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The use of artificial intelligence in marketing: a case study from the Czech Republic

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Abstract

Background: The rapid development of Artificial Intelligence (AI) brings new opportunities for marketing practice, particularly in cost optimisation and increasing campaign effectiveness. This paper responds to the need to explore the practical application of AI within a specific business environment.

Purpose: This paper aimed to investigate whether the use of AI for marketing content created by a selected South Bohemian digital agency leads to reduced costs, increased efficiency, and improved conversions.

Study design/methodology/approach: The research employed quantitative analysis of data from marketing campaigns conducted in 2023 (excluding AI) and 2024 (with AI implementation). Performance metrics, including cost-per-turnover (CPT), were compared, and Chi-square test and Effect size calculations were applied.

Findings/conclusions: AI had a positive impact on campaign performance, contributing to more efficient budget allocation and improved conversion results. The findings are particularly beneficial for SMEs seeking effective marketing solutions. For SME managers, this brings practical implications in the form of more efficient budget allocation, faster campaign optimization, and gaining a competitive advantage.

Limitations/future research: The study involved only one company and a limited number of campaigns, which limits the possibilities of generalisation. It is recommended that the research be extended to more companies and sectors in the future.

Keywords

artificial intelligence, marketing, campaign effectiveness, return on investment, digital marketing, SMEs

Introduction

The advent of artificial intelligence (AI) has fundamentally impacted business processes and transformed various sectors, including marketing. Its use has improved the functioning of organisations and brought several benefits. However, companies still need to continually monitor new trends and innovations to remain competitive (Kumar, et al., 2024; Talíř & Straková, 2023; Pártlová et al., 2020; Dorčák, et al., 2015). Owing to new technologies, there has been a major shift in content personalisation and decision-making (Bobro et al., 2024; Straková & Talíř, 2020). At present, trends in social media marketing are developing rapidly, and the emergence of AI, such as ChatGPT, indicates their further development. Exploring these trends is therefore important to better understand how marketing functions and evolves across various platforms (Oklander et al., 2024; Pártlová, et al., 2022; Pollák & Markovič, 2021). Also, AI is significantly changing marketing communications and streamlining operations in both large and small companies. On social media, it assists in content creation, campaign planning and analysis, thereby increasing communication performance and effectiveness (Krajčovič, 2024; Pollák, et al., 2025). AI also brings new possibilities in customer support, especially through chatbots. In order to use it effectively, marketers need to understand its technical basis well, as their work intertwines business goals, creativity, and working with data (Jain & Kumar, 2024; Dušek, 2023). It can be argued that AI cuts across all components of the marketing mix, significantly impacting not only how value is delivered to customers but also the marketing management itself and the functioning of entire organisations (Jarek & Mazurek, 2019). Although there are some concerns, companies are enthusiastically embracing this new technology along with its various forms and tools (Wirth, 2018). Furthermore, the adoption of AI is transforming content distribution in digital marketing and enabling more effective strategies. AI tools help companies to generate personalised content in different formats such as texts, videos, or images (Amnoun et al., 2024). In addition, AI is reshaping the customer experience and changing the way businesses find, build, maintain, and manage interactive relationships within marketing (Peltier, Dahl & Schibrowsky, 2024). However, the automation of tasks through AI raises the question of whether marketers will accept it as a tool to relieve routine and focus on more creative tasks, or whether they will see it as a threat to their jobs (van Esch & Black, 2021). Still, AI technology plays a key role in intelligent systems that support decision-making (Gupta et al., 2022; Vavrová et al., 2025), with companies using it to streamline campaigns and improve user experience (Simion & Popescu, 2023). AI also provides a number of opportunities for companies to learn more about their customers, predict their needs, and actively engage them in communication (Campbell et al., 2020). Through machine learning and data analytics, it can automate tasks, personalise content, and improve customer understanding (Trgovac, Mandić & Marković, 2024). Advanced AI algorithms allow marketers to analyse data, forecast trends, and create personalised experiences based on customer behaviour. This increases user engagement and improves campaign results, while bringing ethical challenges that require attention (Zaharia et al., 2024).

The primary objective of this paper is to investigate the use of AI in marketing activities of a South Bohemian digital agency and to evaluate its impact on the effectiveness of presented campaigns. The agency deployed AI in 2020, mainly for content creation, ranging from articles, images, topics, and text suggestions to analytics and search engine optimization (SEO). The paper also explores how AI has been incorporated into the daily work of agency employees and what has contributed to its successful use.

To fulfil the objective, the following research questions (RQ1, RQ2, RQ3) are formulated:

RQ1: Does the use of AI-generated content in campaigns by the selected digital agency reduce the percentage of cost-per-turnover (CPT) when compared to non-AI campaigns?

RQ2. What is the impact of using AI on the effectiveness of marketing campaigns by the selected digital agency?

RQ3. Are AI-generated content campaigns able to achieve a comparable number of purchases at lower campaign costs than traditional campaigns?

1. Theoretical background

AI plays an important role in marketing due to its ability to learn and process large amounts of data efficiently. It enables rapid analysing as well as creating predictive models and personalised content, hence optimising campaigns and reducing costs.

An experiment was conducted on the Meta Ads platform comparing AI-set and manual campaigns. The two test groups differed in competency level and targeting, with their behaviour analysed using Kohonen maps. The results showed that AI can effectively influence user behaviour, increasing reach, clicks, and conversions. Thus, AI tools can improve sales and ROI (Turlakova & Shumilo, 2025; Kostiuk et al., 2021).

1.1. Automation of marketing processes

The introduction of AI is shaping the way companies engage with customers and manage marketing campaigns. Through automation, AI is taking over routine tasks such as emailing or social media management, which allows real-time adaptation of strategies based on customer behaviour analyses.

1.1.1. Automation tools

Modern technologies automate repetitive tasks to save time and increase communication accuracy. The most widely used tools include chatbots and automated campaigns. Chatbots are a key tool in marketing and customer service. Due to machine learning, they can respond to requests, modify communications, and serve large numbers of customers around the clock, reducing costs and improving the customer experience. Automated campaigns allow businesses to target customers with adapted messages at the right time. They utilise user behaviour data to accurately target and alter content, and also have the advantage of real-time performance tracking and quick adjustments to strategies. Linking chatbots, automated campaigns, and AI tools enables businesses to combine personalisation with more efficient processes. Additionally, chatbots ensure fast communication, data-driven campaign targeting, and their integration improves both performance and quality of the customer experience.

Ryoo et al. (2025) examined the effectiveness of AI chatbots in campaigns against marijuana-impaired driving, focusing on perceived hypocrisy, gender, and language style. Participants interacted with chatbots of different genders and speech styles. A female speaking informally and a male speaking formally had the greatest effect, which was related to increased feelings of guilt, as explained by Language Expectancy Theory (LET).

1.1.2. Improvement of efficiency and reduction of operating costs

AI and machine learning are no longer merely a research topic - nowadays, they are crucial to maintaining competitiveness. They can ensure more efficient processes, data analytics, accurate predictions, and automation, which is essential for market success (Kolbe et al., 2024). AI technologies allow customer experience adaptation and increase both satisfaction and loyalty (Konečný et al., 2025; Konečný et al., 2024). They also streamline the work of marketing teams that can react faster to changes.

On the other hand, the implementation of AI raises challenges that require specific skills and affect the organisational structure, where the need for training and effective realisation is pivotal. Collaboration between companies and universities can facilitate this process by combining expertise and practical experience (Kolbe et al., 2024). AI and machine learning also influence pricing, especially in B2B environments, where individual discounts are often negotiated. On the grounds of historical data and predictions of customer behaviour, AI helps optimise price offers, hence reducing negotiation costs and increasing deal success (Ning, 2021).

1.2. Personalisation and Customer Experience

One of the main benefits of AI is content personalisation based on the behaviour of customers. By analysing corresponding data, it can anticipate their needs and improve communication relevance and customer support.

Kim et al. (2025) investigated how virtual influencers (VI) can effectively spread socially responsible behaviour. In an experiment involving 320 participants, the influence of VI appearance (realistic vs. anime) and message style (narrative vs. non-narrative) on cyberbullying was tested. Realistic VI were perceived as more trustworthy, especially for the non-narrative style. The results show that the appearance and form of communication influence the effectiveness of prosocial messages.

1.2.1. The role of AI in personalised marketing campaigns

AI allows processing large amounts of data, which leads to creating relevant marketing campaigns. Predictive modelling can help reach the target audience and anticipate their needs.

Generative AI (GenAI) advances personalisation by automatically generating customised content related to customer purchases and preferences. Such content better appeals to emotions and increases the chance of conversion (Lăzăroiu & Rogalska, 2024).

Kapoor and Kumar (2025) examined the effectiveness of personalised video advertisements, or ads, made with GenAI in collaboration with a brand selling organic products. They undertook an experiment on the mobile app WhatsApp, where users were divided into three groups encompassing those with GenAI video ads, personalised image ads, and non-personalised video ads. The personalised ad content followed purchase history, with the results showing that GenAI video ads increased user engagement by 6-9 percentage points and delivered both cost savings and higher productivity.

AI also helps with building a stronger emotional connection with customers and increases conversion rates. Personalised content reduces the mental effort of decision-making, speeds up the buying process, and delivers a more convenient experience by offering relevant products according to customer preferences (Chandra et al., 2022).

Besides, AI ensures accurate and effective interactions with customers by tailoring the shopping journey to their needs. It leverages technologies such as 3D experiences in the metaverse while decreasing the costs of analytics and content creation, freeing up space for strategic planning.

1.2.2. Impact on customer satisfaction and loyalty

As customer satisfaction is a key indicator of success, companies use effective tools to increase it. The implementation of AI assists in maintaining competitiveness and long-term market presence.

Zhang and Song (2022) explored how big data, artificial intelligence, and social media research affect the market orientation of firms. Their survey included 442 executives from four industries in the US. With the MARKOR scale and an assessment of using technology tools, three main areas were distinguished: AI for data analytics and personalisation, customer behaviour identification, and social media research. These factors help improve strategy, respond quickly to changes, and have a competitive advantage.

1.3. AI in predictive analytics and Big Data

Machine learning and big data analytics help companies identify trends and hidden patterns in customer behaviour. AI therefore allows more accurate campaign targeting, prediction of product directions, and efficient use of resources.

Moreover, the use of AI is changing the competitive landscape of marketing, particularly in the banking sector, where customer behaviour is specific. Zatonatska, et al., (2022) aimed to develop a marketing strategy to attract new clients by employing data science tools. This resulted in two econometric models for cash loans and credit cards that facilitate an efficient allocation of advertising budget. The models showed that data-driven campaigns increase the number of clients by 12% and achieve an ROI of 3.18. The findings confirm that data science improves marketing effectiveness and allows for more accurate planning of future campaigns.

1.3.1. Prediction of trends and analysis of customer behaviour

Predictive analytics, together with AI, aids businesses in understanding customers, recognising market trends, and gaining an advantage through more accurate predictions and targeted communications.

A hybrid model combining deep learning and optimisation algorithms can predict customer behaviour with 94% accuracy. It uses RBM for feature extraction and connects a dilated convolutional network with a weighted RNN, optimised with an upgraded cheetah algorithm. Validated on digital marketing data, the model outperformed traditional approaches such as LSTM or DTCN (Sakthi & Sundar, 2024).

Linking machine learning with marketing data makes it possible to process large-scale and unstructured data, overcoming the limits of traditional analytics methods. Although interpreting these models can be challenging, companies that meet this challenge acquire the ability to track customer buying behaviour and identify critical points in the buying process. As a result, they can optimise strategies and raise conversions. Hybrid models such as A-HDL allow for trend prediction, better market segmentation, and tailoring offers to customer preferences, which leads to higher satisfaction and loyalty (Ma & Sun, 2020).

1.3.2. Integration of data analytics into strategic decisions

In B2B marketing, it is important to leverage AI and data analytics at all stages of the customer lifecycle - from outreach to retention.

AI can improve communication and customer relationships, especially in conversion and retention. With predictive analytics, companies anticipate client needs, thereby increasing satisfaction and loyalty. AI also increases productivity, speeds up decision-making, and delivers higher ROI, although it brings challenges such as privacy issues (Moradi & Dass, 2022).

1.4. Ethics and responsibility in using AI

Implementing AI brings about ethical challenges, particularly in the areas of privacy and model bias. The solution lies in greater transparency of algorithms, control over data, and clear rules to ensure trustworthy and fair use of AI.

1.4.1. Ethical issues and algorithmic bias

Since AI is still a relatively new technology, there is a lack of set rules on ethics and data in marketing. This raises questions of algorithm impartiality and responsible use of AI, which should be part of company strategic management (Ferrell & Ferrell, 2024).

Algorithmic bias arises when systems make decisions based on unbalanced data, possibly leading to discrimination related to gender, race, age, or socioeconomic status. Such bias threatens the fairness of decision-making and customer trust. Two approaches have been applied to address this issue: the a priori approach, which focuses on preventing bias during model development, and the post-hoc approach, which seeks to reduce bias after model deployment by analysing results and adjusting the model (Akter et al., 2021).

While using AI, it is crucial to adhere to transparency, accountability, and fairness. These principles should be incorporated into the development of algorithms and viewed as a tool not only for performance but also for positive social change.

Effective and ethical use of AI requires collaboration between managers and developers, an emphasis on equity, transparency, and control of algorithmic bias. Additionally, building trust through responsible data handling and risk management is significant as well (Grewal, et al., 2024).

1.4.2. Privacy and transparency

The introduction of AI into marketing processes has induced serious ethical issues, particularly in relation to privacy and transparency. Thus, it is important to strike a balance between technological advances and ethical principles in order to ensure the responsible and fair development of marketing tools.

Responsible handling of personal data is key to the ethical use of AI and data analytics. Although these technologies enable personalisation based on customer behaviour, they also give rise to privacy and data security concerns (Ahmad & Haque, 2024).

AI assistants enhance the customer experience with both practical and emotional support, increasing satisfaction and trust. Their learning from interactions leads to more empathetic communication, yet privacy is also important to prevent loss of trust (Gelbrich, et al., 2021).

Transparency plays a vital role in building trust between companies and their customers. Companies should communicate how they are using AI to personalise services, while comprehensibly explaining to customers how their data are collected and processed.

Ahmad and Haque (2024) highlight the importance of an ethical approach and the need for human oversight when implementing AI into marketing. To provide fairness and credibility, it is fundamental to establish clear rules that ensure AI serves the benefit of customers without violating their privacy.

Legal and ethical frameworks must keep pace with the rapid evolution of technology to secure compliance from the outset of deployment and prevent abuse. However, should abuse occur, it is essential to have mechanisms in place to deal with errors that may arise in customer data processing.

Large Language Models (LLM) increase the threat of phishing by allowing the creation of compelling, personalised emails without language errors. Until now, however, large-scale studies comparing their effectiveness with human-created emails have been lacking. Bethany et al. (2025) carried out an experiment within a university setting involving 9,000 employees. The results showed that LLM emails were as effective as those composed by professionals, pointing to their dangerous potential. Their study also analysed the vulnerability of different groups and the reasons why people succumbed, with the findings highlighting the need for better education and protection against AI-facilitated phishing.

1.5. AI in B2B Marketing

AI in B2B marketing increases efficiency in generating opportunities, personalisation, and predicting sales. In CRM systems, it evaluates potential customers and replaces mass marketing with a targeted approach.

Chatterjee et al. (2023) investigated how factors such as performance expectations, effort, compatibility, quality, and satisfaction with CRM affect employees' attitudes towards using AI in CRM systems. Data related to 315 users from Indian organisations were analysed with the PLS-SEM method. Questionnaires included 32 items on a five-point Likert scale distributed in cities such as Delhi, Bengaluru, and Mumbai. The results indicated that AI can improve customer relationships and increase efficiency, with a positive user experience being crucial. The research underlines the importance of technical compatibility and employee satisfaction in adopting AI technologies.

1.5.1. Specifics of AI use in the B2B sector

AI in B2B marketing also supports all stages of the customer lifecycle - from identifying potential clients to maintaining relationships. It helps to target offers, predict success, and detect problems early (Moradi & Dass, 2022).

Han et al. (2021) divide the use of AI in B2B marketing into five main areas: personalisation, predictive analytics, customer experience improvement, automation, and strategic optimisation. This categorisation allows companies to comprehend the capabilities of AI and makes it easier to implement. However, despite its value recognition, some companies face challenges, mainly due to the variety of roles that AI can fill. A bibliometric analysis of 221 research articles from 1990 to 2021 confirmed these domains as a basis for assessing the current state and planning future strategies in digital marketing.

1.5.2. Automation of content and optimisation of campaigns

To optimise campaigns and automate content, a three-tiered AI framework - mechanical, thinking, and sentient - is applied. Mechanical AI automates routine tasks and data collection to increase efficiency. Thinking AI analyses data and assists in decision-making and selecting target segments. Sentient AI focuses on customer emotions and fosters relationship building and emotional connection with a particular brand. This framework can be employed in different areas of marketing through the 4P or 4C models (Huang & Rust, 2021).

1.6. Innovation in content creation and communication

Based on target group preferences, AI can create personalised content such as emails, blog posts, videos, or texts. Owing to natural language processing (NLP) technology, these materials can also be produced in multiple languages and a comprehensible form. At the same time, AI systems analyse user sentiment on social media and tailor marketing messages to better respond to current trends and market needs.

Rojas et al. (2024) introduced an AI model to generate marketing texts for medical clinics in Huancayo. The goal was to streamline content creation and better reach local audiences. The model uses NLP and machine learning to generate relevant texts that adapt to community needs. With feedback, the system continuously improves, saving time, increasing consistency, and helping clinics build a stronger digital presence.

1.6.1. Generative AI and its role in creative marketing

Generative AI combined with predictive algorithms and augmented reality is transforming the customer experience. It utilises data and sentiment analysis to create personalised content that increases conversions, builds loyalty, and effectively manages the entire customer cycle (Lăzăroiu & Rogalska, 2024).

Integrating innovation into chatbots is a competitive advantage for companies - assistants not only provide advice but also emotional support. Given AI advances, they can respond empathetically and adapt to customers in different situations.

Gelbrich, et al., (2021) illustrate that emotional support from digital assistants significantly increases customer satisfaction when using technology services. According to an analysis of more than 50 studies, they found that perceived warmth from digital assistants enhances customer experience and encourages repeated service use. Also, digital assistants can respond effectively to negative emotions, outperforming their human counterparts.

1.6.2. Benefits of creating texts, images, and multimedia content

AI is transforming content creation in the creative industries, advertising, and marketing. AI advertisements influence the perception of credibility and creativity, thereby increasing customer adoption and interest. When the parameters are set correctly, effective and attractive content is created (Gu et al., 2024).

AI's transition from text generation to image content creation is significant, yet it requires image authentication. Watermarks can indicate AI origin, though they can be easily removed. Thus, more robust methods need to be developed to authenticate digital content (Jiang, et al., 2023).

AI-generated content is mainly used in creative marketing, e.g. tourism and hospitality. Tools such as DALL-E 2 and GPT-3 save time and costs, making small companies more competitive in creating original campaigns (Tuomi, 2023).

1.7. Strategic frameworks and future development

The future of AI-enabled marketing is moving towards interfacing with machine learning, augmented reality, and predictive analytics. Companies will use it not only for automation but also for strategic decision-making, while investing in innovation, and collaboration with humans will be crucial.

1.7.1. Long-term benefits of AI in marketing strategies

Although manual content still has its place, it cannot compete with the volume and quality of AI-generated output in the long run, which can lead to a decline in quality when trying to keep up manually.

MARK-GEN is a strategic framework with generative AI to create personalised and visually appealing content. It promotes creativity, flexibility, and helps companies gain a competitive advantage in a dynamic marketing environment (Islam et al., 2024). AI integration also helps companies respond to the market and optimise marketing. Assistants such as AIRA simplify customer decision-making, increase trust, and provide a research framework in digital marketing (Kim, 2020).

1.7.2. Future Trends and Challenges

Since the launch of ChatGPT in November 2022, services based on generative AI have experienced rapid growth. Despite the rising market and expanding opportunities, it remains unclear which platform is leading the way or what interface elements are influencing user preferences.

Yeon et al. (2024) examined which interface features of generative AI are preferred by users, applying a conjunctive analysis of five key elements: data type, generation style, output variations, reference style, and generation history. A survey of 500 users revealed that they most value access to the generation history (up to 10 backwards) and prefer footnotes as references. The creative style was less popular due to concerns about false information. In addition to user preferences, they also stress the importance of making generative AI models understandable and transparent. This is also confirmed by Ma and Sun (2020), who point out that although machine learning can efficiently process large volumes of unstructured data and achieve high predictive accuracy, its opacity can be a barrier to using it in marketing. Ma and Sun (2020) also call for the development of a clear framework to link algorithm outputs to human understanding and ensure ethical and effective use of AI in marketing practice. These findings suggest that understanding user needs and expectations is as important as the technology itself when implementing AI in marketing. Factors such as transparency, ease of access, and quality user experience play a crucial role in the successful and sustained employment of generative AI in practice.

1.8. AI as a catalyst for business transformation

In the era of Industry 4.0, physical and digital systems are interconnecting, transforming the way businesses operate (Straková & Kostiuk, 2023). AI enables both content creation and big data processing, creating an innovative and flexible digital ecosystem that considers ethics and security (Ji et al., 2024). It also enables precise targeting and content personalisation, which increases customer engagement. At the same time, it is important to develop companies' internal capabilities in digital transformation, strategic use of AI (Moradi & Dass, 2022; Reim, et al., 2020), and an ethical approach when working with customer data (Simion & Popescu, 2023).

Based on the above research questions, we selected methods appropriate for the available data. We used Chi-square test to compare strategies with and without using AI, with the relationship strength determined by Cramer's V. These approaches provide reliable results in line with quantitative standards.

2. Data and methods

To objectively evaluate the effects of AI in marketing, it was first necessary to identify data sources and select appropriate analytical methods. A quantitative approach allowed us to compare AI campaigns with conventional ones and to estimate not only the statistical significance but also the practical impact of the differences.

2.1. Data

As regards the research, internal data from marketing reports of a South Bohemian digital agency will be used. The agency handles campaigns for an anonymous company (XYZ), which operates in the South Bohemia Region as well, selling spare parts for cars of various brands.

The data concern XYZ's seasonal campaigns from the years 2023 and 2024. Six campaigns in three recurring categories will be analysed: Winter Tyres (October 10 – December 31), Cycling Accessories (June 20 – August 31), and Spring Accessories (April 15 - June 30).

All campaigns were of the same length, allowing for a comparison of results, which focused on whether related textual content was created with or without the use of AI. In 2023, the content was made without AI. However, ChatGPT (the GPT-3.5 and GPT-4 models) was applied in the following year (2024).

2.1.1. Analysed data and indicators

The analysis will include these specific indicators: costs of the campaigns (adjusted by a coefficient to compare the performance), number of purchases, the total value of sales, and CPT (cost-per-turnover) as an indicator of effectiveness, where a lower value means a higher effectiveness of a particular campaign.

2.2. Methods

Differences in campaign budgets will be eliminated by a coefficient to compare effectiveness independently of the capital invested. The objective of the research is to confirm one of the proposed hypotheses (H0, H1):

H0: There is no statistically significant difference in the number of purchases between individual campaigns in 2023 and 2024.

H1: There is a statistically significant difference in the number of purchases between individual campaigns in 2023 and 2024.

Chi-square test will compare the observed and expected numbers of purchases in both sets of campaigns to find whether the differences are statistically significant. The calculation formula for the Chi-square test (Pearson, 2009) is as follows:

$$\chi 2 = \Sigma \frac{(\mathrm{O} - \mathrm{E})^2}{\mathrm{E}} \tag{1}$$

Where:

- O is the observed fraction for the given category,
- E is the expected frequency for the given category.

Effect size will show the magnitude of the difference in purchases between the campaigns. In the research, Cramer's V will be employed to measure the effect between category data, which can be small (0.1), medium (0.3), or large (0.5). Cramer's V formula (Cramer, 1946) for the Effect size is as follows:

$$\mathrm{V} = \sqrt{\frac{\chi 2}{\mathrm{n} \times (\mathrm{k} - 1)}} \tag{2}$$

Where:

- χ2 is the Chi-square test value,
- n is the total number of observations,
- k is the smaller of the number of rows and columns in a contingency table.

3. Results

Data from the 2023 and 2024 campaigns were provided by the digital agency´s marketing department. Costs were adjusted by the aforementioned coefficient so that different budgets do not affect the research results.

The data were analysed with the Chi-square test to determine the statistical significance of differences in the number of purchases. Cramer's V was then applied to define the Effect size. The research focuses on testing the two hypotheses above (H0, H1) and the effect of AI on campaign effectiveness.

3.1. Analysis of differences between campaigns by type

Campaign prices were converted to the corresponding coefficient to assess their effectiveness independent of costs (see Table 1).

Table 1 Comparison of campaigns

Campaign	Price (CZK)	Number of purchases
Winter Tyres 2023	450 701.96	2 563
Winter Tyres 2024	454 893.68	3 563
Cycling Accessories 2023	29 521.35	17
Cycling Accessories 2024	25 989.00	30
Spring Accessories 2023	18 646.02	10
Spring Accessories 2024	9 861.00	46

Source: the authors

3.1.1. Winter Tyres

The Winter Tyres campaign was analysed over the same period in the years 2023 and 2024 (October 10 - December 31). When excluding AI in 2023, the costs reached CZK 450,701.96 and generated 2,563 purchases. With the inclusion of AI in 2024, the costs amounted to CZK 454,893.68, bringing the number of purchases to 3,563.

CPT dropped from 3.6% in 2023 to 2.47% in 2024, indicating a cost efficiency improvement of approximately 31%. Simultaneously, the number of purchases increased by 1,000, or 39% (see Table 2).

Table 2 Results of the Winter Tyres campaign

Year	2023	2024
Spending (CZK)	450 701.96	454 893.68
Number of purchases	2 563	3 563
Value of purchases (CZK)	12 476 876.48	18 386 888.00
CPT (%)	3.60 %	2.47 %

Source: the authors

The value of $\chi^2 = 163.26$ exceeds the critical threshold of 3.84 at p = 0.05, confirming a statistically significant difference between 2023 and 2024. Cramer's V = 0.163 signals a small to medium effect (see Table 3).

Table 3 Chi-square test and Effect size for the Winter Tyres campaign

	Value
Chi-square (χ^2)	163.26
Critical threshold (p =0.05)	3.84
Conclusion for Chi-square (χ^2)	The difference is statistically significant ($\chi^2 > 3.84$)
Effect size (V)	0.163
Interpretation	Small to medium effect

Source: the authors

The above indicators confirm lower costs relative to turnover and more purchases in 2024. The campaign using AI was therefore more effective than the 2023 campaign without AI.

3.1.2. Cycling Accessories

This campaign saw a reduction in costs of CZK 3,532.35 compared to 2023, along with an increase in purchases from 17 to 30. CPT fell from 98.55% to 18.5%, denoting an improvement in efficiency of over 81% and an increase in purchases of 76% (see Table 4).

Table 4 Results of the Cycling Accessories campaign

Year	2023	2024
Spending (CZK)	29 521.35	25 989.00
Number of purchases	17	30
Value of purchases (CZK)	29 954.51	140 398.00
CPT (%)	98.55 %	18.50 %

Source: the authors

The value of $\chi^2 = 4.07$ exceeds the critical threshold of 3.84 at p = 0.05, pointing to a statistically significant difference. Effect size of 0.29 corresponds to a medium effect, proving a measurable impact of AI on campaign performance (see Table 5).

Table 5 Chi-square test and Effect size for the Cycling Accessories campaign

	Value
Chi-square (χ^2)	4.07
Critical threshold (p =0.05)	3.84
Conclusion for Chi-square (χ^2)	The difference is statistically significant ($\chi^2 > 3.84$)
Effect size (V)	0.29
Interpretation	Medium effect

Source: the authors

Based on the reduction in costs and the increase in purchases, it can be verified that the 2024 campaign with AI texts made marketing more effective. Better resource utilisation and higher campaign performance illustrate that AI had a positive impact on the effectiveness and management of marketing activities.

3.1.3. Spring Accessories

The Spring Accessories campaign recorded the biggest decrease in costs, i.e. by CZK 8,785.02. Despite that, the number of purchases increased from 10 to 46. CPT decreased from 51.67% to 7.24%, which is a reduction of over 86%. The 360% increase in purchases at lower costs confirms the higher efficiency after AI deployment (see Table 6).

