vocabulary, and other linguistic dimensions, while often overlooking truly critical aspects such as cohesion, creativity, imagination, reasoning, and or idea development and structure (Ramesh & Sanampudi, 2022). Unlike automated systems, human evaluators can identify subtle nuances that machines might miss, leading to a more refined understanding of content. Additional limitations stem from the nature of the tools themselves, often operated as cloud-based applications without direct control by the institution or evaluator. Variations between different versions of these tools, which can yield dramatically different results, further impact the reliability of evaluations. Notably, there are significant differences between paid and free versions of these tools (Song et al., 2024). The outputs of these tools are also highly dependent on the prompts (with even highly experienced evaluators potentially being poor at prompting the evaluation system), the formulation and detail of the assessment rubrics, and potential biases in the training data or in previously evaluated works (Bui & Barrot, 2024; Xu et al., 2024).

A further significant challenge in automated scoring of student works is the national or linguistic context. Although large language models are typically trained on multilingual corpora, English often dominates the source data. The performance of LLMs (not just in automated scoring) can thus vary depending on the language in which the assignment is conducted. While some studies suggest that language might not significantly impact scoring model outputs, this presumption is contingent on a sufficiently large training dataset (Okubo et al., 2023). Other studies indicate that "automated systems could be used to consistently and accurately score essays written in multiple languages" (Firoozi et al., 2024), though agreement with human evaluators typically ranges between 0.7 and 0.8. Further approaches involving automated translation achieve good results (Jung et al., 2024), but questions remain about the potential loss of information or changes in the nature of the text during machine translation prior to evaluation.

To address the question of to what extent automated scoring tools can be used in the Czech tertiary education environment, this study investigates the extent to which human evaluator assessments align with automated evaluations conducted by large language models.

The context of the study is Czech eco nomic and managerial tertiary education, which, despite long-standing efforts at convergence, is characterized by several specific features compared to Anglo-Saxon business education. One of these specifics is the Czech language. This can be overcome by machine translation, but with the limitations mentioned above. While many large language models are trained on multilingual data, the size and significance of the Czech language in these well-known LLMs are very limited relative to the entire training corpus. Another limitation is the funding of public universities in the Czech Republic, which, due to budget constraints, makes it difficult for institutions to acquire specialized automated scoring systems. This often leads to the use of general AI tools such as ChatGPT or Copilot. Additionally, Czech tertiary education is not deeply accustomed to a systematic approach to verifying learning outcomes (based on comprehensive schemes that from formulating general learning outcomes with regard to graduate profiles to specific assessment rubrics within individual course assessments), as is common in the Anglo-Saxon environment (MEYS, 2016). Evidence of this is the relatively limited number of institutions that have successfully passed international evaluations such as ACBSP or AACSB.

1. DATA AND METHODS

The aim of this study was to investigate the extent to which human evaluator assessments align with automated evaluations conducted by large language models. The research sample comprised (academic) essays submitted by students enrolled in the master's course Strategic Marketing at the Faculty of Management, Prague University of Economics and Business. This is a fundamental theoretical course that forms part of the final state examination and significantly contributes to fulfilling the faculty's graduate profile. The purpose of the assigned essay was to assess the student's ability to understand advanced marketing concepts, conduct a review of primary academic literature regarding the chosen concept, and link theoretical knowledge with practical realities to allow students to reflect on the practical implications of theoretical insights.

The essay assignment involved selecting an area in which the student would develop their work (e.g., disruptive technology, market commoditisation, customer satisfaction). The student then conducted a review of primary academic sources (a pre-selected list of prestigious academic journals in the field of marketing, either ABS 4*, 4-star rating, or Web of Science Q1) and chose a construct to work with in the essay. Examples of such constructs include technology readiness, environmental awareness, fear of missing out, post-purchase regret, among others, depending on the chosen topic.

The academic essay itself had to comprise four parts:

1. Introduction of the Construct. The first part is dedicated to explaining the choice of construct and its relation to the chosen thematic area in which the student is working.
2. Definition. The second part focuses on the definition(s) of the selected construct based on a literature review. The aim of this part is to explain what the construct means, how its conception has evolved in the literature, and (if applicable) compare how it is variously operationalised and measured in different studies.
3. Relationships to Other Constructs. The third part then focuses on the relationship of the selected construct to other constructs, phenomena, events, etc. The aim of this part is to provide an overview of what is influenced by the selected construct, or what the selected construct is influenced by, the types of research in which it appears, the respondent groups for which it has been found significant, the industries in which it is utilised, etc.
4. Validity. The fourth part is devoted to the student's own reflection on the validity of the construct for marketing practice, whether it serves or could serve to measure marketing within a company, etc. The argumentation of the student's own opinion must be supported by sources: i.e., case studies, statistics, overviews, industry and sector reports, etc.

The text is expected to be an academic essay of 7–10 pages in length (excluding the bibliography), with the bibliography containing at least ten sources (primarily high-quality academic journals). The essay is assessed according to the criteria in Tab. 1.

Tab. 1: Essay Evaluation Criteria

Criterion	Description	Points
Construct choice	• The choice of construct is explained in the essay. • The chosen construct relates to the selected topic in InSIS.	5
Definition	• Definitions of the selected construct by various authors are presented. • It is explained what the given construct means, how its conception has evolved in the literature. • A comparison is made, if applicable, of how it is operationalized differently, how it is measured in various studies, etc. • This part is based on a literature review. Cross-referencing of sources and critical evaluation of sources are conducted.	8
Relationships of the selected construct to other constructs	• It is presented what the selected construct influences. • It is presented what influences the selected construct. • Discussion of the types of research in which it appears, the respondent groups for which it has been found significant, the industries in which it is utilised, etc. • This part is based on a literature review. Cross-referencing of sources and critical evaluation of sources are conducted.	12
Validity	• It is explained how the construct is used or could be used in real marketing practice, whether it serves/could serve to measure marketing in the company, etc. • The argumentation of the student's own opinion is supported by sources: i.e., case studies, statistics, overviews, industry and sector reports, etc.	10
Sources	• At least 6 high-quality sources (see list of high-quality academic journals in marketing). • At least 10 sources in total, primarily academic articles. For part four, other sources may include industry reports, studies published by professional or analytical institutions, overviews, annual reports, statistics. • All sources are cited in the text. • All sources are listed in the bibliography.	8
Formal requirements	• Compliance with the provided template. • Logical structure and coherence of individual parts of the document. • Ability to express ideas clearly and describe examined phenomena or events comprehensibly.	7
Total		50

Source: course syllabus

Students submit the essay at the end of the semester. The analysis included essays prepared by students in the part-time (combined) form of study. The submitted works were in the Czech language. A total of 15 randomly selected essays from the group of above-average essays and 15 randomly selected essays from the group of the lowest-scoring essays in the given semester (Fall semester 2023–2024) were included in the analysis. Scoring of selected essays ranged from 0 to 50 points.

The human evaluator's assessments were obtained from the faculty's information system. The automated evaluations were conducted as follows: the LLM systems used were ChatGPT in the paid version 4.0 and Claude 3.5 Sonet, also in the paid version. For the purposes of evaluation in ChatGPT, a specific ChatGPT Assistant was created; while in Claude, a standard chat was used. The prompt was identical for both platforms and was based on recommendations published on 9 May 2024 by Harvard Business Publishing (Mollick & Mollick, 2024) and a document by Adam Peruta (Peruta, 2024).

The evaluation and comparison of all assessments involved comparing the point scores obtained by both methods, specifically assessing whether the human and machine evaluations agreed on the categorisation of essays into pass/fail groups.

2. RESULTS

Descriptive characteristics of the dataset are summarised in Table 1. The evaluations of individual essays are summarised in Figure 1. Figure 2 visually displays the similarity between the evaluations by the human evaluator, ChatGPT, and Claude. Outliers at the zero level in the case of the human evaluator reflect the assessment of detected plagiarism. In these instances, LLMs were unable to detect plagiarism and therefore evaluated the essays as original works.

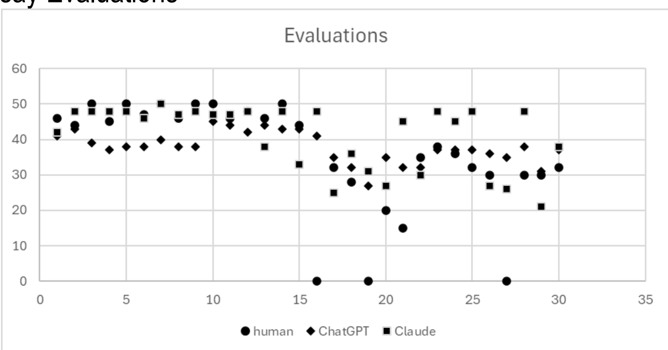
Tab. 2: Descriptive Statistics

	Human	ChatGPT	Claude
Mean	36,67	37,83	40,97
Median	41	38,00	46,50
Variance	236,44	18,90	82,31
Minimum	0	27,00	21
Maximum	50	45,00	50
Interquartile Range	17,25	6,25	15,50
Percentile 25	30,00	35,00	32,50
Percentile 50	41,00	38,00	46,50
Percentile 75	47,25	41,25	48,00

Source: own elaboration

Figure 1 and Figure 2 show that the human evaluator utilised a much broader range of the scoring scale (0–50). Additionally, several instances of plagiarism were detected and were assigned a score of zero. Despite both LLMs being initiated with the same prompt, their results differed. Besides numerical scores, these models also provided verbal feedback on various aspects of the evaluated essays.

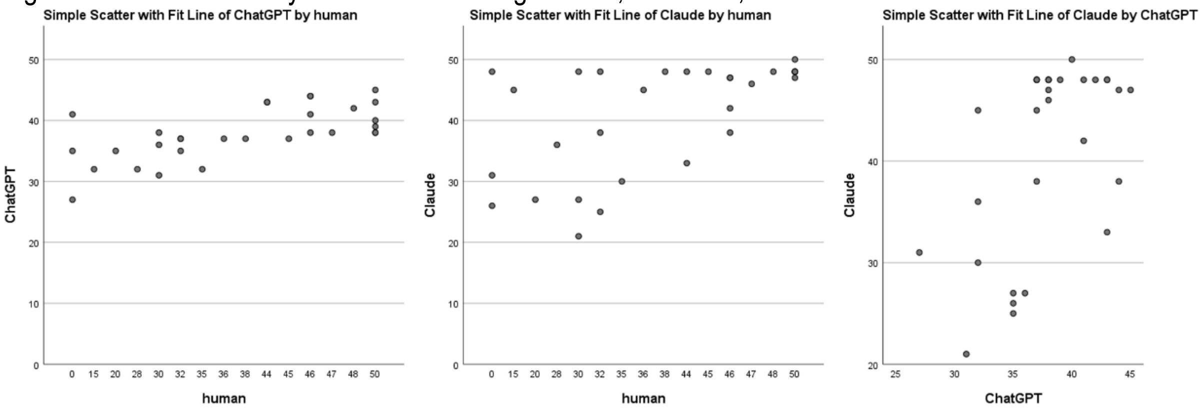
Fig. 1 Comparison of Essay Evaluations



Source: own elaboration

https://doi.org/10.24132/jbt.2024.14.2.25_34

Fig. 2 Similarities in Essay Evaluations Among Human, ChatGPT, and Claude



Source: own elaboration

Generally, ChatGPT offered much more positive verbal feedback. This feedback was also more general and, although it essentially reflected the quality of the work, it did not provide specific guidance for further improvement. For example:

> **ChatGPT (Essay 12), total score 42/50 points:**
> *"The definition of the construct is carefully elaborated and supported by academic sources. Various definitions and methods of operationalisation have been presented, indicating a good literature review. Critical analysis could be expanded with a deeper comparison of how different authors approach the operationalisation of this construct."*
>
> **ChatGPT (Essay 28), total score 31/50 points:**
> *"The essay provides a quality overview of definitions and the historical development of the concept of international segmentation. The author cites key academic sources and shows various approaches to the operationalisation of the construct. However, it would be appropriate to further develop a critical comparison of different segmentation methods and analyse their practical use in specific industries."*

In contrast, Claude was better at identifying shortcomings in individual aspects and reflected them both in the unstructured commentary and in the point evaluation.

> **Claude (Essay 12), total score 48/50 points**:
> *"The essay provides a comprehensive overview of the development of the construct's definition. The author presents various definitions and perspectives on the construct from different authors. The evolution of the construct's conception in the literature is very well described, including changes in its perception. The author critically evaluates different approaches to defining the construct."*
>
> **Claude (Essay 28), total score 21/50 points:**
> *"The essay provides a general overview of distribution channels but does not meet the main requirement of the assignment, which is to focus on a specific, well-defined construct in the field of marketing. This significantly affects the evaluation across all main criteria. The work contains useful information on various aspects of distribution channels but lacks the depth and academic rigour expected at this level of study. The insufficient focus on a specific construct means that the essay could not provide a detailed analysis of definitions, relationships to other constructs, and validity for marketing practice."*

The first hypothesis posits that there is no significant difference between the evaluations of the individual evaluators. To test this hypothesis, Kendall's W metric was utilised. Kendall's W (or Kendall's coefficient of concordance) is not sensitive to violations of the normality assumption and allows for assessing inter-rater reliability when more than two raters are involved. The coefficient ranges from 0 (no agreement) to 1 (complete agreement) and serves as an effect size measure for the Friedman test (Privitera, 2023). The Friedman test did not reveal statistically significant differences between the evaluations of the three evaluators, $\chi^2(2)=4.949$, $p=0.084$, with Kendall's $W = 0.082$, suggesting no significant agreement among evaluations. Human evaluation, ChatGPT, and Claude LLMs do not show a statistically significant level of concordance.

Tab. 2: Pairwise Comparison of Evaluations

	ChatGPT	**Claude**	**Human**
ChatGPT		0.391** (p=0.005)	0.532** (p=0.000)
Claude	0.391** (p=0.005)		0.448** (p=0.001)
Human	0.532** (p=0.000)	0.448** (p=0.001)	

*Note: **. Correlation is significant at the 0.01 level (2-tailed).* *Source: own elaboration*

Further analysis focused on pairwise comparison of evaluations. For this purpose, correlation analysis using Kendall's tau was employed. Kendall's tau is more suitable than Spearman's correlation coefficient because it is less sensitive to small sample sizes and outliers. As shown in Table 2, there is a statistically significant moderate positive correlation between the human evaluation and ChatGPT ($\tau b = 0.532$, $p = 0.000$), and similarly between the human evaluation and Claude ($\tau b = 0.448$, $p = 0.001$). Therefore, while substantial differences existed among the evaluations, pairwise comparisons with the human evaluator indicated a moderately strong, statistically significant relationship with the automated scoring using LLMs ChatGPT and Claude. The differences may have been primarily due to the fact that the automated scoring systems were unable to detect plagiarism in the essays and therefore evaluated the manuscripts as original texts. The human evaluator then attempted to assess the plagiarised essays similarly to original authored texts.

Tab. 3: Pairwise Comparison of Evaluations Without Considering Plagiarism

	ChatGPT	**Claude**	**Human**
ChatGPT		0.391** (p=0.005)	0.560** (p=0.000)
Claude	0.391** (p=0.005)		0.518** (p=0.000)
Human	0.560** (p=0.000)	0.518** (p=0.000)	

*Note: **. Correlation is significant at the 0.01 level (2-tailed).* *Source: own elaboration*

As shown in Table 3, when unethical behaviour by students in writing the essays was not considered, there was a statistically significant moderate positive correlation between the human evaluation and ChatGPT ($\tau b = 0.560$, $p = 0.000$), and similarly between the human evaluation and Claude ($\tau b = 0.518$, $p = 0.000$). Although the correlations between the evaluations are significant, fundamental differences still exist between the assessments by the human evaluator and the automated scoring systems utilising the most commonly used LLMs. In many cases, however, when evaluating complex texts, the focus is not so much on assigning a specific point value as on categorising the works into good and poor (i.e., passed/failed, or a more detailed classification into multiple groups).

The final part of the analysis focused on comparing whether the different approaches could at least similarly categorise the essays as good/poor (according to the point evaluation, without considering plagiarism). See Tables 4 and 5 for more details. For the comparison between the human evaluator and Claude, both sensitivity and specificity are 0.67. For the human evaluator and ChatGPT, sensitivity and specificity are both 0.76. Thus, both models can correctly categorise (assuming the human evaluator's assessment is "correct") approximately two-thirds to three-quarters of the evaluated cases.

Tab. 4: Comparison of Categorisation Between Human Evaluator and Claude

		Human	
		Good	Bad
Claude	Good	12	3
	Bad	3	12

Source: own elaboration

Tab. 5: Comparison of Categorisation Between Human Evaluator and ChatGPT

		Human	
		Good	Bad
ChatGPT	Good	13	2
	Bad	2	13

Source: own elaboration

3. DISCUSSION

This study explored the extent to which automated scoring tools can be utilised within the context of Czech tertiary education, specifically by examining the alignment between human evaluator assessments and automated evaluations conducted by LLMs such as ChatGPT and Claude. The results indicate that (despite considerable enthusiasm and high expectations generated by the advent of LLMs among students and, to a lesser extent, educators) commonly available LLMs are only marginally capable of providing reliable and balanced automated scoring, especially when evaluating complex tasks such as essays. Our empirical evidence demonstrates a significant discrepancy between the scoring provided by AI tools (Claude, paid version 3.5 Sonet, and ChatGPT, paid version 4.0) and that of an experienced human evaluator, coupled with a lack of internal consistency in the AI's scoring methodology. These findings corroborate the results of other studies (e.g. Bui & Barrot, 2024; Guo & Wang, 2024; Klyshbekova & Abbott, 2024; Schmidt-Fajlik, 2023; Shin & Lee, 2024). However, contrary to some prior research (Almusharraf & Alotaibi, 2023), our models did not exhibit a tendency to assign lower scores compared to the human evaluator: instead, their scores were generally higher, and the models were less critical in their evaluations.

Several factors may have contributed to these outcomes. One significant consideration is the quality of the input prompt used for automatic evaluation. Prompt engineering is emerging as a demanding discipline, and educators typically lack the necessary competencies and experience in this area. In addition to other aspects (such as access to paid versions of LLMs), the setting of parameters, over which regular users have limited control through standard web interfaces (e.g., temperature settings), also plays a crucial role (Tang et al., 2024).

Another important factor is the quality and specificity of the assignment instructions and evaluation criteria. Human evaluators may perceive and interpret these differently, potentially incorporating contextual knowledge or long-term experience that is not explicitly part of the assignment. In the Czech context, universities are often not accustomed to the explicit formulation of learning outcomes, including detailed decomposition down to individual subjects, components of evaluation, and the formulation of rubrics that distinguish between levels of achievement of learning outcomes.

The training datasets on which LLMs are based also influence their performance. While these models are often trained on extensive corpora obtained through web scraping, the majority of this data is in English or other widely used languages. Consequently, less commonly used languages like Czech are underrepresented in these corpora, potentially affecting the models' ability to accurately process and evaluate texts in these languages. Although some studies suggest that LLMs may possess capabilities for more exhaustive error detection and can simultaneously evaluate multiple facets of written composition (Bui & Barrot, 2024), it often occurs that these systems focus more on formal attributes of the assessed text (such

as grammar, vocabulary, and other linguistic dimensions) and may overlook critical aspects like cohesion, creativity, imagination, reasoning, or idea development and structure (Ramesh & Sanampudi, 2022).
Another factor contributing to the observed discrepancies is the continuous development and evolution of LLMs. Ongoing changes in algorithms, data storage, representation methods, and the addition of training data and retraining of models can lead to variations in performance. Furthermore, the complex nature of LLMs can introduce instability and randomness, with identical prompts entered at similar times but in different instances of the model potentially yielding significantly different results (Ray, 2023).
Despite the expectations that may arise from limited experience with LLMs on straightforward tasks requiring mainly encyclopaedic knowledge, our study highlights shortcomings when these models are applied to truly complex tasks that demand consistency and reliability in evaluating individual inputs or even in repeated evaluations of the same input.

CONCLUSION

Our study confirms that the use of automated scoring systems based on widely available LLMs—even in their paid versions—still has significant limitations and that these systems do not provide evaluations sufficiently consistent with those of human evaluators. Additionally, inconsistencies emerge between individual models, as well as between different instances or runs within the same model. Randomness and inconsistency in LLM outputs can cause significant problems in the acceptance of such results by students and raise questions regarding the accountability of automated evaluations. This does not imply that automated scoring systems are without utility in essay evaluation. They can assist in automating or expediting a range of supplementary activities. However, to become truly valid assistive technologies, further development and research are necessary. This includes the creation and training of models tailored to specific contexts, as well as the development of educators' competencies to fully exploit the opportunities presented by LLMs. Importantly, it should also involve educating students on the ethical and responsible use of LLMs.

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HOW GENERATIVE AI AUTONOMOUS AGENTS SHAPE THE CURRENT BUSINESS TRENDS AND SMART LEARNING

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Abstract: This paper explores the transformative impact of generative AI autonomous agents on current business trends and smart learning. It examines how these agents are reshaping industries by automating decision-making, optimizing processes, and enhancing customer experiences. Several use cases from marketing, accounting, regulations, financial analysis and business intelligence will be presented. In the context of smart learning, the paper highlights the role of GenAI agents in creating personalized educational environments, enabling adaptive learning, and facilitating content creation. By analyzing key developments and case studies, this paper illustrates the potential of GenAI to drive innovation, streamline operations, and foster intelligent learning systems across sectors.

