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Organizacija (Journal of Management, Informatics and Human Resources) is an interdisciplinary peer-reviewed journal which is open to contributions of high quality, from any perspective relevant to the organizational phenomena.

The journal is designed to encourage interest in all matters relating to organizational sciences and is intended to appeal to both the academic and professional community. In particular, journal publishes original articles that advance the empirical, theoretical, and methodological understanding of the theories and concepts of management and organization. The journal welcomes contributions from other scientific disciplines that encourage new conceptualizations in organizational theory and management practice.

We welcome different perspectives of analysis, including the organizations of various sizes and from various branches, units that constitute organizations, and the networks in which organizations are embedded.

Topics are drawn, but not limited to the following areas:

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Teme so pokrivajo predvsem naslednja področja:

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- vodstveni in podjetniški vidiki izobraževanja;
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- podjetniški inženiring (npr. organizacijsko oblikovanje, upravljanje poslovnih procesov, paradigme preoblikovanja podjetij itd.);
- članki, ki analizirajo organizacijsko uspešnost in prizadevanja za izboljšanje le-te.

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The Impact of Usability and Reliability on ChatGPT Satisfaction among Gen Z and Gen Y

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Background/Purpose: ChatGPT's rapid diffusion has transformed large-language-model (LLM) technology from a specialist tool into a mainstream companion for study and work. However, empirical evidence on what drives user satisfaction outside medical settings remains scarce. Focusing on future business and management professionals in Croatia, this study examines how perceived ease of use and perceived reliability shape satisfaction with ChatGPT and whether those effects differ between Generation Z (18–25 years) and Generation Y (26–35 years).
Methodology: An online survey administered in August 2024 yielded 357 valid responses. The measurement model met rigorous reliability and validity criteria (CFI = 0.96, SRMR = 0.04).
Results: Structural-equation modelling showed that, in the pooled sample, ease of use (β = 0.42) and reliability (β = 0.46) jointly explained 72 % of satisfaction. Multi-group analysis revealed a generational split: both predictors were significant for Gen Z. However, only reliability remained significant for Gen Y. Gaussian graphical models corroborated these findings, indicating a densely interconnected attitude network for younger users and a reliability-centred network for older users.
Conclusion: The study extends technology-acceptance research to the management domain, underscores the moderating role of generation and illustrates the value of combining SEM with network analytics. Insights inform designers and educators aiming to foster informed, responsible and gratifying engagement with generative AI.

Keywords: *Artificial intelligence, Large language models (LLM), Marketing, User satisfaction, Croatia, ChatGPT*

1 Introduction

The advent of ChatGPT at the close of 2022 accelerated public exposure to large-language-model technology, pushing conversational AI from the laboratory into the mainstream almost overnight. Croatian users mirrored this global surge: within a few months, ChatGPT had become a routine aide for homework, report writing and everyday fact-finding. Such dialogic media settings differ fundamentally from the broadcast era in which audiences were passive receivers; they oblige users to craft prompts, evaluate algorithmic output and often remix it into new content. As Seyoung and Park (2023) argue, navigating this landscape demands more than basic digital literacy. It calls for technical fluency—knowing how to interact with and tweak the system—and for cognitive-ethical competence: the capacity to scrutinise accuracy, detect bias, deploy re-

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sults creatively and do so responsibly.

Whether people continue to embrace a tool that imposes these cognitive costs ultimately hinges on the quality of the experience it provides. Prior work on technology acceptance shows that satisfaction with interactive systems is shaped most directly by two beliefs: the perceived ease with which the system can be used and the perceived reliability of the information it supplies. However, the relative weight of these beliefs may not be constant across demographic segments. Generation Z, whose media habits were forged in a mobile-first environment, might value frictionless, always-on access. In contrast, Generation Y could concentrate more on trustworthy performance once basic usability thresholds are met. In addition, everyday knowledge of how large-language models work—or the absence of such knowledge—may colour people's impressions of ChatGPT's intelligence and, by extension, their willingness to rely on it.

A notable gap exists in the literature that addresses these issues. Most empirical studies to date have centred on healthcare professionals, exploring, for example, how physicians or medical students assess AI chatbots for diagnostic assistance and patient education. Research that probes the perceptions of business and management professionals—or, more broadly, the university-educated cohorts who will deploy generative AI in organisational settings—remains sparse. This paper helps close that gap by examining Croatian users whose primary exposure to ChatGPT occurs in academic business courses, entrepreneurial projects and managerial tasks, rather than in clinical practice.

The present study, therefore, sets out to map usage patterns, to quantify how ease of use and reliability shape satisfaction, and to discover whether these relationships diverge between Generation Z (18- to 25-year-olds) and Generation Y (26- to 35-year-olds). Beyond conventional structural equation modelling (SEM), it visualises item-level interdependencies through network analysis, offering a complementary view of the attitude system that underpins user experience.