Table 6 Results of the Spring Accessories campaign

Year	2023	2024
Spending (CZK)	18 646.02	9 861.00
Number of purchases	10	46
Value of purchases (CZK)	36 089.82	136 125.24
CPT (%)	51.67	7.24

Source: the authors

The value of $\chi^2 = 24.32$ exceeds the critical threshold of 3.84, evidencing a statistically significant difference. Cramer's V = 0.65 (a large effect) represents the strongest impact among the campaigns analysed (see Table 7).

Table 7 Chi-square test and Effect-size for the Spring Accessories campaign

	Value
Chi-square (χ^2)	24.32
Critical threshold (p =0.05)	3.84
Conclusion for Chi-square (χ^2)	The difference is statistically significant ($\chi^2 < 3,84$)
Effect size (V)	0.65
Interpretation	Large effect

Source: the authors

The 2024 campaign using AI was more effective than the 2023 campaign without AI. The number of purchases increased by 360%, whereas the costs decreased by 47.12%.

3.2. Comparison of the AI impact across campaign types

The research demonstrated that the use of AI had a positive impact on all campaigns across the product categories. After the AI implementation, CPT decreased, and purchases increased, although the intensity of improvement varied between individual campaigns.

Relating to the Winter Tyres campaign, CPT fell from 3.6% to 2.47% (a 31% decrease), while the number of purchases rose from 2,563 to 3,563 (a 39% increase). Even at similar costs, this signifies an improvement in efficiency, which supports the use of AI in marketing.

In the Cycling Accessories campaign, CPT dropped from 98.55% to 18.5% (a decrease by 81%), yet the number of purchases increased from 17 to 30 (by 76%). The results show a significant streamlining of the campaign and a positive impact of AI on spending optimisation and conversion.

The Spring Accessories campaign made the biggest difference, with spending down by 47.1% (from CZK 18,646.02 to 9,861), but the number of purchases went up by 360% (from 10 to 46). This combination documents the most significant AI benefit of all the campaigns analysed.

The statistical tests confirm that AI substantially impacted the effectiveness of the campaigns. The chi-square test showed statistically significant differences: Winter Tyres $\chi^2 = 163.26$, Cycling Accessories $\chi^2 = 4.07$, and Spring Accessories $\chi^2 = 24.32$ - all above the threshold of 3.84 at $p = 0.05$.

The magnitude of the effect according to Cramer's V varied: Winter Tyres - moderate to medium (V = 0.163), Cycling Accessories - medium (V = 0,29), and Spring Accessories - large (V = 0,65). These results support the positive impact of AI on the campaigns.

3.3. Evaluation of hypotheses

The analysis enabled the research questions and hypotheses to be evaluated. The first research question (RQ1) focused on whether AI reduces CPT in the campaigns. In all three cases, there was a significant decrease in the CPT rates after AI deployment, proving greater financial efficiency. H1 was therefore confirmed.

The second research question (RQ2) investigated the impact of AI on campaign effectiveness. In addition to financial metrics, the number of purchases was also reviewed. After the introduction of AI-generated content, all campaigns experienced a significant increase in conversions. The statistical tests revealed that the differences were significant, hence confirming H1.

The third research question (RQ3) examined whether AI-enabled campaigns achieve the same number of purchases at lower costs. In particular, this was verified for the Cycling Accessories and Spring Accessories campaigns, where increased purchases occurred at lower costs. The Winter Tyres campaign evinced higher costs, yet more purchases and lower CPT, which also resulted in higher efficiency. Thus, H1 was confirmed.

4. Discussion

RQ1: Does the use of AI-generated content in campaigns by the selected digital agency reduce the percentage of cost-per-turnover (CPT) when compared to non-AI campaigns?

The analysis showed a reduction in CPT in all three campaigns after AI deployment. The largest decrease was observed in the Spring Accessories campaign (from 51.67% to 7.24%), followed by the Cycling Accessories campaign (from 98.55% to 18.5%), and the Winter Tyres campaign (from 3.6% to 2.47%). These results vindicate that AI reduces real costs relative to turnover. H0 was therefore refuted.

Kolbe et al. (2024) emphasise the benefits of AI in reducing costs and responding quickly to the market, as verified by the results of this paper. While they focus on the wider impacts, this work demonstrates the benefits of AI specifically on the CPT indicator based on data from the 2023 and 2024 campaigns.

It was possible to quantify efficiencies in line with the agency practice, while the introduction of AI delivered both process simplification and measurable financial savings.

RQ2: What is the impact of using AI on the effectiveness of marketing campaigns by the selected digital agency?

In all the campaigns studied, there was an increase in the number of purchases. Winter Tyres saw an increase of 1,000 purchases, Cycling Accessories 76%, and Spring Accessories 360%. These results confirm the positive impact of AI on conversions.

The chi-square test corroborated the statistical significance of the differences, with all campaigns exceeding the critical threshold (3.84). The Spring Accessories (χ^2 = 24.32) and Winter Tyres (χ^2 = 163.26) campaigns achieved the highest values. The results support the conclusions of Trgovac, et al., (2024) and Huang and Rust (2021) on the benefits of AI for precision targeting. As a result, H1 was confirmed, whereas H0 was refuted.

RQ3: Are AI-generated content campaigns able to achieve a comparable number of purchases at lower campaign costs than traditional campaigns?

The third research question (RQ3) explored the relationship between costs and campaign performance. Campaigns with AI were more effective than those without AI. For instance, Spring Accessories reduced costs by 47.1% and the number of purchases more than quadrupled. As for Cycling Accessories, the costs dropped, yet purchases increased by 76%. Thus, H1 was confirmed, but H0 was disproved.

The findings of this paper align with the findings of Ma and Sun (2020), suggesting that AI can predict buying behaviour and target communication more effectively. Predictive models based on historical data increase conversions and reduce acquisition costs.

This paper also builds on previous research (Ning, 2021; Kapoor & Kumar, 2025) on returns and cost optimisation. The results indicate that AI has a direct impact on reducing costs while maintaining or improving performance.

A limitation of the research is that it does not consider long-term and secondary benefits, such as improved brand awareness or customer satisfaction, which can be significant according to Gelbrich, et al., (2021).

Conclusion

The main contribution of this paper lies in the finding that the use of artificial intelligence in campaign text creation reduces advertising cost-to-revenue ratio (PNO), increases conversions, and improves budget allocation. The results are based on campaign data from 2023 and 2024, showing that AI-supported campaigns (2024) outperformed those without AI (2023). PNO decreased, the number of purchases increased, and return on investment improved. Thus, AI contributed to lower costs, higher conversion rates, and greater customer satisfaction. Answering the above research questions confirmed statistically significant differences between 2023 and 2024, demonstrating that AI delivers better results at lower costs, which can be leveraged not only by large companies but also by SMEs.

The study connects theory on AI in marketing with practice through the example of a South Bohemian digital agency, where theoretical concepts were tested on real data, enabling their validation. The company can apply these insights in further development of digital marketing, strategic planning, and implementation of new tools such as intelligent chatbots in customer support or AI sentiment analysis systems, which allow quicker responses to feedback. Generative AI may also support graphic content creation, increasing efficiency and reducing employee workload. The obtained data can serve as a basis for new campaigns and contribute to more effective marketing.

The study follows methodological and logical principles of scientific research - from clearly defined questions, through suitable methodology, to interpretation of results. It also acknowledges research limitations, as it was conducted within a single company and focused on three campaigns for a specific client, which restricts generalization. Another limitation can be seen in market variability and consumer behaviour. Nevertheless, the findings provide a relevant perspective on the practical use of AI, offer applicable conclusions, and lay the groundwork for further research.

There is potential for extending the research, particularly in the field of generative AI and visual models, which open new opportunities for graphic design and marketing automation. Future research may focus on personalization of offers based on customer behaviour, further increasing campaign efficiency, saving time, and reducing costs of content creation and distribution.

The target audience of this study includes marketing professionals, digital agency staff, SME managers, as well as marketing and IT students. This paper can also serve as inspiration and insight into the practical application of AI tools and their impact on campaign efficiency and budgets, while simultaneously providing a theoretical foundation for further academic work.

Practical implications for SME managers comprise more efficient allocation of marketing budgets based on data-driven indicators (e.g., cost-per-turnover), faster evaluation and comparison of campaign performance using unified metrics, identification and optimization or reallocation of underperforming campaigns, use of AI in customer segmentation and content personalization (enhancing conversion and customer loyalty), easier decision-making on digital marketing investments based on statistically supported findings, and gaining a competitive advantage through better understanding of customer behaviour and more effective communication.

Declarations

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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How to support the implementation of Smart Human Resources 4.0 at the enterprise level - the role of leadership and organizational structure

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Abstract

Purpose: This study examines the role of leadership styles and changes in organizational structure within the implementation of Smart Human Resources 4.0 (SHR4.0) as a result of introducing the Industry 4.0 concept. The aim is to examine the role of leadership styles and organizational structure in the success of the Smart Human Resources 4.0 implementation.

Study design/methodology/approach: A questionnaire survey among top managers of companies operating in Slovakia was used to collect data. The PLS-SEM method was used to test the theoretical research model and proposed hypotheses using SmartPLS 3.0 software.

Findings/conclusions: The findings indicate a statistically significant relationship between Industry 4.0 technology solutions and the implementation of Smart Human Resources 4.0 at the enterprise level, which can be strengthened by the inclusion of mediating variables. The two mediating variables of leadership style and organizational structure changes, independently enhance the overall effect, but their joint mediating effect is of substantial importance. Leadership style plays a significant role, with organizational structure being a supporting element in the investigated relationship.

Originality/value: Based on the findings, technology solutions need to be aligned with the human resource development system and supervisors behavior in the new digital culture. In addition to focusing on HR processes, it demonstrates that SHR4.0 transformation process requires capable leaders and a redesign of structures and processes to enable the use of technology.

Limitations and **future research**: Despite the originality of our findings, we acknowledge the limitations of this study, namely its regional focus (on a single country) and the homogeneity of the industry sample. Future research should delve deeper into advanced talent management, workforce planning, and well-being strategies across industries, which are most affected by smart HR 4.0.

Keywords

Industry 4.0, digitalization, human resources, organizational structure, leadership style.

Introduction

The Industry 4.0 (I4.0) paradigm is gaining increasing attention from both the scientific community and practitioners. However, technological solutions alone do not automatically guarantee success (Dabić et al., 2023; Shet & Pereira, 2021). Industry 4.0 means changing the way, time, and space for doing work, which includes a completely new way of thinking. The deployment of digital technologies supports the emergence of new unique competencies (Bissola & Imperatori, 2020; Da Silva et al., 2022; Nešić Tomašević, 2023). In parallel with these developments, a new generation of employees is entering the labor market, bringing new values and expectations (Črešnar, 2020; Sindhuja & Akhilesh, 2020). Thus, the human factor lies behind Industry 4.0 (Galati & Bigliardi, 2019), and its successful implementation also requires a fundamental transformation of human resource management (Gu *et al.*, 2021; Hecklau et al., 2016; Neumann et al., 2021; Pillai & Srivastava, 2024; Verma et al., 2020). The answer may be the concept of Smart Human Resources 4.0 (SHR4.0), which is emerging as a key enabler to effectively connect humans with machines and harness the value derived from it to support societal development (Caratù et al., 2025; Gouda & Tiwari, 2024; Rana & Sharma, 2019; Sivathanu & Pillai, 2018).

While it is now clearly established that the human being is central to the success of digital transformation (Ietto et al., 2024; Neumann et al., 2021), and the concept of SHR4.0 appears to be an essential strategy for success, organizations are still not sufficiently prepared for this reality. They are aware of the need to design workplaces with new technologies in mind and reconfigure work profiles (Ansari et al. 2020; Da Silva et al. 2022; Hecklau et al. 2016; Liboni et al. 2019; Nešić Tomašević, 2023; Neumann et al. 2021; Pillai & Srivastava, 2024) to reach out to talents with specific characteristics, foster their creativity and manage their performance (Ietto et al. 2024; Pillai & Srivastava, 2024; Sivathanu & Pillai, 2018) and they have been transforming their HR quite successfully in this regard. However, the implementation of AI in HR processes is not fully exploited. HR decisions supported by Big Data analysis, identifying development potential with AI support, and its use in designing personal goals and personalized rewards (Da Silva et al. 2022; Kambur & Yildirim, 2023; Pillai & Srivastava, 2024; Tambe et al. 2019) in practice still lags behind the available options and solutions.

In this context, Da Silva et al. (2022), Kambur and Yildirim (2023), and, Pillai and Srivastava (2024) highlight that AI applications in HRM are still underutilized. Similarly, Tambe et al. (2019) note that AI-supported personalized HR decision-making remains rare in practice. Although the literature (e.g., Galati & Bigliardi, 2019; Gu et al., 2021; Hecklau et al., 2016; Neumann et al., 2021) confirms HR's key role in digital transformation, authors such as Pillai and Srivastava (2024) and Ietto et al. (2024) argue that these insights are not yet fully implemented in managerial practice. Verma et al. (2020) confirm the positive impact of dynamic HR capabilities in Industry 4.0, but detailed mechanisms and interactions remain underexplored. Tambe et al. (2019) and Apascaritei and Elvira (2022) also call for further research into specific success factors and their interrelations. While some studies address organizational change (Fettig et al., 2018; Da Rocha et al., 2022; Stornelli et al., 2021) and leadership in the digital era (Bunjak et al., 2022; Črešnar et al., 2023; Dabić et al., 2023), their combined impact on SHR4.0 implementation remains insufficiently explained. To summarize, although the literature acknowledges the importance of HRM, organizational structure, and leadership in Industry 4.0, a systematic examination of their interrelations and impact on SHR4.0 implementation at the organizational level is lacking. Our study addresses this gap through empirical testing of a model analyzing these relationships.

Based on the above, we can conclude that the research-confirmed recognition of the importance of HR as a key factor for successful digital transformation is not yet fully applied in management practice. On the contrary, managers often declare the unpreparedness of HR for current needs. Formulating clear practices that can be implemented to support SHR4.0 at the enterprise level is therefore desirable. There is a need to theoretically explore the factors that determine the success of SHR4.0 and to understand their interrelationships and interaction.

The success of SHR4.0 implementation at the level of organizations rests on the shoulders of their managers. An element of novelty in our study is precisely looking at the supporting factors in the implementation of the SHR4.0 concept from the perspective of management and its functions. As we know, the adaptation of leadership styles due to I4.0 has proven to be necessary and affects organizational success. Cultural openness (Elnadi & Abdallah, 2023), fostering innovation (Ali et al., 2024; Cugno et al., 2022; Dabic et al., 2023; Hadi et al., 2024), information sharing (Avwokeni, 2024) and learning support (Bunjak et al., 2022) are essential attributes of leadership. Several studies have also addressed the necessary changes in organizational structure, without which successful implementation of I4.0 is not possible (Doblinger, 2022; Gutierrez et al., 2019). These are modifications to organizational structures (Fettig et al., 2018; García De Soto et al., 2022; Mohiuddin et al., 2023; Shaba et al., 2019), supported by the introduction of agility principles (Bouchard et al., 2022; Petermann & Zacher, 2020; Pfaff, 2023; Rane & Narvel, 2021) and self-managed teams (Doblinger, 2022; Gutierrez et al., 2019).

Thus, there is ample evidence that changes in both functions have a demonstrable impact on the success of an organization in an I4.0 environment (Črešnar et al., 2023; Dabić et al., 2023; García De Soto et al., 2022; Parente et al., 2020; Pfaff, 2023). However, what role they play in the inevitable transformation of SHR4.0 remains unexplored to date. Understanding what role organizational structure and leadership styles play in the successful implementation of SHR4.0, and how they interact with each other, has many important implications for how organizations conceptualize HR. By examining these issues, we will fill an important knowledge gap that will support organizations to be successful in implementing SHR4.0, help them to benefit from its effects, and strengthen their sustainable competitive advantage. In doing so, we will also highlight the challenges that still exist in trying to understand the role of the human factor as key in the context of I4.0 and expand the range of solutions for organizations and their managements.

While many studies examine these factors separately, our findings show that transformational, digital, and agile leadership styles foster a culture of openness and innovation, while flexible organizational design enables practical implementation. Thus, the contribution of our study lies in offering an integrated perspective and practical recommendations for managers aiming to achieve successful digital transformation through SHR4.0.

In line with our intention, the paper investigates the following research questions:

1. How does I4.0 influence the need to transform HRM to the SHR4.0 concept?
2. Which factors at the level of organizations support the transformation of HR to SHR4.0?
3. How can the implementation of SHR4.0 be supported at the organizational level?

The paper is organized as follows: section 1 introduces the reader into the theory of human resource management and explains its transformation due to the impact of industry 4.0, section 2 discusses the methodological approach, section 3 presents the research findings, section 4 discusses the findings in the context of previous research, and section 5 presents the conclusions, including theoretical and managerial implications, limitations of the research, and considerations about its future direction.

1. Theory and Hypothesis development

1.1 Industry 4.0

The concept of the Fourth Industrial Revolution was introduced in 2011 and later in 2013 it was complemented by recommendations for the implementation of the strategic initiative "Industry 4.0". The essence of I4.0 is the implementation of cyber-physical systems in a manufacturing environment (Liu & Xu, 2017; Lu, 2017; Peruzzini et al., 2017) against the background of smart grid systems (Culot et al., 2020). It is shaped in particular by digitalization and information technology (Klingenberg et al., 2022; Zhong et al., 2017; Müller et al., 2018; Peruzzini et al., 2017), but changes are happening at the physical, digital and biological levels as a result (Liao, 2017).

At the enterprise level, the adoption of I4.0 is associated with the expectation of higher productivity and flexibility (Culot et al., 2020), efficiency (Castelo-Branco et al., 2022; James et al., 2022), sustainability (Bai et al., 2020), more individualized products with short time to market and higher quality (Zhong et al., 2017).

1.2. Smart Human Resources 4.0

Smart Human Resources 4.0 (SHR 4.0) represents a new concept that is evolving during the fourth industrial revolution and is characterized by the transformation of approaches to the effective management of the next generation of workers as a result of innovations in digital technologies (Gouda & Tiwari, 2024; Alam & Dhamija, 2022; Hecklau et al., 2016). Human resource management is not immune to the impact of Industry 4.0, quite the contrary. The implementation of I4.0 principles requires businesses to pay increasing attention to human resources, as these are becoming critical factors in operational systems (Neumann et al., 2021). Employers need to adopt a more human-centered approach, perceiving the value of their employees, to effectively manage the transition to the new Industry 4.0 paradigm (Ietto et al., 2024). According to Gu et al. (2021), human resources and innovative technologies are complementary factors, therefore, developing new skills for employees and managers seems to be crucial for the successful implementation of the I4.0 paradigm. In doing so, competencies include not only computer literacy but also readiness for collaboration, quick problem solving and understanding of social relationships in a digital context (Nešić Tomašević, 2023). Table 1 captures the essential SHR4.0 challenges underlying this latent variable in our research.

Table 1 Challenges of Smart Human Resources 4.0

Challenges of SHR 4.0	Studies
Reaching and recruiting talent with specific characteristics	Ietto *et al.*, 2024; Pillai & Srivastava, 2024; Sivathanu & Pillai, 2018
Designing jobs with diverse skills and competencies	Ansari et al., 2020; Da Silva et al., 2022; Hecklau et al., 2016; Liboni et al., 2019; Nešić Tomašević, 2023
Use of technology in employee search and selection (apps, Big Data, AI, chatbots)	Da Silva et al., 2022; Kambur & Yildirim, 2023; Pan & Froese, 2023; Pillai & Srivastava, 2024; Tambe et al., 2019
Acclimatizing new employees through augmented reality	Jeske & Olson, 2022; Petrilli et al., 2022; Ybarra, 2023
Identifying employee skill gaps and setting goals through artificial intelligence	Gómez-Martínez et al., 2020; Mer & Virdi, 2023; Sharma et al., 2022
Big data in performance management	Da Silva et al, 2022; Kambur & Yildirim, 2023; Pillai & Srivastava, 2024; Rana & Sharma, 2019; Tambe et al, 2019
Reducing turnover by analyzing staff profiles	Ansari et al., 2020; Da Silva et al., 2022; Hecklau et al., 2016; Liboni et al., 2019; Nešić Tomašević, 2023; Neumann et al., 2021; Pillai & Srivastava, 2024
Virtual education	Rana & Sharma, 2019; Tan et al., 2024; Zajac et al., 2022
Continuous feedback	Hagemann & Decius, 2024; Shet & Pereira, 2021
Retaining staff through new value propositions and internal opportunities	Bissola & Imperatori, 2020; Glaister et al., 2018; Ietto et al., 2024; Sivathanu & Pillai, 2018
Smart IoT-based applications and devices for real-time health monitoring and support	Badri et al., 2018; Kadir & Broberg, 2020; Liboni et al., 2019; Mer & Virdi, 2023,

Source: the authors

Several researches confirm that SHRM 4.0 contributes to organizational performance (Apascaritei & Elvira, 2022; Pillai & Srivastava, 2024). Through the development of dynamic human resource capabilities, their performance increases (Tambe et al., 2019; Verma et al., 2020), which has a direct impact on increasing productivity, reducing costs and maintaining competitive advantage (Verma et al., 2020).

1.3 Relationship between I4.0 and SHR4.0

Implementation of SHR 4.0. is essential to meet the challenges of Industry 4.0 (Verma et al., 2020). Human resources play a key role in the transformation, as they can be a support but also a barrier to the implementation of I4.0 (Sharma et al., 2022). For example, HR departments may act as barriers by failing to adopt agile processes, resisting data-based decision-making, or lacking digital competencies. On the other hand, HR can enable digital transformation by developing adaptive leadership skills, supporting continuous learning, and redesigning job roles for future competencies (Hecklau et al., 2016; Liboni et al., 2019; Nicolás-Agustín et al., 2022). The onset of digitalization is changing the way people work, learn, manage, and interact with each other (Da Silva et al., 2022). It brings about a change in roles and required competencies of employees (Nešić Tomašević, 2023). Thus, the digital trends resulting from Industry 4.0 are significantly affecting the HRM field in different directions. Based on the above, we formulate the following research hypothesis:

H1: Industry 4.0 (I4.0) technologies are positively related to Smart HR 4.0 (SHR4.0).

1.4 Organizational structures

The success of implementing new technologies in I4.0, increasing the productivity of organizations, is contingent on the adoption of complementary non-technological changes. Such changes include, according to the findings of several studies, the transformation of organizational structures (Agarwal et al., 2023; Agostini & Filippini, 2019; Črešnar et al., 2023). Digital transformation places great pressure on businesses in the form of demands on their flexibility, agility, and innovative capabilities. At the same time, changes in organizational structure involve both changes in the organization of processes and the organization of work (Fettig et al., 2018). Acknowledging and accommodating the growing complexity not only in technological dimensions but also in organizational structures has emerged as a pivotal factor for the effective implementation of the Industry 4.0 paradigm (Da Silva et al., 2022; Gama & Magistretti, 2023). While some authors use the term "organizational change" broadly, we refer more precisely to "organizational structure," which includes variables mentioned in table 5 and other structural aspects, like team autonomy, decentralization, and flattening of hierarchies. These are core attributes that enable the successful implementation of SHR4.0 in an Industry 4.0 environment. As shown in Table 2, the identified transformations in OS include flat structures, prevalence of teamwork, virtual and agile teams, decision-making at lower levels, and decentralization of authority and knowledge (Fettig et al., 2018; Chowdhury & Murzi, 2020; Kumar et al., 2022; Kannengiesser, 2023). These features directly support faster decision-making and a more dynamic response to innovation needs.

Table 2 Changes in the organizational structure of enterprises in the context of Industry 4.0

Changes in organizational structure	Studies
Flat organizational structure	Fettig et al., 2018; García De Soto et al., 2022; Mohiuddin et al., 2023; Shaba et al., 2019
The prevalence of teamwork	Chowdhury & Murzi, 2020; Sten et al., 2024
Virtual teams	Kimura, 2024; Morrison-Smith & Ruiz, 2020; Purvanova & Kenda, 2022
Virtual work from anywhere and everywhere	Freeman et al., 2022; Kumar et al., 2022
Self-management of teams	Doblinger, 2022; Gutierrez et al., 2019; Ryu et al., 2022
Decision-making at lower management levels	Davutoğlu, 2020; Nayernia et al., 2022; Parente et al., 2020; Shamim et al., 2016
Subordinates with more authority, responsibility, and knowledge	Kaasinen et al., 2020; Kumar et al., 2021; Shamim et al., 2016
Strengthened communication networks between management and staff	Erol et al., 2016; Narula et al., 2020; Taqi et al., 2023
Agile teams	Bouchard et al., 2022; Petermann & Zacher, 2020; Pfaff, 2023; Rane & Narvel, 2021

Source: the authors

1.5 Relationship between OS and SHR4.0

Along with technology, people and organizations are also at the heart of Industry 4.0 (Stuss, 2023). In such a situation, human resource systems need to be aligned with the new way of doing work. The need for more flexible work organization and greater connectivity requires the emerging SHR4.0 to support a more direct relationship between employees and the organization (Bissola & Imperatori, 2020). Many organizational changes are taking place directly within HR, new working practices and ways of interacting are being defined, HR departments are being slimmed down, and responsibilities are being decentralized (Huettermann et al., 2024). The performance of remote work, enabled by the increase in digitalization, requires not only new technical, but also organizational solutions. For this work to be effective, a balance must be struck between information technology, organizational tools, and behavioral aspects (De Bruyne & Gerritse, 2018).

1.6 Relationship between OS and I4.0

The advent of new technologies is inevitably accompanied by changes in organizational structure, even at the enterprise level. Digital transformation puts great pressure on companies in terms of flexibility, agility, and innovation capacity (Fettig et al., 2018). Fundamental changes in organizational work are occurring to which rigid organizational structures cannot respond with sufficient flexibility. Organizational structure - structures, hierarchies, and processes - must therefore be transformed, as the full benefits of I4.0 cannot be achieved without restructuring organizational processes (García De Soto et al., 2022). Based on the above, we formulate the following research hypothesis:

H2: The relationship between Industry 4.0 (I4.0) and Smart HR 4.0 (SHR4.0) technologies is mediated by the organizational structure (OS) of the enterprise.

1.7 Leading people in the 4.0 era

For the 4.0 era, there is no clearly defined specific style with proven behavioral characteristics of leaders. Bunjak et al., (2022) even state that new technologies create increasingly perplexing leadership challenges. However, scholars agree that this new technological era requires leaders who are value-driven and possess the capabilities to cope with rapid technological change (Črešnar et al., 2023; Dabić et al., 2023; Hernandez-de-Menendez et al., 2020; Schneider, 2018; Veile et al., 2022). A desired outcome of transforming leadership styles in the 4.0 era is for leaders to understand and respond to the values and practices of the new technological and innovative environment (Dabić et al., 2023; Schneider, 2018; Stouten et al., 2018) that contribute substantially to manufacturing productivity in an I4.0 organizational environment (Črešnar et al., 2023; Dabić et al., 2023). These authors reveal the importance of soft values for productivity improvement and the role of leaders in this process and point out that organizational results come from capable leaders who facilitate and support processes and structures to use technology in the right way.

Many studies that address the topic of leadership in the 4.0 era describe existing styles (especially the transformational style) enriched with various aspects of innovation and technology orientation, along with the ability to share information, lead in a network, communicate openly, give and receive feedback, and build trust in teams. In Table 3, we theoretically summarize several approaches to change in the managerial function of leading people under the conditions of the fourth industrial revolution, which form the basis for defining this latent variable in our research.