Keywords: Generative AI autonomous agents, business trends, smart learning, business intelligence, AI-driven Innovation

JEL Classification: O33, L89

INTRODUCTION

The rise of generative artificial intelligence (AI) and autonomous agents is reshaping the landscape of modern business. These technologies are not only enhancing operational efficiency but also driving innovation and creating new business models. This paper explores how generative AI (GenAI) autonomous agents are influencing current business trends, highlighting their applications, benefits, and future potential. In recent months we observe an enormous increase in deployment of GenAI autonomous agents in different businesses, see for example review papers (Amankwah-Amoah et al., 2024), (Bahoo et al., 2024), (Brühl, 2024), (Hanyao et al., 2024), (Veluru, 2024), (Xu et al., 2024). All papers explore how AI, particularly GenAI, is transforming various industries, with a focus on operational efficiencies, decision-making, and future research opportunities. They also share concerns about ethical and practical challenges. Although there is a certain commonality among them, each paper stands out based on its industry focus (e-commerce, finance, social media), specific AI applications (recommender systems, supply chain, financial risk), and methodological approach (bibliometric analysis, economic potential, operational integration challenges). Each provides unique insights relevant to its specific field of study, offering tailored perspectives on AI's impact.

The structure of the paper is as follows. In Section 1 we introduce GenAI autonomous agents and their key components. Key business applications will follow in Section 2 with business use cases in Section 3 and smart learning use cases in Section 4.

1. GENERATIVE AI AUTONOMOUS AGENTS – WHAT ARE THEY?

GenAI refers to algorithms that can generate new content, including text, images, and audio, based on input data. Autonomous agents are systems that can perform tasks independently, learning from their environment and making decisions without human intervention. Together, they form a powerful combination that transforms traditional business processes.

Russell and Norvig (2021) classify agents with respect to their degree of perceived intelligence and capability to simple reflex agents, model-based reflex agents, goal-based agents, utility-based agents and learning agents. Another classification by (Weiss, 2013) distinguishes four classes of agents: logic-based agents, reactive agents, belief-desire-intention agents and layered architectures.

Based on the functionality of GenAI autonomous agents, their interaction with the environment, learning capabilities, and architecture, we find the following characteristics more suitable from the practical point of view. We present them tohether with a schematic explanation for each type.

1. **Rule-based Agents** rely on predefined rules and logic to generate responses or take actions. They do not learn from past experiences but instead follow if-then-else rules. Typical examples are chatbots that use decision trees or static templates to generate responses.
2. **Supervised Learning-based Agents** use a dataset with labeled examples to learn the relationship between inputs and outputs. During deployment, they use this learned mapping to generate responses or actions. However, they typically do not adapt or improve after deployment. They can be found for example in image captioning models trained on large, labeled datasets.
3. **Unsupervised Learning-based Agents** do not require labeled data and learn to generate responses or actions by identifying patterns or structures within the input data. The model tries to group data based on similarities. Advanced examples include Generative Adversarial Networks (GANs) for image generation, where the agent learns to produce realistic images based on unstructured data.
4. **Reinforcement Learning-based Agents** learn by interacting with an environment, receiving feedback through rewards or penalties for actions taken. They improve their decision-making over time by maximizing cumulative rewards. For example, autonomous agents in games (e.g., Monopoly) that learn through playing against themselves or others.
5. **Hybrid Agents** (Multi-modal) combine multiple types of learning techniques (e.g., supervised, unsupervised, and reinforcement learning) or modalities (e.g., text, images, speech) to enhance their generative capabilities. They are often employed in complex environments requiring adaptation and multi-tasking. For example, autonomous driving agents that use both sensor data (vision) and reinforcement learning to navigate and make decisions.
6. **Autonomous GenAI Agents** are designed to autonomously generate novel outputs or perform actions in complex environments without direct human intervention. They often combine elements of reinforcement learning with generative models (e.g., GPT) to create content or perform tasks. These agents can interact with humans or other agents in real-time, adapting dynamically. For example, autonomous content creation systems, or conversational agents that dynamically generate text, images, or other media based on contextual inputs.

Key components in GenAI agents therefore are:

1. **Environment:** The external world where the agent operates.
2. **Agent:** The decision-making entity that interacts with the environment.
3. **Machine learning (ML) algorithm:** The technique that enables the agent to learn from data or interaction (e.g., supervised, unsupervised, or reinforcement learning). In particular deep learning (DL) as a significant subset of ML methods utilize (deep) neural networks for representation learning.

4. **Policy:** The strategy an agent uses to decide its next action based on the current state.
5. **Reward function:** Used in reinforcement learning to evaluate the success of an action.
6. **Generative model:** A model that produces novel data (e.g., images, text) by learning the underlying patterns in the training data.

Each class of agents can be applied to various domains, including natural language processing, image generation, robotics, and virtual environments. In the following, we focus on their applications in business and smart learning.

2. KEY BUSINESS APPLICATIONS

GenAI autonomous agents are at the forefront of transforming business practices across industries. Their ability to enhance efficiency, drive innovation, and create new revenue opportunities positions them as essential tools for modern enterprises. As businesses continue to explore the capabilities of these technologies, those that adapt quickly will likely emerge as leaders in their respective fields. In summary, the integration of GenAI into business operations is not merely a trend but a fundamental shift that will redefine how organizations operate in the future. To demonstrate the timeliness of current trends, some of them are referrenced only as highly cited web articles rather than papers published in scientific journals, where the publication delay is not negligible.

1. **Content creation and marketing:** GenAI can create personalized marketing materials at scale, allowing businesses to engage customers effectively. For instance, it can generate tailored emails or social media content based on customer preferences, enhancing customer experience and driving sales (Jairick, 2024), (McKinsey, 2023).
2. **Customer service automation:** Autonomous agents can handle customer inquiries through chatbots or virtual assistants, providing timely responses and support. This not only improves customer satisfaction but also reduces operational costs associated with human customer service representatives (AppInventiv, 2024), (Podium, 2024).
3. **Data analysis and decision making:** These technologies can analyze vast amounts of data quickly, providing insights that inform strategic decisions. Businesses can leverage GenAI to identify market trends or customer behaviors, enabling them to adapt their strategies proactively (Cognizant, 2023).
4. **Product development:** GenAI facilitates rapid prototyping by generating design concepts or simulations based on specific parameters. This accelerates the product development cycle, allowing companies to bring innovations to market faster (Jairick, 2024), (AppInventiv, 2024).
5. **Operational efficiency:** By automating repetitive tasks such as reporting or documentation, GenAI frees up employee time for more strategic activities. This leads to significant productivity gains across various business functions (McKinsey, 2023), (Cognizant, 2023).

The economic implications of GenAI are substantial. McKinsey (McKinsey, 2023) estimates that GenAI could contribute between \$2.6 trillion to \$4.4 trillion annually across various sectors by enhancing productivity and creating new revenue streams. The technology is predicted to automate 60-70 % of tasks currently performed by employees, fundamentally changing the nature of work (McKinsey, 2023). We can observe the following trends in their adoption:

- **Rapid growth:** The market for autonomous agents is projected to grow at a compound annual growth rate (CAGR) of 42.8 %, indicating a strong demand for these technologies in the business sector (AppInventiv, 2024).
- **Integration with other technologies:** The synergy between GenAI and other emerging technologies like IoT and blockchain is expected to unlock new applications in areas such as smart cities and real-time data processing (AppInventiv, 2024), (Podium, 2024).

- **Competitive Advantage:** Early adopters of GenAI are likely to gain significant advantages over competitors by streamlining operations and enhancing customer experiences through personalization (Jairick, 2024), (Cognizant, 2023).

While the potential benefits are immense, businesses must also navigate challenges and considerations such as:

- **Ethical implications:** The use of AI raises ethical questions regarding data privacy and job displacement. Companies must develop frameworks to address these concerns responsibly (Jairick, 2024), (Cognizant, 2023).
- **Skill gaps:** As automation increases, there will be a need for workforce reskilling to ensure employees can work alongside these technologies effectively (McKinsey, 2023).
- **Implementation costs:** Initial investments in technology infrastructure may be significant, posing a barrier for smaller enterprises looking to adopt GenAI solutions (AppInventiv, 2024), (Podium, 2024).

3. BUSINESS TRENDS USE CASES

3.1. The role of GenAI agents in modern marketing

GenAI is increasingly transforming the field of marketing by enhancing efficiency, creativity, and the capacity for personalized consumer engagement. Recent advancements in ML and AI have demonstrated substantial applications within marketing, ranging from consumer behaviour analysis to the optimization of campaign strategies. GenAI, a specialized subset of these technologies, provides marketers with sophisticated tools to generate impactful content and foster meaningful consumer interactions.

Machine learning has been extensively utilized in marketing for **predicting consumer demand**, analysing behaviour, and **optimizing strategic initiatives**. Techniques such as Bayesian networks, support vector machines, and DL have been applied to model consumer responses and forecast demand (Islam et al., 2024). GenAI augments these traditional capabilities through the automation of marketing content generation, enabling firms to engage consumers with greater precision and efficacy. For instance, (Kshetri et al., 2024) discuss numerous applications of GenAI in content creation, emphasizing its contribution to productivity enhancement by automating labour-intensive marketing activities. Such techniques empower firms to **produce personalized emails, social media content, and advertising campaigns** at scale, thereby optimizing overall marketing efficiency.

A key advantage of GenAI lies in the automation of content production for digital channels. According (Islam et al., 2024) GenAI agents can leverage real-world data to generate targeted, engaging marketing content, fundamentally transforming brands' approaches to digital campaigns. By analysing extensive datasets, generative models can **emulate successful content strategies**, enhancing consumer engagement rates and expediting the creative ideation process. Vidrih and Mayahi (2023) further underscore the potential of AI-generated **storytelling**, illustrating how GenAI can craft narratives that resonate emotionally with consumers, thereby strengthening brand loyalty.

Beyond content automation, GenAI is also advancing **conversational marketing**. Israfilzade (2023) examines the deployment of anthropomorphic GenAI agents as tools for conversational marketing. These agents replicate human-like dialogues, allowing consumers to engage with brands in a more interactive and personalized manner. Such AI-driven interactions are particularly valuable for customer service, offering rapid, tailored responses to consumer inquiries. This personalized engagement can foster trust and cultivate deeper relationships between consumers and brands.

While the current applications of GenAI in marketing are promising, there is an increasing emphasis on innovation and future research directions. Cillo and Rubera (2024) outline a roadmap for leveraging GenAI to enhance innovation processes within marketing strategies. By incorporating AI into both creative and strategic decision-making processes, firms can more effectively respond to shifting consumer preferences and market dynamics, thereby gaining a competitive edge in the evolving digital landscape.

The opportunities presented by GenAI in marketing are manifold, encompassing productivity gains, enhanced personalization, and improved consumer engagement. However, significant challenges remain, including the ethical use of AI-generated content and addressing biases inherent in data. Future research, as proposed by (Kshetri et al., 2024), should address these challenges to enable organizations to effectively implement and leverage GenAI technologies. By focusing on ethical frameworks and best practices, marketers can fully exploit the potential of GenAI while maintaining consumer trust.

3.2. The transformative role of GenAI in accounting

The integration of GenAI into the accounting domain represents a significant paradigm shift, promising to revolutionize traditional workflows and enhance the roles and competencies of accounting professionals. The existing literature underscores the diverse mechanisms through which GenAI is redefining accounting tasks, facilitating efficiency improvements, informed decision-making, and the reallocation of human resources to more strategic endeavors.

GenAI provides considerable opportunities for augmenting productivity within accounting by automating routine, labor-intensive tasks. For example, IBM's research highlights the efficacy of AI technologies in streamlining **financial analytics, audit preparation, and regulatory compliance** (see also individual sections below), thereby enabling accountants to redirect their focus toward strategic activities, such as high-level financial planning (IBM, 2023). Likewise, Evolution AI's insights illustrate the successful deployment of GenAI in automating intricate financial processes, including **loan underwriting, data extraction, and compliance verification** (Evolution.ai, 2024). Such applications significantly curtail the time and effort accountants expend on repetitive tasks, thereby facilitating the delivery of value-added advisory services.

Furthermore, GenAI addresses **inherent structural challenges within the accounting profession itself**, including staffing shortages and heightened burnout rates. Anica-Popa's framework for GenAI integration suggests that AI can play an instrumental role in alleviating these challenges by reshaping the skill set demanded of accounting professionals and automating routine aspects of their work (Anica-Popa et al., 2024). Similarly, a report (Andrusko & Amble, 2024) underscores the potential of AI to mitigate staffing constraints, noting that automation enhances operational efficiency with reduced human intervention, thereby alleviating the burden on practitioners.

In practice, prominent accounting firms are increasingly incorporating AI tools to advance their service offerings. The Master of Code blog (Sergiienko, 2024) delineates several use cases, such as tax preparation, fraud detection, and audit automation, that exemplify the tangible benefits of GenAI. Firms such as Deloitte and PwC have adopted these technologies, recognizing their critical role in increasing efficiency and sustaining competitive advantage. Concurrently, BCG (Demyttenaere et al., 2023) explores how the integration of conventional AI with generative models can optimize processes such as **contract drafting** and **invoice management**, thereby enhancing the broader finance function.

However, despite these advantages, various publications also highlight the challenges and risks associated with AI adoption. The Wolters Kluwer eBook (Miller, 2024) raises pertinent concerns regarding the regulatory and ethical ramifications of deploying AI in accounting, particularly in areas such as client confidentiality and regulatory compliance. It is therefore important to emphasize that accounting professionals must be aware of GenAI's limitations and be careful to follow relevant regulations.

3.3. GenAI agents in credit risk management

The deployment of GenAI in credit risk management is fundamentally transforming the methodologies through which financial institutions evaluate and manage credit risks. Recent trends underscore GenAI's capacity to substantially augment the efficiency, precision, and equity of credit risk models, thereby presenting novel opportunities across the credit life cycle, from client engagement to portfolio oversight.

A principal advantage of GenAI is its role in **refining the modeling of critical credit risk parameters**, including probability of default (PD), loss given default (LGD), and exposure at default (EAD). As expressed by (Folpmers, 2023), GenAI's capabilities in advancing coding methodologies render PD, LGD, and EAD models more precise and well-calibrated. By leveraging diverse datasets and uncovering intricate relationships among variables influencing credit risk, GenAI facilitates a more profound comprehension of a borrower's creditworthiness, thereby enhancing predictive accuracy. Moreover, GenAI **strengthens stress testing** by generating an extensive array of adverse scenarios, equipping financial institutions to anticipate and mitigate a broader spectrum of potential risks.
Another critical contribution of GenAI is its ability to **enhance model validation and data integrity**. As elucidated by (Yusof & Roslan, 2023), GenAI can produce synthetic data for validation purposes, thereby bolstering the robustness of risk models while mitigating challenges such as modeling bias. The utilization of synthetic data also supports the development of more balanced datasets, yielding a more accurate portrayal of default and non-default occurrences, which is pivotal for informed decision-making in credit risk management. Furthermore, GenAI is instrumental in **detecting data quality anomalies** and **identifying outliers**, thereby contributing to the reliability and resilience of credit risk models.
GenAI is increasingly integral to credit decision-making and client engagement processes. The report (McKinsey, 2024) details various applications of GenAI throughout the credit life cycle, including personalized product offerings, streamlined credit underwriting, and advanced portfolio monitoring. By synthesizing a wide array of data in real time, AI can facilitate more nuanced assessments of creditworthiness and deliver tailored solutions that align with clients' needs, while ensuring that risk exposure remains within established thresholds.
However, despite the considerable benefits GenAI offers to credit risk management, several challenges warrant attention. A primary concern is data privacy, as GenAI frequently depends on extensive volumes of personal and financial data. Another pertinent issue is the assurance of fairness and transparency in AI-driven decision-making, given that generative models can inadvertently propagate biases embedded within the training data. Consequently, robust governance frameworks and the continuous surveillance of AI models are imperative to mitigate these risks and uphold regulatory compliance.

3.4. Financial analysis

The integration of GenAI agents into financial analysis represents a profound technological advancement, providing innovative solutions to some of the most persistent challenges in the financial sector (Liu & Wang, 2024). As highlighted in already mentioned BSG article (Demyttenaere et al., 2023), GenAI encompassing tools such as large language models (LLMs) is fundamentally transforming financial services by augmenting data accessibility, enhancing the quality of financial advisory, and improving decision-making paradigms. Among others this study also presents a case study about **drafting responses for investor relations calls**.
GenAI is increasingly employed to generate synthetic data, which has demonstrated substantial utility in **simulating stock markets** and other financial contexts. As noted by (Lee et al., 2024), generative models' capacity to produce high-quality synthetic data addresses critical challenges associated with data deficiency and privacy concerns. Financial analysts frequently require extensive datasets to validate hypotheses or construct predictive models, yet access to real financial data is often hindered by regulatory constraints and ethical considerations. By **generating synthetic datasets** that reflect the statistical characteristics of real data, GenAI facilitates rigorous analysis without compromising data confidentiality.
Furthermore, GenAI is transforming financial advisory services by using LLMs to deliver personalized advice to users. According to (Demyttenaere et al., 2023), the potential of LLMs **to adjust financial planning services** is particularly significant, as these models can make financial advisory services more accessible to individuals who have historically been excluded from such resources. The report underscores the ability

of LLMs to customize financial advice based on individual user profiles, thereby enhancing the personalization and pertinence of financial insights.

Nevertheless, there are significant challenges involved in deploying GenAI within financial analysis. A primary concern is the requirement for domain-specific expertise to ensure that generated insights are both accurate and contextually pertinent (Lo & Ross, 2024). Although generative models are powerful, they necessitate a nuanced comprehension of financial contexts to yield meaningful recommendations. Moreover, the trustworthiness and ethical ramifications of AI-generated advice are pressing issues. Given the sensitive nature of financial decision-making, it is imperative that AI systems conform to rigorous ethical standards and provide reliable guidance to avert misinformation and mitigate the risk of financial harm.

Regulatory oversight is another critical facet of integrating GenAI into financial analysis. As (Lo & Ross, 2024) notes, the deployment of LLMs in finance must be supported by appropriate regulatory frameworks to mitigate risks, such as biases or "hallucinations", the generation of inaccurate or fabricated information by the model. **Regulatory compliance** (implemented for example as a GenAI watchdog) is essential not only for ensuring the safety and reliability of AI applications but also for fostering user trust, which is crucial for the widespread adoption of these technologies in the financial sector.

3.5. Business intelligence analyst

GenAI is fundamentally transforming a wide array of business intelligence (BI) processes. Leveraging recent advancements in GenAI research allows for an in-depth exploration of its potential to revolutionize decision-making and optimize business operations. The potential of GenAI to drive innovation and reshape traditional business processes is extensively documented in several recent papers. Mariani and Dwivedi (2024) articulate the significant role of GenAI in fostering innovation, particularly in facilitating **new product discovery** and enhancing processes across diverse industries, including pharmaceuticals and software development. Similarly, (Feuerriegel et al., 2024) underscore GenAI's transformative capabilities, highlighting its role in streamlining business workflows and enhancing productivity. In the context of BI, GenAI agents enhance decision-making through **sophisticated data analysis, pattern recognition**, and **predictive modeling**, thereby enabling the extraction of nuanced insights from complex and unstructured datasets.

BI applications that stand to benefit significantly from GenAI include **customer segmentation, sales forecasting,** and **anomaly detection**. GenAI enables a more refined segmentation of customers by analyzing purchasing behaviors and uncovering latent trends and patterns that might elude traditional analytical methods. In sales forecasting, GenAI offers enhanced predictive accuracy by integrating historical sales data with external variables such as market dynamics and macroeconomic indicators. Furthermore, in anomaly detection, GenAI can effectively identify irregularities in financial transactions or operational workflows, serving as a robust mechanism for fraud detection and operational efficiency enhancement.

Within managerial contexts, (Baabdullah, 2024) investigated the impact of content quality produced by AI agents on managerial practices, emphasizing the critical role of ethical considerations and innovation in designing these systems. For BI analysts, GenAI serves as an invaluable asset for **generating analytical reports, identifying trends,** and **facilitating informed decision-making**, contingent upon adherence to ethical guidelines that ensure transparency and equity. This is especially pertinent in sensitive applications such as **credit scoring**, where issues of fairness and accuracy are paramount.

Credit scoring represents a domain wherein GenAI exhibits substantial promise. Mancisidor et al. (2020) introduced an innovative approach employing deep generative models for credit scoring through the so-called reject inference. Their study revealed that semi-supervised Bayesian models, by incorporating data from rejected credit applications, significantly enhance classification accuracy, outperforming conventional ML techniques. This indicates that GenAI can facilitate more comprehensive credit evaluations by leveraging a broader spectrum of data, thereby mitigating bias and promoting greater financial inclusivity.

The influence of GenAI on decision-making extends beyond technical improvements to encompass significant ethical implications. Chowdhury et al. (2024) emphasize the necessity for organizations to adopt strategic frameworks for the effective implementation of GenAI, ensuring its integration within existing business operations while adhering to ethical standards. In the realms of BI and credit scoring, this necessitates the development of AI systems that are transparent, interpretable, and equitable, thereby cultivating trust in AI-driven decision processes.

3.6. Regulations and reporting

GenAI has emerged as an indispensable instrument in regulatory compliance and reporting across diverse sectors, including finance, cybersecurity, and sustainability. This technology is particularly transformative in **meeting strict reporting requirements**, such as those stipulated among others by Markets in Financial Instruments Directive (MiFID II), Network and Information Systems (NIS2) directive, EU Data Protection Regulation (EUDPR), Environmental, Social, and Governance (ESG) regulations together with Corporate Sustainability Reporting Directive (CSRD), Non-Financial Reporting Directive (NFRD), etc. By **automating data collection** processes and enhancing data accuracy, GenAI is fundamentally altering the way organizations navigate complex regulatory landscapes.