Our contribution is threefold. First, the study extends the technology-acceptance conversation from clinical to managerial domains, documenting how future business practitioners in a small European market appropriate ChatGPT. Second, it demonstrates that generational differences do, in fact, modulate the satisfaction process: younger users balance usability and reliability, whereas older users hinge largely on reliability. Third, by combining covariance-based SEM with graphical least absolute shrinkage and selection operator (LASSO) networks, the paper supplies both confirmatory evidence and an exploratory map that highlights the specific questionnaire items, such as perceived time-saving and task efficiency, that act as bridges between constructs. These insights offer actionable guidance for AI developers seeking to fine-tune large-language-model interfaces and for educators' intent on cultivating informed, critical and ethically grounded use of generative AI.

Empirically, the research draws on a cross-sectional online survey administered in Croatia during August 2024. A convenience sample of 357 valid respondents, recruited mainly through WhatsApp and Facebook channels linked to the University of Zagreb, completed a battery of closed-ended items that measured perceived ease of use, reliability, satisfaction, usage frequency, perceived intelligence and knowledge of large-language-model technology. The measurement model was validated via confirmatory factor analysis; structural paths were estimated with multi-group SEM, and the graphical structure of item correlations was explored with network analysis. Together, these methods provide a nuanced, generationally informed picture of what makes ChatGPT satisfying or disappointing for business-oriented users in a rapidly evolving AI ecosystem.

2 Literature review

2.1 Language Models Based on Artificial Intelligence

Artificial Intelligence (AI) has experienced significant development since its inception, fundamentally altering how humans interact with machines. AI-based language models, a critical subset of AI, have revolutionised natural language processing (NLP), leading to more sophisticated conversational agents, virtual assistants, and machine translation systems. These advancements have transformed numerous industries, from customer service to content creation, making AI an indispensable tool for modern technology. So, it is worthwhile to explore the theoretical foundation, historical development, core principles, and the advantages and challenges associated with AI-driven language models further.

The definition of AI has evolved as the field has progressed. The American Psychological Association (Neisser et al, 1996) describes intelligence as the capacity to comprehend complex ideas, adapt to change, learn from experience, and engage in logical reasoning. The foundational goal of AI has been to replicate or exceed these human cognitive abilities in machines. The Dartmouth Research Project in 1955 marked the beginning of AI as an academic discipline, with the aim of creating machines capable of autonomous problem-solving and decision-making (McCarthy et al., 2006). Scholars categorise AI into three main types: narrow AI, which is specialised for specific tasks; general AI, a hypothetical construct capable of human-like cognition across multiple domains; and super AI, which could surpass human intelligence and autonomously improve its capabilities (Bringsjord, 2011; McLean, 2021).

While narrow AI dominates contemporary applications, researchers continue to explore the potential for developing more advanced AI systems.

The historical development of AI can be traced back to the early 20th century, when scientists and philosophers speculated about the possibility of machine intelligence. Alan Turing's seminal work, "Computing Machinery and Intelligence" (1950), introduced key concepts like machine learning and the Turing Test, which assesses a machine's ability to exhibit human-like intelligence (Michie, 1993). The 1960s witnessed the emergence of early neural network models and symbolic reasoning approaches, laying the foundation for modern AI systems. Joseph Weizenbaum's ELIZA, developed in 1966, was the first chatbot to mimic human conversation by using pattern recognition and scripted responses (Sharma et al., 2017). Although ELIZA lacked true comprehension, it demonstrated AI's potential in natural language processing.

AI research has experienced periods of rapid progress and stagnation, commonly referred to as "AI winters." The 1980s saw a surge in interest with the rise of expert systems—AI programs designed to emulate human decision-making in specialised fields. However, limitations in computational power and funding constraints slowed progress. The resurgence of AI in the 21st century has been fuelled by breakthroughs in deep learning, data availability, and enhanced computing power. IBM's Deep Blue famously defeated world chess champion Garry Kasparov in 1997, demonstrating AI's ability to process vast amounts of information and make strategic decisions (Feng-Hsiung, 1999). The development of Google's AlphaGo, which surpassed human players in the complex game of Go in 2015, marked another milestone in AI's evolution (Haenlein & Kaplan, 2019).

Several fundamental principles underpin AI research, including machine learning, deep learning, and neural networks. Machine learning involves training algorithms to detect patterns and make predictions based on data without explicit programming (Bolf, 2021; Pejić Bach et al., 2023). Deep learning, a subset of machine learning, utilises artificial neural networks with multiple layers to refine predictions through iterative learning, enabling AI to recognise speech, generate text, and classify images with high accuracy (Singh, 2023). NLP enables AI to understand and generate human language, facilitating applications like speech recognition and sentiment analysis (Yegnanarayana, 1994). Artificial neural networks, modelled after the human brain, consist of interconnected nodes that process information similarly to biological neurons. These networks have evolved significantly, transitioning from basic perceptron models to sophisticated architectures capable of handling complex linguistic and cognitive tasks (McCulloch & Pitts, 1943).