Table 3 Changes in leadership styles in the context of Industry 4.0

Identified changes in leadership styles	Studies
Openness to cultural change with a focus on improving knowledge	Elnadi & Abdallah, 2023; Rüth & Netzer, 2020; Schneider, 2018; Sivathanu & Pillai, 2018
Promoting the introduction of new ideas to increase the innovative strength of the enterprise	Ali et al., 2024; Cugno et al., 2021; Dabić et al., 2023; Erhan et al., 2022; Hadi et al., 2024; Sainger, 2018; Verma & Singh, 2022
Connecting and collaborating between humans and robots	Bader & Kaiser, 2019; Bankins et al., 2024; Goswami et al., 2024; Le et al., 2024; Sarioguz & Miser, 2024
A leadership style that accelerates innovation and learning	Behie et al., 2023; Bosch et al., 2018; Bunjak et al., 2022; Kelly, 2019; Oberer & Erkollar, 2018; Shamim et al., 2016; Turyadi et al., 2023; Yuliza et al., 2024
A leadership style based on information and information sharing	Avwokeni, 2024; Bunjak et al., 2022; Mihardjo et al., 2019; Oberer & Erkollar, 2018; Sikora, 2017; Sivathanu & Pillai, 2018
Leadership style based on continuous knowledge enhancement	Hanschke, 2018; Islam et al., 2017; Mihardjo et al., 2019; Naqshbandi & Jasimuddin, 2018; Nasir & Akhtar, 2019
Rewarding unconventional "out-of-the-box" thinking in the workforce	Bolte et al., 2018; Sivathanu & Pillai, 2018
Eliminating conflicts between multi-generational groups of workers	Camberos, 2023; Fotso, 2024; Sivathanu & Pillai, 2018
Using an agile approach	Akkaya, 2020; Ghamrawi et al., 2024; MacIntyre, 2017; Organa & Sus, 2023; Şahin & Alp, 2020

Source: the authors

1.8 Relationship between LS and SHR4.0

All the leadership changes identified above are directed toward people and their management in the 4.0 era, which must be adapted to this phenomenon. All HR functions in the 4.0 era should be smart. The implementation challenges of the HR4.0 smart concept are not only about breaking down technological barriers (Sivathanu & Pillai, 2018), but more importantly the support of leaders with the values and capabilities of the technological era is needed. Only the latter has the potential to transform complex HR processes (Dabić et al., 2023).

1.9 Relationship between LS and I.4.0

A result of the implementation of Industry 4.0 aspects is not only technological changes and innovations (Bunjak et al., 2022b; Castagnoli et al., 2020; Hamidi et al., 2018; Marcucci, 2021; Muhuri et al., 2019), but also the transformation of managerial functions, including leadership. Many authors argue that new technologies do not automatically guarantee the success of a firm (Bunjak et al., 2022b; Dabić et al., 2023; Shet and Pereira, 2021) and that other factors, particularly affecting human interactions, are equally important (Črešnar et al., 2023; Yang et al., 2020). At the same time, these factors, in the form of soft skills, can remove barriers that hinder the adoption of Industry 4.0 technologies (Agostini & Filippini, 2019; Birkel et al., 2019; Dabić et al., 2023; Dalenogare et al., 2018). Leadership style is thus not only a contextual variable, but a key enabler of digital transformation. Organizational agility is considered a foundational element for survival in this era. This includes styles such as transformational leadership, innovation-oriented leadership, agile leadership (Cutter Consortium, 2017; Şahin & Alp, 2020), digital leadership (Avwokeni, 2024), and shared leadership (Bunjak et al., 2022). Each of these styles emphasizes different but complementary capacities such as technology facilitation, empowerment, adaptation, and communication. Leadership changes in this era enable and increase the leader's influence on the adoption of IT innovations in the organization (Bunjak et al., 2022).

H3: The relationship between Industry 4.0 (I4.0) and Smart HR 4.0 (SHR4.0) technologies is mediated by manager leadership style (LS).

H4: The relationship between Industry 4.0 (I4.0) and Smart HR 4.0 (SHR4.0) technologies is mediated by the firm's organizational structure (OS) and the manager's leadership style (LS) simultaneously.

Based on the above, we formulate the research model of our study, which is shown in Figure 1.

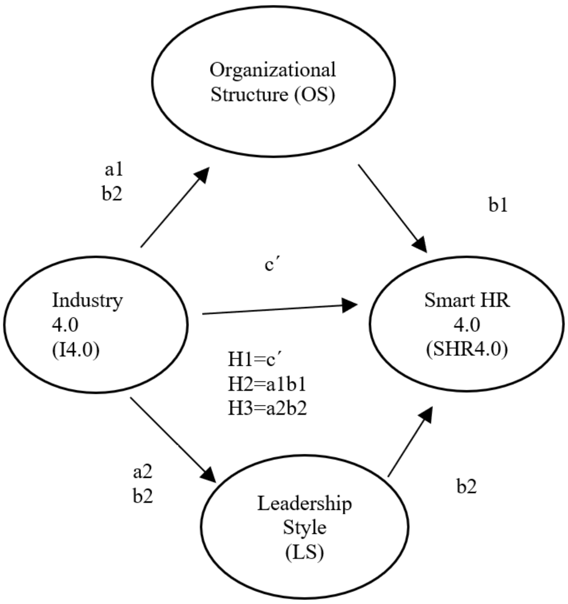

Figure 1 Research model of the study
Source: the authors

2. Design/methodology/approach

We used a questionnaire survey to collect data. Before launching the survey, we conducted validation of the instrument with managers of 5 enterprises. In face-to-face meetings, the content of the questionnaire was consulted to ensure its quality. These were Solved Ltd., Perry Talents, OLO a.s., ČSOB Stavebná sporiteľňa a.s., and the New Generation Bory Hospital, which apply Industry 4.0 principles to some extent and have experience with Management 4.0. In this way, we ensured 2 main components of instrument validation and face and content validity. Within face validity, the experts mainly examined the clarity, appropriateness, logical context, format of the questionnaire items, and its overall structure, including response options. In terms of content, the experts assessed key aspects, namely the relevance, representativeness, and comprehensiveness of the questionnaire items for the construct, or the possible redundancy or overlap of items. We also carried out preliminary testing of the questionnaire with managers of 4 large industrial companies HYDAC Electronic s.r.o., LEYARD EUROPE s.r.o., Muehlbauer Technologies s.r.o., Schüle Slovakia s.r.o., who confirmed the understanding of all questions of the questionnaire (Colbert et al., 2019; Willimack et al., 2023) and enriched our knowledge with personal experiences from their practice.

In the subsequent questionnaire survey, mostly top managers of industrial enterprises in Slovakia were contacted via LinkedIn services and by email communication. We contacted 3,061 managers of such enterprises, based on the Finstat portal database, which aggregates registration, financial and legal data on Slovak and Czech companies and sole traders from dozens of sources. We performed a simple probability sampling (every tenth enterprise) after filtering out enterprises with 50 or more employees. We assumed the application of Management 4.0 tools in these enterprises. Anonymity was ensured by not specifying the name of the company. At the same time, the email message contained an initial introduction to the meaning and purpose of the research, instructions for completing the questionnaire, the time required to complete it, and a notification that by returning the completed questionnaire the respondent agrees to the processing of data. A link to the questionnaire was attached. The entire survey was conducted between March and April 2023. The final research sample consisted of 115 responses. Although the overall response rate was low, we consider the collected data to be relevant and informative due to the extensive number of in-depth personal consultations conducted with managers. These consultations provided qualitative insights and ensured that the participating managers were both highly engaged and motivated to contribute, which supports the credibility and contextual validity of the responses despite the limited sample size. The rest of the research sample consisted of mid-level managers. In terms of location of operations, the sample consisted of companies evenly located throughout the country. In terms of managerial level, the majority of respondents were senior managers (87%). The majority of the businesses analyzed (57%) had 100% foreign participation. The remainder consists of domestic enterprises (33%) and enterprises with a majority foreign participation (10%).

2.1 Common method bias

Since our data for all variables (independent, dependent, and mediating) were collected using the same method, they are subject to bias (Podsakoff et al., 2012). To avoid common method bias as much as possible, we implemented as many corrective measures as possible, especially procedural ones, which are more beneficial in cases where the data cannot be re-collected (Podsakoff et al., 2012). These include clarifying the aim of the research and providing clear instructions to respondents, as well as ensuring understanding of the items by both removing double meanings and brief explanations, avoiding redundancy, and using reverse-coded items. We have also deliberately used negative wording of items for variables because, according to (Dueber et al., 2021) they "disrupt the patterns" of this trap and require a higher focus on the questionnaire items. At the same time, we visually separated the dependent, independent variable, and mediator items in the questionnaire and by using the identification section. Using the VIF indicator, whose values were less than 5.0 (Hair et al., 2019), we found that the model is not subject to collinearity and can be considered free of common method bias.

2.2 Operationalization and Measurements

The 4 latent variables have been the subject of the research.

The Industry 4.0 (I4.0) variable has many definitions. Our study adopts the Boston Consulting Group's multidimensional definition of I4.0 ("Industry 4.0", n.d.), based on which the construct is made up of 9 items representing the different technologies implemented within I4.0. It is a formative construct, where our observed variables that make up the construct also cause it (Ringle et al., 2020). Managers scored the degree of implementation for each item using a Likert scale of 1 (none) to 6 (high).

The SmartHR 4.0 (SHR4.0) variable contains 19 items identifying the essence of HRM in the 4.0 era. The items are taken from the author's conceptual model (Sivathanu & Pillai, 2018) - 12 items and supplemented with additional items that we identified from the authors' studies (Table 1).

Managers scored the level of agreement for each item using a Likert scale of 1 (strongly disagree) to 6 (strongly agree).

The variable Organizational Structure (OS) contains 9 items identifying the essence of organizational structure in the 4.0 era. The items are taken from the author's conceptual model (Sivathanu & Pillai, 2018) - 2 items and supplemented with additional items that we identified from the authors' studies (Table 2).

Managers scored the level of agreement for each item using a Likert scale of 1 (strongly disagree) to 6 (strongly agree).

The Leadership Style (LS) variable contains 9 items identifying the essence of leadership styles in the 4.0 era. The items are taken from the author's conceptual model (Sivathanu & Pillai, 2018) - 2 items and supplemented with additional items that we identified from the authors' studies (Table 3). Managers scored the level of agreement for each item using a Likert scale of 1 (strongly disagree) to 6 (strongly agree).

Table 4 Latent variable categories and descriptors - I4.0 and HRM

KP	Industry 4.0 technologies (I4.0)	AP
I4.0_1	Additive manufacturing	2,69
I4.0_2	Augmented reality	2,38
I4.0_3	Autonomous robots	2,88
I4.0_4	Big Data and Analytics	3,21
I4.0_5	Cloud computing	3,23
I4.0_6	Cyber Protection	4,18
I4.0_7	Horizontal and vertical integration	3,22
I4.0_8	Internet of Things	3,20
I4.0_9	Simulations	3,30
KP	**Identified changes in human resource management (SHR4.0)**	AP
SHR4.0_1	Reaching and recruiting talent with specific characteristics	3,56
SHR4.0_2	Designing jobs with diverse skills and competencies	3,40
SHR4.0_3	Posting job offers on smart/mobile apps	3,30
SHR4.0_4	Automated CV search using AI and Big Data	2,30
SHR4.0_5	Automated customized testing of candidates	2,10
SHR4.0_6	Real-time remote video interviewing on a fast data network	3,71
SHR4.0_7	Chatbots with artificial intelligence interpret and verify candidate responses in real time	1,66
SHR4.0_8	Acclimatizing new employees through augmented reality	1,79
SHR4.0_9	Identifying worker skills gaps through artificial intelligence	1,70
SHR4.0_10	Using artificial intelligence to set individual worker goals	1,63
SHR4.0_11	Rewards based on Big Data	1,86
SHR4.0_12	Motivating and supporting worker creativity	4,08
SHR4.0_13	Reducing turnover by analyzing staff profiles	2,66
SHR4.0_14	Identifying low-performing workers based on Big Data	3,56
SHR4.0_15	Virtual training anytime, anywhere	3,20
SHR4.0_16	Continuous feedback	3,41
SHR4.0_17	Retaining staff through new value propositions and internal opportunities	3,34
SHR4.0_18	Not promoting staff based on KPIs instead of seniority	3,72
SHR4.0_19	Smart IoT-based applications and devices for real-time health monitoring to reduce sick leave	1,93

Source: own elaboration

Note: AP - Arithmetic mean of I4.0 implementation rate (1- none, 6 - high), respectively Arithmetic mean of agreement rate with statements for items SHR4.0 (1- strongly disagree to 6 - strongly agree); KP= variable codes

Table 5 Latent variable categories and descriptors OS and LS

KP	Identified changes in organizational structure (OS)	AP
OS_1	Flat organizational structure	4,20
OS_2	The prevalence of teamwork	4,68
OS_3	Virtual teams	2,95
OS_4	Virtual work from anywhere and everywhere	3,38
OS_5	Self-management of teams	3,84
OS_6	Decision-making at lower management levels	4,03
OS_7	Subordinates with more authority, responsibility, and knowledge	3,77
OS_8	Strengthened communication networks between management and staff	4,06
OS_9	Agile teams	3,54
KP	**Identified changes in leadership styles (LS)**	AP
LS_1	Openness to cultural change with a focus on improving knowledge	3,97
LS_2	Promoting the introduction of new ideas to increase the innovative strength of the enterprise	3,99
LS_3	Disconnection and collaboration between humans and machines	3,87
LS_4	A leadership style that accelerates innovation and learning	3,88
LS_5	Data-driven leadership style	4,03
LS_6	Leadership style based on continuous knowledge development	4,21
LS_7	Rewarding unconventional "out-of-the-box" thinking in the workforce	3,55
LS_8	Eliminating conflicts between multi-generational groups of workers	3,91
LS_9	Using an agile approach	3,79

Source: own elaboration

Note: AP - Arithmetic mean of agreement rate with statements for items OS, LS (1- strongly disagree to 6- strongly agree); KP= variable codes

2.3 Data analysis

Data analysis was performed using the PLS-SEM method (partial least squares structural equation modeling) (Hair et al., 2019) with SmartPLS 3.3 software. That method allows multiple hypotheses to be tested simultaneously under both direct and indirect effects in a complex system (Becker et al., 2018). It is used when samples are relatively small, the research model is complex, the focus of the study is on predicting dependent variables, and when latent variable scores are used for predictive purposes (Roldán & Sánchez-Franco, 2012). We evaluated the measurement model and the structural model. We used all the available tools of this software to verify the reliability and validity of the model. Hypotheses were statistically tested at a significance level of $\alpha = 0.05$.

3. Conclusion

3.1 Measurement model

The evaluation of the first model provides data on the fulfillment of all the common requirements of the model. Individual reliability is confirmed by calculating standardized external variable loadings, which in our model range from 0.555 to 0.944 and, according to (Götz et al., 2009), are considered acceptable. Internal construct reliability was monitored through Cronbach's alpha (values found to range from 0.741 to 0.898), composite reliabilities (CR) (values found to range from 0.837 to 0.929), and rho_A (values found to range from 0.759 to 0.912), all of which were greater than 0.70 and less than 0.95 (Hair et al., 2019) and at the same time, based on theory, rho_A should be between the Cronbach's alpha and CR (Ringle et al., 2020). We assessed the convergent validity by calculating the average variance extracted (AVE), which in our model exceeds the level of 0.5 (Hair et al., 2019) for all constructs, meaning that the construct explains an average of at least 50% of its item´s variance (values ranging from 0.524 to 0.814).

The next step was to assess discriminant validity. We assessed the model according to the heterotrait-monotrait correlation (HTMT) ratio (Ringle et al., 2020), which is measured as the mean value of the indicator correlations across constructs. Since not all values are below 0.9 (Henseler et al., 2015), we applied cross-loading because of the validation of the loading of indicators into latent variables. The results of the analysis indicate that if the cross-loading is applied, a particular indicator should have a higher loading on its latent variable than on the other latent variables in the study (Henseler et al., 2015). Based on the above, discriminant validity is established. We no longer needed to use the Forner-Larcker criterion.

3.2 Structural model

When analyzing a structural model, it is important to assess the R2 (R-squared) value of endogenous indicators, as the stringency of each structural path is determined by the R2 value and identifies the goodness of the model. The R2 value of the variables in our model was in the range of 0.273 to 0.621, indicating that the predictive capability is established since the results are higher than 0.1. (Hair Jr et al., 2017). A Q2 above 0 shows that the model has predictive relevance. The results (ranging from 0.279 to 0.631) show that there is significance in the prediction of the constructs.
Furthermore, the model fit was assessed using SRMR. The value of SRMR was 0.095. SRMR values should be less than or equal to 0.100, indicating an acceptable model fit (Hair Jr et al., 2017).

3.3 Path coefficients and mediating effects

Prior to conducting the mediation in SmartPls software, we conducted a correlation analysis, which shows that all the examined relationships are statistically significant and there are significant positive correlations between the examined variables. In particular, a significant dependence exists for the variable HR and I4.0. Based on the analysis, we can conclude that the implementation of the Industry 4.0 concept is strongly correlated with changes in the managerial function of human resource management, Kendall's tau b=0.612. The coefficient of Eta has a value of 0.855, which represents a very strong correlation.

The next step was to assess the direct and indirect relationships of all latent variables by comparing the β values by testing for their significance level using a t-value test. A nonparametric bootstrapping technique was used. The authors (Hair et al., 2019) state acceptable t-values for a two-sample test of 1.96 at the significance level = 5% with a significant correlation. The results of the effects are presented in the table below.

Table 6 Direct effects, standard deviation, t-value, and p-value

Paths of variables	Original Sample (β)	Sample Mean (β)	Standard deviation	T-value	P-value
I4.0 -> OS	0.529	0.536	0.061	8.722	0.000
I4.0 -> LS	0.574	0.576	0.069	8.313	0.000
I4.0 -> SHR4.0 (H1)	0.490	0.490	0.079	6.180	0.000
LS -> SHR4.0	0.384	0.382	0.105	3.658	0.000
OS -> SHR4.0	0.022	0.029	0.094	0.238	0.812

Source: the authors

The results indicate the existence of significant dependencies for four of the five direct relationships examined that enter into mediation. I4.0 has a significant effect on OS (β=0.529, t=8.722, $p<0.05$), also I4.0 on LS (β=0.574, t=8.313, $p<0.05$), I4.0 on SHR4.0 (β=0.490, t=6.180, $p<0.05$), thus confirming Hypothesis 1. The pathway from LS to SHR4.0 is also significant (β=0.384, t=3.658, $p<0.05$). All direct effects variables show T-values greater than 1.96 and P-values less than 0.05 (significance level = 5%), with only one case between the OS pathway and SHR4.0 (β=0.022, t=0.238, $p>0.05$), suggesting a non-significant relationship. As reported by (Hayes, 2022), statistical significance of paths "a" and "b" is not a condition for mediation according to current thinking. Therefore, we conduct the mediation analysis.

Table 7 Direct, indirect, and total mediation effects through the OS and LS variables

Paths of latent variables	Type of effect	Original Sample (β)	Sample Mean (β)	Standard deviation	T-value	P-value
I4.0 -> OS	Direct effects	0.527	0.532	0.066	7.981	0.000
I4.0 -> SHR4.0		0.573	0.580	0.074	7.727	0.000
OS -> SHR4.0		0.294	0.291	0.076	3.874	0.000
I4.0 -> OS -> SHR4.0 (H2)	Specific indirect effects	0.155	0.153	0.041	3.812	0.000
I4.0 -> SHR4.0	Total indirect effects	0.155	0.153	0.041	3.812	0.000
I4.0 -> SHR4.0	Overall effects	0.728	0.733	0.051	14.398	0.000
Direct, indirect and total mediation effects through the variable LS						
Paths of latent variables	**Type of effect**	**Original Sample (β)**	**Sample Mean (β)**	**Standard deviation**	**T-value**	**P-value**
I4.0 -> LS	Direct effects	0.573	0.579	0.071	8.091	0.000
I4.0 -> SHR4.0		0.505	0.507	0.086	5.870	0.000
LS -> SHR4.0		0.388	0.390	0.082	4.708	0.000
I4.0 -> LS -> SHR4.0 (H3)	Specific indirect effects	0.223	0.225	0.053	4.215	0.000
I4.0 -> SHR4.0	Total indirect effects	0.223	0.225	0.053	4.215	0.000
I4.0 -> SHR4.0	Overall effects	0.728	0.732	0.053	13.824	0.000
Direct, indirect and total mediation effects through OS and LS variables simultaneously						
Paths of latent variables	**Type of effect**	**Original Sample (β)**	**Sample Mean (β)**	**Standard deviation**	**T-value**	**P-value**
I4.0 -> LS	Direct effects	0.574	0.574	0.075	7.696	0.000
I4.0 -> OS		0.529	0.533	0.066	7.955	0.000
I4.0 -> SHR4.0		0.490	0.495	0.077	6.406	0.000
LS -> SHR4.0		0.384	0.384	0.103	3.741	0.000
OS -> SHR4.0		0.022	0.022	0.094	0.239	0.811
I4.0 -> LS -> SHR4.0	Specific indirect effects	0.221	0.222	0.070	3.131	0.002
I4.0 -> OS -> SHR4.0		0.012	0.011	0.050	0.236	0.814
I4.0 -> SHR4.0	Total indirect effects	0.232	0.232	0.051	4.570	0.000
I4.0 -> SHR4.0	Overall effects	0.723	0.727	0.050	14.318	0.000

Source: the authors

For the first mediation through the OS variable, all relationships found are significant, with the total effect being β= 0.728 and the indirect effect being β= 0.155, indicating that the mediating effect of OS within the I4.0 -> SHR4.0 relationship is 21.3%, and the direct relationship is 78.7%.

For the second mediation through the LS variable, all relationships found are significant, with the total effect β= 0.728 and the indirect effect β= 0.223, indicating that the mediating effect of LS within the I4.0 -> SHR4.0 relationship is 30.6%, and the direct relationship is 69.4%.

In the third mediation jointly across the OS and LS variables, not all relationships found are significant. The total effect and indirect effect are β= 0.728 and β= 0.232, respectively, and they are significant, indicating that the joint mediating effect of LS and OS in the I4.0 -> SHR4.0 relationship is 32.1%, and the direct relationship is 67.9%. However, only the LS variable is significantly involved in the indirect effect (β= 0.221). The mediation effect of the OS variable is not significant.

4.Discussion

Our study aimed to further investigate how changes in OS and LS, from managers' perspectives, support the implementation of the SHR4.0 concept, which has become essential for the success of digitalization with the advent of I4.0. Based on the results, we were able to confirm a positive association between the implementation of Industry 4.0 technologies and Smart HR 4.0. This finding is in line with previous studies (Da Silva et al., 2022; Nešić Tomašević, 2023; Sharma et al., 2022), but its verification in the setting of our study extends its validity. The direct effect of the examined relationship is significant ($\beta = 0.490$, $t = 6.180$, $p < 0.05$), indicating that the implementation of I4.0 triggers the need for direct changes in the concepts of human resource management at the level of organizations. We agree with Whysall et al. (2019), that the speed of technological change as a result of the advent of Industry 4.0 has created a significant gap between current workforce capabilities and rapidly evolving demands of tasks, prompting the need to consider new and more effective approaches to human resource development. Consequently, the pressure exerted on its adaptation is immense. The new competencies include not only computer literacy but also the readiness to collaborate, to solve problems quickly, and to understand social relations in a digital context (Nešić Tomašević, 2023). For this reason, it is necessary to make learning and development opportunities available to employees that equip them with the required skills and competencies (Cucculelli et al., 2022). Working with talent becomes an essential part of SHR4.0 (Pillai & Srivastava, 2024; Sivathanu & Pillai, 2018), work environment adaptation (Badri et al., 2018; Liboni et al., 2019), transformation of cultures (Bissola & Imperatori, 2020; Glaister et al., 2018; Ietto et al., 2024) or working with data analytics and Big data (Da Silva et al. 2022; Kambur & Yildirim, 2023; Pillai and Srivastava, 2024). The need to align leadership styles to the SHR4.0 concept as a result of I4.0 is acknowledged. However, the real implementation rate of SHR4.0 elements is at a lower level compared to the expectations of technological advances (see Table 5 for the arithmetic mean of implementation). Therefore, the question arises how this process can be supported at the enterprise level. Our intention was to explore the role of the management functions of organizing and leading people in this context.

Our hypothesis that the relationship between Industry 4.0 (I4.0) and Smart HR 4.0 (SHR4.0) technologies is mediated by changes in organizational structure is confirmed. We agree with the assertion of Agarwal et al. (2023), that Industry 4.0 is characterized by technological disruption and business reorganization. The implementation of I4.0 technologies requires actions that change organizational activities, workplaces, and practices and require the development of new skills and competencies (Cugno et al., 2022). Digitalization enables internal and external stakeholders to share knowledge and collaborate across organizational boundaries, while at the same time increasing their competencies and experiences (Bissola & Imperatori, 2020). The redesign of organizational structures and processes, their decentralization, coupled with the introduction of agile approaches and elements of self-management can help organizations to implement the SHR4.0 concept more smoothly.

Similarly, the hypothesis that the relationship between I4.0 and SHR4.0 technologies is mediated by manager's leadership style was confirmed based on the results of the study. The mediating effect is more intense than that of organizational structure. Our research develops previous findings (Bankins et al., 2024; Bunjak et al., 2022; Črešnar et al., 2023; Dabić et al., 2023; Goswami et al., 2024;

Hernandez-de-Menendez et al., 2020), and complements them with the recognition of the role of leadership as an important factor supporting the implementation of the SHR4.0 concept. If organizations want to successfully transform their HRM systems in line with the needs and demands of digitalization, appropriate leadership styles are a defining attribute in this regard. They need to develop leadership styles in their leaders that support the process of innovation and learning (Behie et al., 2023; Yuliza et al., 2024), information sharing (Avwokeni, 2024; Sivathanu & Pillai, 2018) and rewarding non-traditional "out-of-the-box" thinking by employees (Bolte et al., 2018; Bouchard et al., 2022; Pfaff, 2023).

Since organizations are complex holistic systems where individual processes do not occur in isolation but are integrated, we also verified the assumption that the relationship between I4.0 and Smart SHR4.0 technologies is mediated by OS and LS simultaneously. This hypothesis was equally confirmed. The overall mediation effect is significant despite the low and insignificant influence of one of the variables, namely OS. Although the effect of OS alone is statistically insignificant ($\beta=0.022$; $p>0.05$), its inclusion in the joint mediation with LS increases the total explained variance of the model. This implies that OS may function as a contextual enabler, which strengthens the influence of leadership style on SHR4.0 implementation in specific organizational conditions. (B + tab.7) If organizations support SHR.40 implementations by modifying structures and processes while implementing a digital culture through capable leaders, the effect of leadership styles is demonstrably more significant. The transformation of leadership styles plays a crucial role here, whereas the impact of organizational change is a supporting factor.

Theoretical implications

Our study contributes to a deeper understanding of the complex structural relationships and the role of LS and OS within the relationship between I4.0 and SHR4.0. It confirms their function as mediating variables that influence this relationship. The results of the study enrich the literature in several ways. First, they support the findings of studies that argue that productivity gains do not come from technology as such (Črešnar et al., 2023; Dabić et al., 2023), but it also requires a transformation of human resources to SHR4.0. The massive adoption of digitalization is changing competency models, focusing on decision-making, cultural and intercultural skills, lifelong learning, interdisciplinary thinking, and problem-solving (Coşkun et al., 2019; Hernandez-de-Menendez et al., 2020). Our findings point to the fact that the success of the SHR4.0 transformation process implies that, in addition to focusing on HR processes, it also requires capable leaders and the redesign of structures and processes to enable the use of technology. The implementation of technological solutions, supported by an appropriate leadership style of leaders, in an environment with its setup, structures, and processes that support digital transformation, increases the chances of companies to succeed.

Secondly, the findings draw attention to the need to align technology solutions with the human resource development system, with the new way of working, with the new quality of employees, and with the behavior of supervisors in the new digital culture. The results show that although organizational solutions and process adjustments play a supporting role, the final effect is significantly more influenced by the leader and his/her leadership style. Agile principles (Bouchard et al., 2022; Pfaff, 2023), self-managed teams (Doblinger, 2022), or decentralizing tendencies (Nayernia et al., 2022) in organizational structure can be a solution to facilitate transformation and support human resource development, but the key role is played by a leader who is value-compatible with the new challenges and has the capabilities to cope with rapid technological changes (Črešnar et al., 2023; Dabić et al., 2023; Veile et al., 2022).