In the domain of ESG reporting, GenAI facilitates compliance with the EU Taxonomy by automating data acquisition and delivering real-time analytical insights. As noted by (Dydon.ai, 2024), the deployment of Natural Language Processing (NLP) enables the extraction of key ESG indicators from unstructured data sources, thereby streamlining compliance mechanisms. Such automation not only reduces manual labor but also **ensures the accuracy of reporting in alignment with regulatory expectations**. Furthermore, the integration of AI within the ESG framework helps address the dynamic nature of evolving regulatory requirements, such as CSRD or NFRD, by fostering enhanced transparency and accountability in data disclosure (EIMF, 2024).

GenAI also plays an important role in investment services regulated under MiFID II. The European Securities and Markets Authority (ESMA) underscores the necessity of maintaining compliance with MiFID II when employing AI technologies in investment-related activities. GenAI agents must be utilized in a manner that ensures the precision of financial information and adherence to regulatory standards. Consequently, firms are required to adopt best practices to mitigate potential risks and biases inherent in AI-driven investment processes, thus safeguarding both investor interests and the integrity of financial markets (ESMA, 2024).

In the context of cybersecurity and data protection, GenAI is instrumental in helping organizations fulfill the mandates of frameworks such as NIS2 and the EUDPR. NIS2 promotes the adoption of AI for enhanced cybersecurity capabilities, emphasizing its potential to facilitate efficient incident detection and reporting (Allen, 2024). The European Data Protection Supervisor (EDPS) emphasizes the importance of clearly defining roles in data processing activities when utilizing AI, ensuring conformity with privacy regulations (EDPS, 2024). By responsibly integrating GenAI, organizations can meet the stringent demands of data protection legislation while leveraging cutting-edge technologies to bolster their cybersecurity infrastructures.

4. SMART LEARNING USE CASES FOR BUSINESSES

4.1. GenAI in Smart Learning: Transforming Business Education

The rapid evolution of generative artificial intelligence has precipitated substantial advancements in educational paradigms, particularly in the realm of personalized learning experiences. A Learning eXperience Platform (LXP) is an AI driven peer learning platform delivered using software as a service. LXPs provide a diverse array of content, allowing users to choose what they find most engaging and GenAI autonomous agents are their useful tutors and assistants.

Businesses are increasingly acknowledging the strategic potential of GenAI to cultivate a culture of continuous learning, thereby enabling their transition into dynamic learning organizations. By leveraging GenAI, companies can deliver highly customized learning and development experiences tailored to the heterogeneous needs of their workforce. This section examines several use cases of GenAI within smart learning frameworks in business environments, highlighting its role in augmenting adaptability, fostering engagement, and enhancing overall learning efficiency.

A key application of GenAI in smart learning is the **development of customized training content for employees**. Binhammad et al. (2024) elucidates that GenAI possesses the capability to analyze individual learning styles, performance metrics, and engagement data to create bespoke educational materials. Within a business context, this translates to training modules that align with the specific needs and preferences of each employee, thereby enhancing both motivation and efficacy. For instance, an employee with a preference for visual learning can be provided with instructional videos or infographics, while another who thrives through hands-on practice may be offered interactive simulations. Such a personalized approach ensures sustained engagement and optimal knowledge retention, ultimately fostering employee proficiency.

Another prominent use case for GenAI in smart learning lies **in adaptive assessments**. As articulated in a perspective article by (Arslan et al., 2024), GenAI can facilitate the creation of personalized assessments that are dynamically adjusted to reflect an individual's learning trajectory. In corporate settings, this enables organizations to appraise employee skills and knowledge with greater nuance, thereby deriving actionable insights for targeted development. For example, an adaptive assessment can pinpoint areas where an employee may need additional support, prompting the provision of focused training resources to address identified deficiencies. Such an approach not only enhances learning outcomes but also ensures that employees maintain confidence and competence in their professional roles.

GenAI also plays a critical role in the development of **immersive learning experiences** for corporate training (Guettala et al., 2024) underscores the capacity of GenAI to elevate engagement through the creation of interactive and dynamic learning environments. In a corporate context, this might involve employing AI to generate realistic scenarios in which employees can hone their skills within a safe and controlled framework. For instance, sales teams may utilize AI-driven simulations to practice negotiation techniques or customer interactions, enabling them to refine their capabilities prior to real-world implementation. Such immersive experiences render learning more compelling and effective, thereby contributing to an organization's overall success.

Furthermore, GenAI has the potential to assist businesses in **transitioning towards becoming learning organizations** by fostering a culture of continuous improvement. The study on (Pesovski et al., 2024) posits that AI-driven personalization can significantly enhance engagement and satisfaction by providing content that is directly aligned with individual career aspirations. In a corporate environment, this translates into increased employee participation in lifelong learning initiatives, as they perceive tangible benefits from these personalized learning experiences for their professional growth. This shift towards an ethos of continuous learning equips businesses to remain agile and competitive in an increasingly dynamic market landscape.

CONCLUSION

In this short review paper, we focused on using GenAI autonomous agents in businesses by presenting general concepts and several important use cases from marketing, accounting, credit risk management, financial analysis, business intelligence and regulatory. To keep the text reasonably short, many other areas were not covered, such as corporate law, assistance to movable property and real estate, security, transportation, logistics and supply chain and probably many other areas. **With a certain degree of exaggeration, we can predict that, sooner or later, GenAI agents will find their way into every business**.

Speaking about smart learning within business environments, GenAI presents substantial opportunities for advancing. Through the provision of personalized training content, adaptive assessments, and immersive learning experiences, AI can facilitate the cultivation of a culture of continuous learning and adaptability. The effective deployment of these technologies not only yields benefits for individual employees but also bolsters the organization's growth and competitiveness, **ultimately enabling businesses to thrive as learning organizations.**

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OPEN REGIONAL DATA AND THE USE OF AI

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Abstract: This paper focuses on the topic of open data in public administration, specifically in a higher territorial self-government unit such as the Hradec Králové Region. It also describes the cooperation of the Hradec Králové Region as a public administration entity with the University of Hradec Králové in the field of research activities for open data and practical use through the application of artificial intelligence. The result of this cooperation was awarded the highest possible recognition by the expert community by winning the IT Project of the Year 2023 Award. The paper describes the process of cataloguing open data at the higher self-government units. Open data is centrally stored in a local open data catalogue according to the recommended rules of open formal standards. The local open data catalogue of this unit is part of the data portal of the region, which is a central information point for the public. Open data sets must be registered in the National Open Data Catalogue. One of the practical uses of open data is to implement applications for the public, as has been done with a research application using AI. An added bonus with this application is the practical use of AI for users. The design of the app was implemented during a hackathon by students of the University of Hradec Králové. Also, the quality of the open data of the Hradec Králové Region, over which this application is implemented, has been awarded the highest prizes by the expert community not only in the Czech Republic but also in Europe. The project of the Data Portal of the Hradec Králové Region was placed by the Organization for Economic Co-operation and Development (OECD) in the international catalogue of case studies of the Observatory of Public Sector Innovation (OPSI).

Keywords: Open data, maps, data portal, hackathon, artificial intelligence

JEL Classification: I28, J1, M1, O36, O38

INTRODUCTION

The paper focuses on the topic of open data in public administration, which has become a phenomenon of our time. Open data ensures transparency of public administration entities, innovative data sharing for citizens, their ability to participate in public affairs. They are a fundamental pillar for the implementation of new applications that serve the general public, such as a map of public transport stops or the state of a region's road surface. A current innovative trend among regions is the placement of open data datasets in local catalogues that are part of regional data portals. The data portals are thus a central information point for the public, where data from internal regional data sources and external data sources, publicly available, are visualized. Hackathons are used to determine the quality of open data processing. These are competitions to design and develop applications using open data. During hackathons, entirely new, timeless application designs are created that take advantage of new trends and challenges, such as the use of artificial intelligence (AI). Whether it is possible to leverage this innovative trend within open data in practice and make working with large open data sets more efficient, especially for developers and data analysts, is the focus of this paper. It is possible to find out how innovation can be implemented with minimum cost and maximum performance, to develop research with application in practice on a large scale of positive impact, including effective dissemination of awareness, relevance and usefulness of the whole area of open data in public administration not only in the Czech Republic but also abroad.

1. OPEN DATA

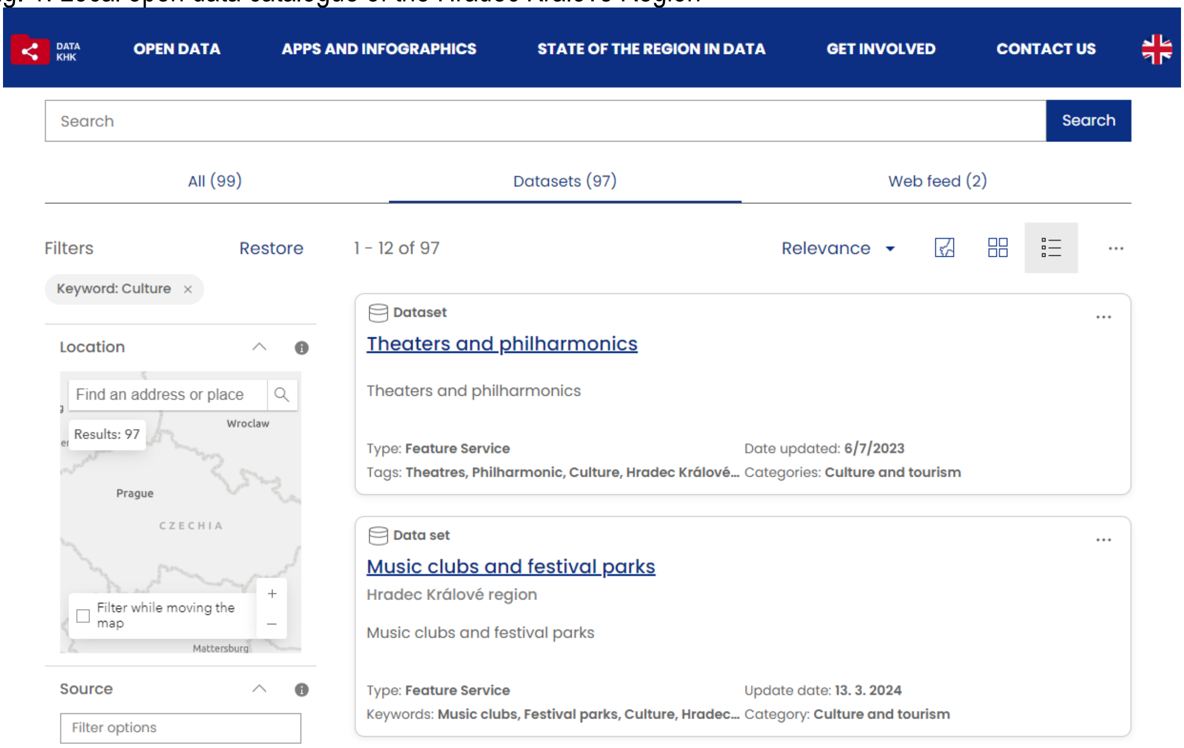
Open data is one of the essential media through which information shared with the general public can be streamlined. Open data enables the realization of a single data base, thus providing the basis for many innovative solutions for cities and regions, new opportunities for their management (Digital and Information Agency, 2020). They are important for the development of research in many areas and sectors. They support the development of new treatments and technologies in the health sector. Also in education, as access to quality teaching materials is made possible, educational methods are being innovated (Digital and Information Agency, 2020). With open data, there is a change in the public's approach to obtaining and processing information. Public administration is opening up to the general public and to professionals in professional forms of output, while at the same time ensuring transparency and thus social accountability. These are also closely linked in the area of innovation and citizen involvement in public affairs through scrutiny of the activities of public administration bodies and their expenditure. Such freely available data enables the implementation of new applications and pioneering services with higher performance, with the consequent promotion of economic growth, while fostering collaboration between other actors (European Data Portal, 2020). The public sector is not the only area where open data cataloging occurs, as there are open data catalogs established and maintained by universities, non-profit organizations or companies. (Kučera, Chlapek, & Nečaský, 2013). The goals of open data are many and the unstoppable progress in the digitization of public administration is making their application increasingly evident. The whole process of creating open data is very demanding in terms of the overall quality and standard of data to be published. There is a need to standardize data entry into information systems, to prepare a methodology for processes across the authority so that data can be processed in a uniform way and outputs in the form of open data can be obtained. This process supports the computerization of public administration, its positive effects are still evolving and are gradually and inexorably being reflected throughout the public administration. The trend towards transparency in public administration is thus beginning to be fulfilled and realized through the use of open data. Information is coming to the public in various forms in an increasing range of not only quantitative but also qualitative forms. There are countless areas of published data and each public administration body has its own agenda with data sets that it uses in the performance of its activities, in addition to identical data according to its level of activity.

The definition of open data is regulated by Act No.106/1999 Coll. on free access to information. This legislation is linked to the regulations of the European Union. Open data are specified in several legal formulations. Firstly, these are the formats of data files, which open data are precisely defined. The way they are published must be in an open and machine-readable format, their use is not restricted in any way, and the condition for their designation as open data is registration in the National Open Data Catalogue (Act No. 106/1999 Coll, 1999). For greater clarity, open data datasets should preferably be catalogued in their own local open data catalogue. The datasets are then registered in the aforementioned National Open Data Catalogue, which is an information system designed for the publication of open public administration data (Digital and Information Agency, 2020). This complies with the legal provisions and completes the legislative process of opening up data. Open data sets of public administration entities are centralized at the state level, thus creating the possibility of interconnectivity of multiple data sources for subsequent processing and visualization, e.g. in the form of applications. The National Open Data Cataloguer gives a comprehensive overview of all open data of public administration at a given time within the Czech Republic.

1.1. Local Open Data Catalogue

Preparing data for the local open data catalogue is a very demanding job on the part of analysts. For proper and ideal cataloguing, attribute columns must be maintained and uniformly aligned, giving them the potential for interconnectivity in their use. In the local catalogue of the Hradec Králové Region, a web page with a description, data table and metadata was created for each open data set. Each data record is unique and has its own identification number. The data catalogue of the region enables innovative map display of open data, each data point is provided with spatial coordinates. At the same time, the so-called open formal standards have been observed, which are binding for providers according to Act No. 106/1999 Coll. on free access to information. These are technical recommendations for selected datasets that allow them to be interoperable when published by different providers, thus increasing their use regardless of which provider they are from (Digital and Information Agency, 2020). A sample of the local open data catalogue of the Hradec Kralove Region is shown in Figure 1.

Fig. 1: Local open data catalogue of the Hradec Králové Region

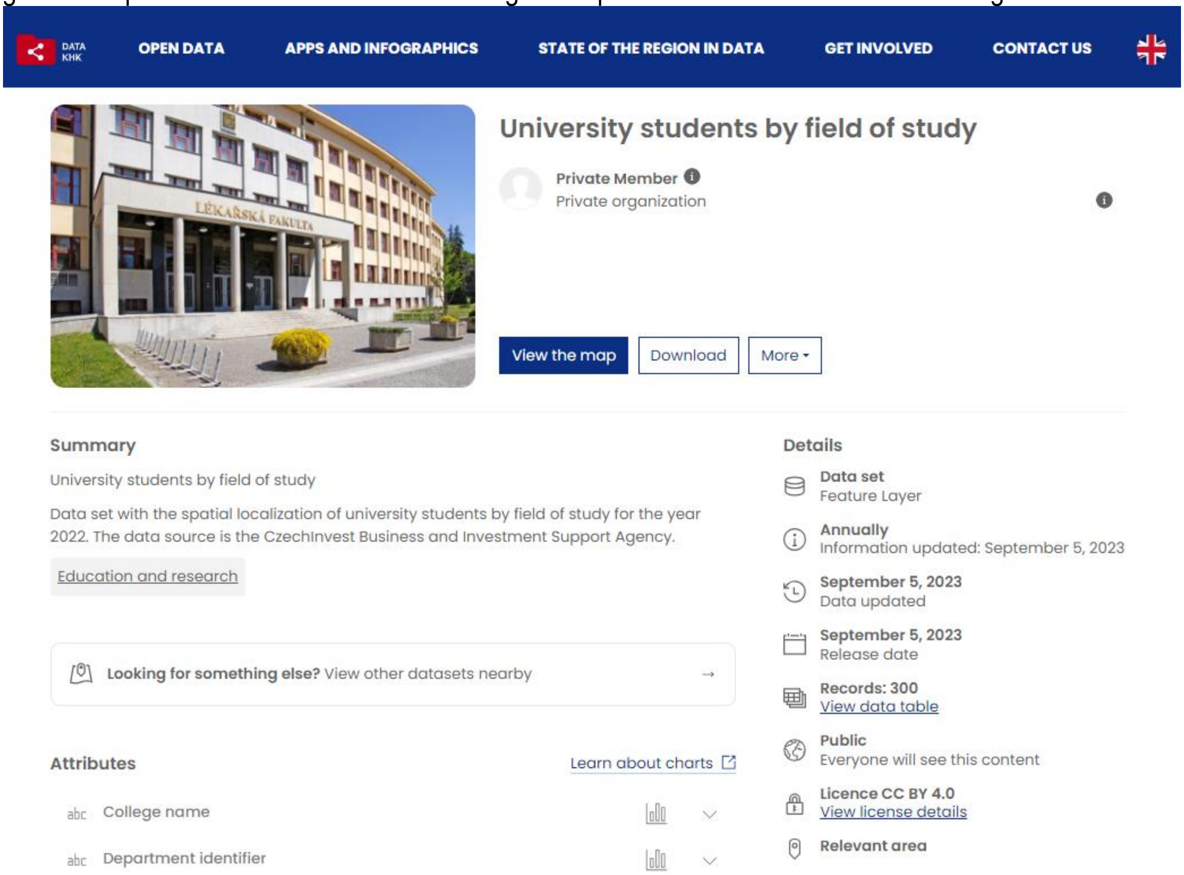


Source: Data KHK

Data catalogues in the Czech Republic are most often created in machine-processable CSV formats (Digital and Information Agency, 2020). The CSV format is uniform, easy to process by machine, without graphic elements. In addition, the regional data catalogue contains spatial data that use other data formats. This spatial data identifies a specific location, an area. They are also provided with coordinates. As open data, they are most often given in the GeoJSON format, suitable for further processing in the form of map applications and map outputs. The structure of the data and its content are described by records in the regional data catalogue, which are called metadata. These descriptions must also follow the rules given in open formal standards. Metadata can be characterized as information that describes a dataset in terms of the substantive content of the datasets. This refers to attributes, how often the data is updated and by which entity it is maintained. Metadata allows better traceability and existence of the dataset in the data catalogue where it is registered. These records are stored centrally for each dataset through the National Open Data

Catalogue. The published regional open data is clear and gives a comprehensive overview of the state of open data at a national level. An example of the metadata in the local open data catalogue of the Hradec Králové Region is shown in Figure 2. When preparing the cataloguing of open data in the local catalogue, it is necessary to cleanse the datasets of personal data. Personal data in open data is a possible obstacle that needs to be removed in the process of sharing public administration information. There are too high risks in disclosing personal data in that they may infringe on the privacy rights of individuals (Digital and Information Agency, 2020). Therefore, if datasets contain, for example, email addresses with personal data, contacts of specific persons, the datasets need to be organized in terms of content and attributes in such a way that these columns with these data are preferably omitted and the content of the datasets is interesting to process even without these data. For an efficient and seamless data sharing process, this is the simplest rule of thumb that is recommended to accept.

Fig. 2: Example of metadata in the local catalogue of open data of the Hradec Králové Region

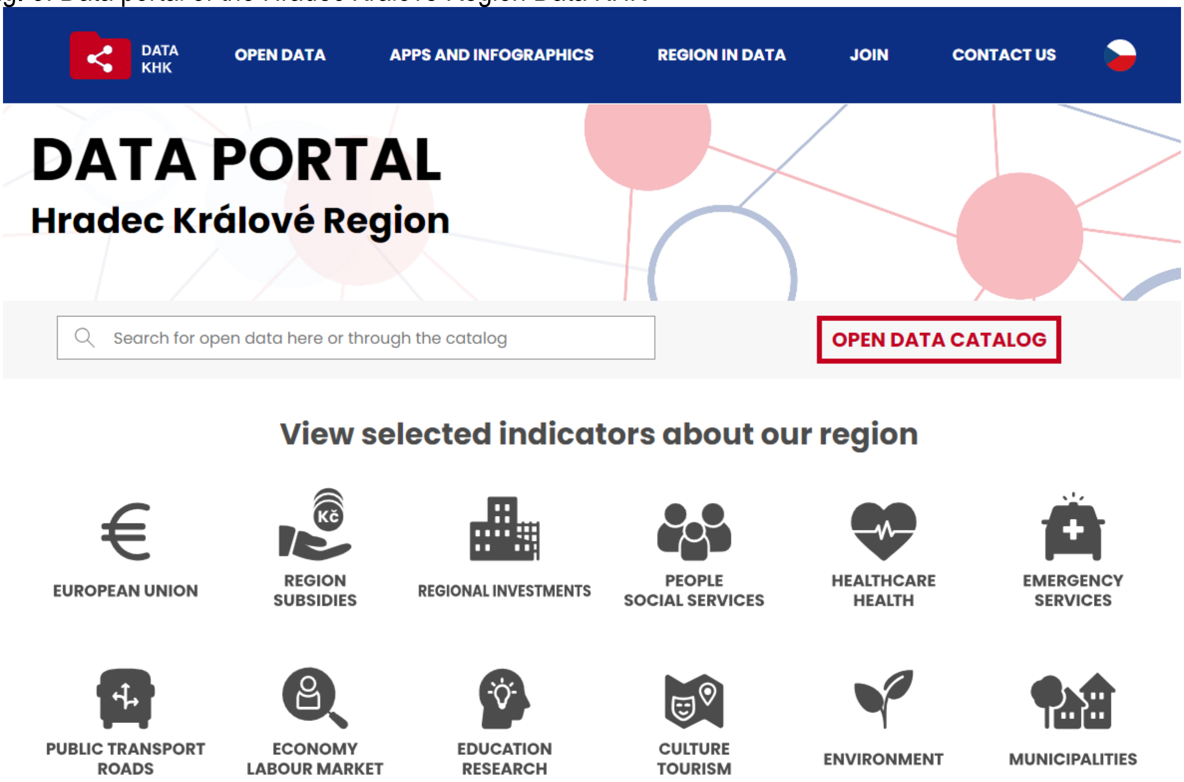


Source: Data KHK

1.2. Data Portal

A current innovative trend is the placement of a local open data catalogue within the data portals of higher territorial self-government units, which serve the public and are a valuable source of information. Through the regional data portal, a completely new process of data sharing for citizens is taking place. It is a new service for the general public consisting in easier access to information, in a completely simple way. The data of the Hradec Králové Region are visualized in the form of interactive graphs and open data in the form of map outputs. This makes it quite clear what data the region provides to the citizens of the region and what is the specific content of the datasets placed in the local catalogue. This allows for greater public engagement and feedback from citizens. This innovative platform of data portals, which is being progressively implemented by each region of the Czech Republic, could help in the future in sharing the same data area, different analysis options and linking multiple data sources from different regions to better inform the public. Data portals, sharing data for citizens, providing datasets in the form of open data that will help develop applications for subsequent use by the public, are the support for the whole course of innovative activities to provide new and better services for citizens. The whole process supports the creation of new analytical units within the authorities, where unified data bases are created, the methodology of data entry and outputs from information systems is modified, leading to efficient management and thus to the efficiency of public funds. At the same time, management control takes place, as any fluctuations in financial indicators outside the normal range provide the basis for a detailed analysis of the causes of any inefficiencies and control activities. An example of the Hradec Králové Region Data Portal is shown in Figure 3.