Practical Implications

Several practical implications also emerge from this study. To be successful in implementing I4.0 solutions, organizations need to focus on the human factor in addition to the technology itself. The adaptation and development of human resources play a demonstrably key role (Ietto et al., 2024; Pillai & Srivastava, 2024). Evolving job profiles and employee competencies will be crucial (Ansari et al., 2020; Neumann et al., 2021), accompanied by a stronger focus on talent management (Ietto et al., 2024; Sivathanu & Pillai, 2018) and the strategic use of data analytics (Da Silva et al., 2022; Pillai & Srivastava, 2024). In this area in particular, the HRM of organizations is still lagging behind the possibilities and not fully exploiting the available potential. Employers are advised to adopt three basic strategies. First, focus on creating continuous development programs, making them accessible to employees and fostering a culture of learning at the workplace (Nešić Tomašević, 2023). The arrival of Generation Z in the labor market with profiles that match Industry 4.0 technologies is an advantage for organizations (Hernandez-de-Menendez et al., 2020).

An appropriate strategy would be to focus on the competencies of leaders, whom, according to the study findings, can significantly increase the effects of SHR4.0 by overcoming the barriers that hinder the adoption of IT innovations (Bunjak et al., 2022) and Industry 4.0 technologies (Agostini & Filippini, 2019; Birkel et al., 2019). Organizations should focus their attention on the selection of leaders and their further development as a strategy to support the implementation of SHR4.0. This factor appears to be a key element based on the findings of the study. In addition to leadership development, it is crucial to align organizational structure with SHR4.0 goals. This includes redesigning workflows for agility, promoting decentralized decision-making, supporting team-based work, and ensuring structural flexibility (Fettig et al., 2018; Petermann & Zacher, 2020). A holistic approach that combines both human and structural elements is more likely to produce a sustainable transformation.

Finally, organizations should continuously assess their SHR4.0 implementation level and use these insights to refine both HR practices and organizational architecture. The supporting role is played by organizational solutions in the form of flat structures with a predominance of teamwork and self-managing teams, decentralization of decision-making, and strengthening of communication networks between management and employees. Based on the findings, these solutions appear to be relatively well-established. However, organizations have not yet fully exploited the opportunities for virtual teamwork, agile solutions, and empowerment at lower levels of management. This is where the potential for new approaches opens up.

Research limitations

Although this study provides valuable insights, it also has certain limitations regarding sample selection and methodological decisions. This is a cross-sectional study where data collection was limited to a one-off questionnaire. A longitudinal study was not possible in this case due to the complexity of the topic, the inability of obtaining responses from the same respondents over time, and the complexity of determining the time interval between data collection stages. We believe that it is the cross-sectional design for a new and complex topic that is appropriate and beneficial. Additionally, the low return rate of 115 responses out of 3,061 contacts (approx. 3.8%) can be considered a limitation. However, this limitation is mitigated by the fact that respondents were mostly top managers (87%) with relevant expertise in I4.0 and SHR4.0 topics, and their participation was confirmed in personal consultations during the pilot phase. Therefore, the quality of responses is prioritized over their quantity, following recommendations in elite sampling methods for complex topics (Willimack & Snijkers, 2013). The study was carried out in the conditions of enterprises operating in the Slovak market, while the geographical limitation and low return in the formation of the research sample may be partly limiting. The sample size of the study was adequate for the current analysis, however, a larger and more diverse sample could increase the credibility of the statistical conclusions. On the other hand, from a regional perspective, the sample covers the whole territory of Slovakia, which could support the generalization of the results to the Slovak business environment. However, given the relevance of the topic and the global nature of the discourse surrounding the implementation of I4.0, we assume that the findings have relevance on a broader scale as well. Future studies could address these limitations by applying mixed methods, such as combining quantitative survey data with qualitative interviews or case studies. Moreover, to better capture causal relationships between I4.0, LS, OS, and SHR4.0, longitudinal or experimental research designs could be implemented. Use of techniques such as dynamic panel modeling or qualitative comparative analysis (QCA) may reveal different configurations of influence and temporal effects.

Although we used several steps to mitigate common method bias, we did not use data collection from a variety of sources and this was due to the high expertise of the topic, which was particularly suited to senior management. Future research can focus on management perspectives on the areas under study and combine these with complementary techniques such as observation, which will strengthen the validity of the findings and allow triangulation of the data. Despite these limitations, our study offers a valuable foundation for future research on the key role of LS in the implementation of I.4 in the context of SHR4.0 development.

Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. Additional supporting materials or clarifications can also be provided upon inquiry. For any data-related questions, please contact the corresponding author.

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National Culture and Technological Entrepreneurial Orientation: A Study Utilising Hofstede's Theoretical Framework

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Abstract

Background: The expansive advancement of technology has prompted scholars to investigate the links between external factors that influence the success of technology-based entrepreneurs, with particular emphasis on the link between national culture and technological entrepreneurial orientation.

Purpose: This paper examines the relationship between national culture and technological entrepreneurial orientation during the early stages of entrepreneurial activity, utilizing Hofstede's national culture dimensions as a theoretical framework.

Study design/methodology/approach: The empirical analysis was conducted using multiple linear regression, based on data obtained from the Global Entrepreneurship Monitor (GEM) database. The sample comprises 8,000 participants from Southeastern Europe.

Findings/conclusions: The research findings indicate a statistically significant relationship between national culture and technological entrepreneurial orientation. A similar standard of living, associated with a lower index of power distance, is positively linked to technological entrepreneurial orientation, whereas the perception of entrepreneurship as a desirable professional career, typical of an individualistic society, is statistically significant but negatively associated with technological entrepreneurial orientation. A lower index of Power distance encourages innovativeness and efficiency in entrepreneurial ventures within high-tech sectors; conversely, Individualistic societies lead to a greater prevalence of enterprises in low-tech sectors.

Limitations/future research: A group of drivers of technological entrepreneurial orientation was examined. We recommend that future research, in addition to national culture, also considers other factors, such as individual or sociodemographic factors.

Keywords
National culture, Technological Entrepreneurial Orientation, Hofstede's culture dimensions, Southeast Europe, GEM

Introduction

The expansive advancement of technology has prompted scholars to investigate the links between external factors that influence the success of technology-based entrepreneurs (Cardon, 2008; Steers, et al., 2008; Abbasi, et al., 2015; Ma & Turel, 2019; Jan, et al., 2022), with particular emphasis on the link between national culture and technological entrepreneurial orientation (Steers et al., 2008; Halac, 2015). Technological entrepreneurial orientation (TEO) refers to an individual's ability to recognise, adopt, and utilise new technologies. TEO is a crucial construct of superior performance in the contemporary economy (Zhou, et al., 2005), essential for long-term growth, sustainability, and development in the early stages of entrepreneurial activities (Kraus, et al., 2019). In the literature, TEO is often associated with the final results of the product innovation process. However, it also refers to the application, improvement and/or transfer of technologies that will be used in these processes (Halac, 2015, Raković, et al., 2022, Nigbor Drożdż, et al., 2024).

TEO can be measured using various methodologies, but Hofstede's theoretical framework is one of the most common and is widely employed across several fields, including cross-cultural management, international business, and cross-cultural psychology (Taras, et al., 2012; Beugelsdijk & Welzel, 2018; Lee, et al., 2022; Espig, et al., 2022; Bate, et al., 2025). Geert Hofstede was a Dutch social psychologist who conducted pioneering research on cultures. His concepts regarding dimensions of culture were so radical that seventeen publishers rejected the manuscript before a visionary at Sage accepted it. The book was published in 1980, and the rest is history (Hofstede, n.d.-a, pp. 2-3). Hofstede analysed the cultural orientations of managers, employing the 6-D Model of National Culture, which comprises: Individualism/Collectivism, Power Distance, Masculinity/Femininity, Uncertainty Avoidance, Long-term/Short-term Orientation, and Indulgence/Restraint (Hofstede, et al., 2010; Hofstede, 2011; Hofstede, n.d.-c). Numerous scholars have utilized dimensions to explore the links between national culture and technology, including: the effects of Individualism and Collectivism on an individual's Technology Acceptance Behaviour (Abbasi et al., 2015), the implications of individualism and collectivism on the effectiveness of technology-mediated learning (Hornik & Tupciu, 2006), the relationship between national culture and uncertainty avoidance in technology acceptance (Cardon, 2008), etc. Hofstede (2001) posits that countries characterised by low Power distance-those promoting egalitarian social structures-and a high degree of uncertainty avoidance-reflecting a strong preference for stability and predictability-are more likely to prioritise both the advancement and adoption of technology. In contrast, societies that uphold hierarchical structures or demonstrate a greater tolerance for ambiguity and uncertainty tend to place less emphasis on these technological pursuits.

Over time, Hofstede's model has also prompted researchers to make various modifications (McSweeney, 2002; Dimitrov, 2014; Minkov, 2018; Bojadjiev, et al., 2023). For example, Hofstede's 6-D model of national culture was modified into a three-dimensional framework consisting of (1) Collectivism-Individualism, (2) Duty-Joy, and (3) Distrust-Trust (Beugelsdijk & Welzel, 2018; Cieslik, et al., 2023). Beugelsdijk and Welzel (2018) integrate Inglehart's dynamic concept of culture with Hofstede's dimensional approach, highlighting that this amalgamation addresses their mutual deficiencies. Furthermore, House R. proposed nine cultural dimensions (performance orientation, future orientation, assertiveness, power distance, human orientation, institutional collectivism, in-group collectivism, uncertainty avoidance, and egalitarianism), introducing a GLOBE model that expands upon Hofstede's work (House, et al., 2002). Moreover, Hofstede's framework enables us to understand that the adoption of new technologies is not solely a matter of technical efficiency but also involves cultural values that shape TEO.

Notwithstanding the substantial body of research exploring the relationship between national culture and TEO, studies that specifically focus on the Southeast European region remain notably limited. Moreover, with due respect, there remains a scarcity of research utilising Hofstede's theoretical framework to examine that link. This paper aims to bridge that gap. The primary focus of this research revolves around the capacity of technology-based entrepreneurs to synchronise their enterprises with prevailing cultural norms and values, while simultaneously responding to the demands imposed by the globalised market, including the proliferation of contemporary technological solutions. The research aims to identify the key factors of national culture that contribute to enhancing the TEO. By identifying these factors, we strive to provide insight into how the cultural context can either serve as an incentive or a barrier to the adoption and application of new technologies. This paper leverages the GEM database, Adult Population Survey (GEM, APS), which encompasses data about national culture and the technological perceptions of entrepreneurs. The subjects of this research are entrepreneurs from Southeast Europe who have undergone significant political and social transformations in recent decades; they have engaged in business during phases of transition and reform, while also confronting the global economic crisis (World Bank Group, 2016).

Thus, the questions arising in this paper are: Which national culture dimensions, according to Hofstede's theoretical framework, contribute to TEO? How do factors such as Individualistic societies or Power distance affect entrepreneurs' likelihood of entering high- or low-technology sectors?

This paper begins with a theoretical overview of Hofstede's theoretical framework and national culture dimensions. This is followed by the presentation of the methodology, research findings, and a discussion of the results. The paper concludes with final remarks and offers recommendations for future research.

1. Literature review

In global competition, technology-based entrepreneurs often face barriers such as national cultural specificities, specific attitudes, characteristic values, among others. National culture as a set of values, norms, and beliefs characterises a society and makes it recognisable in a wider context. It embodies the shared cognitive framework of a population that differentiates them from other groups (Hofstede, 2001), illustrating how a collective approaches problem-solving and navigates challenges (Trompenaars & Hampden-Turner, 1998); it is a heritage shared by a specific group in a particular area (House, et al., 2004). From an economic perspective, the adoption of new technologies and business practices is shaped by the prevailing national culture (Steers et al., 2008; Ozbilen, 2017; Hooks, et al., 2021; Festing & Proff, 2025).

Technology-based entrepreneurs focus on technologically innovative businesses, creating value from the initial stage; they launch new ventures, introduce new applications, and exploit opportunities that rely on scientific and technical knowledge (Bailetti, 2012). These are mostly young enterprises, emphasising early entrepreneurial activity rather than organisational size. In contrast to traditional entrepreneurs, who gradually develop performance and navigate multiple business phases toward success, technology-based entrepreneurs prioritise a proactive entrepreneurial strategy, tending to explore emerging technology opportunities (Liu, et al., 2005, Ognjenović, 2024). They compensate for their lack of financial, human, and other resources with their capacity for learning and the advantage of possessing specific resources and knowledge (Shane & Venkataraman, 2000). TEO is one of the superior performances of technology-based entrepreneurs also influences the competitiveness of organisations (Ogbari, et a., 2022). Halac (2015) indicates that technology orientation is a multidimensional construct, showing that it is a culture-based strategic orientation characterised by top management capability, strong technological capability, and a commitment to learning and change to remain competitive. A technological orientation is a path to competitiveness, ensured by strong beliefs throughout the organisation about managerial and technological capabilities, as well as a commitment to continuous learning.

Hofstede's theoretical framework and his well-established cultural dimensions opened the way to the implications of national culture for TEO.

Collectivism vs. individualism in societies has been conceptualised as the degree to which individuals are integrated into groups (Hofstede, 2001). In collectivistic societies, individuals tend to subordinate their interests to those of the group (Khan & Cox, 2017) and also have a predisposition to value participation and acceptance within social groups (Prim, et al., 2017). Success in a collectivist society is linked to state regulation, adopted laws, strategies, and government programmes. These programmes offer support such as business development services, facilitation of technology transfer, including government initiatives, incubators, and accelerators (Soetanto & Jack, 2016). Entrepreneurs in collectivistic conditions are less preoccupied with the fear of failure and are freer to take risks when introducing new business trends, innovations, and technologies. On the other hand, an individualistic society supports the independence of the individual, allowing autonomy for generating ideas, thereby boosting innovation performance (Rinne et al., 2012; Prim et al., 2017), personal responsibility, and independent decision-making. Decision-making regarding new technologies occurs within the company, often without wider consultation with institutions or the community. Individuals need not worry about the opinion of the group; they express their own opinions (Andrijauskiene & Dumciuviene, 2017). Namely, personal responsibility and motivation to achieve success contribute to more intensive engagement of entrepreneurs in the development and application of innovations (Andrijauskiene & Dumciuviene, 2017; Khan & Cox, 2017). Hornik and Tupciu (2006) state that the horizontal and vertical dimensions of individualism and collectivism have many implications for how individual learners use and respond to interactive technologies. They explored how cultural dimensions-namely horizontal individualism, vertical individualism, horizontal collectivism, and vertical collectivism - influence the effectiveness of technology-mediated learning (TML); the findings show that these four cultural orientations differently affect the use of TML communication tools, the sense of community experienced by learners, their satisfaction with the TML environment, their perceived learning, and their acquisition of declarative knowledge. Furthermore, Song, Kyung and Yeonbae (2020) analysed the effect of social security on technology-based entrepreneurial activity and found that technology-based ventures require consideration of societal factors in addition to economic factors; they find that social security has a positive effect on the share of technology-based entrepreneurial activity, and that the positive impact of social security shows a gradual decline as individualism increases.

In addition, individualistically oriented societies often have developed mechanisms of market competition, which additionally encourage entrepreneurs to follow technological trends to preserve or improve their market position. In this sense, technology is not only perceived as a tool but as a strategic resource, the use of which directly affects the business performance and long-term sustainability of the company (Kraus et al., 2019, Dukanac et al., 2025). Additionally, some studies suggest that individualistic societies may perceive entrepreneurship as a desirable activity. However, a significant majority of future entrepreneurs opt to start businesses in low-tech sectors due to the quick and safe initiation of entrepreneurship, which primarily refers to the traditional services and products sector. However, Rantanen and Toikko (2017) state that both individualist and collectivist values promote entrepreneurial intentions, namely, a society does not have to be purely collectivist or individualist, due to the fact that organisations can have characteristics of both dimensions (Lee, et al., 2019).

“Long Term Orientation stands for the fostering of virtues oriented towards future rewards, in particular, perseverance and thrift. Its opposite pole, Short Term Orientation, stands for the fostering of virtues related to the past and present, in particular, respect for tradition, preservation of 'face,' and fulfilling social obligations” (Hofstede, 2001, p. 359). Featuring dimension also indicates different entrepreneurial orientations. Zhou et al., (2005) linked different entrepreneurial orientations, through organisational learning, to radical innovations and business success. Research results indicate that market orientation encourages technological innovation, but at the same time inhibits market-based innovation. Then, that technological orientation has a positive effect on technology-based innovations, but does not affect market-based innovations, while entrepreneurial orientation encourages both types of revolutionary innovations.

Long-term oriented cultures strive for the strategic accumulation of resources and the continuous improvement of business ventures. In such an environment, technology is not merely an instrument for short-term profit acquisition but a strategic resource that is constantly evolving. Entrepreneurs in these societies focused on adopting technological platforms, developing patents, and establishing research and development functions. This approach contributes to the creation of a stable, innovative, and technological ecosystem. New technologies enhance the effectiveness of existing production methods and serve as a foundation for the development of new added-value products (Augner, 2010). Consequently, the adoption of new technologies is classified as a long-term entrepreneurial strategy, correlated with the diffusion of new technology-based sustainable products (Jaiswal & Zane, 2022). Furthermore, House et al. (2004) contend that a nation's commitment to acquiring or developing advanced technologies is closely associated with its cultural emphasis on long-term orientation, a strong inclination to avoid uncertainty, and institutional collectivism. Such an environment with a well-developed long-term entrepreneurial perspective is conducive to the development of TEO.

On the other hand, short-term oriented societies focus on the present. Technology-based entrepreneurs in these societies launch startups with the aim of rapid scaling, seeking to expand the business quickly to increase the number of users, market share, or production in the short term. Gerlich (2023) investigates short-term strategy orientation in an environment where the annual reward system is a key factor in prioritising short-term strategy orientation. In such an environment, managers, shareholders, and the supervisory board only reward short-term results, leading managers to favour short-term goals. These authors propose a model that can serve as a guideline for any company transitioning from short-term to long-term strategy orientation, as the preferred option. In this context, innovations and technology acquisitions are predominantly a response to the current market situation and less a part of long-term strategic planning.

A Power distance dimension indicates the extent to which members of a society accept the uneven distribution of power and authority in institutions and organisations. Power distance refers to the acceptance of social stratification (Jones & Davis, 2000). In the context of TEO, this dimension plays a vital role in shaping decisions related to new technologies, innovation, knowledge acquisition, as well as a business group performance (Chen, et al., 2022). A high index of Power distance suggests the acceptance of a hierarchical structure, such as centralised decision-making. In societies with a pronounced Power distance, the adoption of new technologies is initiated by top management. Conversely, in societies with a lower Power distance index, the emphasis is on equal opportunities for success, equal access to resources and information, as well as comparable living conditions, regardless of social or professional status. Additionally, organisational structures are decentralised, and decision-making processes occur through horizontal and participatory mechanisms (Hofstede et al., 2010; Hofstede, 2011). In such a cultural context, access to technology and its development require the cooperation of different organisational teams and transparency in communication. Kwon and Kim (2025) emphasise both the theoretical significance and practical relevance of participative decision-making in advancing innovation and organisational adaptability. For practitioners and policymakers, the study highlights the importance of fostering a participatory organisational culture to stimulate employee creativity and encourage voice behaviour. Nevertheless, previous research indicates that lower Power distance boosts innovation rate (Shane, 1993; Rinne, et al., 2012). Therefore, a high index of Power distance enables the rapid introduction of technological changes, requiring defined strategic decision-making. The negative implications of a high index of Power distance are indicated by limited employee creativity, a lower level of cooperation, and the absence of constructive criticism, which can ultimately reduce the innovative and technological capacity in the long term. Similarly, a strong but negative relationship exists between Hofstede's dimensions of Power distance and the Global Innovation Index (GII). Moreover, a Southeast European countries exhibit a high Power distance index (PDI) and a low Individualistic culture index (IDV) according to Country comparison graphs (Hofstede, n.d.-b): Greece (PDI=60, IDV=35), Slovenia (PDI = 71, IDV = 27), Croatia (PDI = 73, IDV = 33), and Serbia (PDI=86, IDV=25).

Uncertainty avoidance reflects the extent to which people feel uncomfortable with ambiguity and uncertainty, and their desire for a predictable environment. Entrepreneurship thrives in regions that prioritise equality and openness to uncertainty (Filippopoulos & Fotopoulos, 2025). Societies with strong uncertainty avoidance prefer a minimum of risk through established systems. These societies exhibit limited tolerance for unconventional ideas or behaviours (Hofstede, 2001). For instance, individuals may experience ambiguity due to mixed or uncertain attitudes towards technology. In these conditions, strategic decisions are long-term and have technical reliability. Innovations are developed in controlled frameworks, often with government support. Entrepreneurs tend to innovate incrementally, relying on already proven technologies. Hooks et al. (2021) found that institutional factors related to technology adoption, namely political stability and absence of terrorism and violence, have a positive impact on Technology adoption rates as well as cybersecurity and competitiveness. The other side of uncertainty dimensions, i.e. cultures with a low index of uncertainty avoidance, have a high tolerance for risk. Technological entrepreneurs in these societies do not perceive uncertainty as a threat, but as a space for creativity and innovativeness. In these societies, the market approach implies a high degree of autonomy and decentralisation in decision-making (Hofstede, 2001).

"According to Hofstede's theoretical framework, masculine societies are characterised by competition, prestige and material achievements, as well as proactive behaviour and entrepreneurial innovativeness" (Zheng, et al., 2025). In such societies, entrepreneurs foster ventures with the aim of rapid integration into new markets by applying aggressive growth strategies and perceiving a business risk. In contrast, women's societies value interpersonal relationships, community care, and work-life balance. Femininity is a management manner characterised by a low level of conflict (Papula et al., 2018). Also, females, according to higher femininity orientation and independent self-construal indicate a lower growth intention compared to those with lower independent self-construal (Zampetakis, et al., 2016). In women's societies, innovation is not a tool for market competition, but an instrument for sustainable development and improvement of business quality. Understanding these cultural dimensions is key to shaping policies that promote more inclusive and sustainable technological development.

The Indulgence vs. Restraint dimension indicates how culture shapes innovation dynamics and entrepreneurial mindsets. In permissive cultures, entrepreneurs have a greater degree of freedom, self-confidence, and are more risk-averse (Hofstede, 2001). The positive impact of indulgence on firms' risk-taking behaviour is strongest when both unlimited resources are abundant and growth opportunities are large (Alipour & Yaprak, 2022, Matić, et al., 2023). This environment encourages the development of entrepreneurship and the individualisation of technological solutions. When companies face uncertainties and changes in the environment that require adaptation, technological innovation is presented as a decisive factor for differentiation and competitiveness (Fagerberg, 2003). In contrast, in restrained cultures, where norms of self-control, social restrictions, and restraint in the expression of desires are dominant, technological entrepreneurship tends to be more conservative. Lee et al. (2022) found that cultural factors have diminished in their influence on innovation, especially in developing countries, suggesting that cultural development cannot significantly impact the innovation output of developing countries without the construction of the appropriate systems. In such societies, longer-term processes and careful evaluation of technological solutions are encouraged, which can slow down development but contribute to the long-term sustainability of business models. In practice, successful entrepreneurial strategies often require a balance between these two values.

Drawing on the previous premises, the following research hypothesis was formulated: H1 - The explanatory variables representing national culture predict the outcome of the dependent variable TEO, indicating a significant relationship between national culture and TEO.

Furthermore, taking into account earlier research examining the relationship between national culture and TEO, we delved deeper into this issue, making some additional assumptions based on Hofstede's dimensions of national culture.

That is:

H1.1 A significant relationship exists between low Power Distance Index and TEO, as reflected in entrepreneurs' perceptions that the majority of people in their country prefer a more equal standard of living.

Societies with a lower Index of Power Distance emphasise equality regardless of social or economic status; they promote social cohesion and stability, not differences. This hypothesis emphasises the connection between low Index Power distance and TEO.

H1.2 There exists a significant association between Individualistic societies and TEO, based on entrepreneurs' perceptions that initiating a new business represents a desirable career option.

Based on Hofstede's cross-country comparison charts data and previous empirical research, two additional hypotheses are proposed, taking into account the specific context of Southeast Europe (SEE). Following Hofstede's theoretical framework, national culture can be analysed according to low or high power distance, as well as from the perspective of individualism and collectivism, with the potential for positive or negative relationships. By proposing the first additional hypothesis, the research aims to contribute to a deeper understanding of entrepreneurial orientation, filling the theoretical and empirical gap between national culture, i.e. low Power distance and TEO. The second additional hypothesis refers to individualistic societies, taking into account both individualistic and collectivist aspects of this dimension. The relationship between individualistic and collectivist societies and TEO in the context of SEE remains unclear, with limited research on this topic, although it has significant potential to clarify the business transformation from low-tech to high-tech entrepreneurs.

2. Methodology and research results

The empirical analysis draws on data from the 2018 GEM APS database (Global Entrepreneurship Monitor [GEM], 2018, 2020). Within its framework, GEM assesses entrepreneurial activity through the Total Early-Stage Entrepreneurial Activity (TEA) indicator (GEM, 2018). TEA encompasses: (1) individuals in the pre-operational phase of starting a business, (2) nascent entrepreneurs who have been meeting business obligations and paying salaries for a minimum of three months, and (3) owner-managers who have maintained continuous salary payments for forty-two months (Reynolds, et al., 2004; Wagner, 2004; Stephan, et al., 2015). GEM measures the degree of entrepreneurial activity, aspirations of entrepreneurs, and identifies determinants in order to develop entrepreneurship at the national, regional and global level.

The participants in this research are from the Southeast European countries (Table 1).

Table 1 Research sample

Country	Frequency	Percent	Valid percent	Cumulative percent
Greece	2000	25,0	25,0	25,0
Bulgaria	2000	25,0	25,0	50,0
Croatia	2000	25,0	25,0	75,0
Slovenia	2000	25,0	25,0	100,0
Total	8000	100,0	100,0	

Source: the authors' research based on GEM APS data

For this empirical study, the research sample consisted of entrepreneurs operating in Greece, Bulgaria, Croatia and Slovenia. Two specific criteria were employed in the selection of these four countries. First, they belong to the Southeast European region, and second, similar cultural norms and values characterise the entire example. The research sample comprises 8000 participants, with 50% from countries classified as *efficiency-driven* (Bulgaria, Croatia), and 50% from *innovation-driven* countries (Greece, Slovenia).

The research framework was structured around one dependent variable, TEO: Technology level of the sector, which is one of the GEM Index; it measures the entrepreneurial technology ability/orientation by indicating the level of technology sector by participants between the ages of 18-64. The model additionally included six predictor variables designed to capture participants' attitudes toward national culture. The first variable, Equalinc Qi5, refers to the belief that, in the respondent's country, most people would favour an equal standard of living for all; taking into account Hofstede's theoretical framework, it refers to the power distance dimension. The remaining five predictor variables were as follows: The second variable, Nbgoodc Qi6, represents the proportion of individuals aged 18-64 who perceive starting a new business as a desirable career choice, an indicator linked to individualistic societies within Hofstede's theoretical framework. The third variable, Nbstatus Qi7, measures the percentage of the 18-64 population who believes that successful entrepreneurs enjoy a high level of social status and respect, reflecting the High Status to Successful Entrepreneurs Rate. The fourth variable, Nbmedia Qi8, captures the percentage of respondents who report frequent exposure to media or online stories about successful new businesses, indicating the level of media support. The fifth variable, Easystart Qi9, denotes the share of the population who considers starting a business to be easy, thus serving as an indicator of the general entrepreneurial rate. Finally, the sixth variable, Nbsocent Qi10, reflects the prevalence of businesses primarily aimed at addressing social problems, representing a measure of social entrepreneurship activity.

To test the proposed hypotheses, data analysis was conducted using SPSS software. Multiple linear regression analysis (MLR), a statistical technique that employs multiple explanatory variables to estimate the outcome of a dependent variable, was applied to predict TEO values in the context of early-stage entrepreneurial activity. TEO, as the response variable, based on a range of explanatory variables, tries to demystify the entrepreneurial perception of national culture values, following the explanation of Hofstede's national culture dimensions. In addition, regression analysis was applied to determine which variables function as stronger predictors compared to others.

All variable sets were incorporated into a linear regression model using the enter method. Before analysis, the assumptions of MLR and multicollinearity were examined. The findings revealed no substantial correlations, and the correlation matrix presented in Table 2 confirms the absence of multicollinearity among the variables.

Table 2 Correlation Matrix

Variable	1	2	3	4	5	6	7
TEO	1						
Qi5	,084	1					
Qi6	-,188	,069	1				
Qi7	-,005	-,042	,064	1			
Qi8	,011	,108	,031	,177	1		
Qi9	-061	,107	,034	,008	,162	1	
Qi10	-,005	,149	,081	-,008	,085	,111	1

Source: the authors' research based on GEM APS data

Table 3 provides an overview of the MLR model alongside the overall fit statistics. The model yielded a correlation coefficient of $R = 0.222$ and a coefficient of determination $R^2 = 0.049$, reflecting a relatively low explanatory power. This outcome may imply one of two scenarios: firstly, the presence of participant subgroups exhibiting larger effect sizes contrasted with others displaying smaller effects; secondly, depending on the research domain, a low R^2 value can still hold scientific and theoretical relevance, as small yet reliable coefficients have been acknowledged in prior studies (Vacha-Haase & Thompson, 2004; Lecuna, Cohen & Chavez, 2017, p. 153). Additionally, the Durbin-Watson statistic resulted in a value of $d = 2.104$, which falls within the acceptable range of 1.5 to 2.5. This indicates the absence of first-order linear autocorrelation in the dataset, thereby satisfying a key assumption for proceeding with further model analysis.

Table 3 Model Summary

Model	R	R Square	2Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0,222	0,049	0,037	0,427	2,104

Source: the authors' research based on GEM APS data

In the context of Table 4, the Analysis of Variance (ANOVA) demonstrates the results of the F-test. The F-test in linear regression operates under the null hypothesis, which posits that the model does not account for any variance in the response variable. The findings reveal a statistically significant F-test, suggesting that the model does explain a portion of the variance in TEO. Specifically, the results are reported as $F(6, 453) = 3.914$, with a p-value less than 0.05. Consequently, the ANOVA results indicate that the overall model offers a statistically significant fit to the observed data.

Table 4 ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,283	6	0,714	3,914	0,001[b]
	Residual	82,611	453	0,182		
	Total	86,893	459			

Source: the authors' research based on GEM APS data

According to the information presented in Table 5, several key observations can be made regarding the data. Firstly, the Variance Inflation Factor (VIF) values for all examined variables are below the threshold of 10, with the highest value recorded at 1.075. This indicates a low potential for multicollinearity among the variables. Secondly, the Tolerance values for each variable exceed the minimum acceptable level of 0.10. Collectively, these findings suggest that multicollinearity is absent among the explanatory variables, thereby validating the integrity of the regression analysis.

Table 5 Coefficients

Model		Unstandardized Coefficients		Stand. Coeff.	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Const.)1	0,158	0,054		2,913	0,004	0,051	0,264		
	Qi5	0,101	0,046	0,104	2,210	0,028	0,011	0,191	0,956	1,046
	Qi6	-0,176	0,042	-0,194	-4,196	0,000	-0,258	-0,093	0,985	1,015
	Qi7	0,009	0,041	0,010	0,213	0,831	-0,072	0,090	0,960	1,041
	Qi8	0,013	0,042	0,015	0,315	0,753	-0,070	0,096	0,930	1,075
	Qi9	-0,068	0,047	-0,068	-1,448	0,148	-0,160	0,024	0,958	1,044
	Qi10	0,001	0,044	0,001	0,032	0,975	-0,085	0,088	0,961	1,041

Source: the authors' research based on GEM APS data

The results presented in the above table indicate that the explanatory variables Qi5 and Qi6 are statistically significant at the $p < 0.05$ level and serve as more influential predictors relative to the other variables. Specifically, Qi5, which represents Power Distance, shows a positive beta coefficient ($b = 0.101$, $p < 0.05$), whereas Qi6, denoting Individualistic societies, exhibits a negative beta coefficient ($b = -0.176$, $p < 0.05$). An increase in the Qi5 variable is associated with a corresponding increase in the level of TEO, while an increase in Qi6 corresponds to a decrease in TEO. Holding all other predictors constant, a 1% increase in the Power Distance measure is estimated to result in approximately a 10% increase in TEO. Conversely, a 1% increase in the Individualism measure predicts approximately a 17% decrease in TEO. The other variables related to entrepreneurial perceptions of national culture-Qi7, Qi8, Qi9, and Qi10-did not reach statistical significance and exhibited only minimal associations, although they contribute to the predictive model to a limited extent.

The regression equation derived from this model can be formulated as follows:

$$TEO=0.158+0.101Qi5-0.176Qi6+0.009Qi7+0.013Qi8-0.068Qi9+0.001Qi10$$

The equation offers a quantitative formulation that characterises the relationship between national culture and TEO, with each coefficient representing the expected change in the value of TEO, resulting from a one-unit change in the corresponding cultural dimension, assuming all other variables remain constant.

3. Discussion

Consistent with our hypotheses, the findings from the multiple linear regression analysis demonstrate a significant link between the national culture explanatory variables and the dependent variable TEO. This finding is consistent with previous research supporting this construct (House, et al., 2004; Hornik & Tupciu, 2006; Cardon, 2008; Abbasi et al., 2015). The adjusted coefficient of determination indicates that the explanatory variables explain 4.9% of the variance in TEO. While the relationship may be considered weak, we have obtained valuable insights from the data, as some datasets exhibit a notable amount of unexpected variation.

Accordingly, the results support the acceptance of hypothesis H1. Moreover, the study extended this investigation by positing a significant relationship between lower Power Distance and TEO. The findings offer statistically significant and positive evidence in favour of hypothesis H1.1. These outcomes align with Hofstede's (2001) theoretical framework, which posits that lower Power Distance is conducive to both technological advancement and adoption. However, in societies with a low power distance index, organisational structures have a higher degree of decentralisation and horizontally established communication, which allows for greater participation of employees in strategic and operational processes. Uniform access to information removes hierarchical barriers in the flow of information. In such conditions, the implementation of new technologies is more efficient, and entrepreneurs react promptly and make optimal decisions. In this context, the TEO does not depend solely on the availability of technical and financial resources, but also on the cultural context that encourages cooperation, open communication and trust between different levels of management. In such a culture, employees test new ideas and drive innovations without fear of failure. Low index power distance implies an environment in which the organisational culture is adapted to dynamic technological development, and entrepreneurs feel that they can integrate new technologies into their business models.

Furthermore, we assumed a significant

relationship between Individualistic societies and TEO, which aligns with previous research (Abbasi et al., 2015; Hornik & Tupciu, 2006). Research results suggest a statistically significant but negative confirmation of H1.2. Entrepreneurs' perception that starting a business is a desirable choice may lead to entrepreneurship in less-developed technology sectors, due to a combination of subjective perceptions, limited resources, and lower entry barriers in those sectors. Specifically, when entrepreneurs view entrepreneurship as a desirable and achievable path, they are more inclined to start a business even under conditions of limited technological competence or lack of access to highly developed markets. Low-tech sectors often require less initial capital, less specialised knowledge, and allow for quicker implementation of business ideas, making them more appealing to entrepreneurs who are motivated yet insufficiently technically equipped or connected to innovation ecosystems. Moreover, in economies with limited institutional support for high-tech entrepreneurship, operating in low-tech sectors presents a more favourable option for entrepreneurs and further encourages them to focus on these areas. Low-tech sectors, such as trade, catering, or simple service activities, feature a lower level of technical complexity and clearer management models. This facilitates faster realisation of a business idea without the need for innovation or extensive product development, and entrepreneurs tend to utilise older technological solutions that are not competitive enough for the high-tech sector. In this context, a positive perception of starting a business does not necessarily reflect a strong orientation towards technology and innovation, but rather conveys optimism and confidence regarding success in a predictable environment. These research results indicate that technology-based entrepreneurs in the TEA stage from Southeastern Europe may be more suited to a collectivist culture that values cooperation, stability, and interdependence, which could potentially provide a more suitable environment for starting ventures requiring a higher level of innovation and technological readiness.

Furthermore, countries in Europe that have a lower Power distance index and a high index Individualism culture index, are: Austria (PDI = 11, IDV = 55), Denmark (PDI = 18, IDV = 74), the Netherlands (PDI = 38, IDV = 80), Sweden (PDI = 31, IDV = 71), Norway (PDI = 31, IDV = 69), and Great Britain (PDI = 35, IDV = 89) (Hofstede, n.d.-b). These cultural values suggest that decisions in these societies are made collaboratively, with an emphasis on personal freedom, initiative, and responsibility. Such cultural environments are particularly conducive to fostering entrepreneurial activity and encouraging technological innovation, as they facilitate more flexible organisational structures and openness to new technologies. Such cultural contexts are particularly favourable to the development of entrepreneurial activity and TEO, because they support more flexible organisational structures and openness to the adoption of new technologies.

Conclusion

The purpose of this paper was to explore the effect of national culture on TEO by identifying key determinants of national culture that contribute to this formation, utilising Hofstede's theoretical framework.

The practical implications of this paper relate to the ability of technology-based entrepreneurs in the early stage of entrepreneurial activity to align their business performances with prevailing cultural norms and values while responding to the demands imposed by the globalised market, including the improvement of TEO.

First and foremost, the findings of the present study indicate that TEO is a complex phenomenon influenced by numerous factors. We discovered that technology-based entrepreneurs from SEE, with a strong technology orientation, favour an environment characterised by a low Index of Power distance while conducting their business in high-tech sectors. Although these findings are not uncommon, it is apparent that high Power distance prevails in the SEE region, as illustrated by the Country comparison graphs. This suggests that the opposing sides of the Power distance dimension-namely, low and high-are intertwined, which is not unusual while these countries are classified as partially efficiency-driven (e.g., Bulgaria, Croatia, Serbia, Macedonia). In these nations, entrepreneurs with a more innovative structure, i.e., those possessing a higher degree of technological orientation, drive technological prosperity, in contrast to traditionalists who prefer a well-established system and operate in familiar sectors where low technology is predominant. This cultural context fosters the development of new entrepreneurial ventures, including technological ones. These findings entail several implications for technology-based entrepreneurs: 1) Entrepreneurs functioning in societies with a low index of Power distance should fully leverage the advantages of decentralised decision-making as a strategic asset in high-tech sectors. Such an environment enables them to build teams based on knowledge rather than formal hierarchy. They should promote open communication, involve all team members in the decision-making process, and cultivate a culture where feedback is encouraged. 2) Additionally, they should capitalise on the easy access to support networks, such as incubators and accelerators. By employing agile work methodologies, entrepreneurs can ensure quicker adaptability to the market and enhanced competitiveness. In summary, technology-based entrepreneurs should be grounded in the principles of openness and participatory decision-making, as these elements constitute the foundation for successful business in high-tech sectors.

But for the conclusion to be complete, other dimensions related to TEO must also be taken into account. Our findings show that if entrepreneurs perceive the environment as Individualistic, that leads more likely to operating in low-tech sectors. This is not an unusual finding, as entrepreneurs, although having greater freedom in decision-making and being able to develop their ideas more freely than in collectivist cultures, still choose to operate in well-known low-tech sectors. A few studies indicate that the fear of failure is still present in SEE, due to social context and historical heritage, which may cause this individual behaviour. Entrepreneurs who perceive society as individualistic and operate in low-tech sectors, and who aspire to move into high-tech sectors, should adopt a proactive approach, by investing in knowledge, technological modernisation and establishing cooperation with stakeholders. Although individualistic values encourage independence and personal initiative, success in high-tech industries also requires the development of social networks and partnerships with research centres and technology firms. Entrepreneurs must be flexible, risk-averse and continuously innovate. In this context, although the government has a significant role in creating an enabling environment through various benefits and infrastructure that support research and development, the key shift must come from the entrepreneurial sector itself, through strategic transformation and the adoption of a business model that supports TEO.

In the context of Serbia, the practical implications underscore the importance of formulating targeted programs and initiatives aimed at facilitating the transition of entrepreneurs from low-technology sectors to high-technology industries. Education systems should establish a robust knowledge base that fosters the development of technology entrepreneurship, particularly in environments characterised by low power distance and a negative association between individualism and TEO. Enhancing connections with startup incubators and technology parks will foster entrepreneurs' proactive access to innovations and technologies aligned with the business models of global high-tech ecosystems.

The theoretical implications of this study lie in its contribution to the field of cross-cultural management as well as technology entrepreneurship by examining the relationship between national culture and TEO during the early stages of entrepreneurial activity, utilizing Hofstede's national culture dimensions as a theoretical framework. The study contributes to an understanding of the role of cultural values in shaping technology and innovation adoption, sectoral-technological mobility and entrepreneurial decision-making. Additionally, the study seeks to fill a gap in existing literature regarding the link between national culture and TEO.

A limitation of this study is that the empirical findings are generalizable solely to entrepreneurs within the four countries of the Southeastern European (SEE) region. We investigated only one set of drivers of TEO. Besides these factors, it would be valuable to expand the scope to include capabilities such as individual knowledge, skills, experience, fear of failure, or socio-demographic factors, which may also influence TEO.

Declarations

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Identifying User Behavioral Intentions Towards Accepting And Using Mobile Payment Systems: An Extended UTAUT2 Model

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Abstract

Background: Mobile payments represent a rapidly growing method of performing financial transactions, primarily due to the widespread use of smartphones and related technologies. Despite their numerous benefits, the global acceptance of mobile payments remains inconsistent, particularly in developing countries.

Purpose: This study aims to examine factors influencing the intention to accept and use mobile payment systems among consumers in Central Serbia. The research model is based on the UTAUT2 framework, extended by perceived trust and perceived risk.

Study design/methodology/approach: A quantitative research approach was employed, using a structured questionnaire distributed to 845 potential respondents, of which 239 valid responses were obtained. Data were analyzed using SPSS with descriptive statistics, correlation, and multiple regression analyses to test the proposed hypotheses.

Findings/conclusions: The study reveals that performance expectancy, effort expectancy, facilitating conditions, price value, habits, perceived trust, and perceived risk significantly influence behavioral intention to use mobile payments. Moreover, habits, behavioral intention, and facilitating conditions also significantly influence actual use behavior. Social influence and hedonic motivation were found to have no significant impact on behavioral intention. Additionally, perceived trust significantly reduces perceived risk, highlighting the interplay between these two constructs in user behavior. The model explains 72% of the variance in behavioral intention and 45.5% in use behavior.

Limitations/future research: The study is limited to Central Serbia, with a modest sample size and overrepresentation of older respondents. Future research should include broader geographic coverage and examine the moderating roles of gender and age on mobile payment adoption.

Keywords: Mobile payment, UTUT2, perceived risk and trust, behavioral intention, Serbia

Introduction

In the past few years, the pace of development of information and communication technologies has accelerated significantly, which has consequently affected the development of mobile technology and all those activities that are based on electronic and mobile commerce (Shareef, Davies &Rana, 2019). While the adoption of mobile technology is widespread and embedded in daily consumer activities, mobile payment remains relatively underutilized compared to other mobile services. (Schierz et al., 2010), because in general, consumers in Serbia reluctantly adopt new payment systems due to their deeply rooted "status quo" behavior (Weichert, 2008). Smart mobile phones are used as a medium to carry out financial transactions called mobile payment, i.e. the process of money transfer through mobile phones without waiting in line at banks (Abrahão, Moriguchi & Andrade, 2016; Fatima, Kashif, Kamran & Awan, 2021). The mobile payment system enables combining the requested service with payment via a mobile phone, thus providing users with the opportunity to initiate, approve and realize a financial transaction in which money is transferred via a cellular network or wireless communication technologies (WLAN) to the recipient (Lu, Yang, Chau, & Cao, 2011; Slade, Williams & Dwivedi, 2013). As noted by de Sena Abrahão et al. (2016), advancements in technology and the growing prevalence of smartphone usage have encouraged consumers to engage in mobile-based purchasing and payment activities. A study on the habits and expectations of active card users, conducted in 2021 by Mastercard Serbia, shows that contactless payments using payment cards and mobile phones in Serbia are a reality for 81% of citizens. A third of respondents are interested in payments exclusively via mobile phones, i.e. contactless payments by mobile phone from an application that contains a digitized payment card. Actually, mobile payments refer to NFC (Near Field Communication) payments, contactless payments, digital wallets, mobile wallets, SMS-based payment methods, etc. In order to make a payment with a mobile phone, it is necessary for the user to have a payment card, to install a bank application that provides this service on a mobile device, or to activate the native application for mobile payment on the Android platform (Google Pay) or on the iOS platform (Apple Pay), turn on the NFC option on the phone and enter all the necessary data from the card into the selected application. Physically, mobile payment is realized by bringing the mobile phone to the POS terminal, which also accepts the option of contactless payment by payment card.

Acceptance and use of mobile payments by consumers is one of the most common research topics, making it a relevant and current research area (Hussain et al., 2018). One of the first studies on this topic is the one by Lee, Warkentin & Choi (2004) and Chen & Adams (2005), who investigate consumer behavioral intentions to accept and use a new payment system, mobile payment, in America and South Korea. Lee et al. (2004) identify important factors influencing individual adoption and acceptance of mobile payment technology. In finding factors, this study extends the perspective of previous studies by including the moderating role of technology anxiety in the relationship between intention and final adoption, and includes technological and demographic characteristics. Chen et al. (2005) develop a framework for future quantitative research on consumer behavior and motivations related to mobile payment adoption. Looking at previous studies on this topic, their research focus is mainly on Western countries, such as the USA (Morosan & DeFranco, 2016), Great Britain (Slade et al., 2015), Finland (Karjaluoto et al., 2020), France (Koenig-Lewis et al., 2015) and in the last few years countries like Bangladesh (Hussain et al., 2018) and India (Gupta et al., 2019). The main determinants of intentions to use mobile payment systems, which have been identified in previous literature, are perceived ease of use, perceived usefulness, perceived security, trust, social influence and facilitating conditions (Zhanga et al., 2011; Cocosila and Trabelsi, 2016; Karsen et al., 2019). Researchers frequently rely on a range of theoretical models—such as the Diffusion of Innovations, Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology—to conceptualize user acceptance of technological innovations (Rogers, 1995; Eysen, 1985; Taylor & Todd, 1995; Davis et al., 1989; Venkatesh et al., 2003; Peter & Tarpey, 1975; Slade et al., 2013). Venkatesh et al. (2003) show that the UTAUT model provides a significantly better understanding of the behavioral intention and use behavior regarding a particular technology. The basic UTAUT model consists of four key factors, namely performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). Based on previous studies, it can be concluded that some authors extend the UTAUT model with different factors, resulting in a large number of different factors and extended UTAUT models for researching the adoption and use of mobile payment (Al-Saedi, Al-Emran, Ramayah&Abusham, 2020). In recent work, authors have expanded the UTAUT2 framework further by incorporating behavioral economics variables, gamification, and psychological trust triggers (Saravanos et al., 2022; Dahlhaus & Welte, 2025).

The research subject of in this paper is mobile payment systems, as well as factors that influence the adoption and use of mobile payment systems. That is, this research focuses on the study and analysis of defined factors that influence consumers' intention to accept and use mobile payment systems in the Republic of Serbia. In the research part of the paper, the UTAUT2 model (Venkatesh, Thong, &Xu, 2012) is applied, and extended by perceived risk and perceived trust (Slade et al., 2013). Recent empirical research confirms the robustness and flexibility of the UTAUT2 model when applied to mobile payment adoption in different cultural and technological contexts (Wu & Liu, 2023; Sharma & Kaul, 2021). Previous research studies on the acceptance of mobile payment systems point to key factors affecting the adoption and use of mobile payment systems (Hongxia et al., 2011; Sripalawat et al., 2011; Yu, 2012; Zhou, 2012). Therefore, this study aims to examine the behaviors of respondents in Serbia in the context of their knowledge and skills in using mobile payment systems (Tsai and LaRose, 2015), ease of use of the chosen system, enjoyment of using it, sociological consequences faced by respondents when using mobile payments, the development of the infrastructure for the implementation of mobile payment systems (Smitha et al., 2012), the price of using the mobile payment service (Yang et al., 2012), the perceived risk and trust in the use of mobile payment systems (Abrahão et al., 2016).

The paper's objective is to identify the key determinants of respondents' behavioral intentions to accept and use mobile payment systems in general, in the Republic of Serbia in particular. Considering the research focus and aims, the study integrates both qualitative and quantitative methodologies. The qualitative approach is employed to establish a theoretical framework through a comprehensive literature review, which then informs the subsequent quantitative phase used to test the proposed hypotheses. The quantitative methodology is particularly suited for studies grounded in the Unified Theory of Acceptance and Use of Technology, as it enables the examination of relationships among multiple independent and dependent variables. The empirical part of the study was conducted in Central Serbia, involving adult respondents who provided answers via a structured survey. The collected data were analyzed using appropriate statistical techniques.

This study is organized into five main sections. Following the introduction, a review of the relevant literature is presented, forming the basis for the development of research hypotheses. The third section outlines the applied research methodology. In the fourth section, findings from the empirical investigation are discussed. The final section summarizes key conclusions, underscores the study's contributions, and proposes avenues for future research.

1. Literature Overview

Kim et al. (2010, p. 310) define mobile payment as "any payment in which a smartphone is used to initiate, authorize and execute a financial transaction". However, some authors believe that mobile phones without smart support can be used for mobile payment of various digital contents, such as music, video games, etc. (Kim et al., 2010; Petrvoic & Sakal, 2024). What is crucial for successful technology implementation is understanding the critical factors that encourage or challenge the acceptance of these new technologies among end users. Some of the studies already mentioned in the introduction use several different models to predict technology acceptance and use. According to Souiden, Ladhari and Chaouali (2021), the most commonly used models for assessing the acceptance of a specific technology are TAM, Technology Acceptance Model (Davis et al., 1989) and UTAUT, Unified Theory of Acceptance and Use of Technology. In the first years of application, both models were intended to be used in an organizational context, that is, to explain the adoption of modern and new technologies by employees. Hussain et al. (2018) believe that the UTAUT model is better for understanding compared to all other models, with Patil et al. (2020) sharing their views and propagating the popularity of the UTAUT model for examining the adoption of mobile payment technology. According to Gupta and Arora (2019), the UTAUT model represents a contemporary theory that emerged as a result of the synergy of eight different theories such as social cognitive theory (SCT) (Compeau and Higgins, 1995), theory of reasoned action (TRA) (Fishbein and Ajzen, 1975), motivation theories, technology acceptance model (TAM) (Davis et al., 1989), theory of planned behavior (TPB) (Ejsen, 1985), diffusion of innovation (DOI) (Rogers, 1995) and computer usage models. The UTAUT model consists of four key factors, namely performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). In addition, the model includes factors such as gender, age, experience in using technology and voluntary use of a particular technology as moderator variables, which analyze and interpret differences in the behavior of different groups of people (Min et al., 2008) in different geographical areas. Vankatesh et al. (2012) expanded the basic UTAUT model by including three new behavioral factors, such as hedonic motivation, price value and habit, which led to the renaming of the old model to UTAUT 2. As opposed to the original UTAUT model, where a greater focus is placed on the organizational context, UTAUT2 emphasizes the consumer's perspective. As a pilot project of the new, extended model, a survey of the acceptability of mobile Internet technology was conducted in Hong Kong, the results of which show a positive impact on consumer’s intention to use mobile Internet. The original UTAUT model investigated the influence of mobile phone users' attitudes on the adoption and use of mobile payment systems, as evidenced by a large number of research papers on this topic (Lee, Choi, & Warkentin, 2004; Peng, Xu, & Liu, 2011; Qasim and Abu-Shanab, 2016). Similarly, several authors have conducted research in the context of acceptance and use of mobile payment systems using the UTAUT 2 model (Koenig-Lewis et al., 2015; Morosan and DeFranco, 2016; Gupta et al., 2019; Fatima et al., 2021; Bommer et al., 2022). Hussain et al. (2018) also apply this theory to mobile payment in Bangladesh but extend it with an additional parameter, lifestyle, and examine its impact on behavioral intention. Some other scholars also focus on extending the theory by including other external variables, e.g. Brohi et al. (2018) analyze compatibility, risk and innovativeness, while Abrahão et al. (2016) examine perceived risk. When it comes to mobile payments, which involve money transfer electronically, perceived risk and trust are dominantly relevant and, therefore, these two factors represent the proposal of the extended UTAUT 2 model in this study (Slade et al., 2013).

Based on the review of the relevant literature, the paper conceives a new research model, which consists of the basic determinants of the UTAUT2 model, such as performance expectancy, effort expectancy, social influence, facilitating conditions, habit, price value, hedonic motivation, behavioral intention and use behavior, as well as additional behavioral factors such as perceived risk and perceived trust that extend the model. The results of previous studies have shown that perceived trust and risk are important factors in the adoption of mobile payment systems (Slade et al., 2013; Manaf & Ariyanti, 2017; Karjaluoto et al., 2020). According to this conceptual model, all these UTAUT2 variables directly influence the behavioral intention regarding mobile payment, and behavioral intention together with facilitating conditions and habit directly influences use behavior.

2. Methodology

2.1. Development of hypotheses and research model

Performance expectancy refers to the user's perception of a specific technology that provides benefits for the realization of certain activities (Venkatesh et al., 2012; Abdallah et al., 2018; Baabdullah et al., 2019; Savić & Pešterac, 2019). According to C. Goularte and Zilber (2018), performance expectancy represents the degree to which a person believes that using a specific technology will increase their efficiency. The three factors that dominantly affect performance expectancy are perceived usefulness, extrinsic (external) motivation and suitability for the job (Shin, 2009). Performance expectancy has been proven to be a key indicator of behavioral intention in various studies analyzing mobile banking (Oliveira, Faria, Thomas & Popovič, 2014; Sarfaraz, 2017; Abdallah et al., 2018; Baabdullah et al., 2019; Mohd Thas Thaker et al., 2021) and mobile commerce (Lai & Lai, 2010; Shaw and Sergueeva, 2019; Marinković et al., 2020). Several previous studies have identified a positive influence of performance expectancy on the attitude of mobile phone users in the context of acceptance and use of mobile payment systems (Berman & Thelen, 2018; Alaeddin et al., 2018; Gupta et al., 2020; Widyanto et al., 2021; Upadhyay et al., 2022). In accordance with the results of previous studies, the following research hypothesis is defined:

H1: Performance expectancy significantly affects consumers' behavioral intention to use mobile payment systems in Serbia.

Effort expectancy refers to the degree of ease of use experienced by the consumer when using a specific technology and innovation. This parameter is derived from the perceived ease of use as a component of the technology acceptance model (TAM) (Venkatesh et al., 2012). The easier a mobile payment system is to use, the more likely consumers are to use it to complete their financial transactions. Research results have shown that this factor is relevant and crucial in various studies on mobile banking (Tan & Lau, 2016; Abdallah et al., 2018; Mohd Thas Thaker et al., 2022). Zhou et al. (2010) find a negative impact of bank clients' effort expectancy on the adoption and use of mobile banking technology, but at the same time confirm a positive relationship between effort expectancy and clients' performance expectancy. While prior studies have largely demonstrated that effort expectancy significantly impacts individuals' intention to adopt mobile payment technologies (Slade et al., 2013; de Luna et al., 2019; Shin & Lee, 2021), findings by Aslam et al. (2017) indicate that this relationship may not hold universally, as their research in Pakistan revealed no statistically significant link. According to the mentioned results, the following hypothesis is developed:

H2: Effort expectancy significantly affects consumers' behavioral intention to use mobile payment systems in Serbia.

Social influence represents the level to which consumers perceive the importance of using a certain technology based on the opinions of reference persons such as family, friends and colleagues (Baishya & Samalia, 2020; Upadhyay et al., 2022). Venkatesh et al. (2012, p. 159) define this factor as "the extent to which consumers perceive that people important to them (e.g. family and friends) trust and feel they should use a particular technology." This factor is significant for examining consumers in Serbia, because according to Malaquias and Hwang (2016), in developing countries, social influence plays a key role in the formation of trust in various modern technologies. That is, social influence represents the influence of people from an individual's immediate environment on his/her perceptions and overall behavior toward the adoption of a certain technology. Marinković and Kalinić (2017) believe that social influence loses its importance if the individual is not sufficiently informed and knowledgeable about a specific technology. Many previous studies have confirmed that social influence is directly related to an individual's behavioral intention to use mobile payment systems (Yang et al., 2012; Musa et al., 2015; Widyanto et al., 2021). For example, Slade et al. (2015) find that social influence has a positive statistical relationship with consumers' behavioral intentions to use mobile payment systems, while on the other hand, authors such as Gupta et al. (2019) conclude that social influence does not have a statistical effect on consumer behavioral intentions to accept and use mobile payment systems in India. Based on previous research, the following research hypothesis is defined:

H3: The social environment significantly influences consumers' behavioral intention to use mobile payment systems in Serbia.