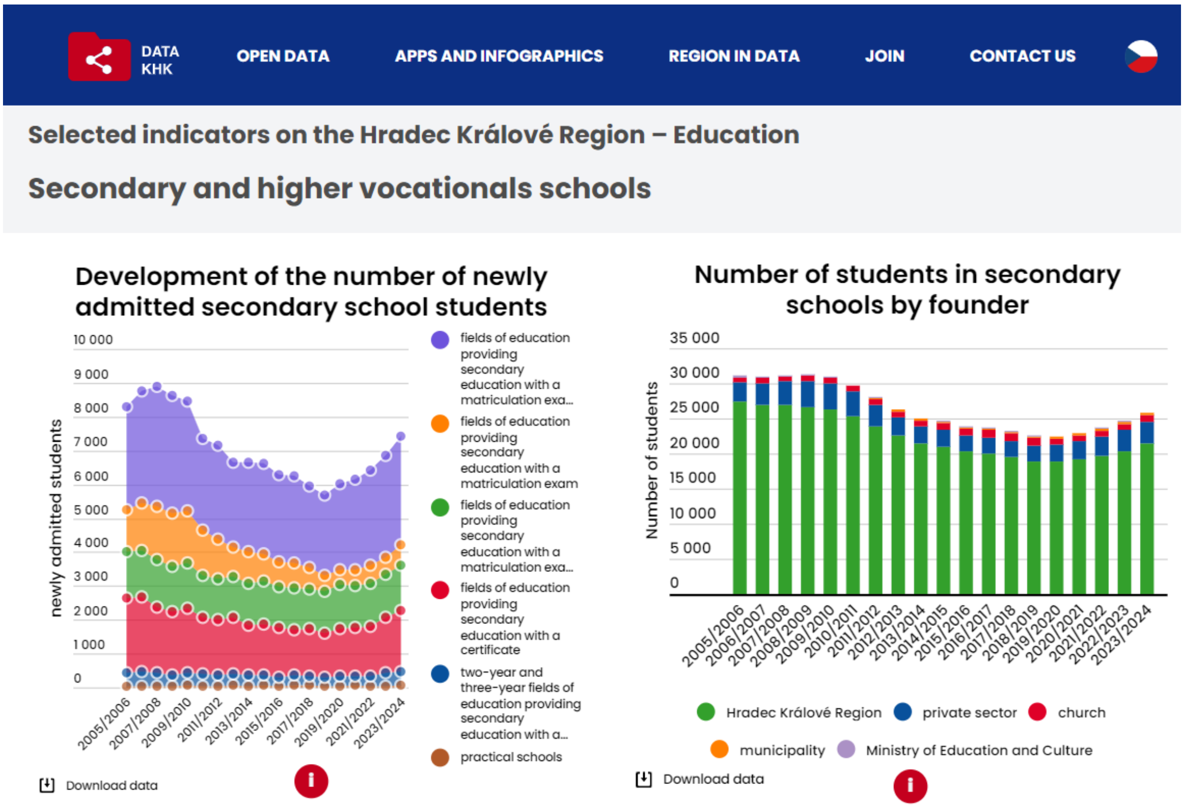
Fig. 3: Data portal of the Hradec Králové Region Data KHK



Source: Data KHK

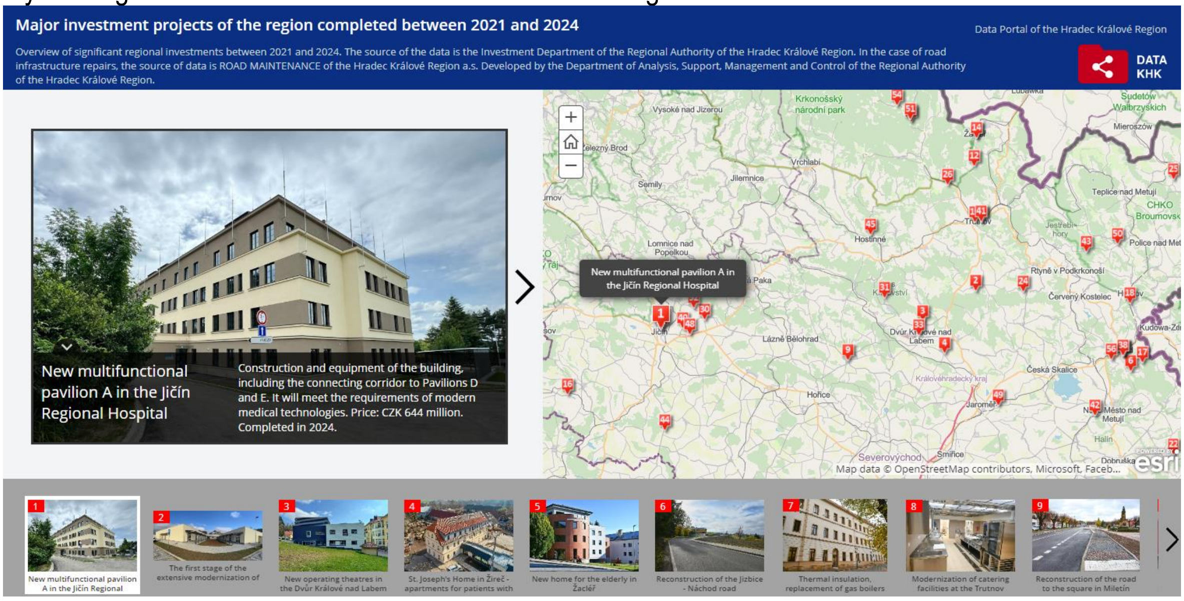
The data portal of the region includes data from its internal sources and external sources. Internal sources are data outputs from the information systems of the region such as the subsidy portal or the economic information system, external sources are data from the Czech Statistical Office or various ministries. These are then processed and visualized in the form of interactive outputs, various dashboards, graphical data cards, maps and map stories. An example of these outputs is shown in Figure 4 for the education sector and in Figure 5 in the form of a map story for major investment projects in the Hradec Králové Region. The data portal serves both as a signpost to all portals and applications of the region and as a source of current strategies, which are important documents for the next range of activities and activities of the public administration entity in the coming years. Regional data portals with open data catalogues are a new trend of our time and an innovative service for sharing data for citizens of the whole region. They support the process of electronification of public administration and at the same time increase the digital skills of employees within the authority, the rapid monitoring of public finances and the development of the region.

Fig. 4: Example of data visualization on the Hradec Králové Region Data Portal KHK data in the form of a dashboard for the education sector



Source: Data KHK

Fig. 5: Data visualisation on the data portal of the Hradec Králové Region Data KHK in the form of a map story with significant investments in the Hradec Králové Region



Source: Data KHK

1.3. Hackathons

This unique innovation process is followed by public scrutiny of the accuracy of the data by specialists and developers. They give unique feedback on the quality of this valuable digital resource, published open data, in hackathons. For the fourth year, the Hradec Králové Region, in cooperation with the University of Hradec Králové, Faculty of Informatics and Management, is implementing a hackathon for students of secondary and higher education. The hackathons are used to develop applications on open data and are aimed at programmers and analysts who can use the open data sets prepared in this way to implement new applications. They also support digital education of students, the development of research on new information technologies and the use of artificial intelligence. High school and university students create application designs that can then be developed into final form if desired. The competition is very inspiring for the students, it is an opportunity to gain further experience in the context of a requirement directly from practice and it will also give them the opportunity to use the knowledge they have acquired during their education. This activity of the region is an inspiration for other entities of higher self-government units to organize similar innovative hackathons. The success of these unique activities over the open data of the counties has been reflected up to the central level, with the SAI organizing for the second year a central hackathon for the finalists from the regional rounds.

2. PRACTICAL USE OF AI IN OPEN DATA

One of the practical examples of innovation, how the design of an application from a hackathon can be implemented with maximum success and transferred to practical use for the public, is the implementation of a research application utilizing AI. As part of these hackathons, students designed an entirely new application concept that simplifies working with open data catalogues. In the framework of the cooperation between the Hradec Králové Region and the Faculty of Informatics and Management of the University of Hradec Králové, the students implemented this application to its final form. The process was carried out through the implementation of a selection project, which was dedicated to research activities for which the students received credits for their study activities. The application was implemented with minimal cost in a short period of 3 months. The application and its research solution included the implementation of AI. This project was entered into the IT Project of the Year 2023 competition organized by the Czech Association of Information Technology Managers CACIO. The competition aims to reward the best projects of development and implementation of information technology. The application was awarded as one of the winning projects. The unique idea, the key cooperation between the public administration and the university in the research and use of artificial intelligence, the minimum cost of the innovative project with subsequent use in practice were appreciated from the best IT experts. The victory of this new application is the result of the high quality performance of the students of the Faculty of Informatics and Management of the University of Hradec Králové and their ability to create innovative and useful projects, as well as the significant cooperation of the research and scientific sector with the public administration and representatives of the Hradec Králové Region. This example of unique cooperation is another key to the development of meaningful research activities with immediate practical application for the general public with a large scope of action and thus a positive impact on public interests. It is worth noting the minimal cost of this new activity, which has enabled further development of the region and its territory. This successful and significantly awarded research activity is a phenomenal example of the meaningfulness of the whole process of open data in public administration, up to the organisation of innovative hackathons where open data is already being used in practice. Since participating in the hackathon, the students have gone on to become top IT professionals with the highest possible accolades from the professional community. The Hradec Králové Region has gained further points on its prestigious position in the field of innovation and open data. This innovative data sharing process opened the way for young talented personalities and through the cooperation of the region with the university in research activities, further development of public administration in the field of data science and its digitalization took place. The benefit is unique, repeatable to other public administration entities, as this application is transferable to any open data catalogue of public administration entities, including the National Open Data Catalogue at the central level.

2.1. Research application for open data catalogue using AI

The research application with AI is used to simplify work with open data sets of the Hradec Králové Region. The main innovation is the possibility to work with multiple datasets at the same time. They can all be displayed in one map, edited before being downloaded by developers. The biggest innovation is the implementation of AI, which selects tailored datasets after a prior text conversation with the user about their requirements. It is also capable of full conversations about the datasets. The GPT-4 turbo service is used for the AI function. Conversation with AI is maintained throughout the usage period. The AI model is treated with a unique innovation barrier, preventing it from answering irrelevant questions, which is a very important feature of the application for the public administration domain.

The application includes a display map of datasets. The underlying map allows for any kind of customization, offering day and night cycles and display in 3D format, see Figure 6 (Kubišta, T., Doležal, J., & Kyzr, J., 2024). When visualizing multiple sets on one map, each set has a unique coloring. Click on a point on the map to see detailed information. The application offers the ability to display a table for each dataset, including the ability to completely customize its interface and columns. These features greatly facilitate the user's work with datasets, making effective use of artificial intelligence in the form of a dataset finder. Conversation with AI is maintained throughout the use of the application (Kubišta, T., Doležal, J., & Kyzr, J., 2024). An added value is the fact that on the main page of the app, the user can see what the app can do, how to use it. It is possible to view information not only for regular users but also for developers.

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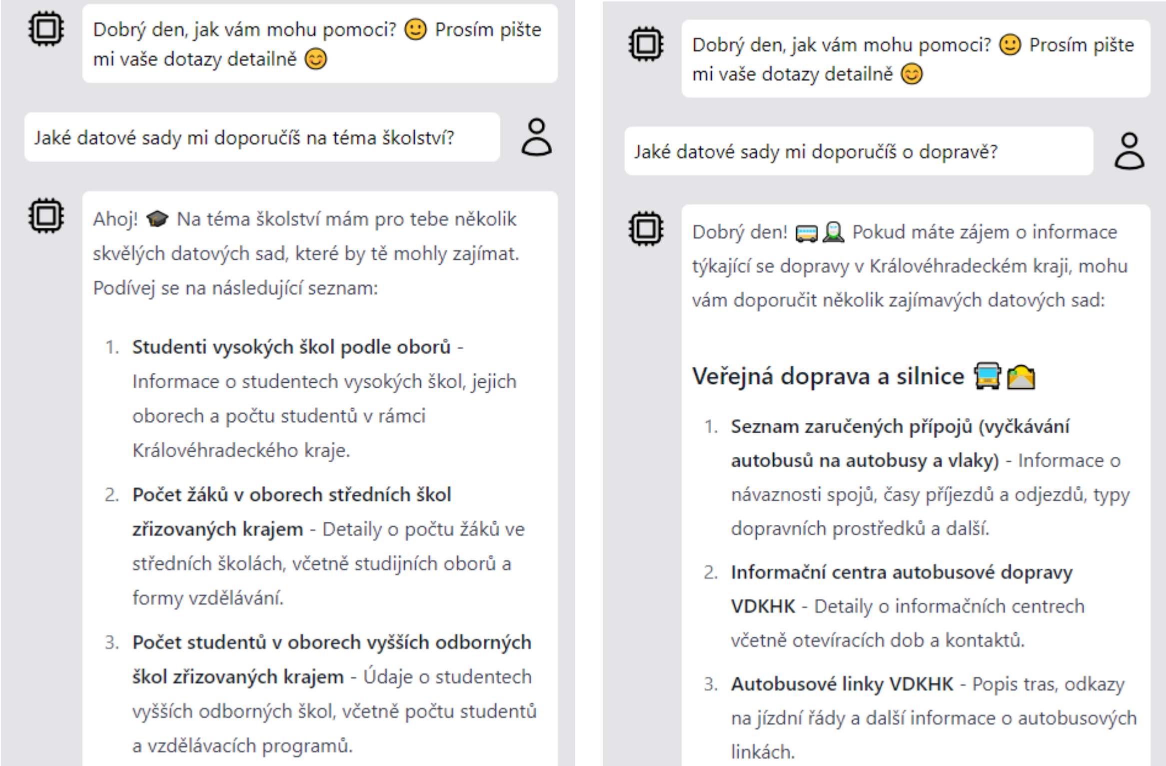
Fig. 6: Example of open data display in the research application with AI in 3D format

Source: katalog.datakhk.tech

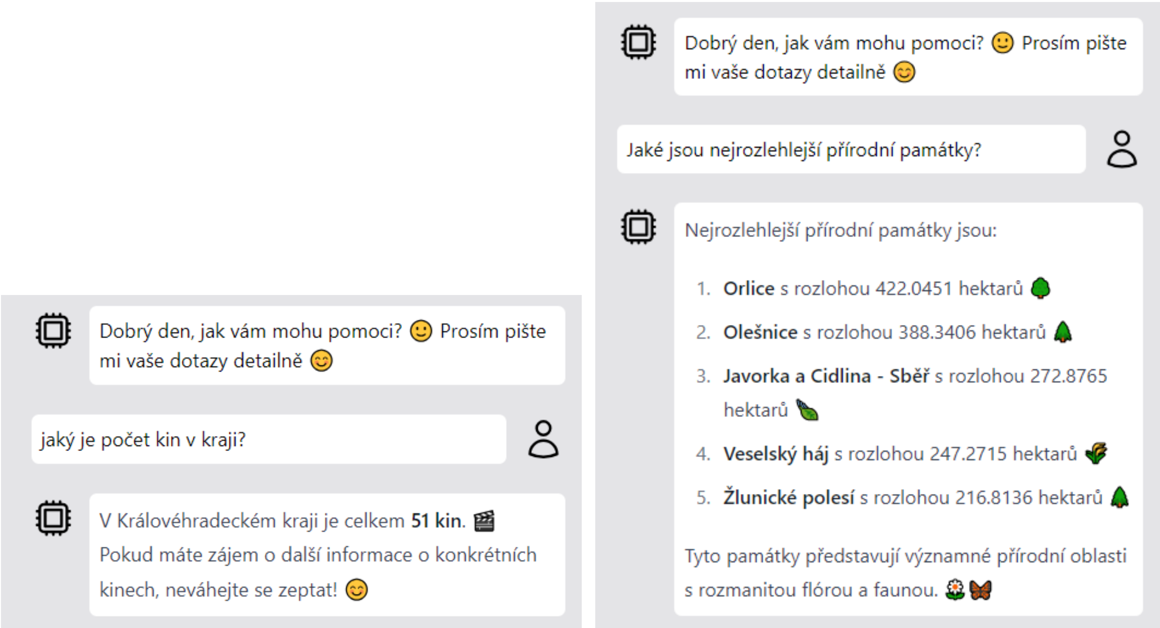
The original scope of the project was only a web application with a modified data catalogue and the possibility to easily search, view and download datasets. The final scope was enriched with a 3D format of the underlying map in day and night mode, tutorials for using the application and AI, due to the implementation of current developments and sufficient time for implementation. The original solution was to use services from OpenAI for AI implementation. The latter is used in the application for easier handling of datasets. It works on the basis of recommending sets based on communication with the user. At the same time, it can search the information contained in the datasets see Figure 7 and Figure 8. It is a semantic search in the embedded vector store, relevance decision is made by pre-generated examples (Kubišta, T., Doležal, J., & Kyzr, J., 2024). The model is able to understand the meaning of datasets based on their content. Another original and novel solution is the 3D formats of the underlying map (Kubišta, T., Doležal, J., & Kyzr, J., 2024). The map displays color separated geographic information from selected datasets. There is a day and night cycle. The application allows unique selection from a large volume of datasets at once, their editing before downloading and automatic updating. It can be applied to other catalogues with a large volume of datasets, without the need for third party software. The implementation of artificial intelligence language models has significantly facilitated and optimized work with large data sets. The most important project benefit is the necessity of a high degree of customization of available AI solutions for the needs of public administration and sufficient time for its testing. The cooperation of the Hradec Králové Region through the team of analysts with the University of Hradec Králové through key and highly qualified experts, gifted students with a high level of creativity and unique talent, was a great contribution to the success of the entire research process, which is a timeless innovative solution of today. The positive experience was the students' will and effort to find a solution across the original constraints that meets the maximum requirements of the user, which is a public entity, and is also original and innovative.

Fig. 7: Example of a user interacting with an AI chat bot recommending open data sets



Source: katalog.datakhk.tech

Fig. 8: Demonstration of a user interacting with an AI chatbot in the research application



Source: katalog.datakhk.tech

3. SHARING GOOD PRACTICE BETWEEN PUBLIC ADMINISTRATION ENTITIES AND THE PROFESSIONAL PUBLIC

There is a great interest in the data portal and local catalogue of open data with map outputs, including its solution, the way of sharing data and information for citizens. At the same time, the topic of processing open public administration data at a highly professional level, including its visualization in the form of map outputs, so friendly for citizens and the public, has been opened. Currently, these portals have already been implemented in other regions within this inspiring and innovative way of data sharing solutions for citizens in the Hradec Králové Region. These are in particular the Liberec, Olomouc, Pardubice and Karlovy Vary regions and the city of Hradec Králové.

The Data KHK data portal and its local open data catalogue has won several prestigious awards as an innovative project for higher territorial self-government units and has thus become well-known among public administration entities. The first award was the 1st place in The Best 2021 E-government competition in the category of regions. The portal was subsequently included in the collection of 40 inspiring public administration projects of 2021 and representatives of other regions approached the Data KHK team of analysts to share good practices. Subsequently, the portal won 1st place in the national round of the Golden Crest competition as the most innovative electronic service for citizens. The Innovation in Public Administration Award 2021, awarded by the Ministry of the Interior of the Czech Republic as a citizen-oriented innovation, was another prestigious award for the region and the team of analysts for their innovation process. The portal was one of the four finalists in the competition for the best digital resource within the EU at the international conference ALL DIGITAL SUMMIT 2022. It also won the national round of the QUALITY INNOVATION AWARD 2022 organized by the Czech Society for Quality and was ranked 2-3rd in the international round of this competition for the public administration sector. The portal was the winner of the Smart Cities 2022 competition in the Project for the Region category. The topic of open data in public administration has also started to resonate within Europe, where the portal of the Hradec Králové Region has currently won a prestigious award for exceptional innovation in the category "Innovation in Public Administration" in the form of a "Certificate of Good Practice" from the European Institute of Public Administration EIPA among hundreds of projects. It has become a finalist in the Innovation in Politics Awards 2024 competition within Europe and has been ranked among 70 inspiring European projects. It is a semi-finalist of the SDGs 2024 Award. The Data KHK portal was contacted by the Organization for Economic Co-operation and Development (OECD) with an offer to place the project in the international catalogue of case studies Observatory of Public Sector Innovation. The Data KHK project has thus historically become the second Czech project in this prestigious innovation catalog after the National Open Data Catalog (OECD, 2024). The team of analysts shares good practices for the field of open data and the whole described innovation process up to the hackathon, the use of AI and cooperation with the University of Hradec Kralove at professional conferences in the Czech Republic and abroad. He collaborates with university students on other projects and student work. It develops this cooperation not only with the University of Hradec Králové, but also with other regions and public administration entities such as the Ministry of Finance of the Czech Republic or the Digital and Information Agency. The region is a member of the working group for the information society of the Government Office, and participates in the implementation of educational events within the Czech Digital Week. This whole process has an impact on the sustainability, transferability and overall impact of the project, which has been awarded the highest marks in the field of innovation, research and public administration-researcher cooperation within the university by the expert community.