Facilitating conditions refer to consumers' opinions about the availability of the necessary infrastructure, resources and support for the adoption and use of certain technologies (Venkatesh et al., 2012; Upadhyay et al., 2022). According to the original UTAUT model, performance expectancy, effort expectancy and social influence affect behavioral intention to use a particular technology, while behavioral intention to use and facilitating conditions also predict the use of that technology (Venkatesh et al., 2003). Several studies on this topic have found that facilitating conditions significantly influence consumers' behavioral intentions to use mobile payment systems (Cheong et al., 2004; Sivathanu, 2019). However, there are studies that have come to the conclusion that facilitating conditions do not have a positive impact on consumers' behavioral intention to use mobile payment systems (Brown et al., 2003; Oliveira et al., 2016). It is considered that availability and mobility of infrastructure (training and technological infrastructure) and knowledge to support the use of mobile payment systems would help consumers realize contactless payment through their smart mobile phones. According to the mentioned results, the following hypotheses are developed:

H4: Facilitating conditions significantly influence consumers' behavioral intention to use mobile payment systems in Serbia.

H4a: Facilitating conditions significantly affect the use of mobile payment systems in Serbia.

Hedonic motivation is defined as the fun or pleasure derived from the use of technology and has also been shown to play a key role in the technology acceptance process (Venkatesh et al., 2012; Brown and Venkatesh, 2005). Hedonic motivation is fundamentally related to the psychological and emotional experiences of an individual, which can be caused by character traits and cognitive states (Ryan &Deci, 2000). When it comes to studies that analyze the adoption of mobile banking technology, Baptista and Oliveira (2016) point out that hedonic motivation is a very important indicator of bank customers' behavioral intention to accept the use of mobile banking. On the other hand, a study analyzing 48 empirical studies on this topic concludes that users of mobile payment systems expect to increase emotional value through enjoyment and fun, which arise when using these systems (Bommer et al., 2022). Based on previous research, the following research hypothesis is defined:

H5: Hedonic motivation positively predicts consumers' behavioral intention to use mobile payment systems in Serbia.

Price value is defined as "the consumer's psychological trade-off between the perceived benefits of using a chosen technology and the financial costs incurred as a result of using that technology" (Venkatesh et al., 2012, p. 161). Accordingly, the price value is positive when the benefits of adopting a technology are greater than the financial costs of using that technology (Baptista & Oliveira, 2016). An important distinction between consumer use and company use of technology is that end consumers usually bear the costs of implementation while company employees are exempt from those costs (Venkatesh et al., 2012). There are studies on this topic that have confirmed the influence of price value of a specific technology on consumers' behavioral intentions to use mobile payment systems (Chong, 2013; Susanto et al., 2020; Boomer et al., 2022), as well as those studies that find the opposite relationship between these two factors (Yang et al., 2012; Abrahão et al., 2016; Hussain et al., 2018). In accordance with the results of previous studies, the following research hypothesis is defined:

H6: Price value significantly affects consumers' behavioral intention to use mobile payment systems in Serbia.

Habits represent the ambition to use technology automatically as a result of learned behavior, whereby experience becomes an inevitable, but not crucial, condition for habit generation (Venkatesh et al., 2012; Slade et al., 2013). According to Limay et al. (2007), a habit is created solely on the basis of three mandatory criteria: past achievements and behavior, reflexive behavior, and the individual's life experience. Past behavior and achievements represent the user's previous behavior in specific situations and their discoveries. Reflexive behavior refers to customs that make everyday life known in advance. Individual experience refers to the accumulation of experiences from established routines, norms and habits for using technological products. Gupta et al. (2019) conclude that habit is the most convincing factor of behavioral intention to use, because today's generations increasingly use smartphones for the realization of daily life activities, which directly affects the development of the habit of performing various financial transactions via mobile phones. Other mobile payment literature highlights a positive relationship between habit and behavioral intention to use, as well as a positive relationship between habit and use behavior regarding mobile payment systems (Keramati, Taeb, Larijani&Mojir, 2012; Morosan et al., 2016; Hussain et al., 2018). Habitual behavior in mobile financial transactions has been further confirmed by recent empirical analyses on digital payment usage in post-COVID environments (Dahlhaus & Welte, 2025). The following research hypotheses are developed based on a review of previous studies:

H7: Habits significantly influence consumers' behavioral intention to use mobile payment systems in Serbia.

H7a: Habits significantly influence the use of mobile payment systems in Serbia.

Except for the UTAUT 2 model factors, some previous research has identified perceived risk and perceived trust as important potential influencing factors on the consumer's behavioral intention to use new and modern technological systems.

Perceived risk refers to any possible financial risk, social risk, and product-related risk that a consumer perceives when initiating an online transaction (Madan, 2016). Gillett (1976) points out that perceived risk is a key parameter for evaluating a purchase by consumers and that it varies depending on whether it is a conventional or unconventional purchase. Buying and paying via mobile phone is significantly riskier for consumers than traditional trade and payment at the point of sale. Mobile phones automatically store personal data, which can lead to security and privacy issues for those involved in any mobile phone transaction. Authors who integrate this factor in their research confirm its positive and negative impact on the behavioral intention to use mobile payment (Riquelme and Rios, 2010; Amoroso and Magnier-Watanabe, 2012; Slade et al., 2015; Susanto et al., 2022). Perceived risk can also be used as a moderator variable in examining the influence of behavioral intention to use on the use behavior when it comes to mobile payment

(Neto & de Figueiredo, 2022). Additional recent studies reinforce the critical role of trust and perceived risk, particularly in environments with lower digital literacy or regulatory uncertainty (Qasim et al., 2016; Apaua & Lallie, 2022; Sarini & Khasa, 2023). According to the mentioned results, the following hypothesis is developed:

H8: Perceived risk significantly affects consumers' behavioral intention to use mobile payment systems in Serbia.

The relationship between buyer and seller depends first of all on the mutual trust between them. Perceived trust is the subjective belief that the seller will fulfill their obligations to the buyer. Trust plays a crucial role in uncertain financial transactions where users of mobile payment systems are sensitive to possible financial losses (Lu et al., 2011; Slade et al., 2013). Mobile payment is more critical in terms of trust than other commercialized technological systems for several reasons: innovative versions of various programs and technological devices are constantly appearing, a dynamic environment and a huge presence of operators of different mobile providers. Previous studies on mobile payment adoption have recognized this factor as a strong predictor of behavioral intention to use mobile payments (Amoroso and Magnier-Watanabe, 2012; Arvidsson, 2014; Kumar et al., 2018). Widyanto et al. (2021) point out that perceived trust has a statistically significant and direct impact on consumers' behavioral intention to use a mobile payment system. On the other hand, perceived risk in that research has a negative direct impact on behavioral intention, but a positive indirect impact through perceived trust, as a mediator variable. According to Lim (2003), perceived trust predicts and reduces perceived risk while together these two factors predict consumers' attitudes and behavioral intentions to use mobile payments. Also, Slade et al. (2015) find that trust negatively affects respondents' perceived risk. Based on the above, the following hypotheses are derived:

H9: Perceived trust significantly affects consumers' behavioral intention to use mobile payment systems in Serbia.

H9a: Perceived trust significantly affects the perceived risk of mobile payment system users.

According to Venkatesh et al. (2012), behavioral intention represents the desire and ambition of the consumer to reliably use the future product. That is, that intention represents the potential probability that an individual will use the mobile payment system to achieve their own goals. In general, behavioral intentions can be considered the best indicator of actual consumer behavior, as proven when evaluating the use of any new technology (Liebana-Cabanillas et al., 2017; Kalinić et al., 2019; Gupta et al., 2019; Sivathanu, 2019). The proposed research model, which was used in this study, includes seven main factors that influence consumers' behavioral intention to use mobile payment. In addition to the usual seven factors of the UTAUT2 model, two additional factors (perceived risk and trust) that influence consumers' behavioral intention to use mobile payment are integrated into the research model. Therefore, the last research hypothesis is derived:

H10: Behavioral intentions to use mobile payment systems in Serbia significantly influence their use behavior.

Finally, the use of technology represents the dependent research variable, while behavioral intention is also positioned in the model as a dependent variable, with its impact on the use of technology also measured. In the context of mobile payments, there are only a few studies that have analyzed this relationship, that is, confirmed or rejected the potential influence of behavioral intention on the use of mobile payment systems (Gupta et al., 2019; Patil et al., 2020). According to the above, Figure 1 presents the proposed research model.

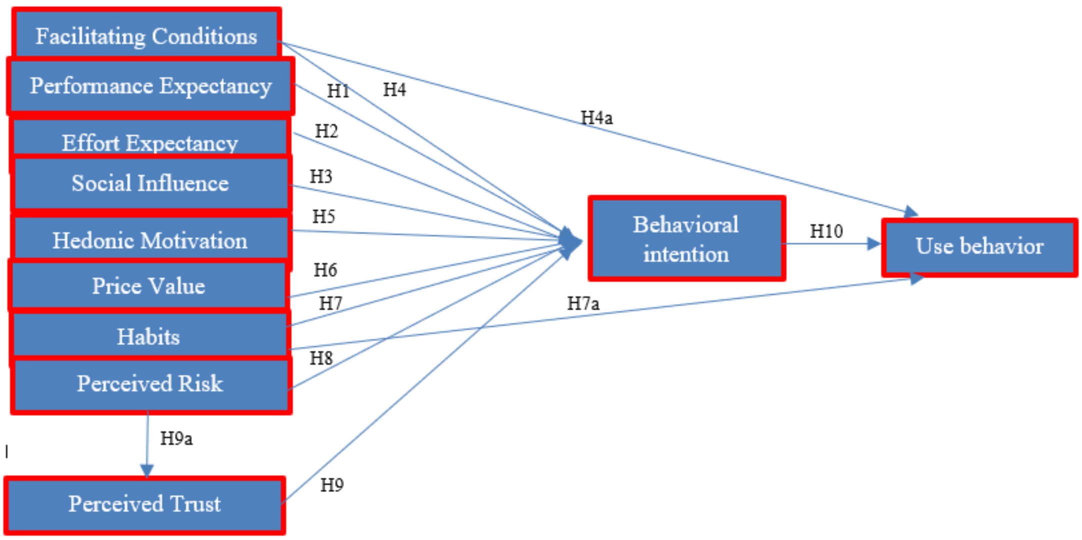

Figure 1 Research model
Source: the authors

2.2. Research methods

The empirical research is based on the analysis of primary data collected from 239 respondents through a questionnaire on the territory of Central Serbia, in order to identify the impact of key factors of mobile payment on consumers' behavioral intentions to use this technology to perform their daily financial transactions. The questionnaire was distributed to 845 different addresses online, and 28.2% of respondents (239 respondents) answered it in the period from 27 July 2024 to 19 August 2024. In order to get relevant answers, only respondents who had experience in using different mobile payment systems completed the questionnaire. Specifically, the questionnaire included an introductory note stating that only individuals who currently use or have previously used mobile payment services were eligible to participate. The content of the questionnaire was divided into two parts. In the first part of the questionnaire, respondents described their basic demographic characteristics (gender, age, professional education, work status), while the second part consisted of 38 items that were divided into 11 different groups, i.e. variables. Respondents expressed their degree of agreement with the given item based on a seven-point Likert scale, circling the grades from 1 (Absolutely disagree) to 7 (Absolutely agree). The statistical program SPSS (The Statistical Package for the Social Sciences) was used to process and analyze the collected primary data. Statistical methods such as descriptive statistical analysis, reliability analysis, correlation and regression statistical analysis were used in this study.

Table 1 Sample structure

Respondent characteristics		Frequency	Percentage
Gender	Man	105	43,9%
	Woman	134	56,1%
Age	18-24	44	18,4%
	25-44	143	59,8%
	45-55	40	16,7%
	55 and more	12	5,0%
Level of education	Secondary school	41	17,2%
	High school	27	11,3%
	Bachelor	101	42,3%
	Master	60	25,1%
	PhD	10	4,2%

Employment status	Employed	181	75,7%
	Unemployed	30	12,6%
	Student	22	9,2%
	Retiree	6	2,5%
Total		239	100%

Source: the authors

As shown in Table 1, there are more women (56.1%) than men (43.9) in the sample. Observed according to the age structure, the most numerous category of respondents is in the age group of 25 to 44 years (59.8%). When it comes to professional education, more than half of the sample consists of respondents with completed basic and master's academic studies (67.4%), followed by those with secondary education (17.2%) and those with high education (11.3%) while only 4.2% are respondents who obtained a doctorate. If the work status of the respondents is observed, a dominant representation of employed respondents (75.7%) is observed, while a significantly smaller number of respondents are unemployed (12.6%), students (9.2%) or retired (2.5%).

3. Results

Preliminary descriptive statistical analysis was conducted to assess the consistency of respondents' attitudes, focusing on the calculation of arithmetic mean and standard deviation values. Respondents' attitudes are more favorable when the value of the arithmetic mean is higher and vice versa, while if the values of the standard deviation are lower, the attitudes are more homogeneous and vice versa. It can be concluded on the basis of the calculated values of the arithmetic mean in Table 2 that the most favorable attitudes of the respondents are with the item “I believe that I can perform financial transactions faster via a smart mobile phone compared to performing cash transactions at the counter of a bank, post office, payment point, etc.” where the value of the arithmetic mean is the highest and is M=6.48. On the other hand, the most unfavorable attitudes of respondents are with the item related to the perceived risk “I do not feel safe when giving personal data when using the mobile payment system” with the lowest arithmetic mean M=3.02.

The reliability and internal consistency analysis indicates that all variables demonstrate satisfactory levels, as reflected by Cronbach’s Alpha values exceeding the 0.6 threshold (Robinson et al., 1991). The highest degree of reliability is characteristic for performance expectancy ($\alpha = 0.911$) and behavioral intentions ($\alpha = 0.943$), with other variables also characterized by a higher level of reliability (effort expectancy: $\alpha = 0.876$, social influence: $\alpha = 0.742$, facilitating conditions: $\alpha = 0.795$, hedonic motivation: $\alpha = 0.858$, habit: $\alpha = 0.749$, perceived trust: $\alpha = 0.894$, perceived risk: $\alpha = 0.869$, use behavior: $\alpha = 0.804$) When it comes to price value ($\alpha = 0.612$), it has the lowest degree of reliability of all the other analyzed variables, but it meets the limit value of reliability.

Table 2 Arithmetic mean and Cronbach's Alpha coefficients of the analyzed variables

	Items	Mean	Cronbach's α	Source
PE1	Using the mobile payment system helps me realize daily life activities faster and more easily.	6,21	0,911	Venkatesh et al., (2012); Al-Jabri (2015); Gupta &Arora (2019)
PE2	Using the mobile payment system makes it significantly easier for me to solve everyday life tasks.	6,00		
PE3	I find mobile payment systems very useful and easy to carry out financial transactions.	6,15		
PE4	I find that I can make financial transactions faster through a smartphone compared to making cash transactions at the counter of a bank, post office, payment point, etc.	6,48		
EE1	I find mobile payment systems easier to use.	6,07	0,876	Venkatesh et al., (2012); Gašević et al., (2016); Savić&Pešterac (2019)
EE2	I find it quite easy to learn how to use mobile payment systems.	6,20		
EE3	I find that using a mobile payment system does not require too much mental effort.	6,09		
EE4	I find mobile payment systems readily available.	6,20		
SI1	Friends and family advise me to use a mobile payment system.	4,94	0,742	Alalwan et al. (2017); Thakur and Srivastava (2013); Tak and Panwar (2017); Gupta &
SI2	People who influence my behavior think I should use a mobile payment system.	4,89		
SI3	Most of the people around me use the mobile payment system.	5,13		

SI4	People who use mobile payment systems in my environment are more respected than those who don't.	4,04		Arora, (2019)
FC1	I have all the necessary resources (smartphone, internet connection, mobile bank application, executed payment card, etc.) to use the mobile payment system.	6,40	0,795	Venkatesh et al., (2012); Gupta & Arora, (2019)
FC2	I have the necessary knowledge to use the mobile payment system.	6,37		
FC3	I can get help from others (online bank support, friends, etc.) when I have difficulties using mobile payment systems.	6,09		
HM1	Using the mobile payment system is pleasant.	5,90	0,858	Alalwan et al. (2017); Tak and Panwar (2017); Gupta & Arora (2019)
HM2	Using a mobile payment system is exciting.	5,05		
HM3	Using a mobile payment system is fun.	5,09		
PV1	I find that I can save money by using a mobile payment system.	5,36	0,612	Venkatesh et al., (2012)
PV2	Mobile payment systems provide their users with valuable promotions.	4,43		
H1	Using the mobile payment system has become a habit for me.	5,41	0,749	Alalwan et al. (2018); Tak and Panwar (2017); Gupta & Arora (2019)
H2	Using a mobile payment system is something I would do without a second thought.	5,51		
H3	I consider myself addicted to using mobile payment systems.	3,21		
PT1	I have absolute confidence in mobile payment systems.	5,27	0,894	Kalinić et al., (2019); Al-Saedi et al., (2019)
PT2	Mobile payment systems offer different services that are interesting to me.	4,87		
PT3	I find mobile payment systems reliable and secure.	5,46		
PT4	I believe that all the data on financial transactions carried out via mobile phone are reliable.	5,37		
PR1	I don't feel safe giving out personal information when using a mobile payment system.	3,02	0,869	Al-Saedi et al., (2019)
PR2	Friends and family advise me to use a mobile payment system.	3,03		
PR3	There is a high chance that something wrong can happen (incorrect data entry, theft, etc.) when using the mobile payment system.	3,61		
BI1	I intend to use the mobile payment system in the future.	6,10	0,943	Yu (2012); Tak and Panwar (2017); Gupta & Arora (2019)
BI2	I will continue to use the mobile payment system in the future.	5,97		
BI3	I will continue to use the mobile payment system because I have a smartphone that has internet access.	5,90		
BI4	I think it's a smart idea to use a mobile payment system.	5,93		
UB1	Sometimes I use the mobile payment system.	4,17	0,804	Tak and Panwar (2017); Gupta & Arora (2019)
UB2	I often use the mobile payment system to perform various financial transactions.	5,22		
UB3	I regularly use the mobile payment system to perform various financial transactions.	5,10		
UB4	I exclusively use the mobile payment system to perform various financial transactions.	4,17		

Note: PE – performance expectancy; EE – effort expectancy; SI – social influence; FC – facilitating conditions; HM – hedonic motivation; PV – price value; H – habit; PT – perceived trust; PR – perceived risk; BI – behavioral intention; UB - use behavior

Source: the authors

In order to examine the dependence between two (or more) variables, it is necessary to establish the existence of a correlation between those variables. A positive Pearson's coefficient indicates the tendency that the growth of the value of one variable is related to the growth of the value of another variable, while on the other hand there is also a negative Pearson's coefficient that also indicates the tendency that the growth of the value of one variable is related to the decline of another variable. For the value of positive or negative coefficient from 0 to 0.4 (-0.4) the correlation is weak, from 0.4 to 0.6 (-0.4 - -0.6) moderate, while a strong correlation exists when this coefficient is in the interval of 0.6 to 1 (-0.6 - -1). The results of the correlation analysis in Table 3 confirm that there is a statistically significant correlation, with a probability of 99% and 95%, among most pairs of variables. The correlation is statistically insignificant between perceived risk and facilitating conditions, as well as the price value because it is below the threshold level of statistical significance. The lowest degree of linear dependence is between perceived risk and social influence (r = -0.047**), while the highest degree of linear dependence is between behavioral intention and performance expectancy (r = 0.710**). Other pairs of variables show predominantly moderate correlations, as the Pearson coefficient between those variables averages around 0.5.

Table 3 Linear correlation

	PE	EE	SI	FC	HM	PV	H	PT	PR	BI	UB
PE	1										
EE	.657**	1									
SI	.260**	.353**	1								
FC	.599**	.637**	.229**	1							
HM	.588**	.626**	.331**	.435**	1						
PV	.348**	.383**	.332**	.201**	.538**	1					
H	.575**	.502**	.353**	.279**	.665**	.423**	1				
PT	.587**	.521**	.471**	.374**	.702**	.547**	.721**	1			
PR	-.332**	-.229**	-.047	-.145*	-.315**	-.113	-.261**	-.437**	1		
BI	.710**	.517**	.305**	.594**	.590**	.306**	.657**	.702**	-.377**	1	
UB	.567**	.470**	.373**	.403**	.551**	.327**	.599**	.574**	-.221**	.617**	1

**. Linear correlation is statistically significant at the 99% level
*. Linear correlation is statistically significant at the 95% level

Source: the authors

In order to test the set research hypotheses, a multiple regression analysis is conducted, which examines the influence of independent variables on the dependent variable, and the results are shown in Table 4. First of all, it is necessary to fulfill the condition of multicollinearity in order to successfully conduct a multiple regression analysis. The calculated values of the VIF coefficient range from 1.0 to 3.6 which is less than the accepted value of 5 (Akinwande, Dikko & Samson, 2015) and these values suggest that there is no problem of multicollinearity. According to the obtained results, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, perceived trust and perceived risk predict and describe 72% (R2 = 0.720) of the variability of respondents' behavioral intention to use mobile payment. The first regression analysis in the paper can conclude that performance expectancy (β = 0.274; $p < 0.01$), effort expectancy (β = -0.17; $p < 0.05$), facilitating conditions (β = 0.353; $p < 0.01$), habits (β = 0.279; $p < 0.01$), price value (β = -0.09; $p < 0.05$), perceived trust (β = 0.318; $p < 0.01$) and perceived risk (β = -0.073; $p < 0.1$) significantly influence respondents' behavioral intentions to use mobile payment, which confirms hypotheses H1, H2, H4, H6, H7, H8 and H9. Other research hypotheses related to the first regression model are rejected, because they result in a statistically insignificant influence of the independent variables on the dependent variable.

Table 4 Testing of research hypotheses

The results of the second regression model reveal a statistically significant negative relationship between perceived trust and perceived risk in the context of mobile payment usage (β = -0.437; $p < 0.01$), thereby supporting hypothesis H9a. In other words, increased trust among users contributes to a reduction in perceived risk associated with mobile payment systems. The model explains 19.1% of the variance in perceived risk, as indicated by the coefficient of determination ($R^2 = 0.191$).

Based on the analysis of the first regression model, solely significant statistical influences of the UTAUT2 model factors on the behavioral intention to use mobile payment meet the condition of having a significant influence on the use of mobile payment in the third regression model as well. Based on the results in Table 4, it can be concluded that the coefficient of determination is 0.455, which means that 45.5% of the variability of the final use of mobile payment is described by the given regression model. In the third regression model, user habit (β = 0.364; $p < 0.01$) has the strongest, statistically significant, influence on the use of mobile payments in Serbia, followed by behavioral intentions (β = 0.307; $p < 0.01$) and finally facilitating conditions (β = 0.119; $p < 0.1$) with the weakest influence. The results of this research confirm research hypotheses H4a, H7a and H10.

	Hypotheses	*β*	*t*	*p*	*VIF*	*R^2*
H1	PE > BI	.274	4.936	.000	2.511	
H2	EE > BI	-.176	-3.152	.002	2.557	
H3	SI > BI	-.007	-176	.861	1.389	
H4	FC > BI	.353	7.120	.000	2.004	
H5	HM > BI	.006	0.106	.915	2.791	.720
H6	PV > BI	-.094	-2.112	.036	1.617	
H7	H > BI	.279	4.966	.000	2.586	
H8	PT > BI	.318	4.779	.000	3.620	
H9	PR > BI	-.073	-1.769	.078	1.372	
H9a	PT > PR	-.437	-7.480	.000	1.000	.191
H4a	FC > UB	.119	1.956	.052	1.598	
H7a	H > UB	.364	5.605	.000	1.820	.455
H10	BI > UB	.307	3.963	.000	2.593	

Source: the authors

4. Discussion

In this research, the basic theoretical model for understanding and analyzing the acceptance and use of mobile payment in Central Serbia is the UTAUT2 model. The proposed research model integrates seven primary factors (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habits) with two additional factors (perceived trust and perceived risk), through the investigation of thirteen different hypotheses. The extended research model is a response to the observed research gap, according to which this research tries to remove the observed gap and conduct research with an extended model, i.e. introduce variables that describe the trust and risk of consumers when using different mobile payment systems.

The findings suggest that among all examined factors, facilitating conditions have the most pronounced effect on behavioral intention to adopt mobile payment in Central Serbia, while perceived trust, habit, performance expectancy, effort expectancy, price value and perceived risk follow it in terms of intensity of influence. Factors such as social influence and hedonic motivations do not have a statistically significant impact on the behavioral intention to use mobile payment. This lack of statistical significance may be attributed to the prevailing payment culture and demographic composition of the sample in Central Serbia. In contexts where mobile payments are still in the early stages of mass adoption, hedonic elements and peer influence may be less compelling compared to factors such as trust, convenience, and security (Khatimah et al., 2024; Samudera et al., 2024). Social influence, in particular, often becomes significant only when the technology reaches a critical mass of adoption, enabling peer recommendations and societal expectations to play a stronger role (Shaw & Sergueeva, 2019). In developing markets, however, the decision to adopt mobile payment systems tends to be more individualized and utilitarian rather than socially driven (Gupta et al., 2019). Similarly, the role of hedonic motivation might have been muted in this study due to the limited novelty or entertainment value that users associate with mobile payments. Studies conducted in mature markets also suggest that enjoyment does not necessarily translate into adoption unless combined with perceived value and usefulness (Slade et al., 2015; Upadhyay et al., 2022). Thus, the insignificant findings related to these constructs could reflect the current stage of digital payment ecosystem development in Central Serbia, where instrumental benefits outweigh experiential or social drivers. Several previous research studies (Morosan and DeFranco, 2016; Gupta et al., 2019; Patil et al., 2020) confirm the significant influence of facilitating conditions on the behavioral intention to use technology in the mobile payment domain as well as on the final use of mobile payments (Zhou et al., 2010). In contrast, authors such as Slade et al. (2015), Hussein et al. (2018) and Lee et al. (2019) identify a negative impact of facilitating conditions on the behavioral intention to use mobile payment. Therefore, such research results indicate that the availability of infrastructure and support to consumers affects behavioral intention of those consumers to use mobile payment. The majority of survey participants reported owning up-to-date digital devices, including modern smartphones, laptops, and mobile payment applications. Factors such as the convenience of using mobile phones at any time, their user-friendly user interface and the presence of social networks on mobile phones develop consumers' habit to make their payments through mobile phones (Gupta et al., 2019). Based on the research results, consumer habits predict their behavioral intention to use mobile payment and final use of mobile payment, which corresponds to the conclusions reached by Tang et al. (2014) and Hussain et al. (2018). Performance expectancy with a positive result implies that consumers feel safe, knowledgeable, informed, which implies higher productivity and quick transactions of those users after using a mobile payment system. The positive performance expectancy is consistent with previous research by numerous authors who analyzed the adoption and use of mobile payments around the world (Hongxia et al., 2011; Yan & Yang, 2015; de Sena Abrahão et al., 2016; Widyanto et al., 2021; Upadhyay et al., 2022).

Based on previous research, perceived trust and risk are significant factors of consumers' behavioral intention to use mobile payment in Central Serbia. It is assumed that the more trust consumers build in a mobile payment system, the more likely they are to continue using it. As for risk, consumers in Central Serbia believe that risk significantly predicts their behavioral intention to use mobile payment, while consumer trust reduces their perceived risk, on the basis of which it can be concluded that there is a significant direct relationship between perceived risk and behavioral intention to use mobile payment, but also that there is an indirect connection. Slade et al. (2015) reach similar results and find that perceived trust has a statistically significant impact on both perceived trust and respondents' behavioral intention to use mobile payment systems. On the other hand, Widyanto et al. (2021) find that in Indonesia there is no direct relationship between perceived risk and consumer behavioral intention to use mobile payment, but there is an indirect relationship through perceived trust that significantly affects both perceived risk and behavioral intention to use mobile payment systems. Effort expectancy significantly affects behavioral intention to use mobile payment, which can be linked to the fact that modern mobile phones are more and more practical and that problems related to screen size, Internet speed, RAM memory size, etc. have been eliminated. Some authors also find that effort expectancy affects behavioral intention to use mobile payment (Abrahão et al., 2016; Gupta et al., 2019; Shin & Lee, 2021). Finally, price value achieves a statistical impact on consumer's intention to use mobile payment in Central Serbia, which is in line with other studies such as Chong et al. (2013), Oliveira et al. (2016) and Bommer et al. (2022). Mobile payment applications work for free, as they allow consumers to pay solely for the price of the desired product, but each mobile payment transaction requires a commission for the bank if it is a *Mastercard*, *Visa* or *American Express* digitized payment card.

According to the results, hedonic motivation and social influence did not prove to be predictive factors of consumers' behavioral intention to accept and use mobile payment systems. If there is an option for consumers to receive certain rewards for using the mobile payment system, only then is it possible to meet the expectations of reference persons, because social influence is a voluntary, not an obligatory activity (Shaw & Sergueeva, 2019; Gupta et al., 2019). Upadhyay et al. (2022) find that social influence exerts a non-significant influence on behavioral intentions to use mobile payments, due to the COVID-19 pandemic and the fundamental need to initiate contactless transactions. When it comes to hedonic motivation, the results show that the users were satisfied, but that they did not enjoy nor were excited about using the mobile payment system. If the majority of the sample consisted of young people aged 18-24, it is assumed that hedonic motivation would be at a much higher level. Authors such as Koenig-Lewis et al. (2015), Agrebi and Jallais (2015) point out that perceived pleasure or hedonic motivation does not have a statistically significant impact on the behavioral intention to use mobile payment. When it comes to the consumers' intention to use mobile payment in Central Serbia, the research shows that these same intentions have a statistically significant effect on the use behavior regarding mobile payment as in Escobar-Rodrguez et al. (2014), Patil et al. (2020), Shin & Lee (2021), Bailey et al. (2022), Upadhyay et al. (2022). Consumers in Serbia are used to using cash as a means of payment and it is assumed that consumers who express a strong intention to use mobile payment would very likely use such services.

Conclusion

The research was conducted with the main goal of examining which mobile payment determinants have an impact on consumers' behavioral intentions in Serbia to use mobile payment systems, as well as on their final use behavior. In the research, the expanded UTAUT2 model was used as a starting model, to identify consumer behavioral intentions regarding different types of technological innovations in a certain geographical area. Based on that model, the influence of performance expectancy, effort expectancy, facilitating conditions, social influence, habits, price value, hedonic motivation and additional variables such as perceived trust and risk on consumers' behavioral intentions to use mobile payment systems was observed, as well as the influence of those intentions, facilitating conditions and habits on use behavior. The research results reveal that facilitating conditions represent the strongest indicator of the behavioral intention to adopt mobile payment in the Republic of Serbia, while the weakest predictor of the intention is perceived risk.

This research fills a research gap by proposing an extended UTAUT2 model with additional factors, i.e. perceived trust and risk. The scientific contribution of the conducted research is reflected in the expansion of existing knowledge about the influence of the determinants of mobile payment on behavioral intentions, as well as on the use behavior regarding mobile payment systems in transition countries. Also, independently of analyzing consumers' intentions towards using mobile payment systems, the study additionally analyzed the impact of respondents' perceived trust on their perceived risk toward using specific systems. A key contribution of this study lies in its examination of the relationship between consumers' behavioral intention and their actual use of mobile payment systems, offering a more in-depth perspective on the adoption process. As such, the paper presents a comprehensive view of the critical factors influencing mobile payment adoption and usage.

Mass adoption of mobile payment systems is of crucial importance for providers and innovators of mobile payment systems. This paper has important implications for providers, local banks and inventors of mobile payment systems that are intensively trying to launch their products on the markets of developing countries, in this case a country in transition. First, in order to effectively promote the mobile payment service, providers and local banks should create co-branded advertising messages emphasizing the basic benefits that can be realized from the initial and each subsequent use of this service. Promotional messages should be focused on two target consumer groups, those who favor paying in cash in financial institutions where cost benefits stand out and those who prefer conducting transactions at a distance, in order to retain them and additionally convince them that it is the best option. Second, providers and all future creators of mobile payment systems should pay attention to the security factors that consumers face when using a particular system, as well as the protection of personal data entered when accessing the mobile payment application itself. Some of the proposals refer to the most modern and innovative security methods, which are used in mobile technology to authorize access to various applications, such as Advanced Face Recognition, which would record the face during the use of the mobile payment system, as well as defining a fixed amount that can be used for mobile payment within one day. In conservative countries dominated by a high degree of risk towards the adoption of innovations such as mobile payment, it is necessary to focus on minimizing fear and risk. Third, based on the results of social influence on consumers' intentions to use mobile payment, it is concluded that providers of various mobile payment systems and local banks should make the systems more popular among young people, specifically by integrating high-tech and modern add-ons and functions into the system structure, which would be interesting to young people and urge them to start using the system. Fourth, in order to raise citizens' awareness of the usefulness of mobile payment systems, it is necessary for commercial banks, together with providers, to develop promotional campaigns about a new and practical method of payment, which is free. Fifth, the provider's user support in the form of live chat and video tutorials in the application would significantly facilitate the use of mobile payment systems.

As with all empirical studies, this research has several notable limitations. First, the data were collected exclusively within the territory of Central Serbia, which may limit the generalizability of the findings. It is likely that regions such as Vojvodina and the Belgrade metropolitan area exhibit higher levels of behavioral intention toward mobile payment adoption. Future research should therefore aim to include respondents from all regions of Serbia, as well as neighboring Western Balkan countries, to obtain a broader perspective. Second, the relatively modest sample size may influence the stability and generalizability of the statistical results. Upcoming studies should consider expanding the respondent pool, particularly among the 18–24 age group, whose behavioral intentions may differ significantly from those of older participants who dominated the present sample. Third, the current model did not account for the potential moderating effects of demographic variables such as gender and age on the relationships between independent and dependent variables. Examining these moderating influences could provide additional depth and clarity, especially in understanding how user characteristics shape attitudes and behaviors toward mobile payment adoption.

Declarations

Availability of data and materials

To provide a link to the Availability of data and materials, detailing how the data can be accessed or put: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Generational Dynamics and the Bandwagon Effect in Consumer Electronics E-Commerce

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Abstract

Background: Online purchasing of consumer electronics has expanded rapidly, and differences between Generations X and Y, as well as social contagion phenomena such as bandwagoning and herding, may shape how consumers form online purchase intentions.

Purpose: To assess how microeconomic bandwagon/herding effects interact with social influence and effort expectancy, moderated by generational groups (Gen X vs. Gen Y), to shape online purchase intention for consumer electronics in an extended UTAUT framework.

Study design/methodology/approach: The authors modified the Unified Theory of Acceptance and Use of Technology (UTAUT) and have implemented Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to validate the research model as well as to research the generational groups' influence. Furthermore, the authors imposed the microeconomic theoretical bandwagon effect and herding behavior to clarify if there are statistically significant results in the e-commerce landscape for consumer electronics products.

Findings/conclusions: The paper's major findings showed a direct and indirect (via effort expectancy) social influence on Generation X's consumer intention to purchase consumer electronics products online. However, such influence was not identified for Generation Y, suggesting that e-commerce forms a stronger bandwagon effect on the generation that was not born with the e-commerce technology, unlike Generation Y.

Limitations/future research: The limitations of the paper are seen in the unequal generational groups' data size. The potential for further research is evident in capturing a longer time frame, conducting cross-cultural comparisons, and including new generational groups.

Keywords

technology acceptance model; UTAUT; consumer electronics; e-commerce; Generation X&Y

Introduction

This paper explores the differences in the bandwagon effect on Generation X and Y. The specific topic on which these differences are tested is e-commerce in the purchase of consumer electronics; it is not uncommon that consumers base their decisions on the actions of others, particularly when there is uncertainty or a lack of personal knowledge, according to Gurtner et al., 2024; Banerjee (1992). Furthermore, customer satisfaction with the purchased product or service is the key determinant in online shopping. The risk of negative comments is much higher in online shopping due to the easier information dissemination than in traditional retail, and thus, customer support before and after the purchased product or service becomes more important (Boruah et al., 2021).

At the same time, the COVID-19 pandemic can be considered an external factor that significantly influenced the use of online shopping (Ali, 2020; OECD, 2021). Environmental changes, such as those caused by the COVID-19 pandemic, greatly influenced online shopping development (Grashuis et al., 2020).

Companies are always seeking answers on approaching each generational group as their online shopping preferences vary (Optimonk, 2024; Iskiev, 2022). Due to the big demand, the research community has researched mainly one generational group (Pavlić et al., 2021; Nguyen et al., 2022), while some research a combination of two or more groups in the e-commerce landscape (Feng et al., 2023). Additionally, very few have explored the moderating effect of generational groups X & Y on consumer electronics online buying, especially in the Republic of Croatia, which is the main topic of this paper. This is mainly due to the general research focus on determinants that directly impact the intention to adopt new technologies. Age has been used as a moderator in the shopping motivation context (Kumar et al., 2021), acceptance of mobile payment (Liébana-Cabanillas et al., 2015; Sung et al., 2015), anxiety of using online shopping (Celik, 2016), and similar. Generation groups have proved to be a significant model moderator on the technology usage topic (Calvo-Porral et al., 2019). Therefore, this research focuses on Generation X and Generation Y. Generation Y, or "millennials", were born between 1981 and 1996. They are characterized as consumers with significant purchasing power, desire, and willingness to accept new technologies and gain new personal experiences (Cabeza-Ramírez, 2022). On the other hand, Generation X includes consumers born between 1965 and 1980 who grew up in a time of technological development, but are not necessarily "addicted" to using the Internet like Generation Y (Gurau, 2012). Furthermore, both generation groups either grew together with technology development or adapted to it and have therefore accepted Internet usage for business and private purposes.

To be able to show the impact of the generational groups on the consumers' intention to purchase online electronic products, the Unified Theory of Acceptance and Use of Technology (UTAUT) is used as a foundation. In this paper, the UTAUT model is further modified to include generational groups and determinants that have an impact on the paper's research focus. Due to its strength and flexibility, the UTAUT model has been used in many previous studies to investigate technology acceptance and usage behaviors. UTAUT is more useful than other information technology adoption and acceptance models since it explicates a broader comprehension of a problem and allows for more variation concerning context and parameters. In this paper, a research question (RQ) - Is it possible to indicate a moderating generational group influence on the research model determinants relation? has been implemented. The model has rarely been used in the online shopping context for consumer electronics, especially with an additional component of generational age groups moderating influence in the Republic of Croatia. With this paper analysis, the aim is to contribute to the existing literature by expanding the moderating generational groups' influence in the online consumer electronics shopping environment. By implementing such an analysis, it can be researched which determinants influence the intention to use online shopping, leading to an expanded consumer behavior, thereby providing new knowledge in this research area.

For this paper analysis, the authors gathered responses from consumers in the Republic of Croatia at the end of the COVID-19 pandemic, when consumer habits had already been influenced by the COVID-19 pandemic shift in the way of purchasing online consumer electronics and therefore have been changed indefinitely (Gu et al., 2021). Structural Equation Modeling (SEM) is used to examine the moderating generational impact on the model variables, which are formed as latent variables consisting of manifest variables (Mueller et al., 2018), while Confirmatory Factor Analysis (CFA) is used for model validity. The observed variables' factor structure is analyzed by the proposed method (Hoyle, 2000).

The structure of this article is as follows. The following part presents the literature review. The third section provides a detailed research methodology review. The fourth part of the research represents the research findings. The final section of the paper contains the concluding remarks, limits, and suggestions for future research.

1. Literature review

Researchers have developed theory-driven models that specify the determinants of technology-use intention. The theory of reasoned action (TRA) proposed by Fishbein and Ajzen suggests a relationship between user attitude and behavior, assuming rational user decision-making as a prerequisite for behavior (Ajzen et al., 1969). The theory is limited to "willed" user behavior, and in 1985 it was expanded into the theory of planned behavior (TPB) (Ajzen, 1985). The TPB theory introduces the perceived behavioral control notion, which significantly determines users' behavioral intention (Armitage et al., 2001). Encouraged by the mentioned research and new knowledge, Davis (1989) develops a Technology Acceptance Model (TAM) directed towards the insight into technology acceptance user determinants. The main model determinants are Perceived Usefulness (PU), which represents the more efficient task execution from the user perspective, and Perceived Ease of Use (PEU), which represents the new system's ease of use from the consumer perspective. Both determinants affect the Attitude Toward Using (ATU), which further affects the Actual System Usage (ASU). The TAM model has been changed and upgraded a large number of times from its initial form through various scientific and professional papers. Thus, the TAM2 technology acceptance model was created in 2000 in collaboration between Davis and Venkatesh (Venkatesh et al., 2000), from which UTAUT was developed (Venkatesh et al., 2003) and the TAM3 technology acceptance model (Venkatesh et al., 2008).

Through the UTAUT model, four determinants were introduced, performance expectancy, effort expectancy, social influence, and technology usage facilitating conditions (Venkatesh et al., 2003). The paper subject will not be facilitating conditions, although it is one of the UTAUT model determinants. The research interest is directed towards generation groups moderating influence on the intention to buy consumer electronics online, and thus, this determinant does not contribute to explaining the purchase intentions like the three determinants previously mentioned (Lim et al., 2016).

Performance expectancy (PE), indicates the benefit that a consumer realizes when adopting a new technology. By buying consumer electronics products online, the customer potentially makes a more efficient purchase (Chen et al., 2021). This variable is the main predictor that affects the intention to buy consumer electronics online, as it has the greatest impact on all the independent variables of the UTAUT model (Van Droogenbroeck et al., 2021). Ademi et al., 2024 also show that brand-related cognitions can translate into higher purchase intention among younger cohorts, underscoring the role of perceived value benefits.

Effort expectancy (EE) refers to the ease and simplicity of usage for online consumer electronics shopping (Venkatesh et al., 2000). Swift product search, as well as a dedicated e-commerce platform, is one of the main determinants of purchase decisions. The new technology's ease of use greatly increases its wider application and acceptance speed (Wei et al., 2021). The design, main menus, and simple shopping flow in the case of online shopping contribute greatly to its prevalence and more efficient use (Scaria et al., 2020).

Social influence (SI), such as colleagues, family, and wider and close environment opinions, influences the personal decision to use new technology (Venkatesh et al., 2003). A new technology user can play a pioneering role within their group of family and friends. Such users are important because of the information they transmit to other potential users. A positive comment from such users increases the possibility of a positive attitude of other users towards new technologies and the purchase itself (Saprikis et al., 2018). Evidence from Gen Z contexts shows that sponsorship disclosure can lift purchase intention indirectly via brand awareness and influencer credibility (Sesar et al., 2023), while “connected consumers” (Generation C) rely on social-media information during evaluation and are more prone to impulsive purchases (Vuković et al., 2023). These patterns align with SI’s pathways and with social-proof mechanisms in digital environments. Furthermore, there might be indirect effects through other variables, such as performance expectancy and effort expectancy, on the consumer's intention to purchase. If consumers are influenced by their close friends or family and receive greater benefits in using e-commerce platforms, their intention to purchase will also increase. Additionally, there is a similar case with effort expectancy, where consumers tend to understand that if the e-commerce platform is easy to use, they will have a higher intention to purchase products online.

According to Prospect Theory, consumers evaluate outcomes relative to a reference point and assign greater weight to losses than to comparable gains. Under online uncertainty, this asymmetry amplifies the impact of reviews, ratings, and Q&A on purchasing. Various research papers report that better review quality reduces perceived risk and increases purchase intention, most notably for cross-border and high-involvement products. Furthermore, multiple electronic word of mouth channels co-vary with sales, aligning risk framing with UTAUT via performance and effort expectancies (Phamthi et al., 2024; Feng et al., 2023; Wang et al., 2022; Dobos et al., 2024).

Given the strong COVID-19 pandemic impact on the global economy, there is a need to research its impact on online shopping and consumer habits. Various variables such as age, education, geographic location, and similar potential influences have been used in papers on the online shopping topic (Colaço et al., 2021; Mofokeng (2021)). For European e-commerce in consumer electronics specifically, fuzzy c-means clustering reveals distinct generational patterns across countries in the COVID period (Jajić et al., 2025). Beyond the pandemic context, research in other domains also shows that generation expectations systematically shape intentions (for example, Gen Z job seekers' expectations predicting job-pursuit intentions in a transition/emerging economy) (Nguyen et al., 2022). Fewer papers have taken age as a moderating variable. Due to that, Generation Y & X are ideal generation groups for studying the influence of the relationships within the research model variables and gaining insight into the online consumer electronics shopping intention.

According to Leibenstein (1950), the bandwagon effect occurs when individuals adopt behaviors or make purchasing decisions based on observing others, driven by a desire to conform to the majority. In e-commerce, this effect is amplified by features like "top-rated" badges, customer reviews, and popularity rankings, which act as social proof (Chen et al., 2021). For consumer electronics products, such cues simplify decision-making and reduce perceived risks by leveraging the credibility of others' choices. Similarly, herding behavior occurs when individuals follow the decisions of others due to the belief that a group makes a more informed decision than the individual. In the e-commerce segment, this can be seen in a special sale action of a product in high demand, where individuals join the group because they think this product is worth more (Pavlović-Höck (2021); Ali et al., 2021). Therefore, these microeconomics concepts are included in the research analysis to show if similar patterns are happening in the generational groups' online consumer electronics purchasing field, as there is a lack of such approaches in the current research literature.

This paper's goal is to show the determinants' impact on the consumer intention to buy online consumer electronics, as well as the influence of generation groups (Generation X and Y) on those determinants' relations in the research model. Various determinants that impact online consumer electronics shopping intention during the COVID-19 pandemic will be shown. The same will be achieved by implementing the UTAUT model with certain modifications. Although some variables are similar to other models, such as TAM, they lack the internal structure necessary to investigate the moderating effects of generational differences in detail and have a lower explanatory power (Rondan-Cataluña et al., 2015). Due to this gap in the other models and for the goals of this research in determining the generational groups' moderating influence on online consumers' intention to purchase consumer electronics in the Republic of Croatia, the modified UTAUT model has been used. Thangavel et al. (2021), Sharma et al. (2023), and Hakim (2024) papers are the inspiration for this research regarding the generational groups' component. Thangavel et al. (2021) compare Generation Y and Z to find their similarities or differences, with the conclusion that Generation Z emphasizes more enjoyment when purchasing online. Furthermore, Sharma et al., (2023) compared Generations X, Y, and Z in purchasing online, but for a specific type of products, branded ones. Their findings indicate that Generation Z is much more interested in this aspect than the other two generations. Lastly, Hakim, 2024 compared Generation X, Y, and Baby Boomers and how they respond to peer behavior. The results showed that Generation X follows their peers' advice, and is influenced by product reviews much more than other generations before making a purchase.

Building on the literature, authors expect (1) performance expectancy and (2) effort expectancy to relate positively to purchase intention in both generations; (3) social influence to increase performance and effort expectancy (and thus indirectly relate to purchase intention), and (4) the direct effect of social influence on purchase intention to be stronger for Generation X than for Generation Y. Authors assess these expectations with a multi-group model (Gen X vs. Gen Y) and report between-group differences and indirect effects.

To test the mentioned relations and potential moderating influence, the authors utilize SEM, a method that includes latent variables in the model and quantifies them using manifest variables. Further validity testing will be imposed by the Chi-square and Goodness-of-fit indicators. Normally, a sample size of 10 participants per manifest variable is minimally required for this type of statistical analysis (Wolf et al., 2013). Given that the initial research instrument has 14 manifest variables, and multi-group analysis will be used to investigate the age-moderating impact, the required sample is set at 280 respondents. A multi-group analysis will be conducted to investigate the moderating age influence expressed through customers belonging to Generation X and Y.

2. Methodology

The empirical part of this research uses CFA, SEM, and multigroup analysis for model evaluation. Furthermore, goodness-of-fit indicators are implemented in this part of the paper as well.

2.1. Research instrument

The primary research includes Generation Y and X respondents in the Republic of Croatia, and responses were gathered by using an online questionnaire. Generation Y includes respondents born between 1981 and 1996, while Generation X includes respondents born between 1965 and 1980.

The research instrument consists of two parts. The first part refers to the research instrument questions, grouped into three dimensions containing 14 manifest variables and one elimination question. In the first part, the questions are formed in a Likert scale type format (1 – strongly disagree, and 5 - strongly agree), which is often used and suitable for data analysis using the SEM method (Bouranta et al., 2009). The last part of the questionnaire contains questions about the respondents' demographic characteristics.

The survey questionnaire was constructed by comparing several scientific papers. It is used to examine the determinants that influence consumer electronics online buying intention during the COVID-19 pandemic and the moderating influence of generation groups (Venkatesh et al., 2012; Venkatesh et al., 2003; Driediger et al., 2019; Thangavel et al., 2021). The original questionnaire was adapted from Venkatesh et al., (2003) and Venkatesh et al., (2012), who in the aforementioned papers developed and refined the Unified Theory of Acceptance and Use of Technology model. Papers by Driediger et al., (2019) and van Droogenbroeck et al., (2021) were used as an inspiration to create a model for examining consumer electronics online shopping intention during the COVID-19 pandemic. The moderating generational groups' influence with the associated Generations X and Y was added due to a lack of age influence representation in previous papers, and inspired by the work of Thangavel et al., (2021). Furthermore, it is possible to define three groups of consumer electronics: business, communication, and leisure (Bali, 2007). The mentioned product groups are classified in the Croatian Bureau of Statistics Industrial Products Nomenclature - NIP 2020, and for the purpose of this research, business and communication groups are the paper focus.

Respondents were asked to participate in the research through social media such as Facebook/Meta and LinkedIn. The questionnaire was distributed at the end of the COVID-19 pandemic period. According to research by Gasman (2016) and Burrus et al., (2021), today's research distribution is mostly based on the use of the Internet and social networks, with additional third-party software usage in collecting respondents' answers having seen an increase in usage.

A pilot study was conducted to test the initial research instrument's correctness and comprehensibility. After the pilot study, there was no need for additional questionnaire modification, and it was used to collect respondents' answers for this study. The research elimination question was included for better customer response segmentation. The research authors wanted to gain only the intentional consumers in their research sample, for those who will buy consumer electronics in the future. By having such a consumer response base, it can be more beneficial to determine the intention determinants than from the others.

Dependent and independent variables are explained through manifest and latent categories as well as through the item measurement. The dependent variable, Online consumer electronics shopping intention (BI) reflects the consumers' intentions to purchase electronics online, incorporating items that measure both future purchasing intentions and the frequency of past online purchases. Performance expectancy (PE), Effort expectancy (EE), and Social influence (SI) are the independent variables of this analysis. The PE variable reflects the perceived benefits associated with online shopping for consumer electronics. This variable is based on the assumption that consumers perceive the online shopping experience as offering greater selection, better pricing, and time efficiency (Venkatesh et al., 2012). The EE variable captures the ease with which consumers navigate online platforms for purchasing consumer electronics. This variable, also taken from the UTAUT model (Venkatesh et al., 2012), emphasizes how the user-friendly nature/ease of use of e-commerce platforms affects purchasing behavior. The SI variable, another key factor, evaluates the impact of close friends and family on the individual consumer and their online shopping behavior. This variable foundation is in social influence theories, which suggest that individuals often base their decisions on the behaviors of others (Venkatesh et al., 2012). Lastly, respondents' age serves as a demographic control variable, categorizing participants into two generational groups: Generation X (ages 42–57) and Generation Y (ages 26–41). This categorization, based on a multiple-choice question, allows for an examination of how generational differences affect the intention to purchase consumer electronics online, considering the broader context of post-pandemic e-commerce behavior.

The research phases were carried out in several stages. In the first step, CFA analysis was performed. The statistical program JASP with the lavaan R package was used for this purpose (Rosseel 2012). Also, in addition to JASP, the statistical program SPSS 13.0 was used for the additional statistical analysis. The CFA analysis was conducted for the research model according to the generation groups (Hurley et al. 1997). In the second step, the SEM was used to test the relation between the model variables. Variable research is carried out through the SEM validity evaluation and the latent variables' statistical significance (Mueller et al. 2018).

2.1. Statistical analysis

Construct validity is needed for establishing research accuracy. It is to what extent the theoretical assumptions meet the latent research constructs (Hair, 2010). Firstly, sample characteristics are denoted for easier understanding of the research respondents' base. Secondly, the research instrument validity will be determined by the CFA. To determine the CFA goodness-of-fit validity, Chi-square, Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Tucker-Lewis Index (TLI), Goodness of fit Index (GFI), and Standardized Root Mean Squared Residual Index (SRMSR) indicators will be used (Hurley et al. 1997). The CFA is followed by the SEM method, which is used to examine if the measurement instrument represents the research model variables, which are formed as latent variables consisting of manifest variables (Mueller et al., 2018). The CFA analysis serves to confirm the observed variables' factor structure (Hoyle, 2000). Finally, multigroup analysis is used to investigate the moderating age influence defined by the consumers' Generation X or Generation Y group on the online consumer electronics shopping intention in the context of the research model (Mueller et al., 2018). In doing so, the research sample is divided into two subgroups, and the SEM part is repeated separately for each age group, i.e., Generation X and Y. The moderating age influence is examined by comparing the estimated parameters of the regression coefficients for the research variables. In this way, two SEMs are used to test the research variables, with the first model testing research model variables on a Generation X respondents' sample, and the second model testing the same variables on a Generation Y respondents' sample. To perform the proposed statistical analysis, JASP and SPSS 13.0 software are used.

3. Research findings

The research distributed a questionnaire and gathered 352 responses. The respondents' demographics sample showed a higher number of Generation Y to Generation X participants. Most of the respondents, 258 (73.3%), belong to Generation Y (26-41 years old). Generation X (between 42 and 57) includes 94 respondents (26.7%) out of the total number of 352. The majority of respondents completed secondary education, 141 of them (40.1%). Furthermore, 94 of them (26.7%) completed graduate studies, 75 (21.3%) college, 39 (11.1%) postgraduate studies (MBA, PhD), and three of them (0.9%) primary school. A slightly higher number of respondents are female, 191 of them (54.3%), while the number of male respondents is slightly lower, 161 of them (45.7%). According to the questionnaire, 158 respondents (44.9%) are employed by their employer, followed by 123 students (34.9%), 38 self-employed respondents (10.8%), 24 retired (6.8%), and 9 unemployed respondents (2.6%). To make online consumer electronics purchases, most respondents, 142 to be precise (40.3%), use laptops, 136 (38.6%) use smartphones, and 72 (20.5%) respondents use personal desktop computers.

All manifest variables are statistically significant according to the Shapiro-Wilk test results at 1% probability, which indicates that the data are not normally distributed. Accordingly, Mann-Whitney U non-parametric tests were used. The manifest variables that comprise the latent variable EE are statistically significant at 1% and 10% probability. Other statistically significant differences were recorded for manifest variables PE2 and SI1, with a statistical significance at 5% probability, while differences in other manifest variables are not statistically significant. Cronbach's alpha is also shown for each latent model variable's mean values. All values are above 0.8, which indicates that the model's latent variables are reliable (Kline, 1999). Authors assessed potential common-method bias using an unrotated Harman single-factor test, a common latent factor (CLF) within CFA/SEM, and full collinearity VIFs for latent variables. These diagnostics did not indicate a dominant single factor or material model distortions, and VIFs were within conventional thresholds (Podsakoff et al., 2003; Kock, 2015).

Furthermore, the research model is shown in Figure 1.