CONCLUSION

Through the Data portal of the Hradec Králové Region Data KHK and the local open data catalogue, the Hradec Králové Region has opened up to the public in a completely new way and thus ensured innovation in the field of public administration, especially among the regions. The region as a higher territorial self-government unit thus ensures quality, innovative, digital and responsive public administration for citizens by enabling new development of their services based on the use of quality data in digital form. It brings public administration closer to citizens, researchers and students, while at the same time digitizing it in a completely new and innovative way. Using the data portal and the local catalogue, digital skills are being promoted for the general public as well as for the employees of the authority. Digital education is being developed for students through hackathons in cooperation with the University of Hradec Králové, and for school teachers through lectures and workshops. Applications are developed over open data using state-of-the-art technologies, including AI through research and innovation activities. Students are involved in the development of the portal in the form of semester, bachelor and diploma theses, projects. In cooperation with the professional community, the data portal is presented at conferences and at international levels. Within this new digital data resource, the development of the digital economy for the region and within the organization is enabled. Citizens' feedback on how the public administration manages and uses public funds is ongoing. This promotes the financial literacy of citizens, the supervision of public finances, how these funds are spent, how different areas of public administration are developed, including the promotion of investments and subsidies in different areas of the region. The scope for innovation, for novelty, is on a large scale towards the public. The success and impact of the innovation of this project is unique and is an inspiration not only for other public administration entities in the Czech Republic, but also on a global level. Being approached by the OECD to be included in the catalogue of global innovations is proof of this, and this whole innovation process continues to carry positive energy to further spread and develop the whole area of open data in the world. It is possible to continue to develop this process, to support the further development of research activities on this area and to put this solution into practice with the potential to develop the field of digitization of public administration and data science.

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THE USE OF ARTIFICIAL INTELLIGENCE IN FINANCIAL ADVISORY

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Abstract: This article analyzes the potential benefits and challenges of utilizing artificial intelligence (AI) in financial advisory based on a survey conducted among financial advisors. The results indicate that most advisors perceive AI as a tool capable of enhancing various processes, from data processing to financial planning and client service personalization. The study identifies key areas where AI can reduce administrative burdens, accelerate data analysis, and support better decision-making. However, respondents also expressed concerns regarding data security, the need for more reliability, and the transparency of AI algorithms, which could limit the broader adoption of these technologies. Although AI is a significant advancement, its full implementation in financial advisory will require a balanced approach combining technological solutions with human advisory. This research overviews the current state and highlights potential directions for AI development in financial advisory, emphasizing the need for an ethical framework and transparency.

Keywords: Artificial intelligence, financial advisory, efficiency, data security.

JEL Classification: G2, O33

INTRODUCTION

Artificial intelligence (AI) is becoming one of the critical tools transforming the financial sector, with applications ranging from the automation of administrative processes to predictive analysis and personalized advisory. In recent years, AI has proven capable of accelerating and streamlining decision-making processes and making financial services more accessible to a broader range of clients (Mhlanga, 2020). Current studies indicate that AI, in the form of generative models and tools such as robo-advisors, brings a novel approach to financial advisory, enabling the processing of vast amounts of data and delivering personalized recommendations in real-time (Bhatia et al., 2021; Arenas-Parra et al., 2024).

However, implementing AI in financial advisory brings benefits and challenges. Financial advisors still face concerns regarding data security, algorithmic transparency, and maintaining trust between advisors and clients (Truby et al., 2020). Trust is particularly crucial when AI is used for more complex tasks, such as investment advisory, where clients continue to prefer human interaction. At the same time, more straightforward transactions are more amenable to technological solutions (Northey et al., 2022).

This study examines financial advisors' attitudes toward using AI and analyzes their perceptions of future opportunities and risks associated with AI in financial advisory. Based on a survey conducted among financial advisors, this study provides insights into how AI tools are currently employed and identifies areas with the most significant potential for development. The findings focus on AI’s role in decision support, process efficiency, and service personalization while addressing the obstacles that could hinder the broader adoption of these technologies.

1. THEORETICAL BACKGROUND

1.1. Application of Generative Artificial Intelligence in Practice

Generative artificial intelligence represents a significant advancement in machine learning and automation, capable of generating new content or models based on data inputs. This approach is utilized across various fields, from art creation to technical design and scientific research. Typical generative AI models include Generative Adversarial Networks (GANs) and variational autoencoders (VAEs), which can produce realistic data similar to the training data used in their development (Liu et al., 2023; Shi et al., 2023). These models have applications across numerous industrial sectors, including materials science, medicine, and marketing (Dwivedi et al., 2021; Liu et al., 2023; Rasiwala & Kohli, 2021). Generative AI has proven especially valuable in automated text generation, graphic design, creating new materials, supporting research, and reducing development time (Liu et al., 2023).

One of the advantages of generative AI is its ability to process large volumes of data and extract meaningful patterns. This capability facilitates applications in automated writing, translation, and complex process modeling (Dwivedi et al., 2021; Manser Payne et al., 2021; Rabbani et al., 2023; Yasir et al., 2022). Additionally, generative AI is widely used in research fields to aid in developing new drugs or improving diagnostic tools in healthcare (Liu et al., 2023).

Generative AI models, such as ChatGPT, are becoming increasingly common in customer-company communication, enhancing customer support and overall customer experience (Rasiwala & Kohli, 2021). These tools can simulate dialogue or provide real-time support (Truby et al., 2020; Dwivedi et al., 2023). Consequently, generative AI is gradually becoming an indispensable part of industries that require rapid and efficient solutions when dealing with large volumes of data (Mhlanga, 2020).

Generative AI is also applied in the education sector, where its applications in teaching and learning processes are being explored. Generative AI can improve personalized learning and optimize educational processes, leading to better learning outcomes (Hooda et al., 2022; Dwivedi et al., 2021). In this context, GAI is used, for example, to create individualized study plans or to automate student assessments (Ivanashko et al., 2024; Hooda et al., 2022).

1.2. Application of Generative Artificial Intelligence in Finance

In the financial sector, generative AI is becoming one of the primary tools for service innovation and enhancing process efficiency. One of the most significant applications is automated financial advisory (robo-advisory), where AI systems analyze investment data and recommend optimal investment strategies (Bhatia et al., 2021). These systems are designed to broaden access to financial services, lowering entry barriers for small investors (Arenas-Parra et al., 2024).

Another significant benefit of generative AI is its role in predicting market trends. AI technologies enable the analysis of large amounts of historical data to forecast future market movements, thus improving decision-making for financial institutions and investors (Mhlanga, 2021; Shi et al., 2023). This process is crucial for portfolio management and enhancing investment performance (Arenas-Parra et al., 2024).

In credit risk analysis, generative AI plays a vital role by enabling financial institutions to assess clients' financial histories and predict their ability to repay loans. This approach is precious in emerging economies, where traditional credit risk assessment methods often fall short (Mhlanga, 2020; Rabbani et al., 2023). Through machine learning, alternative data such as publicly available information and social media can be analyzed, improving the accuracy of credit risk assessments.

Banks use AI tools to monitor real-time transactions and detect unusual activities, enabling quicker responses to potential fraud (Manser Payne et al., 2021; Rabbani et al., 2023). This approach enhances security for banks and their clients while reducing the costs associated with manual transaction monitoring.

Generative AI is also a valuable tool for improving customer experience. Chatbots and other AI-based services increase the efficiency and personalization of customer support, leading to higher client satisfaction

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(Northey et al., 2021; Northey et al., 2022). Banks implementing AI systems have seen improvements in operational efficiency and customer trust (Rabbani et al., 2023). Studies show that while customers prefer human advisors for complex financial decisions, they favor the speed and efficiency offered by AI for more straightforward transactions (Ivanashko et al., 2024).

2. METHODOLOGY

This study is based on quantitative research conducted through a survey distributed among financial advisors. The questionnaires were electronically distributed to financial advisory professionals with experience with AI technologies. The questions were designed to capture advisors' attitudes toward AI use, identify critical advantages and disadvantages of this technology, and assess its potential for future applications. The questionnaire consisted of two main sections. The first section included questions related to respondents' demographic data (e.g., age, years of experience), while the second section focused on evaluating the benefits and risks of AI in financial advisory and its potential future applications.

The study was conducted at an undisclosed headquarters in Southwestern Bohemia, within the largest advisory firm in the Czech Republic. The survey was distributed to respondents during the summer of 2024, and 61 responses were received.

The results of th is survey are presented in charts and descriptions in the following section. A vital outcome of the study is a set of potential suggestions for the practical application of generative artificial intelligence among financial advisors, offering innovative ideas that could facilitate the work of professionals in the field.

3. RESULTS

The survey results indicated that the majority of respondents perceive AI as a positive asset in the field of financial advisory. The specific survey results are divided into three sections. The first section covers the respondents' demographic data, the second assesses the current use of AI tools, and the final section focuses on the future potential and utilization of AI tools.

3.1. Respondent Demographics

The demographic data of the respondents are presented in Table 1 below. Key demographic variables include gender, age group, and highest level of education attained.

Tab. 1: Respondent Demographics

Demographic and variable	Frequency, n (%)
Gender	
Male	37 (60.7)
Female	24 (39.3)
Other	0 (0)
Age	
Under 20	3 (4.9)
20 – 30 years	44 (72.1)
31 – 40 years	13 (21.3)
41 – 50 years	1 (1.6)
51 – 60 years	0 (0)
61 years and more	0 (0)
Educational level	
Secondary education with planned graduation	4 (6.6)
Secondary education with completed graduation	38 (62.3)
Higher vocational education	0 (0)
Bachelor	11 (18)
Master	8 (13.1)

Source: Processed by the author, 2024

The survey revealed that among the 61 participants, the majority were male (60.7%), while females comprised 39.3%; no respondent identified as another gender. The age structure of the respondents was predominantly younger, with 72.1% falling into the 20–30 age group and 21.3% in the 31–40 age range. Only 4.9% of respondents were younger than 20, and there was only one respondent in the 41–50 age category; there were no respondents in older age groups.

Regarding educational attainment, most participants had completed secondary education with a graduation diploma (62.3%). Additionally, 18% held a bachelor's degree, and 13.1% had a master's degree. Only 6.6% of respondents had secondary education without a completed graduation diploma, and no respondents reported having higher vocational education.

3.2. Assessment of Current Use of AI Tools

Table 2 below presents the respondents' answers regarding the current use of artificial intelligence in practice. Specifically, this section of the questionnaire focused on questions related to the current attitudes toward using AI tools, as well as the benefits and risks associated with their use.

Tab. 2: Assessment of Current Use of AI Tools

Assessment of Current Use of AI Tools and variable	Frequency, n (%)
Attitude Toward AI Use	
1 – None	1 (1.6)
2 – Low	1 (1.6)
3 – Medium	19 (31.1)
4 – High	25 (41)
5 – Expert	15 (24.6)
Current Use of AI	
Yes	35 (57.4)
No	26 (42.6)
Frequency of AI Use	
Daily	2 (3.3)
Several times a week	18 (29.5)
Several times a month	20 (32.8)
Less frequently	9 (14.8)
Never	12 (19.7)
Purpose and Application of AI Use	
Chatbots and virtual assistants	28 (71.8)
Robo-advisors (investment portfolio management)	0 (0)
Data analysis and financial trend prediction	7 (17.9)
Regulatory technology	3 (7.7)
Service personalization	4 (10.3)
Data processing	13 (33.3)
Creation of educational materials	19 (48.7)
Creation of business materials	12 (30.8)
Not in use	1 (2.6)
What Are the Main Benefits of Using AI?	
Increased work efficiency	41 (80.4)
Better data-driven decision-making	29 (56.9)
Improved customer experience	7 (13.7)
Reduced operational costs	4 (7.8)
Enhanced data processing	1 (2)
Improved material aesthetics	1 (2)
Inspiration	1 (2)
Useful advice	1 (2)
Idea and concept generation	1 (2)
Connectivity and experience	1 (2)
Have You Encountered Any Risks When Using AI Tools?	
Yes	36 (59)
No	25 (41)
What Risks Have You Encountered When Using AI Tools?	
Insufficient accuracy and reliability of tools	34 (85)
Complicated integration with other systems	7 (17.5)
High costs of implementation and maintenance	1 (2.5)
Lack of expertise to use AI tools	16 (40)
Data security and privacy concerns	8 (20)

Source: Processed by the author, 2024

The data indicate varying levels of acceptance and usage of artificial intelligence (AI) among respondents, with attitudes towards AI ranging from basic to expert levels. The most significant proportion of respondents, 41%, identified with a "high" level of AI knowledge, while 24.6% reported expert knowledge. Only 3.2% of respondents rated their knowledge as very low or nonexistent, suggesting a relatively high awareness of the technology within this group.

More than half of the respondents, 57.4%, indicated that they currently use AI actively, with varying frequencies. Regular usage several times a week or month was reported by 62.3% of respondents, while only 3.3% use AI daily. The remaining 19.7% said they do not use AI tools.

The most common uses of AI include "chatbots and virtual assistants," cited by 71.8% of respondents, followed by "data processing" (33.3%) and "creation of educational materials" (48.7%). In contrast, respondents currently do not use areas like portfolio management via robo-advisors (0%). These data suggest that most users focus on areas where AI supports work processes and communication efficiency. At the same time, more complex applications, such as investment management, still need to be expected.

Regarding the main benefits of using AI, respondents most frequently mentioned "increased work efficiency" (80.4%) and "better data-driven decision-making" (56.9%). Other cited benefits included improved customer experience (13.7%) and reduced operational costs (7.8%). These results suggest that AI is primarily viewed as a tool to boost productivity and optimize decision-making processes.

Regarding risks associated with AI usage, 59% of respondents answered affirmatively, with the most frequently cited issue being "insufficient accuracy and reliability of tools" (85%). Other mentioned risks included "lack of expertise" (40%) and "data security and privacy concerns" (20%). These data indicate that, while AI tools are widely accepted in financial advisory, concerns remain regarding their reliability, integration, and security.

3.3. Proposals for Future Use of AI Tools in Financial Advisory

The responses indicate that the majority (70.5%) of participants plan to expand or modify their use of artificial intelligence in their practice. The remaining respondents were either uncertain (26.2%) or did not intend to change their current use of AI tools (3.3%). This uncertainty may reflect concerns about AI's reliability and security.

These results suggest that while AI is seen as a promising tool with substantial potential to enhance financial advisory, its broader adoption may be conditional on overcoming existing obstacles, such as the need for technical expertise and the reliability of the technology.

The survey revealed a wide range of perspectives among financial advisors regarding the future use of AI in their practice. Key areas where respondents see potential for AI include the automation of routine tasks, data processing, and decision support. Many respondents indicated that AI could significantly improve efficiency by taking over administrative activities, such as processing insurance claims, preparing financial plans, and managing email correspondence with clients. This creates a vast potential for generative AI as a personal virtual assistant. A prerequisite for such use would be training the assistant properly, providing it with essential information and materials, and teaching it to accurately locate answers to specific questions. Other areas where respondents see AI benefits include generating financial plans, personalizing services, and accelerating client project processing. Respondents anticipate that AI will enhance client education and support the practical training of colleagues, especially in developing educational and business materials. Some also mentioned AI as a tool for market analysis and financial trend prediction, which could improve the quality and accuracy of their advisory services.

Conversely, some respondents expressed uncertainty or skepticism about AI's use due to a lack of familiarity with the technology or concerns about its relevance for specific job tasks. Training sessions or workshops could be considered for these respondents to improve their knowledge of AI applications.

In summary, most respondents view AI as a significant tool for enhancing efficiency, accuracy, and service customization, though they have some reservations and questions about its practical application and reliability.

4. DISCUSSION

The research findings confirm a growing interest among financial advisors in AI applications within the field, particularly in areas such as automating routine tasks, data analysis, and support for financial planning. This trend aligns with current literature, highlighting AI's potential for fundamentally transforming financial services. Studies indicate that AI tools can significantly enhance efficiency (Mhlanga, 2021).
From the perspective of specific applications, respondents primarily view AI as a support tool for data processing. This is consistent with Manser Payne et al. (2021) findings, who report that AI in finance can analyze vast volumes of data and deliver more accurate financial recommendations. In this way, AI can mitigate cognitive biases that often affect human decision-making, as supported by Hasan et al. (2023), who emphasize AI's role in reducing bias in investment decision-making.
Despite most respondents' optimistic stance, challenges remain that need to be addressed. Key obstacles identified in the survey include insufficient accuracy and reliability of AI tools, data security and protection concerns, and complications in AI integration with other systems. These concerns align with the conclusions of Truby et al. (2020), who highlight the need for stricter AI regulations in the financial sector to ensure worker trust and the protection of client personal data.
Another finding is that AI needs to be more utilized in complex applications, such as portfolio management through robo-advisors. As Bhatia et al. (2021) noted, robo-advisory services can expand access to financial services for a broader client base. However, their implementation requires a high level of user trust. Survey results indicate that some financial advisors have reservations about the risks associated with fully automating investment processes, which could limit AI's use in more complex areas of financial advisory.
Respondents also indicated that AI has the potential to save time in administrative tasks, a benefit supported by Dwivedi et al. (2021), who view automation of routine tasks as a significant advantage of generative AI in the field. At the same time, it was noted that some more complex issues still require a human approach, as confirmed by Northey et al. (2022), who found that clients often prefer human advisors for complex decisions while being more open to AI for more straightforward transactions.
In light of these findings, it can be concluded that while AI offers substantial benefits for enhancing efficiency and quality in financial advisory, its application in this field will require a balanced approach that combines technology and the human factor. Further research should focus on practical ways to integrate AI to foster user trust and extend its use into more demanding areas of financial advisory.

CONCLUSION

The research findings indicate that AI is perceived as a vital tool for enhancing efficiency and accuracy in financial advisory, especially in automating administrative tasks and accelerating data analysis. Financial advisors particularly value AI's potential to streamline processes, increase the accessibility and accuracy of services, and reduce time-consuming routine activities. Nevertheless, challenges remain, particularly concerns about data security and the potential loss of human-client interaction.
The study also identified barriers that could limit the broader adoption of AI in financial advisory, such as a need for more expertise and concerns over the reliability of AI tools. As Dwivedi et al. (2021) suggest, implementing AI in practice requires a balance between technological advancement and the ability to ensure client trust and data security, which may lead to the development of hybrid models that combine technological approaches with human advisory. Such a balanced model could ensure that AI is a valuable supplement for human advisors rather than a complete replacement.

In the future, it will be essential for financial institutions and AI technology providers to ensure transparent and ethical implementation of these tools. Further research should focus on optimizing AI methods to support decision-making processes in more complex areas of financial planning and developing training programs that help advisors adapt AI technologies to meet clients' specific needs effectively.

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QUESTIONNAIRE DESIGN USING GENERATIVE AI: A CASE STUDY FROM MARKETING

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Abstract: There is an ongoing exploration of Generative AI in redesigning the teaching and learning process and investigating the validity of these practices. The case study addresses this call by presenting an experience from the teaching and learning process at the Faculty of Economics. Marketing is an area where the application of AI tools is already commonly used in corporate practice. The exercise was designed to apply knowledge from marketing on the one hand, and prompt engineering on the other. The activity took place in early 2024 and proved to be a rather challenging task not easy to accomplish, especially due to the low experience of the students in prompt engineering for Generative AI. The findings of this study suggest that today's teaching and learning process at universities should be transformed to train students to be future-ready for employment in a society powered by Generative AI. The student experience of Generative AI is changing, and the use of practical activities that can be applied in future practice seems to be a valuable innovation in education.

Keywords: Generative AI, higher education, innovation of education, prompt engineering

JEL Classification: I23, M3

INTRODUCTION

Higher education institutions (HEIs) have responded in a diverse and fragmented way to emerging opportunities for Generative AI implementation in the teaching and learning process in 2023/2024. Generative AI, demonstrated by Large Language Models such as ChatGPT or Gemini, has reshaped how machines interact and produce text that closely resembles human writing. These AI models have surprised the world with their ability to understand complex and diverse human languages and produce rich and structured human responses.

Scholars in education are exploring its applications in research, pedagogical matters, and strategies, while also taking into account ethical considerations (Bobula, 2024; Laupichler et al., 2022; Lopéz-Chila et al., 2024; Peres et al., 2023). Moreover, there is an ongoing exploration of Generative AI in redesigning the teaching and learning process and investigating the validity of these practices.

On the one hand, we use Generative AI to innovate teaching itself (from syllabus creation to student assessment), but on the other hand, our task is to prepare students to work effectively with this technology for corporate practice and actual tasks in their future jobs and lifes. Educators are tasked not only with developing and delivering educational materials to their students but also with giving them feedback, and assessing their performance (Michel-Villarreal et al., 2023; Sullivan et al., 2023).