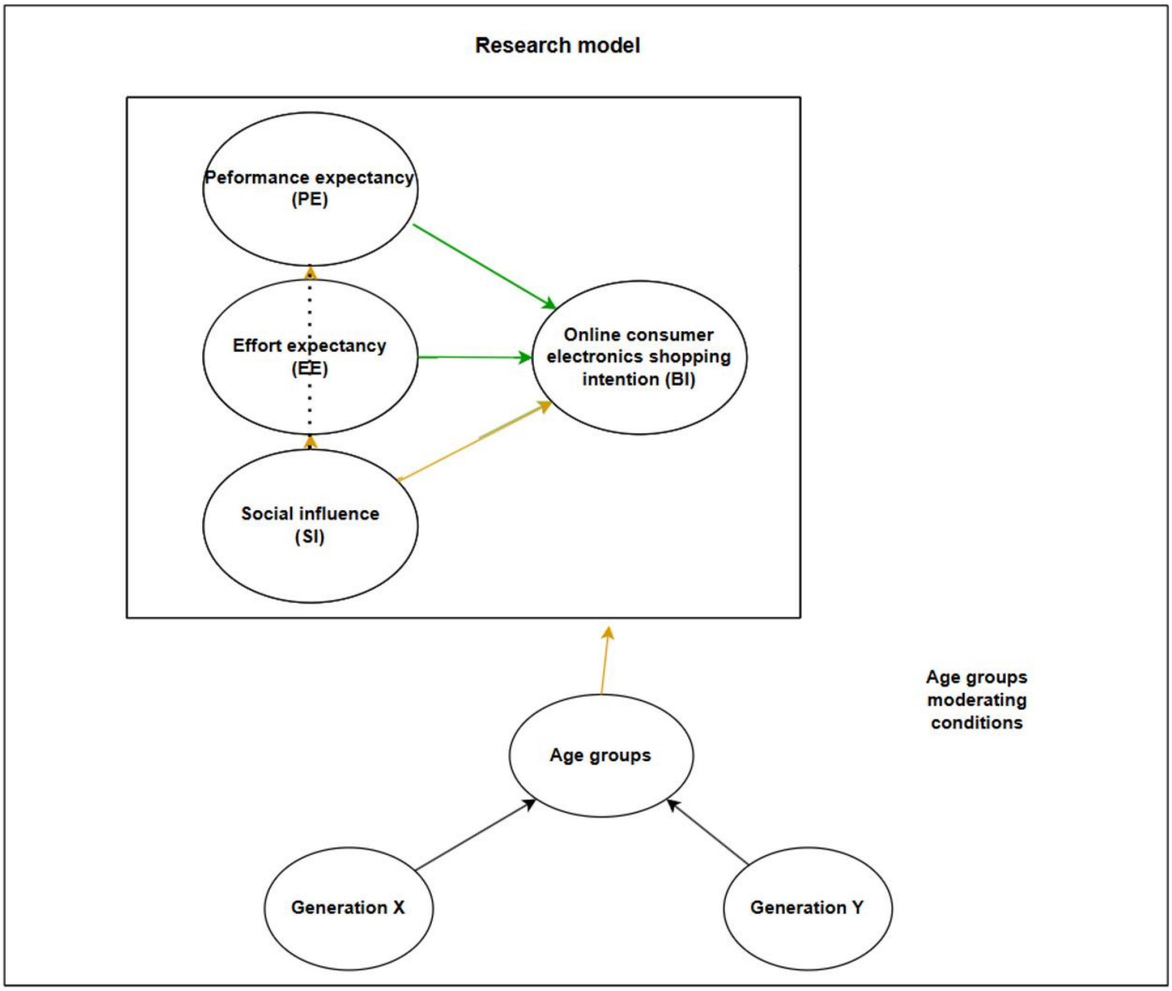

Figure 1 Research model
Source: the authors

The research model CFA results with the influence analysis of the generation groups were performed using the JASP programming tool and the lavaan R software package (Rosseel, 2012) shown in Table 1 (size). The number of observations is 352, and the representativeness of the model is shown through several parameters. The Chi-square for the basic model is 223.431 with 71 degrees of freedom (df) and is statistically significant at 1% probability, which indicates the statistical significance of the proposed model compared to the null model. Furthermore, the observation number is 258 for Generation Y and 94 for Generation X, and the model representativeness was tested through several parameters. The Chi-square for research model by generation group's influence is 324.092 with 142 degrees of freedom and is statistically significant at 1% probability. To additionally examine the research model instrument on the entire sample, it is necessary to conduct a representativeness analysis through the most important indicators, such as CFI, TLI, GFI, RMSEA, and SRMSR, shown in Table 2.

Table 1 Sample sizes (CFA)

Group	n
Overall sample	352
Generation Y	258
Generation X	94

Source: the authors

The comparative fit index is the most used representativeness index and is used to compare the null and proposed models (Savalei 2018). It is recommended that the CFI index values be greater than 0.9. The research model shows a value of 0.921, while generation groups show a value of 0.942, which is higher than the usual value, and it can be concluded that the model is representative according to the CFI indicator.

The Tucker Lewis index compares the normalized chi-square values for the null and the proposed model, taking into account the complexity of the model (Taasoobshirazi et al., 2016). If the value is above 0.9, the representativeness is excellent, while the value of 0.8 is the lower acceptable limit. The research model shows a value of 0.903, while the generation group influence shows a value of 0.925, which indicates the excellent model representativeness measured by the TLI index.

The Root Mean Square Error of Approximation index represents (Savalei 2018) a deviation measure according to the degree of freedom between the presented covariance and the existing model covariance. The recommendation for the RMSEA value is as low as possible (below <0.08, but results below <0.10 are also recognized), which indicates better representativeness. The research model shows a value of 0.078, while the generation group's influence shows a value of 0.085, which indicates representativeness according to the RMSEA index.

The Standardized Root Mean Square Residual index is a supplement to the RMSEA index and represents a standardized index of the average residual value, calculated by the difference between the presented matrix covariance and the presented model matrix covariance (Taasoobshirazi et al., 2016). As with the RMSEA index, the lower the value of the SRMSR index (below <0.08), the better the representativeness. In this case, the value of the SRMSR index is 0.054, while the generation group's influence shows a value of 0.060, which is lower than the acceptable limit, so this index confirms the representativeness. Considering the mentioned representativeness indicator values, it can be concluded that the specified model is representative.

Table 2 Model fit indices

Model / Grouping	χ^2 (df)	p	CFI	TLI	RMSEA	SRMSR
Basic CFA (overall)	223.431 (71)	< .01	0.921	0.903	0.078	0.054
Multi-group CFA (Gen X & Gen Y)	324.092 (142)	< .01	0.942	0.925	0.085	0.060

Source: the authors

The next CFA step refers to the latent constructs and manifest indicators relationship assessment (Shevlin et al. 1998). Standardized factor loadings (λ) and estimated coefficients of determination (R^2) for each basic research model manifest variable are tested here. According to Hair et al. (2010), the values should be greater than 0.5 and above 0.7 ideally. Results below 0.5 are not satisfactory. The results indicate that all the research basic model manifest variables are satisfactory, because no value is below 0.5. Statistical significance is present for all manifest variables at 1% probability. Furthermore, with the coefficient of determination (R^2), this research shows how much variance is explained by the corresponding factor. The manifest variable EE1 is the only one that has a slightly lower R^2 (0.355) than the others, which mostly have a coefficient of determination above 0.5. This proves that the manifest indicators explain the latent factors' variance well enough. All basic research model manifest variables are satisfactory, as no value is below 0.5 at a 1% probability. For Generation X, the manifest variable PE2 has a slightly lower R^2 (0.434) than the others, which mostly have a coefficient of determination above 0.6. Therefore, it indicates that the manifest indicators explain the latent factors' variance sufficiently well. For Generation X, the manifest variable EE1 has a slightly lower R^2 (0.309) than the others, which mostly have a coefficient of determination above 0.6. Therefore, it can be concluded that the manifest indicators explain the latent factors' variance well, as shown in Table 3.

Table 3 Model fit indices

Group	Indicator	R^2
Overall sample	EE1	0.355
Generation X	PE2	0.434
Generation X	EE1	0.309

Source: the authors

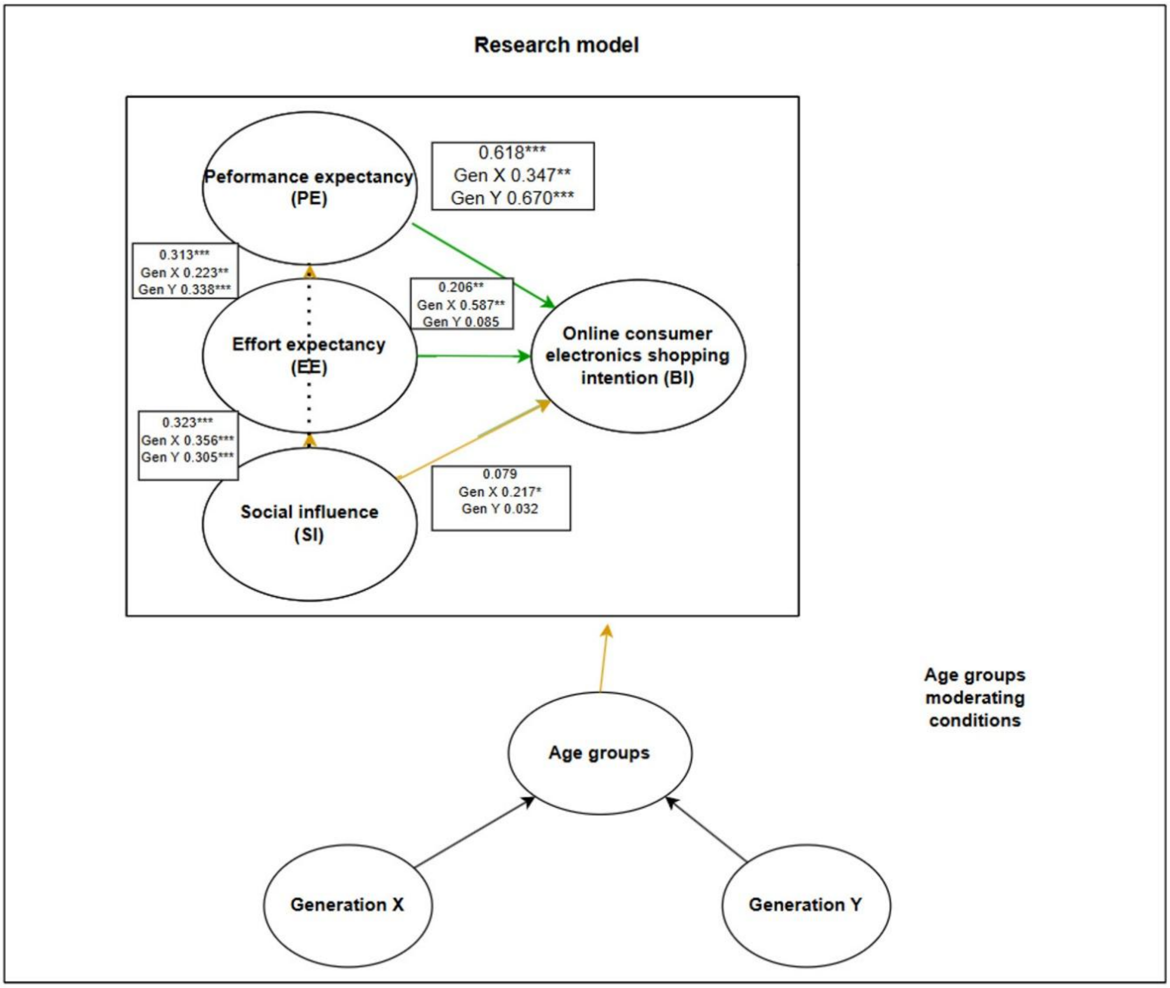

Figure 2 Research model coefficients with generation groups influence – SEM (β coefficients)
Source: the authors

Figure 2 shows the research model and the influence of generation groups on regression coefficients using the SEM method. Variable PE has the greatest impact on BI, where an increase in PE of 1 increases BI by 0.618 with a statistical significance at 1% probability. This means that consumers tend to benefit from online purchases of consumer electronics. The least statistically significant impact is visible in the EE and BI relationship, where a 1-unit increase in EE results in a 0.206-unit increase in BI, with a 5% probability of statistical significance. Therefore, consumers tend to use e-commerce platforms to purchase consumer electronics due to ease of use. The SI and BI relationship is statistically insignificant, meaning that there is no statistically significant social influence on the consumers in the online purchase of consumer electronics. The main differences between generations X and Y are visible in the relationship between the two pairs of variables. The pairs SI – BI and EE – BI are significant in Generation X, while they are not in Generation Y. The results prove that the older generations make a greater effort and question the environment more before deciding to buy consumer electronics online.

Table 4 shows the research model by generation groups (X and Y) chi-square values. The research model and the same model with the generation groups have a statistically significant chi-square difference at a 5% probability. The results indicate that there is a difference in the SEM research model estimation when considering the influence of the generation groups, compared to the standard SEM research model. In other words, the multigroup analysis indicates that there is a statistically significant and positive age influence on certain relationships between the SEM model's latent variables.

Table 4 Research model by generation groups (X and Y) chi-square values

Category	All respondents' research model – SEM1	Research model by generation groups (X and Y) (multigroup analysis) - SEM1-multigroup	Difference	p-value
Chi-square ($\chi 2$)	223.431	324.092	100.66	0.011835**
Degrees of freedom (df)	71	142	71	

Note: Statistical significance at ***1% probability and ** 5% probability

Source: the authors

The following part of the paper shows the theoretical and managerial implications. The subsections were created for easier understanding of the research results.

3.1. Theoretical implications

The research findings are mostly aligned with the Driediger et al., 2019 and van Droogenbroeck et al., 2021 papers, except for the social influence role. The case of non-aligning with the specified papers through the social influence on consumer intention to buy online consumer electronics might be in the research sample itself (the majority of Generation Y respondents) and in the specific product segment, which this research was focusing on. On the other hand, the Generation X social influence variable has a significantly positive relation towards the online consumer electronic behavioral intention, while Generation Y does not. This suggests a generational difference in buying patterns, where Generation X is more oriented to product reviews, ratings, and peer advice, while Generation Y is more direct in making online purchases of consumer electronics. The positive and statistically significant relationships support Sung et al.'s (2015) findings, confirming that social influence positively affects performance expectancy and effort expectancy. However, the rejection of direct social influence suggests that social influence alone is not enough to predict behavioral intention to buy consumer electronics, especially without considering generational differences. Therefore, this is a contribution of this paper due to the emergence of the bandwagon effect, following the indirect social influence impact on online consumer electronic behavioral intention, especially for Generation X. Furthermore, it is aligned with Banerjee's 1992 and Hakim's, 2024 research. Following other opinions drives the demand in Generation X participants to make an online consumer electronics purchase.

3.2. Managerial implications

In practice, companies selling consumer electronics online should tailor cues to generational differences. For Generation X, emphasize credible social proof to reduce perceived risk, surface verified reviews and reviewer profiles, highlight expert badges and "most bought" labels, and make returns, warranty, and repair options prominent on product and checkout pages. For Generation Y, focus on utility and frictionless flow: foreground key specifications and performance benefits, provide guided comparisons, and enable fast checkout (wallets, pay-later) to strengthen performance and effort expectancies. On high-involvement stock keeping units, pair popularity and review-quality indicators with transparent delivery and price-match policies to resolve hesitation quickly; position the most informative review content ("top questions answered") above the fold. After purchase, solicit photo/video reviews and reward helpful Q&A to maintain a steady stream of high-quality electronic word of mouth that supports both generations.

Conclusion

The paper's goal was to show various determinants that affect consumer online intention to purchase consumer electronics, as well as to indicate the moderating generation groups (Gen X and Gen Y) influence on the variables in the research model. The modified UTAUT model has been used for this purpose. Performance expectancy, Effort expectancy, and Social influence were independent variables, while the Online consumer electronics shopping intention was the dependent variable of the research model. The strongest impact has been recorded for the personal consumer benefit of using e-commerce platforms to purchase consumer electronics, seen through the performance expectancy variable relation with the dependent model variable. Furthermore, the findings indicate that the impact of Social influence variable on the dependent variable was only significant for Generation X, while there was also an indirect social influence through effort expectancy toward online consumer electronics purchase intention for both generations. Furthermore, there is a stronger connection between the bandwagon effect and herd behavior for Generation X compared to Generation Y. Therefore, this paper's findings confirm that Generation X consumers are keener on product reviews, ratings, and peer advice before making a purchase. Due to that, Generation X is making more online consumer electronics purchase decisions based on other consumers' intentions. In other words, the social influence variable alone is not able to determine consumer intention to purchase consumer electronics online, and therefore, a moderating role of generational groups was needed for better consumer understanding as shown in this paper. Furthermore, the research question - "Is it possible to indicate a moderating generational group influence on the research model determinants relation? "was confirmed as there is an evident moderating influence of generational groups on the model variables.

This paper has limitations as well. They are seen in the non-equal sample size for both generational groups, as well as the reliance on self-reported data. Participants might not always accurately recall how easy or useful they find online shopping, or they might be influenced by a desire to present themselves in a certain way. Therefore, a real-case scenario where consumers would purchase online consumer electronics in real time would be potentially more useful. By doing so, the dataset could be enlarged with the specific web metrics as well. The potential usage of eye-tracking technology would be interesting. On the other hand, to capture a longer time frame, longitudinal studies would be needed. Cross-cultural comparisons could illuminate how cultural factors interact with generational differences in online shopping behavior, as the research authors focused on the Republic of Croatia only, and therefore would be interesting to compare the results with other European countries. It would be interesting to distinguish both generations, Gen X and Gen Y, into two parts, where younger and older participants of both generation groups would be questioned. Furthermore, another comparison with Gen Z would be interesting with the addition of applications used for online shopping. On the other hand, prospective business owners might find this research interesting due to the distinction between generational groups and their way of online shopping. By knowing the consumer habits and preferences, it will be easier for them to market and distribute consumer electronics products to their consumer base. Future research can move beyond the current findings and offer a broader understanding of how different generations navigate the ever-evolving online shopping landscape.

Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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> Ljubojević, T.K. (1998). Ljubojević, T.K. (2000a). Ljubojević, T.K. (2000b).
> Ljubojević, T.K., & Dimitrijević, N.N. (1994).

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Authors must be listed by their last names, followed by initials. Publication year must be written in parentheses, followed by a full stop. Title of the article must be in sentences case: only the first word and proper nouns in the title are capitalized. The periodical title must be in title case, followed by the volume number, which is also italicized:

> Author, A. A., Author, B. B., & Author, C. C. (Year). Title of article. *Title of Periodical, volume number* (issue number), pages.

➲ **Journal article, one author, paginated by issue.**

Journals paginated by issue begin with page 1 in every issue, so that the issue number is indicated in parentheses after the
volume. The parentheses and issue numbers are not italicized, e.g.

> Seliverstova, Y. (2021). Workforce diversity management: A systematic literature review. *Strategic Management*, *26*(2), 3–11. https://doi.org/10.5937/StraMan2102003S

➲ **Journal article, one author, paginated by volume.**

Journals paginated by volume begin with page 1 in issue 1, and continue page numbering in issue 2 where issue 1 ended, e.g.

> Perić, O. (2006). Bridging the gap: Complex adaptive knowledge management. *Strategic Management, 14*, 654–668.

- **Journal article, two authors, paginated by issue.**

  Dakić, S., & Mijić, K. (2020). Regression analysis of the impact of internal factors on return on assets: A case of meat processing enterprises in Serbia. *Strategic Management*, *25*(1), 29–34. https://doi.org/10.5937/StraMan2001029D

- **Journal article, two authors, paginated by volume.**

  Ljubojević, K., & Dimitrijević, M. (2007). Choosing your CRM strategy. *Strategic Management, 15*, 333-349.

- **Journal article, three to six authors, paginated by issue.**

  Marić, S., Uzelac, O., & Strugar-Jelača, M. (2019). Ownership structure as a measure of corporate performance. *Strategic Management*, *24*(4), 28–37. https://doi.org/10.5937/StraMan1904028M

- **Journal article, three to six authors, paginated by volume.**

  Boškov, T., Ljubojević, K., & Tanasijević, V. (2005). A new approach to CRM. *Strategic Management, 13*, 300-310.

- **Journal article, more than six authors, paginated by issue.**

  Ljubojević, K., Dimitrijević, M., Mirković, D., Tanasijević, V., Perić, O., Jovanov, N., et al. (2005). Putting the user at the center of software testing activity. *Management Information Systems, 3*(1), 99-106.

- **Journal article, more than six authors, paginated by volume.**

  Strakić, F., Mirković, D., Boškov, T., Ljubojević, K., Tanasijević, V., Dimitrijević, M., et al. (2003). Metadata in data warehouse. *Strategic Management, 11*, 122-132.

- **Magazine article.**

  Strakić, F. (2005, October 15). Remembering users with cookies. *IT Review*, *130*, 20-21.

- **Newsletter article with author.**

  Dimitrijević, M. (2009, September). MySql server, writing library files. *Computing News, 57,* 10-12.

- **Newsletter article without author.**

  VBScript with active server pages. (2009, September). *Computing News,57,* 21-22.

B. BOOKS, BROCHURES, BOOK CHAPTERS, ENCYCLOPEDIA ENTRIES, AND BOOK REVIEWS

Basic format for books

Author, A. A. (Year of publication). *Title of work: Capital letter also for subtitle*. Publisher.

➲ **Book, one author.**

Ljubojević, K. (2005). *Prototyping the interface design*. Faculty of Economics in Subotica.

➲ **Book, one author, new edition**

Dimitrijević, M. (2007). *Customer relationship management* (6th ed.). Faculty of Economics in Subotica.

➲ **Book, two authors.**

Ljubojević, K., Dimitrijević, M. (2007). *The enterprise knowledge portal and its architecture*. Faculty of Economics in Subotica.

➲ **Book, three to six authors.**

Ljubojević, K., Dimitrijević, M., Mirković, D., Tanasijević, V., & Perić, O. (2006). *Importance of software testing*. Faculty of Economics in Subotica.

➲ **Book, more than six authors.**

Mirković, D., Tanasijević, V., Perić, O., Jovanov, N., Boškov, T., Strakić, F., et al. (2007). *Supply chain management*. Faculty of Economics in Subotica.

➲ **Book, no author or editor.**

Web user interface (10th ed.). (2003). Faculty of Economics.

➲ **Group, corporate, or government author.**

Statistical office of the Republic of Serbia. (1978). *Statistical abstract of the Republic of Serbia.* Ministry of community and social services.

➲ **Edited book.**

Dimitrijević, M., & Tanasijević, V. (Eds.). (2004). *Data warehouse architecture*. Faculty of Economics.

➲ **Chapter in an edited book.**

Repa, V. (2019). Deriving Key Performance Indicators from Business Process Model. In M. Pańkowska & K. Sandkuhl (Eds.), *Perspectives in Business Informatics Research. BIR 2019. Lecture Notes in Business Information Processing, vol 365.* (pp. 148–162). Springer. https://doi.org/10.1007/978-3-030-31143-8_11

➲ **Encyclopedia entry.**

Mirković, D. (2006). History and the world of mathematicians. In *The new mathematics encyclopedia* (Vol. 56, pp. 23-45). Faculty of Economics.

C. UNPUBLISHED WORKS

➲ **Paper presented at a meeting or a conference.**

Ljubojević, K., Tanasijević, V., Dimitrijević, M. (2003). *Designing a web form without tables*. Paper presented at the annual meeting of the Serbian computer alliance, Beograd.

➲ **Paper or manuscript.**

Boškov, T., Strakić, F., Ljubojević, K., Dimitrijević, M., & Perić, O. (2007. May). *First steps in visual basic for applications*. Unpublished paper, Faculty of Economics Subotica, Subotica.

➲ **Doctoral dissertation.**

Strakić, F. (2000). *Managing network services: Managing DNS servers*. Unpublished doctoral dissertation, Faculty of Economics Subotica.

➲ **Master's thesis.**

Dimitrijević, M. (2003). *Structural modeling: Class and object diagrams.* Unpublished master's thesis, Faculty of Economics Subotica.

D. ELECTRONIC MEDIA

The same guidelines apply for online articles as for printed articles. All the information that the online host makes available must be listed, including an issue number in parentheses:

Author, A. A., & Author, B. B. (Publication date). Title of article. *Title of Online Periodical, volume number* (issue number if available). https://www.anyaddress.com/full/url/

➲ **Article in an internet-only journal**

Tanasijević, V. (2003, March). Putting the user at the center of software testing activity. *Strategic Management*, *8* (4). https://www.ef.uns.ac.rs/sm2024

➲ **Document from an organization**

Faculty of Economics. (2008, March 5). *A new approach to CRM*. https://www.ef.uns.ac.rs/papers/acrm.html

➲ **Article from an online periodical with DOI assigned.**

Jovanov, N., & Boškov, T. A PHP project test-driven end to end. *Management Information Systems*, 2 (2), 45-54. https://doi.org/10.5937/StraMan213302003S

➲ **Article from an online periodical without DOI assigned.**

Online journal articles without a DOI require a URL.

Author, A. A., & Author, B. B. (Publication date). Title of article. *Title of Journal, volume number*. https://www.anyaddress.com/full/url/

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REFERENCE QUOTATIONS IN THE TEXT

➲ **Quotations**

If a work is directly quoted from, then the author, year of publication and the page reference (preceded by "p.") must be included. The quotation is introduced with an introductory phrase including the author's last name followed by publication date in parentheses.

According to Mirković (2001, p. 201), "The use of data warehouses may be limited, especially if they contain confidential data".

Mirković (2001, p. 201), found that "the use of data warehouses may be limited". What unexpected impact does this have on the range of availability?

If the author is not named in the introductory phrase, the author's last name, publication year, and the page number in parentheses must be placed at the end of the quotation, e.g.

He stated, "The use of data warehouses may be limited," but he did not fully explain the possible impact (Mirković, 2001, p. 201).

➲ **Summary or paraphrase**

According to Mirković (1991, p. 201), limitations on the use of databases can be external and software-based, or temporary and even discretion-based.

Limitations on the use of databases can be external and software-based, or temporary and even discretion-based (Mirković, 1991, p. 201).

➲ **One author**

Boškov (2005) compared the access range…

In an early study of access range (Boškov, 2005), it was found...

➲ When there are **two authors**, both names are always cited:

Another study (Mirković & Boškov, 2006) concluded that…

➲ If there are **three or more authors** the abbreviation "et al." (Latin for "and others") is employed in APA in-text citations when referencing works with three or more authors. The format is to include only the first author's last name, followed by "et al.," a comma, and the year of publication. For instance, (Dakic et al., 2024) would be used as an example.

➲ **Unknown author**

If the work does not have an author, the source is cited by its title in the introductory phrase, or the first 1-2 words are placed in the parentheses. Book and report titles must be italicized or underlined, while titles of articles and chapters are placed in quotation marks:

A similar survey was conducted on a number of organizations employing database managers (Limiting database access, 2005).

If work (such as a newspaper editorial) has no author, the first few words of the title are cited, followed by the year: (The Objectives of Access Delegation, 2007)

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➲ **Organization as an Author**

If the author is an organization or a government agency, the organization must be mentioned in the introductory phrase or in the parenthetical citation the first time the source is cited:

> According to the Statistical Office of the Republic of Serbia (1978), …

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The overview is limited to towns with 10,000 inhabitants and up (Statistical Office of the Republic of Serbia [SORS], 1978).

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➲ When citing **more than one reference from the same author**: (Bezjak, 1999, 2002)

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When two or more manuscripts are cited parenthetically, they must be cited in the same order as they appear in the reference list, separated by a semicolon.

> (Bezjak, 1999; Griffith, 2004)

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> Survey results published in Theissen (2004a) show that…

➲ To **credit an author for discovering a work** when you have not read the original:

Bergson's research (as cited in Mirković & Boškov, 2006)…

Here, Mirković & Boškov (2006) will appear in the reference list, while Bergson will not.

➲ When **citing more than one author**, the authors must be listed alphabetically:

(Britten, 2001; Sturlasson, 2002; Wasserwandt, 1997)

➲ When there is **no publication date**: (Hessenberg, n.d.)

➲ **Page numbers must always be given for quotations**:

(Mirković & Boškov, 2006, p.12)

Mirković & Boškov (2006, p. 12) propose the approach by which "the initial viewpoint…

➲ **Referring to a specific part of a work**:

(Theissen, 2004a, chap. 3) (Keaton, 1997, pp. 85-94)

➲ **Personal communications, including interviews, letters, memos, e-mails, and telephone conversations**, are cited as below. (These are *not* included in the reference list.)

(K. Ljubojević, personal communication, May 5, 2008).

FOOTNOTES AND ENDNOTES

A few footnotes may be necessary when elaborating on an issue raised in the text, adding something that is in indirect connection, or providing supplementary technical information. Footnotes and endnotes are numbered with superscript Arabic numerals at the end of the sentence, like this.1 Endnotes begin on a separate page, after the end of the text. However, *Strategic Management* **does not recommend the use of footnotes or endnotes.**

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