We must address this educational problem and gain insight into how Generative AI can be utilized effectively for meaningful learning activities. The educational process still lacks information on subjects and learning activities that effectively utilize Generative AI applications.

This study seeks to address this gap by presenting an experience from the teaching and learning process at the Faculty of Economics. The case study shows how students were able to use Generative AI to solve a real-world marketing research assignment. It should be noted that this was in the context of gaining their first experience with this technology in a complex real-world task. The key questions being explored are:

- RQ1: How effective is using Generative AI in making students active learners in the learning activity of a business subject?
- RQ2: Do the results from Generative AI align with those from traditional teaching and learning?
- RQ3: What are recommendations for Generative AI-related activities for educational innovation?

1. THEORETICAL BACKGROUND

1.1. AI implementation in the teaching and learning process

AI is opening up new frontiers that will affect the way we learn, communicate, work, and spend our leisure time. The growing body of literature has started to document the potential challenges and opportunities posed by AI in education at the university level. Implementation of AI in the teaching and learning process requires us to innovate existing practices to be prepared for its relevant use in the future

The discussion about Generative AI in education should focus not only on its potential use by students but also examine how it can assist educators in the areas of learning and teaching to enhance the outputs of this process. Educators must inevitably transition to a future of education where Generative AI will be embraced rather than shunned (Lim et al., 2023; Zhang & Aslan, 2021).

Generative AI brings opportunities like the advancement of learning efficiency, further development of the concept of personalized learning, new support not only for students but also for educators, and also opportunities for skill enhancement (Sarker et al., 2023; Zhang & Aslan, 2021). Further, Slimi (2023) underlines that AI has a positive impact on the learning experience by facilitating the acquisition of new knowledge and skills.

For example, in their review Crompton and Burke (2023) found that AI in education was used for: assessment/evaluation, predicting, AI assistant, intelligent tutoring systems, and managing student learning.

Once again, practice is ahead of our educational process. It is appropriate to incorporate Generative AI in educational activities in fields where it has already been applied in practice. The integration of AI has brought many advantages to different functional areas within organizations, with marketing seeing a significant positive impact (cf. Knihová, 2024; Kumar et al., 2024; Labib, 2024). Therefore, the case study is from a marketing research activity.

In a course focused on research methodology, students were asked to create a specific questionnaire. Therefore, we will first give some background information on the semantic differential.

1.2. Semantic differential

Semantic differential scales are used in a variety of social science research and are also used for marketing purposes. It is a very general technique of measurement that has to be adapted to different research contexts depending on the aims of the planned study (Hair et al., 2021; Verhagen & Meents, 2007). Semantic differential scales can be used to evaluate and compare profiles of different organisations or firms, brands or products.

A semantic differential scale is a type of measurement in which the conclusions of the public about attitudes are deduced from statements about their opinions, views, feelings, behaviour, etc. towards an object or category of object. Usually there is one object and a related set of attributes. Its great advantage is easy administration and relatively fast evaluation (Klement et al., 2015).

In his original research, Osgood et al. (1957) used three factors (components) named evaluation, potency and activity. Rating items (questions) are combined to measure, for example, a wide variety of components of an image. Each component is described by a pair of opposite adjectives. Respondents evaluate each item on a bipolar scale and can vary the position of positive or negative adjectives. The respondents indicate their level of support for a selected construct (Youngman, 1994). For each concept of an image the resultant measure or scale is represented by combining the scores for each of the rating items (Saunders et al., 2019). Data are usually gathered through specially designed questionnaire. Since three factors are combined for the semantic space, the recommended number of questionnaire items is 9, 12 or 15. Each factor (item) is described by a pair of opposite adjectives (bipolar scale). See examples: (evaluation) good - bad, pleasant – unpleasant, friendly - unfriendly, modern - old, clean - dirty, (potency) large – small, hard – soft, strong – weak, high quality – low quality, (activity) fast – slow, passive – active, difficult – easy, heavy - light. Each scale should measure only one factor. One potential problem is the use of an odd number of scale points (5 or 7 is recommended). Researchers must be careful when selecting bipolar descriptors and should follow the rules set by Osgood, cf. Hair et al. (2021) or Saunders et al. (2019).

2. METHODOLOGY

This case study explores the topic of AI implementation in the teaching and learning process in the field of marketing. The activity that was evaluated was included in the subject curriculum at the Faculty of Economics and is focused on improving student learning and performance using AI tools. The purpose is to expand our experience with the application of AI in university settings. Predominantly a qualitative approach is used in the conducted case study (Gray, 2009).

The described case study is based on the analysis of selected student learning activities, the results of the learning process (written assignment), and the final assessment of this pilot learning activity.

The data capture introductory information on F2F teaching and the learning process before the key students' activity with Generative AI. The results of this activity are shown in Table 1. Next, a detailed description of the final written student report and feedback from groups of students is presented. It is important to note that the emphasis is on the qualitative description of the result.

3. RESULTS

This case study was developed as part of the learning activities in the course focused on a research methodology at the Faculty of Economics at the master's level. This learning activity was implemented in the middle of the 2024 summer semester.

At the start of the semester, all the students attended an introductory lecture on Artificial Intelligence, with an emphasis on the applications of Generative AI. The students were informed about the positive and negative aspects of working with Generative AI, as well as the necessity of complying with ethical guidelines and GDPR regulations. This introductory information was limited to a 45-minute session.

Detailed information on the selected activity follows.

- In the first seminar, a review of students' knowledge of questionnaire design (a topic is covered at the undergraduate level) was conducted. This review involved a comprehensive test (a didactic test) where students evaluated whether the presented questionnaire items (examples) were correct or contained errors. After each partial task, the teacher provided feedback and, if necessary, comments on the correct solutions. The next part of the didactic test focused on the differences between nominal, ordinal and cardinal data, highlighting the distinct possibilities for statistical analysis associated with each type of data. In the final part, the instructor summarized fundamental recommendations for overall questionnaire design and administration.
- Subsequently, a basic explanation of the semantic differential and its application in marketing research was provided. Emphasis was placed on creating relevant factors for the research purpose and ensuring their balance in the design of this specialized questionnaire. A practical application was demonstrated through a study of the school's image (e.g. Eger et al., 2018). Student groups (comprising 3-5 members) were then tasked with preparing (using pencil and paper) and presenting a semantic differential focused on evaluating the image of a passenger car. After their presentations

and evaluation of their outputs, the teacher presented examples of semantic differential questionnaires from published studies (e.g. Hair et al., 2021). Thus, through the traditional face-to-face teaching and learning process, students were adequately prepared for the subsequent task.

- The following week, in the subsequent seminar, students were tasked with creating a semantic differential questionnaire for a given focus area in small groups, using Generative AI, specifically ChatGPT 3.5 and Gemini. An optional additional task involved creating a relevant image using Bing Creator. The seminar provided 45 minutes for this activity. The groups were required to submit their outputs to the teacher as an email attachment.

3.1. Evaluation of Student Group Activity: Creation of Semantic Differential Using Generative AI

As shown in Table 1, not all groups attempted to create the semantic differential questionnaire in both Czech and English, despite the prior recommendation. Only 5 groups, in addition to creating the questionnaire, also experimented with generating an image related to the topic.

Tab. 1: Results of prompt engineering

	CZ Quest.		ENG Quest.		Picture
Project	Gemini	ChatGPT	Gemini	ChatGPT	
Café1	**	**	0	**	OK?
Café2	**	**	0	**	OK
Café3	**	**	**	**	OK??
Library1	*	**	*	**	OK
Library2	0	0	0	0	0
University1	**	* x	*		OK???
University2	*	*	*	*	0

Source: own

*Note. * only factors, ** factors and bipolar adjectives, *** balanced factors and bipolar adjectives*

The primary issue lies in the quality of the output. The semantic differential questionnaire was supposed to balance items across three factors (evaluation, potency and activity). None of the groups achieved this balance (one of the key indicators of quality), despite it being emphasized in the seminar the previous week, where both positive and negative examples were shown. The output was not semantic differential questionnaires, but a Likert scale battery that aimed to meet the required assignment's purpose. What was the main problem that emerged during the students' work with Generative AI?

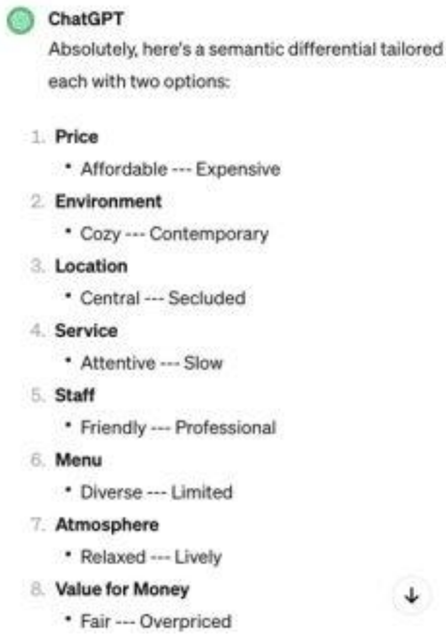
- Two groups explicitly mentioned that they struggled with task assignment to the AI. This indicates that the main problem the students faced can be classified under prompt engineering.
- Café2: the questionnaire contained only 5 items, the next prompt expanded the output to 10 items.
- Café3: questionnaire contained 8 items, but a three-point rating scale, additional prompts improved the output.
- Library1: the questionnaire had 7 items. Students tested a short and a long prompt.
- Library2: bad prompt, result = library evaluation query not semantic differential.
- University1: the role was used in the prompt (!), the questionnaire had 12 items, but the students had the Czech version translated (they also tried to use ChatGPT, Gemini was better - so they decided to use only Gemini).
- University2: the questionnaire had multiple items but no bipolar adjectives. The final questionnaire even had 22 items, which was not recommended.

Students commented on the creation of an image as follows: “The generated faces of the people sitting in the café were terrifying” (Café1), “The picture contained captions that were of very poor quality” (Café3), “Students in the library, the picture is quite OK” (Library1).
Feedback was provided to the students in a summary during the following week, where the best solutions were presented, and the teacher highlighted the following points:

A. It is important to apply the knowledge of the basic principles of effective prompt engineering.
B. The challenging task requires good knowledge of the subject matter (in this case, the methodology of creating a semantic differential questionnaire).

With a solid knowledge of the subject matter, it is impossible to effectively tackle complex specific tasks, as we are not able to prompt effectively and cannot adequately evaluate the AI-generated outputs (RQ1 and 2). Below, selected examples are provided to document this specific exercise with Generative AI.

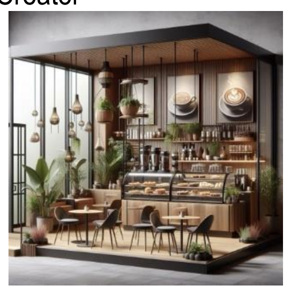
Fig. 1: Example of prompting, ChatGPT


ChatGPT
Absolutely, here's a semantic differential tailored to the café's image using the specified criteria, each with two options:

1. **Price**
   - Affordable --- Expensive
2. **Environment**
   - Cozy --- Contemporary
3. **Location**
   - Central --- Secluded
4. **Service**
   - Attentive --- Slow
5. **Staff**
   - Friendly --- Professional
6. **Menu**
   - Diverse --- Limited
7. **Atmosphere**
   - Relaxed --- Lively
8. **Value for Money**
   - Fair --- Overpriced

‘Source: Seminar assignment, ChatGPT application

Fig. 2: Example of creating picture, Bing Creator



Source: Seminar assignment, Bing Creator application

4. DISCUSSION AND IMPLICATION

The application of AI in education is gaining popularity in practice. Given its relative newness and complexity, it is not surprising that its role is not being adequately investigated in the teaching and learning process.

The findings from the study show that attention to prompt engineering is necessary to work effectively with Generative AI (RQ3). Prompt engineering is the practice of designing and refining prompts to elicit desired responses from AI models like ChatGPT or Gemini. It is evident that effective prompt engineering is essential for obtaining accurate, relevant, and coherent responses.

Prompting is the way we interact with technology, and this specific knowledge and skill is constantly evolving. Students in early 2024 did not have enough experience with the Generative AI application. This case study shows that many of them had a problem just communicating with AI.

Prompt engineering involves designing and refining prompts (also questions or instructions) to obtain specific responses from AI models. Today, prompt engineering is the bridge ensuring effective human-AI communication. The quality of outputs from this communication is heavily reliant on the precision and clarity of prompts.

Understanding the recommended rules is crucial, especially when utilizing Generative AI tools. Key elements of a prompt are:

- Instruction. This is the core directive of the prompt. Users should tell the model what they want it to do.
- Context. Context provides additional information that helps the model understand the broader scenario or background of running communication.
- Input data (if available). This is the specific information or data that users want the model to process. It could be a word (expression), phrase, longer text, a set of numbers, etc.
- Output indicator. This element guides the model on the format or type of response desired (e.g. stylistic direction, level of academic output).

Some techniques are recommended that can help.

Firstly there is Role-playing. For example, in our case, the students could start: “I want to act as a marketing expert…” (but only one group used role-playing).

Iterative refinement. The user starts with a broad prompt and gradually refines it based on the model's responses. The process of iteration aids in honing the prompt to perfection with the aim to receive a more accurate and reliable answer. Iterative prompt engineering is a systematic approach to creating prompts and refining them through successive iterations (only some groups used this approach).

Feedback loops. Feedback loops are key to training an AI model to improve over time. This is usually not a task for learning activity in the teaching and learning process.

As the findings from this case study also show, subject matter expertise is very important. Depending on the application, domain-specific knowledge is very important both for starting prompting and for assessing outputs.

The study by Kumar et al. (2024) highlights key marketing areas where AI promises transformative effects. These are, for example, AI-driven customer insights, measuring marketing performance, automated marketing strategies, ethical implications, enhancing customer experiences, and growth opportunities with AI implementation. The use of AI in business has the potential to gather and analyse large amounts of data, generate consumer insights, and enable managers to make quick and efficient decisions. Inspiration for prompting can also be found in specific guides, here for example for ecommerce (Smarty, 2024) or for marketing (Knihová, 2024; Macready, 2023).

It could be summarized that AI is a positive disruptive force, but its limitations, potential threats to privacy and security, as well as ramifications of biases, misuse, and dissemination of misinformation should also be highlighted (cf. Kumar et al., 2024). In conclusion, it can be stated that AI skills should not only be taught to children or students of school age but are also essential for students in higher and adult education (Laupichler et al., 2022).

CONCLUSION

Generative AI brings opportunities for learning efficiency, and new support not only for students but also for educators. The case study shows how students were able to use Generative AI to solve a real-world marketing research assignment. The findings from the study indicate that attention to prompt engineering is necessary to work effectively with Generative AI. Today, prompt engineering is the bridge ensuring effective human-AI communication. Key elements of a prompt are instructions, context, input data, and output indicators. Recommended techniques include role playing, iterative refinement, and feedback loops. Furthermore, subject matter expertise is very important.

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IMPLEMENTATION OF GENERATIVE AI AS TOOL FOR MARKETING COMMUNICATION SEMINARS IN UNIVERSITIES

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Abstract: Generative AI is reshaping the education landscape, particularly in domains requiring innovation and creativity, such as marketing communication. This paper explores the integration of Generative AI into university-level marketing communication seminars, focusing on its potential as a tool for enhancing learning outcomes and preparing students for real-world challenges. The study evaluates the impact of Generative AI applications like ChatGPT and Gemini on the learning process through a case study approach, identifying benefits, challenges, and key recommendations for effective implementation. The findings suggest that incorporating Generative AI tools into educational frameworks fosters critical thinking and practical skills, essential for contemporary marketing professionals.

Keywords: Generative AI, marketing communication, higher education, seminar innovation, AI-driven learning

JEL Classification: I23, M3, O3

INTRODUCTION

Not only Higher education institutions face the challenge of adapting to rapid technological advancements. Generative AI, exemplified by tools such as ChatGPT and Gemini, has emerged as a transformative force, particularly in disciplines like marketing where creativity and strategic communication are paramount. While corporate environments increasingly utilize AI-driven tools for content creation, customer engagement, and market analysis, universities have been slower to integrate these technologies into teaching frameworks even AI solutions are very dominantly used in in everyday user-facing interactions (Kumar et al., 2024).

This study focuses on implementing Generative AI in marketing communication seminars at universities, addressing critical questions:

RQ1: How can Generative AI enhance the learning process in marketing communication seminars?

RQ2: What are the challenges of using Generative AI tools in educational settings?

RQ3: What strategies can be recommended for the effective use of Generative AI in higher education?

This paper presents a case study conducted at University of Business and administration, department of marketing communication, in Prague, where Generative AI tools were introduced to facilitate innovative seminar activities in seminar Content marketing. The study examines the outcomes of these activities and provides actionable insights for educators.

1. THEORETICAL BACKGROUND

1.1. Generative AI in Education

Generative AI technologies are redefining the landscape of education by enabling personalized learning experiences, automating administrative tasks, and enhancing creative. AI has 'taken the world by storm, with notable tension transpiring in the field of education' (Lim et al., 2023). This process has started sixty years ago with first experts programming learning systems (Tzirides et al., 2024). These technologies hold particular promise for disciplines that require innovative thinking and strategic decision-making, such as marketing communication (Kumar et al., 2024). Research highlights the potential of Generative AI to improve learning efficiency and foster critical skills like problem-solving and adaptability. However, its integration into educational settings necessitates careful consideration of ethical, technical, and pedagogical factors. The incorporation into educational methodologies is the key for future pedagogical excellence (Yu, 2024). Generative AI promises revolutionize pedagogical approach in adaptive learning (Tzirides et al., 2024). Recent insights underscore the dual-edged nature of Generative AI in education, citing academic integrity concerns alongside opportunities for innovation and equity. There is recommendation to add AI skills in curriculum as needed (Hashmi, Bal, 2024) Furthermore, AI literacy has emerged as a critical skill for students navigating modern educational environments. Balancing the integration of Generative AI with a focus on ethical principles can cultivate a deeper understanding of the implications and applications of these tools.

1.2. Synergies Between Human and Artificial Intelligence in Education

Recent studies have emphasized the importance of integrating human and artificial intelligence to foster AI literacy in higher education. This approach advocates for a balanced perspective, where AI tools complement human creativity and critical thinking. There has been growing interest in moving away from human cantered Ethnography thinking approach (Vilalta-Perdomo et al., 2023). Understanding AI's impact on socio-material networks, emphasizing the necessity of ethical considerations and interdisciplinary collaboration.

1.3. Marketing Communication and AI

Marketing communication is a dynamic field that increasingly relies on AI-driven tools for crafting persuasive messages, analysing consumer behaviour, and optimizing campaign strategies (Ferraro et al., 2024). By incorporating AI into educational activities, students can gain hands-on experience with tools that are already integral to industry practices but is known that not all population of educators in universities are willing to do change teaching practices (Lee at al.,2024). Furthermore, marketing communication leverages AI to enhance segmentation, predict trends, and create dynamic content. Generative AI, specifically, allows for rapid development of tailored communication strategies (Labib, 2024). For example, AI can assist in generating persuasive copy, optimizing SEO, or creating social media campaigns and their content (Bormane, Blaus, 2024). The ability to simulate and test marketing scenarios in real-time positions Generative AI as a critical asset in both professional practice and education.

2. METHODOLOGY

This case study examines the implementation of Generative AI in a series of marketing communication seminars at the University of Prague. Chat GPT could be used to enhance education (Vilalta-Perdomo et al., 2023). The seminars were designed to:

1. Introduce students to the capabilities of Generative AI.
2. Engage students in practical activities using AI tools.
3. Evaluate the effectiveness of AI-assisted learning in achieving course objectives.

Participants: The first semester of master's level students enrolled in the Marketing Communication program.

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Procedure:
Introduction Session: Students attended a content marketing seminar in marketing communication study. This session included examples of successful AI-driven marketing campaigns and interactive discussions on ethical considerations.
Workshop Activity: Students worked in small groups to develop marketing communication strategies using tools like ChatGPT – free version Each group created:

1. Persona
2. AI-generated content, including examples of social media posts, email templates, and banner ads.
3. A reflective report analysing the AI's effectiveness and limitations plus overall evaluation of attitude to innovative way of creation via using AI and standard way of method.

Evaluation: Groups presented their outputs, followed by peer and instructor feedback. Criteria included creativity, alignment with objectives, and professional viability.
Data Collection: Qualitative data were collected through observation, student feedback, reflective reports, and evaluation of group outputs. Quantitative assessments included rubric-based scoring of student presentations and AI-generated content quality.

3. RESULTS

Overall results are divided in to three main areas: Engagements, Challenges, Output evaluation.

3.1. General Engagement of group work and Learning Outcomes

Enhanced Creativity: Students demonstrated increased creativity in developing creating Personas and campaign concepts. The ability to iterate quickly on ideas using AI significantly boosted brainstorming sessions and consultations between individual steps of creation.
Practical Skill Development: The use of AI tools enabled students to gain experience in generating and refining marketing content. Many reported newfound confidences in their ability to integrate AI into future projects.

3.2. Identified Challenges

Prompt Engineering: Many students struggled with crafting effective prompts to obtain desired outputs. This highlighted a gap in understanding how to communicate effectively with AI tools.
Tool Limitations: AI-generated content often required significant refinement to meet professional standards. For example, students noted inaccuracies in tone and cultural references.
Ethical Concerns: Students expressed concerns about the potential misuse of AI-generated content, particularly in cases where originality and authenticity were paramount. Addressing these concerns is essential for fostering ethical AI use in educational contexts.

3.3. Evaluation of Outputs

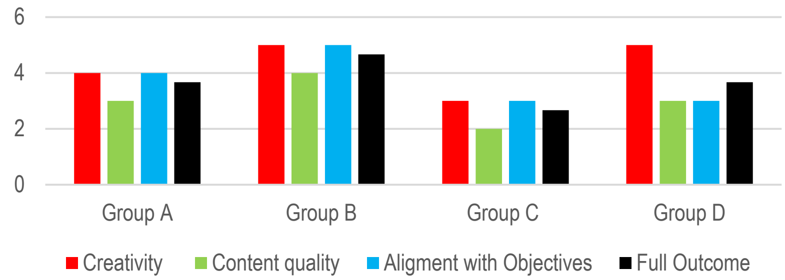
Table 1 summarizes the quality of group outputs based on specific criteria. Additional qualitative observations revealed that groups using iterative prompt strategies produced more polished outputs compared to those using one-off prompts.
Each group have to present in front of other groups three main outputs:
1. Persona
2. Draft of direct email
3. Draft of social media post
Dividing students in to 4 groups was on free selection between present 20 students.

Tab. 1: Quality of group outputs

Group	Creativity (1-5)	Content Quality (1-5)	Aligment with Objectives (1-5)
A	4	3	4
B	5	4	5
C	3	2	3
D	5	3	3

Source: own

Fig. 1 Evaluation of Groups outputs



Source: own

The outputs produced by students during the seminar were evaluated using three key criteria: creativity, content quality, and alignment with campaign objectives. Each group's outputs were rated on a scale of 1 to 5 for each criterion. The following summarizes the results and insights:

Creativity (1-5):
Average Score: 4.3
Student outputs demonstrated innovative ideas, leveraging AI to craft unique narratives and campaign concepts. However, human intervention was often required to refine the initial ideas and align them with the target audience.
Analysis:
Group B demonstrated exceptional creativity, earning a perfect score of 5, with highly innovative campaign concepts that leveraged the unique capabilities of Generative AI tools. Group D also achieved high creativity, integrating AI-generated outputs into visually compelling and innovative ideas. Group C, with a score of 3, struggled to extend beyond basic AI-generated ideas, highlighting a gap in creative engagement.
Insights:
Creativity was highest when groups experimented with iterative AI prompts, demonstrating how effective usage of AI tools can enhance ideation.

Content Quality (1-5):
Average Score: 4.0
The AI-generated materials generally exhibited high-quality language and structure, though occasional inaccuracies and stylistic inconsistencies were noted. Groups that employed iterative refinement produced more polished final outputs.
Analysis:
Group B's content quality score of 4 reflects well-structured, coherent, and contextually relevant outputs, though minor refinements were necessary to achieve professional standards. Group C scored the lowest (2), with outputs requiring significant rework to improve clarity and alignment with expectations.
Insights:

The variation in scores indicates the importance of prompt engineering and iterative feedback loops in improving content quality. Groups that emphasized review and editing achieved better results.

Alignment with Objectives (1-5):
Average Score: 4.1
Most groups successfully aligned their campaign outputs with the seminar objectives. However, some submissions lacked coherence, with AI-generated elements occasionally diverging from the original campaign strategy.
Analysis:
Group B again excelled with a score of 5, closely aligning their campaign outputs with the seminar objectives. Conversely, Groups C and D both scored lower, with instances where AI-generated content deviated from the intended campaign strategy, reducing overall coherence.
Insights:
Effective alignment required not only AI outputs but also strategic refinement by students to ensure consistency with objectives.

Overall Performance
Group B achieved the highest overall score, reflecting their ability to maximize the potential of AI tools while maintaining alignment with the seminar objectives. Groups A and D achieved comparable overall scores, though with differing strengths—A excelled in alignment while D excelled in creativity. Group C lagged behind with an overall score, indicating areas for significant improvement in all three criteria.

Recommendations:
1. Enhance Prompt Engineering Skills: Integrating dedicated sessions on crafting effective AI prompts could bridge performance gaps between groups. This specific prompting could bring more relevant outcomes for lower skilled groups. (Knihová, 2024)
2. Emphasize Collaborative Review: Group activities that prioritize collaborative reviews of AI outputs can enhance content quality and alignment with objectives for the main principles of required 21st century skills (Chiu, 2024).
3. Incorporate Reflective Practice: Encouraging reflective practice allows students to critically analyse the effectiveness of their AI-driven outputs and iterate for improvement and provide for students more integrated solutions (Chiu, 2024).

This evaluation highlights the potential of Generative AI tools to enhance creativity and content quality in educational settings while underscoring the need for strategic oversight to align outputs with learning objectives. For example, ChatGPT have several advantages like understanding of context and bringing relevant answers, his advantage lead to advance language generation and produce contextually accurate and grammatically correct outcomes (Bobula, 2024). The findings provide a roadmap for optimizing the integration of Generative AI in marketing communication education as according to Eger et al. (2018) the syllabus of seminar is not so important as the actual teaching process.

4. DISCUSSION AND IMPLICATIONS

The findings suggest that Generative AI can be a valuable tool for enhancing marketing communication seminars. However, its effectiveness depends on addressing key challenges:
Prompt Engineering Skills: Educators should provide training on effective prompt crafting. This could include examples of well-designed prompts and iterative refinement techniques (Knihová, 2024).

Critical Evaluation: Students must be encouraged to critically assess AI outputs for quality and relevance. Incorporating peer review sessions can foster collaborative learning and critical thinking.
Ethical Awareness: Ethical considerations should be an integral part of AI-related activities. Discussions should cover topics such as bias, copyright, and the implications of automated content creation. The urgency of addressing these issues should lead to responsible AI integration in education.

4.1. Practical Implications

1. Universities should integrate AI tools into marketing courses to align with industry practices.
2. Techers need adequate training to effectively facilitate AI-driven learning activities.
3. Investing in robust AI tools and supportive infrastructure is critical for successful implementation.

The discussion also highlighted the multifaceted benefits and challenges of AI integration. For instance, while tools like ChatGPT enhance productivity, their outputs require human refinement to meet professional standards. Incorporating structured activities that simulate real-world marketing challenges (Ding et al., 2024) can ensure students are well-prepared for industry demands what starts to be general standard for graduate starters in companies.
In addition, the data-driven evaluation framework used in this study—considering creativity, content quality, and alignment with objectives—can serve as a model for future assessments in similar contexts. This comprehensive approach ensures a balanced evaluation of AI-enhanced outputs, offering insights into areas of improvement while celebrating innovation.
Moreover, ethical considerations remain a cornerstone of AI integration. Educators must prioritize transparency and fairness, addressing issues such as bias and data privacy. By fostering a culture of ethical awareness, institutions can guide students to become responsible users of AI technologies (Hashmi, Bal, 2024).

CONCLUSION

Generative AI offers significant potential for transforming marketing communication education. Generative AI is beneficial for students to become better in organisation of research ideas for their final study paper works (Parker et al., 2024) By enabling students to engage with industry-relevant tools, universities can foster practical skills and innovative thinking. However, challenges such as prompt engineering, critical evaluation, and ethical considerations must be addressed to maximize its effectiveness. Universities must commit to equipping educators and students with the skills necessary to use AI responsibly, ensuring that these tools are integrated in a way that enhances rather than undermines learning. However, successful integration requires a balanced approach that addresses pedagogical, ethical, and technical challenges.
Moreover, the findings of this study emphasize the need for a structured approach to integrating AI tools into curricula. This includes developing comprehensive guidelines, providing training for faculty, and ensuring access to advanced AI technologies. By embedding Generative AI into the core of marketing education, institutions can create a robust framework that not only supports academic integrity but also aligns with industry expectations. One of the most significant findings of this study is the potential of Generative AI to enhance student creativity and professional readiness. Students who utilized iterative refinement techniques produced innovative outputs closely aligned with seminar objectives.
Future research should focus on long-term studies to assess the sustained impact of AI integration in educational settings. Additionally, collaborations between academia and industry could provide valuable insights into emerging AI trends and best practices. By doing so, universities can remain at the forefront of educational innovation, preparing students for a future where AI plays a pivotal role in shaping marketing strategies and communication practices.
As the educational landscape continues to evolve, embracing Generative AI as a core component of learning processes is not merely an option but a necessity. The ongoing dialogue between educators, students,

and industry stakeholders will ensure that the integration of AI technology is both effective and ethically sound. Institutions that lead this transformation will not only enhance their academic offerings but also empower graduates to excel in an increasingly AI-driven world. By integrating AI literacy into curricula, providing targeted faculty training, and embedding ethical considerations into activities, universities can align academic practices with industry demands.

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INNOVATION OF THE EDUCATION PROCESS TOWARDS IMPLEMENTING AI TOOLS

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Abstract: Artificial intelligence (AI) is transforming education by offering personalized learning experiences, breaking traditional barriers, and preparing students for the future workforce. It enhances adaptability to modern educational demands and business trends while empowering both students and educators through innovative tools and methods. Our paper examines students' perceptions of AI and maps how they utilize AI tools, highlighting their role in meeting the challenges of today's educational and professional life. By analysing data collected through a structured questionnaire, we identified key themes, including the usefulness, ease of use, attitudes, and concerns surrounding AI. These findings serve as a foundation for understanding the role of AI in education and its potential to enhance learning experiences and adaptability to future challenges. The Kruskal-Wallis tests revealed significant differences in students' perceptions and use of AI based on demographic factors such as gender, study level, socioeconomic status, and place of residence. Female students reported greater difficulty using AI, highlighting the influence of historical gender stereotypes surrounding technology. Master's students, likely due to their advanced academic exposure, demonstrated higher confidence and a stronger inclination to use AI for learning. Socioeconomic background and urban residency were linked to more supportive attitudes toward AI integration in education and privacy concerns. Additionally, students further along in their academic journey reported more frequent use of AI tools for language learning.

Keywords: Artificial intelligence (AI), students, attitudes, learning process, education

JEL Classification: O34; M21; I23

INTRODUCTION

Artificial intelligence (AI) is increasingly permeating various aspects of our lives. Its integration into educational processes is essential, as these innovations can enhance adaptability to emerging trends in the business world. AI is revolutionizing education by offering personalized learning experiences tailored to individual needs. It enables students to access resources and tools anytime, breaking the barriers of traditional classroom settings. AI-powered systems can adapt new teaching methods based on a student's progress, enhancing understanding and retention. Additionally, it streamlines administrative tasks for educators, allowing them to focus more on teaching and mentoring. By integrating AI, students gain access to advanced technologies, preparing them for the future workforce. AI fosters creativity by offering innovative solutions to complex problems, promoting critical thinking. It also facilitates collaboration and knowledge sharing through interactive platforms. Furthermore, AI tools can assist in identifying learning gaps, enabling targeted interventions for better outcomes. The use of AI in education supports lifelong learning by providing flexible and accessible learning opportunities. Ultimately, AI empowers both students and educators to achieve greater efficiency, adaptability, and success in the learning process. Therefore, our paper focuses on this very issue, examining students' perceptions of AI and mapping how they utilize AI tools in their educational and learning processes. By understanding student´s attitudes and integrations AI into their studies, we aim to highlight its role in enhancing adaptability to modern educational demands and emerging trends in the business world.

1. LITERATURE REVIEW

Artificial intelligence (AI) has become increasingly important in recent decades, impacting numerous fields, such as medicine, finance, law, industry, and entertainment. Education is no exception, as there is a growing body of research into AI applications for education, including intelligent tutoring systems, adaptive learning, assessment design, and learning analytics (Salas-Pilco & Yang, 2020). As educational institutions strive to meet the diverse needs of learners, AI technologies offer new ways to personalize and enhance the educational experience, making learning more engaging, accessible, and effective. The integration of technology in education has rapidly evolved over the past 30 years. Initially designed as assistive tools, technologies like text-to-speech, predictive text, and search engines have expanded beyond their original purpose. Today, these tools are essential features embedded in digital platforms, reflecting a broader trend of technological integration in daily life. These advancements now augment the learning interactions of students globally, opening new possibilities for teaching and designing educational experiences (Popenici & Kerr, 2017). AI's presence in education can be traced back to the introduction of computers in the 1990s. Since then, research has focused on developing AI-enhanced learning environments, including intelligent tutoring systems and adaptive learning platforms, which manifest significant improvements in automated approaches to education (Chen et al., 2020). These innovations have empowered educators to create more dynamic and adaptive curriculums, catering to individual learning speeds and preferences. AI's influence extends beyond learning and teaching, encompassing administrative processes within educational institutions. According to Zhang and Aslan (2021), AI in education is an interdisciplinary field that integrates computer science, learning sciences, psychology, neuroscience, and other disciplines. This multidisciplinary synergy is vital for understanding how students learn and how technology can best support their educational journey, driving the development of adaptive and effective learning environments to optimize traditional education. AI has the potential to achieve sustainable change at all levels, not only in pedagogy but also in the management of educational institutions.

Baker and Smith (2019) identified three main educational processes impacted by AI applications: learning, teaching, and administration. AI supports students' learning through adaptive systems, assists teachers by automating tasks like grading and feedback, and aids administrators by providing data-driven insights for decision-making. These capabilities streamline educational processes, reduce costs, and improve the quality of education, allowing educators to focus more on student engagement and instruction. The benefits of AI in education are diverse. Owoc et al. (2021) highlighted advantages such as automating repetitive tasks, supporting teachers through AI facilitators, and providing adaptive learning experiences that cater to individual students' needs. AI-powered systems can offer personalized feedback, improve spaced repetition for better knowledge retention, and even detect academic misconduct. These examples show how AI simplifies educational logistics while introducing data-driven methods to enhance learning. Furthermore, AI has been integrated into higher education campuses worldwide. Universities use data to analyze trends and patterns in student behavior, enabling educators to gain a holistic understanding of their students' needs. This data-driven approach allows for the development of personalized learning platforms that adapt to each student's pace and progress (Popenici & Kerr, 2017). As AI continues to advance, it is expected to provide even more sophisticated tools for enhancing student learning.

A recent advancement in AI that holds promise for education is generative AI. Lv (2023) describes generative AI as a subfield capable of producing new and original content, such as text, audio, video, and code. This ability to produce diverse content autonomously has made generative AI a versatile tool across multiple industries, including entertainment, marketing, and education, where it can create engaging learning materials or provide instant feedback. Unlike traditional AI systems, which are explicitly programmed, generative AI can creatively adapt to different contexts, leading to more dynamic and personalized interactions with users (Feuerriegel et al., 2023). One notable example of generative AI in education is ChatGPT, which can revolutionize teaching and learning in higher education by serving as an AI-powered tool for various tasks (Lim et al., 2023). ChatGPT can function as an independent tool or integrate into existing educational platforms, providing personalized feedback, facilitating collaborative problem-solving, and even assisting with curriculum design. According to Hwang and Chen (2023) the use of ChatGPT can facilitate students learning experiences, generate alternative ways of expressing ideas, and based on data supplied by students or teachers, immediately give each student personalized feedback. Such capabilities make ChatGPT a valuable resource for enhancing student engagement and supporting differentiated instruction, allowing educators to address individual learning needs more effectively. Moreover, ChatGPT can be used as a collaboration coach to assist groups in researching and solving problems together, as a guide on the side to navigate physical and conceptual spaces, and as a codesigner to help in the designing or updating of curricula. Additionally, ChatGPT can be employed as an exploratorium to provide tools for exploring and interpreting data, as a study buddy to help students reflect on learning material and as a motivator that offers games and challenges to extend learning. These varied roles demonstrate the potential of ChatGPT to act not just as a passive tool but as an active partner in the learning journey, adapting to the evolving needs of students and educators alike. It can act also as a dynamic assessor for students' assignments and other evaluation tasks (Ivanov & Soliman, 2023).

However, the adoption of AI, including ChatGPT, is not without challenges. According to Lund et al. (2023), ethical considerations and concerns about plagiarism, privacy, and regulation are significant. The potential for misuse, coupled with the need for robust AI-detection mechanisms, has raised apprehensions among educators and institutions. A primary concern expressed by numerous universities and educators revolves around the potential escalation of plagiarism and cheating among students. Furthermore, there exist apprehensions regarding the efficacy of current plagiarism detection tools when faced with written content generated by ChatGPT (Cotton et al., 2023). This raises the need for developing more robust AI-detection mechanisms and establishing clear guidelines for ethical use of AI-generated content within academic settings. Moreover, the absence of regulation surrounding ChatGPT is also a concern, as it facilitates rapid development without adequate exploration of potential risks and shared protocols. Additionally, the tool's inability to discern between veracity and falsehood, right and wrong, raises concerns pertaining to cognitive bias (Kasneci et al., 2023). These biases, if not properly addressed, could lead to misinformation and misrepresentation, negatively impacting students' learning outcomes and perpetuating harmful stereotypes. Other concerns encompass privacy, accessibility and commercialization, necessitating meticulous deliberation and regulation to ensure fairness and equity in the application of AI tools in higher education (Rudolph et al., 2023). Ensuring that these tools are designed with privacy safeguards and equitable access is essential for their responsible deployment, making it crucial for policymakers and institutions to collaborate on standardized frameworks. Recent study found that providing teachers with AI knowledge and practical experience can reduce their concerns and improve their trust in AI tools. Sessions on AI-powered assessment and the use of an AI tool positively impacted teachers' knowledge, perceptions, attitudes, trust and willingness to adopt AI tools (Nazaretsky et al., 2022). This suggests that proper training and support can play a significant role in overcoming resistance to new technologies, ensuring that educators are well-prepared to integrate AI in a way that complements their teaching. Despite the benefits and challenges, there is still a gap in research specifically focusing on the use of ChatGPT by students in higher education. More empirical studies are needed to understand how students interact with AI tools, the perceived benefits, and potential issues that may arise with widespread usage. Such research is essential for developing strategies that encourage effective adoption and integration of AI technologies in academic settings.

The successful adoption of AI technologies like ChatGPT depends on several critical factors, which can be analyzed through the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003). This model emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants influencing students' attitudes towards adopting new technologies. Addressing these factors can ensure that AI tools are perceived as beneficial, easy to use, and well-supported, ultimately shaping the future of learning in higher education (Strzelecki & ElArabawy, 2023). Performance expectancy refers to the degree to which a person believes that using a system will enhance their job performance. In the context of using ChatGPT, this translates to students' perceptions that the tool will improve their study practices. Specifically, it reflects their belief in the usefulness of ChatGPT for academic tasks, such as drafting essays, clarifying complex topics, or providing quick answers to queries. For instance, students might find that ChatGPT helps them improve productivity and comprehension, making it an essential aid in their learning process. Similarly, effort expectancy is characterized by the ease of use of the system and the level of comfort associated with it. In the study of ChatGPT, this pertains to how user-friendly and accessible the tool is, along with its ability to minimize distractions and streamline tasks. A user-friendly interface, intuitive commands, and seamless integration with existing educational platforms can significantly enhance students' willingness to engage with ChatGPT, as they can focus on learning rather than struggling with the technology itself. The simpler the system is to use, the more likely students will be to incorporate it into their study habits. Moreover, social influence plays a crucial role in technology adoption. It is defined as the extent to which a person perceives that significant others—such as peers, educators, or even broader societal groups—believe they should use a particular system (Strzelecki & ElArabawy, 2023). In the case of ChatGPT, peer recommendations, instructor encouragement, and the general acceptance of AI tools within the academic community can all shape students' attitudes towards integrating the tool into their educational practices. The more positive the social reinforcement, the greater the likelihood that students will feel encouraged to adopt ChatGPT as a part of their learning environment. Facilitating conditions represent the perception that a supportive administrative and technological framework is in place to assist in using the system. Within the study examining ChatGPT adoption among college students, these conditions can be especially significant because they directly impact how easily students can access and utilize the tool. Ensuring reliable internet access, availability of technical support, and effective integration with learning management systems are critical factors that can either encourage or hinder the effective use of ChatGPT. When these conditions are well-established, students are more likely to engage with the technology confidently, without facing barriers to access. These four determinants—performance expectancy, effort expectancy, social influence, and facilitating conditions—interact to influence students' behavioral intentions to use ChatGPT. According to Venkatesh et al. (2003), technology use behavior is positively impacted by behavioral intention. Therefore, if students perceive ChatGPT as beneficial, easy to use, and well-supported by their educational environment, their intention to use the tool is likely to translate into actual usage, further integrating AI into the academic ecosystem. This alignment of user expectations and system capabilities is essential for the sustained adoption of AI technologies, ultimately shaping the future of learning in higher education (Strzelecki & ElArabawy, 2023).

However, as AI continues to evolve, it also brings about anxieties and concerns regarding its impact on society. On the one hand, various AI events impact individual psychology. On the other hand, various studies and expert opinions have also incited anxiety (Li & Huang, 2020). The McKinsey Global Institute estimates that 400 to 800 million workers will be replaced by AI by 2030 (McKinsey Global Institute, 2017). This prediction has sparked a global debate about the implications of AI on the workforce, including concerns

about job security, economic inequality, and the future of work. Recently, scholars have begun focusing on the existing problems and defects of AI. Therefore, anxiety has arisen concerning autonomous AI and personal privacy (Carsten & David, 2018). First, there are concerns that AI may produce artificial consciousness, which will give rise to a condition where AI exists independently and may not be controlled by humans. Second, there are worries concerning the opacity of AI operations and decision-making processes, which introduces unpredictable risks (Clarke, 2019). Third, AI makes decisions through calculations and pros-and-cons analysis, which results in concerns about discrimination and bias. These biases can manifest in unexpected ways, particularly when AI systems are trained on data that contains implicit biases, leading to unfair treatment of individuals based on gender, race, or other factors. Fourth, some worry that AI will not abide by human ethics, resulting in ethical violations such as murder by autonomous weapons. Fifth, future super AI applications may pose a threat to human survival (Leavy, 2018). These ethical and existential concerns have prompted calls for stricter regulation and oversight in the development of AI technologies. In addition to these particular anxieties, AI may generate a wider range of anxieties than computer anxiety, including job replacement anxiety, privacy violation anxiety, and safety and regulation anxiety. According to Erkin et al. (2009) privacy violation anxiety occurs when users experience direct violations of privacy by AI. This anxiety can arise because datasets used by AI may violate personal privacy, which is disturbing. For example, targeted advertising and face recognition can be performed automatically by unsupervised AI, leading to a risk of personal data leakage and hence the invasion of privacy. In particular, privacy anxiety concerning the widespread use of biometrics is rising. The misappropriation or modification of a user's privacy data when face recognition is used to verify identity has serious consequences. These concerns highlight the need for transparent AI systems that prioritize user privacy and data security. AI also generates learning anxiety that resembles anxiety related to other technologies. When AI is applied in various fields, various forms of anxiety arise spontaneously. In the future, new anxieties and safety issues will arise as AI technologies such as face recognition and autonomous driving enter the mainstream (Zhou et al., 2020).
Kemp et al. (2019) identified seven primary factor groups that were relevant to student attitudes towards educational technologies: attitude, affect and motivation, social factors, usefulness and visibility, instructional attributes, perceived behavioral control, cognitive engagement and system attributes. According to Kemp et al. (2024) many technology acceptance models used in education were originally designed for general technologies and later adopted by education researchers. This previous research suggested that an effective extended educational technology acceptance model should include perceived usefulness, perceived ease of use, cognitive engagement, class interaction and communication, feedback, instructor practice, access and convenience, system attributes, self-efficacy and comfort and well-being. These factors represent all of the primary factor classes suggested by the taxonomy, except attitude, in addition to the factors suggested by Kemp's (2023) qualitative study. COVID-19 had a significant impact on education globally causing disruptions in learning delivery. It was therefore important to explore how student attitudes towards educational technologies may have evolved during this period. The pandemic accelerated the adoption of digital tools, and many students who previously had little exposure to online learning had to quickly adapt, leading to new insights into how these technologies could be improved. In a separate qualitative study (Kemp, 2023), student attitudes to using Zoom for learning were investigated, revealing that social comfort and well-being, cognitive engagement, instructor practice, class interaction and feedback, access and convenience and system attributes were important considerations. These findings underscore the importance of designing educational technologies that are user-friendly, engaging, and supportive of both students and educators in diverse learning environments.
In conclusion, artificial intelligence (AI) represents a transformative opportunity for the education sector, offering the potential to enhance learning experiences, streamline administrative tasks, and provide personalized educational support. However, for AI to be successfully integrated into educational settings, a balanced and strategic approach is necessary. This approach must prioritize not only the technical reliability

and performance of AI systems but also the ethical considerations that come with the use of such advanced technologies. Issues such as data privacy, security, bias, and the potential misuse of AI-generated content must be carefully addressed to ensure that these tools benefit students and educators without compromising their rights and well-being.

2. DATA AND METHODOLOGY

In this paper, we explored students' perceptions and use of AI in their educational and learning processes. To identify significant differences between student groups, we analyzed primary data collected through an online questionnaire. The questionnaire was divided into two sections. The first section included demographic and background questions, where respondents provided information about their gender, place of residence, level and year of study, field of study, and socioeconomic status. The second section focused on students' use of AI and was structured into several thematic parts: (1 - PU) questions about the perceived usefulness of generative AI; (2 - PE) questions on the perceived ease of use of AI; (3 - SE) scenarios involving AI usage; (4 - BI) questions about plans and ideas for integrating AI into learning; (5 - ATT) questions on students' attitudes toward AI; (6 - ANX) questions addressing privacy concerns related to AI use; and (7 - FRQ) questions about the frequency of AI use in specific activities. All responses in this section were recorded using a Likert scale. The survey participants were exclusively students specializing in business studies. Data collection took place between September and November 2024 as part of a pilot study.

The Table 1 provides a comprehensive summary of the descriptive characteristics of the research sample, encompassing various demographic and academic dimensions. The gender composition reveals that 67.1% of respondents are female, while 32.9% are male, indicating a notable gender imbalance. The entire sample (100%) is comprised of students specializing in Business and Management, demonstrating a homogeneous focus on a single field of study. Such specificity may enhance the relevance of findings for exploring trends, challenges, or patterns within business education. Additionally, all participants are enrolled in public universities and reside in Slovakia (SVK). While this ensures a high degree of regional specificity, it also limits the study's applicability to other geographic or institutional contexts, particularly those outside the Slovak educational system. The urban-rural distribution reveals a relatively balanced composition, as 53.7% of respondents reside in urban areas, while 46.3% come from rural regions. This balance contributes to the diversity of geographic representation within the sample, enabling potential insights into socioeconomic or educational disparities based on place of residence. Regarding educational levels, the sample is predominantly comprised of bachelor's students, who constitute 65.9% of respondents, while 34.1% are enrolled in master's programs. The prevalence of undergraduate students suggests that the research largely reflects individuals in the earlier stages of higher education, which may influence results related to academic motivation, preparedness, or career planning. When examining the year of study, the majority of respondents (65.9%) are in their second or third year, indicating a strong concentration in the mid-stages of their undergraduate programs. A smaller proportion are in their first year (8.5%), while 23.2% are in their fourth or fifth year. Only 2.4% of respondents have exceeded the standard duration of study. This distribution highlights the predominance of students who are actively engaged in their academic programs and likely approaching critical phases of career preparation and decision-making. Socioeconomic status was assessed on a scale ranging from 1 (poorest) to 9 (richest). The findings indicate a limited presence of respondents from the lowest income brackets, with 1.2% representing the two lowest levels and 4.9% occupying level 3. The majority of participants fall within the middle and upper-middle wealth categories, particularly at level 5, which accounts for 32.9% of the sample. Furthermore, levels 6 and 7 comprise 13.4% and 22.0%, respectively, whereas the highest levels (8–9) are underrepresented. This distribution indicates that the sample largely reflects individuals from middle-income backgrounds, with minimal representation from economic extremes.

Tab. 1: Descriptive characteristics of the research sample

GENDER	%	FIELD_STUDY	%
Male	32.9	Business and Management	100.0
Female	67.1	UNI_TYPE	%
COUNTRY	%	Public	100.0
SVK	100.0	SOCIOECONOMIC STATUS*	%
PLACE_RES	%	1	1.2
Urban	53.7	2	1.2
Rural	46.3	3	4.9
STUDY_LEVEL	%	4	8.5
Bc	65.9	5	32.9
Master	34.1	6	13.4
YEAR_STUDY	%	7	22.0
First year	8.5	8	14.6
2-3 years	65.9	9	1.2
4-5 years	23.2		
Over 5 years	2.4		

**1=the poorest; 9=the richest*

Source: own processing

According to the questionnaire design, the following research hypotheses were established:
H1: Perceived usefulness of generative AI is influenced by the demographic and background characteristics of students (gender, place of residence, level of study, year of study, and socioeconomic status).
H2: Perceived ease of use of AI is influenced by the demographic and background characteristics of students (gender, place of residence, level of study, year of study, and socioeconomic status).
H3: Using of AI in specific situations is influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H4: Plans for using AI in learning are influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H5: Attitudes towards AI are influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H6: Concerns about the use of AI in the context of privacy are influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H7: Frequency of using AI in specific activities is influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status). To determine whether statistically significant differences existed between groups of respondents (based on specific classification factors), the Kruskal-Wallis test was employed. The Kruskal-Wallis test serves as a non-parametric equivalent to one-way analysis of variance (ANOVA) for a single factor.

3. RESULTS

The results presented in Table 2 summarize the outcomes of the Kruskal-Wallis Test, examining associations between several dependent variables and independent categorical factors, namely gender, place of residence, study level, year of study, and wealth. The table highlights statistically significant relationships where p-values fall below conventional thresholds of significance ($p < 0.05$, $p < 0.01$, $p < 0.001$). Regarding gender, significant results emerge for certain variables. Specifically, PE2 ($p = 0.046$), PE3 ($p = 0.003$), and

PE4 (p = 0.005) demonstrate meaningful associations, suggesting that gender differences exist in these measures. Conversely, most of the other variables across the table fail to show significant gender-based differences, indicating that gender generally does not play a substantial role in influencing outcomes for most of the measured constructs. For place of residence, a limited number of significant results are observed. Notably, ATT2 (p = 0.036) and ANX3 (p = 0.030) indicate differences between urban and rural participants. These findings imply that place of residence may impact specific attitudes and experiences, though its influence does not extend across most of the variables assessed. The variable study level produces a broader range of significant findings. For instance, differences are noted for PE3 (p = 0.006), PE4 (p = 0.027), SE1 (p = 0.028), SE4 (p = 0.031), BI1 (p = 0.034), BI3 (p = 0.046), and ATT4 (p = 0.005). These results suggest that the level of study (e.g., Bachelor vs. Master) significantly influences participants' perceptions and attitudes for several constructs, particularly those related to performance expectations, self-efficacy, and behavioural intention. In contrast, year of study reveals limited statistical significance, with only FRQ7 (p = 0.045) showing a notable association. While many of the variables do not exhibit significant differences, this isolated result suggests that progress through academic years might influence frequency-related outcomes to a small extent. Lastly, the wealth variable does not demonstrate significant associations across most measures. One exception is ATT5 (p = 0.048), where wealth shows a meaningful relationship. However, the absence of significance in other variables indicates that socioeconomic status, as measured here, has a minimal impact on the assessed constructs.

The analysis reveals that gender and study level exhibit the most consistent influence on the measured variables, with significant differences observed in multiple constructs. Place of residence and year of study show more limited effects, while wealth demonstrates minimal association overall. These findings suggest that demographic and academic factors play a variable role in shaping participants' perceptions, attitudes, and experiences, with specific constructs being more sensitive to certain factors than others. The results underscore the need to further explore these relationships to better understand the underlying dynamics influencing the measured outcomes.

Tab. 2: Kruskal-Wallis Test results

	PU1	PU2	PU3	PU4	PE1	PE2	PE3	PE4	SE1	SE2	SE3
GENDER	0.228	0.605	0.772	0.650	0.083	***0.046**	****0.003**	****0.005**	0.432	0.746	0.453
PLACE_RES	0.166	0.210	0.108	0.245	0.134	0.158	0.233	0.921	0.251	0.642	0.953
STUDY_LEVEL	0.302	0.254	0.431	0.573	0.163	0.329	****0.006**	***0.027**	***0.028**	0.387	0.447
YEAR_STUDY	0.074	0.117	0.074	0.204	0.574	0.730	0.098	0.227	0.055	0.564	0.505
WEALTH	0.512	0.230	0.429	0.126	0.084	0.651	0.378	0.361	0.441	0.363	0.918
	SE4	**BI1**	**BI2**	**BI3**	**BI4**	**BI5**	**BI6**	**ATT1**	**ATT2**	**ATT3**	**ATT4**
GENDER	0.476	0.701	0.527	0.597	0.768	0.132	0.206	0.413	0.509	0.862	0.961
PLACE_RES	0.630	0.587	0.686	0.314	0.950	0.761	0.568	0.270	***0.036**	0.602	0.421
STUDY_LEVEL	***0.031**	***0.034**	0.132	***0.046**	0.423	0.293	0.162	0.055	0.266	0.115	****0.005**
YEAR_STUDY	0.219	0.148	0.167	0.119	0.756	0.556	0.572	0.420	0.638	0.389	0.099
WEALTH	0.660	0.773	0.324	0.621	0.579	0.668	0.933	0.491	0.705	0.405	0.629
	ATT5	**ATT6**	**ATT7**	**ATT8**	**ANX1**	**ANX2**	**ANX3**	**FRQ1**	**FRQ2**	**FRQ3**	**FRQ4**
GENDER	0.604	0.340	0.512	0.305	0.572	0.208	0.793	0.087	0.122	0.187	0.404
PLACE_RES	0.836	0.589	0.820	0.992	0.938	0.761	***0.030**	0.913	0.893	0.144	0.289
STUDY_LEVEL	0.664	0.559	0.302	***0.038**	0.565	0.340	0.802	0.884	0.887	0.214	0.532
YEAR_STUDY	0.510	0.760	0.637	0.180	0.275	0.373	0.581	0.997	0.246	0.489	0.380
WEALTH	***0.048**	0.283	0.440	0.477	0.537	0.826	0.768	0.458	0.814	0.722	0.605
	FRQ5	**FRQ6**	**FRQ7**	**FRQ8**	**FRQ9**	**FRQ10**	**FRQ11**	**FRQ12**	**FRQ13**	**FRQ14**	**FRQ15**
GENDER	0.247	0.777	0.670	0.587	0.543	0.682	0.184	0.574	0.987	0.890	0.352
PLACE_RES	0.078	0.392	0.098	0.173	0.256	0.195	0.489	0.724	0.394	0.857	0.267
STUDY_LEVEL	0.553	0.823	0.876	0.410	0.907	0.347	0.401	0.151	0.917	0.258	0.321
YEAR_STUDY	0.544	0.572	***0.045**	0.053	0.943	0.665	0.090	0.381	0.687	0.368	0.346
WEALTH	0.177	0.062	0.968	0.882	0.876	0.559	0.910	0.762	0.256	0.978	0.598

*Notes: *** p<0.001, ** p<0.01, * p<0.05*

Source: own processing

PE2: Perceived difficulty in learning how to use AI

The Kruskal-Wallis test yielded statistically significant differences in perceived difficulty in learning how to use AI (PE2) based on gender (p-value = 0.046). This finding may reflect the context of our research, conducted among university students, where gender disparities in learning how to use artificial intelligence are evident. Supporting studies indicate that gender significantly shapes how AI tools are perceived and utilized in educational settings, with male students generally rating their competencies higher compared to female students (Ofosu-Ampong, 2023; Armutat et al., 2024).

PE3: Perceived clarity and comprehensibility in using AI
A Kruskal-Wallis test yielded statistically significant differences in perceptions of clarity and comprehensibility in using artificial intelligence (PE3) based on gender (p-value = 0.003) and study level (p-value = 0.006). These results suggest that gender and level of study influence how individuals perceive the clarity and comprehensibility of AI tools. Research by Armutat et al. (2024) highlights that men generally have a more positive view of AI applications and demonstrate greater trust in the technology compared to women. Differences between bachelor and master students may stem from varying levels of exposure and experience with AI technologies.
PE4: Perceived ease of becoming skilled in using AI
A Kruskal-Wallis test yielded statistically significant differences in perceptions of ease of becoming skilled in using artificial intelligence (PE4) based on gender (p-value = 0.005) and study level (p-value = 0.027). These findings are supported by Nouraldeen (2022), who observed that male students tend to perceive becoming skilled in using artificial intelligence as easier than female students. Similarly, bachelor students are more likely to find it difficult to become skilled in AI compared to master students due to differences in prior experience and exposure to relevant technologies.
SE1: Concerns about technical skills in using AI
A Kruskal-Wallis test revealed a statistically significant difference in concerns about technical skills in using artificial intelligence (SE1) based on study level (p-value = 0.028). Chan & Hu (2023) explored university students' perceptions of generative AI technologies, noting that concerns about accuracy, privacy, and ethical issues influence their willingness to engage with AI. These concerns were linked to their technical skills and prior exposure to AI, aligning with our observation that study level influences apprehensions about using AI.
SE4: Confidence in using AI with only an online guide available
A Kruskal-Wallis test indicated statistically significant differences in confidence in using AI with only an online guide available (SE4) based on the level of study (p-value = 0.031). Biswas & Murray (2024) propose that master’s students likely have greater exposure to AI concepts, contributing to their higher confidence in using online guides compared to bachelor’s students.
BI1: Preference for using AI for learning
A Kruskal-Wallis test revealed statistically significant differences in students' confidence in using AI for learning activities (BI1) based on their level of study (p-value = 0.034). Both bachelor’s and master’s students commonly use AI tools, such as chatbots, but the extent and nature of AI usage differ between these groups, shaped by their academic level and specific needs. Supporting this, Parshutina & Kamaletdinova (2024) emphasize that the academic level influences how students engage with AI technologies for educational purposes.
BI3: Intention to use AI frequently for learning when given the choice
A Kruskal-Wallis test revealed statistically significant differences in students’ intent to frequently use AI for learning when given the choice (BI3) based on their level of study (p-value = 0.046). According to Ferreira (2024), the disparity in AI adoption between bachelor’s and master’s students may stem from differences in exposure and familiarity with AI technologies. Master’s students likely have more opportunities to engage with AI in specialized courses, which may explain their higher intent to utilize these tools.
ATT2: AI can improve access to educational resources and materials
A Kruskal-Wallis test revealed statistically significant differences in students’ belief that artificial intelligence can improve access to educational resources and materials (ATT2) based on their place of residence (urban vs. rural), with a p-value of 0.036. This finding suggests that perceptions of AI’s role in education differ notably between urban and rural settings. Yang & Zheng (2021) argue that these differences may arise from disparities in technology access and the quality of existing educational infrastructure, which influence how residents perceive AI’s potential to enhance educational access.

ATT4: AI can help identify areas where students may need additional support

A Kruskal-Wallis test revealed statistically significant differences in students' belief that artificial intelligence can help identify areas where they may need additional support (ATT4) based on their level of study (p-value = 0.005). Research by Gouveia et al. (2023) indicates that master's students, who may have greater exposure to AI tools in their academic activities, are more likely to believe in AI's capability to provide additional support.

ATT5: AI technologies should be integrated into curricula to prepare students for future job market applications

A Kruskal-Wallis test revealed statistically significant differences in students' belief that artificial intelligence technologies should be integrated into curricula to prepare students for future job market applications (ATT5) based on their socioeconomic status (p-value = 0.048). Supporting our result, Ma et al. (2024) note that wealth impacts attitudes toward AI in education through factors such as trust, digital competency, and interest in AI, shaping perceptions and acceptance of AI in educational settings.

ATT8: AI can help provide personalized feedback to students

A Kruskal-Wallis test revealed statistically significant differences in students' belief that artificial intelligence can help provide personalized feedback to students (ATT8) based on their level of study (p-value = 0.038). Supporting our result, Castro et al. (2024) suggest that this difference may stem from varying levels of exposure to AI technologies and differing educational needs.

ANX3: Predictions regarding preferences, such as well-recommended ads or websites, create a sense of privacy invasion

A Kruskal-Wallis test revealed statistically significant differences in students' belief that AI predictions regarding preferences, such as well-recommended ads or websites, create a sense of privacy invasion (ANX3) based on their place of residence (urban vs. rural), with a p-value of 0.030. Supporting our result, Carmody et al. (2021) note that the difference in privacy concerns between urban and rural residents may be influenced by varying levels of exposure to AI technologies and differing socio-economic factors. Residents of urban areas, which tend to be more technologically advanced, may be more aware of and concerned about privacy issues related to AI.

FRQ7: Frequency of using AI for activities such as language learning (e.g., Duolingo)

A Kruskal-Wallis test revealed statistically significant differences in the frequency of using AI for language learning activities (e.g., Duolingo) (FRQ7) based on year of study (first year, 2-3 years, 4-5 years, more than 5 years), with a p-value of 0.045. This finding suggests that students at different stages of their education may engage with AI tools for language learning at varying rates. Chen et al. (2021) note that students' intention to use AI for language learning is influenced by factors such as their knowledge of AI applications, attitudes towards AI, perceived ease of use, and social norms. These factors are likely to differ by year of study, as students become more familiar with AI technologies over time.

CONCLUSION

The findings from the Kruskal-Wallis tests reveal several significant differences in students' perceptions and use of artificial intelligence (AI) based on demographic factors such as gender, study level, socioeconomic status, and place of residence. These differences highlight the complex ways in which individuals' experiences and attitudes toward AI are shaped by their background and educational context.

Significant gender differences were found in students' perceived difficulty in learning how to use AI (p-value = 0.046), with female students reporting more difficulty than male students. This may be influenced by historical gender stereotypes surrounding technology and AI. Additionally, gender and study level were significant factors in perceptions of AI's clarity (p-value = 0.003; p-value = 0.006), ease of use (p-value = 0.005; p-value = 0.027), and skill acquisition (p-value = 0.028), with male students and master's students generally exhibiting more favorable views toward AI. Study level also played a crucial role in shaping students' confidence (p-value = 0.031), preference for using AI for learning (p-value = 0.034), intention to use AI for learning (p-value = 0.046), perceptions of AI's potential to provide personalized support (p-value = 0.005), and perceptions of AI's potential to deliver personalized feedback (p-value = 0.038). Master's students, likely due to their greater exposure to AI technologies in their academic programs, were generally more confident in using AI independently and more inclined to adopt AI tools for educational purposes. Furthermore, socioeconomic status (p-value = 0.048) and place of residence (p-value = 0.036; p-value = 0.030) were found to influence students' perceptions of AI's role in education. Students from higher socioeconomic backgrounds and those living in urban areas were more likely to support the integration of AI into curricula and express concerns about privacy issues related to AI. Finally, students' use of AI for language learning also varied depending on their year of study (p-value = 0.045), with those further along in their academic journey showing more frequent engagement with AI tools for learning activities. These findings suggest that factors such as gender, study level, socioeconomic status, and place of residence significantly impact students' attitudes and engagement with AI in education. Understanding these factors can help educators and policymakers design more inclusive and effective AI-related interventions in educational settings.

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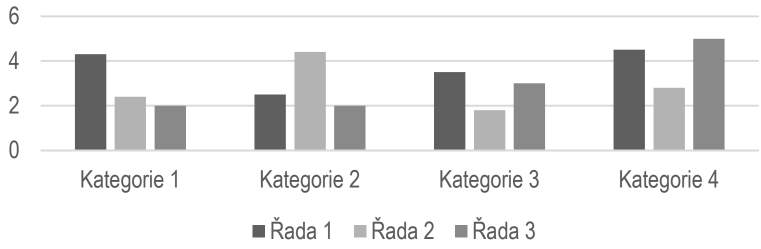

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