AI offers numerous advantages across various industries, including enhanced efficiency, automation of repetitive tasks, and data-driven decision-making. AI-powered chatbots and virtual assistants provide real-time customer support, minimising the need for human intervention and optimising service delivery (Sotala, 2012). In healthcare, AI models assist in medical diagnoses and predictive analytics, improving patient outcomes. The finance sector leverages AI for fraud detection and risk assessment, streamlining complex financial processes (Bolf, 2021). AI's ability to process vast datasets enables businesses to personalise user experiences and refine marketing strategies (Banjac & Palić, 2020). However, AI also presents substantial challenges. The development and maintenance of AI systems require significant financial investments, often limiting accessibility to larger corporations (Girdhar, 2022). Ethical concerns, such as bias in AI decision-making and data privacy risks, remain key issues that must be addressed (Hua et al., 2024). AI bias can result from skewed training data, leading to discriminatory outcomes in hiring, lending, and law enforcement applications (Isada, 2024). Additionally, fears of widespread job displacement due to automation highlight the socio-economic impact of AI adoption.

To maximise AI's benefits while mitigating its risks, ongoing research focuses on improving model transparency, reducing bias, and implementing robust governance frameworks. As AI continues to evolve, the importance of ethical considerations and responsible deployment will shape its integration into society. Future advancements in AI-driven language models are expected to enhance human-computer interactions, making AI more adaptive, context-aware, and capable of generating nuanced responses. These innovations will further bridge the gap between machine intelligence and human communication, solidifying AI's role as a transformative force in technology and beyond.

2.2 User Satisfaction and Key Factors in AI-Based Large Language Models

User satisfaction is a crucial factor in evaluating AI-driven services, as it determines long-term engagement, trust, and adoption rates. AI-based large language models (LLMs) such as Chatgpt, Google Bard, Claude, Deepseek, Grok, and other NLP-powered systems have gained widespread use, offering users intelligent, responsive, and context-aware interactions. However, their effectiveness in delivering high-quality service experiences is contingent on several key factors. These include perceived service quality, trust, personalisation, and perceived benefits. This paper provides a comprehensive exploration of the concept of satisfaction, key determinants influencing user perceptions, and their implications for AI-based language models.

The concept of customer satisfaction has been extensively studied in service marketing and consumer behaviour research. Kotler and Armstrong (2017) emphasise that beyond delivering products, businesses must ensure that their services align with customer expectations. Satisfaction is a psychological state that arises when the perceived performance of a product or service meets or exceeds user expectations (Churchill & Surprenant, 1982). If expectations are not met, users experience dissatisfaction, which can lead to disengagement or negative word-of-mouth. Crosby et al. (1990) argue that satisfaction plays a vital role in fostering long-term customer relationships, enhancing retention rates, and encouraging brand loyalty. In the context of AI, satisfaction is influenced by various cognitive and emotional factors, such as trust in the system's accuracy, perceived efficiency, and the relevance of AI-generated responses.

One of the most important determinants of satisfaction in AI-based services is perceived service quality. Zeithaml (1988) defines perceived quality as the user's subjective assessment of a service's overall excellence. AI-generated services, including LLMS, must deliver high levels of accuracy, coherence, and contextual relevance to be perceived as valuable. The SERVQUAL model, developed by Parasuraman et al. (1988), identifies five key dimensions of perceived service quality: reliability, responsiveness, assurance, empathy, and tangibility. In the context of AI, reliability refers to an AI model's ability to generate accurate and meaningful responses consistently. Responsiveness is the system's ability to understand and quickly address user queries. Assurance relates to the confidence users have in the system's credibility and correctness, while empathy involves the AI's capacity to recognise and adapt to user-specific needs. Although AI lacks human emotions, advancements in sentiment analysis and personalisation algorithms have improved AI's ability to deliver context-aware responses that enhance user engagement.

Trust is another critical element in determining user satisfaction. Users must feel confident that AI-generated responses are accurate, unbiased, and free from manipulation (Ou et al., 2024). Trust in AI systems depends on multiple factors, including transparency in how AI processes information, data privacy assurances, and the ability of AI to acknowledge errors. When AI models provide misleading or incorrect information, user trust diminishes, potentially leading to abandonment of the service. Research suggests that users are more likely to trust AI when they understand how it functions and when it demonstrates consistent accuracy in its outputs (Papenmeier et al., 2022). Additionally, users trust AI more when they perceive it as fair and free from bias (Adeiza et al., 2022). Bias in AI-generated language models has been a growing concern, as AI systems trained on biased datasets may produce skewed or discriminatory outputs. Addressing these concerns through explainable AI (XAI) techniques and fairness-enhancing algorithms can improve user trust and overall satisfaction (Singh, 2023).

Personalisation plays a crucial role in enhancing the user experience with AI-based language models. AI systems that adapt their responses based on user preferences, history, and context are more likely to deliver relevant and engaging interactions. Personalisation in AI services involves learning from previous interactions, adjusting responses to align with individual preferences, and offering tailored recommendations. Studies show that AI-driven systems that incorporate personalised experiences lead to higher levels of user satisfaction and retention (Rust & Oliver, 1994). However, personalisation also raises privacy concerns, as AI systems require extensive user data to optimise their interactions. Balancing personalisation with data privacy is a challenge that AI developers must address to maintain user trust while delivering customised experiences.

Perceived benefits are another key determinant of satisfaction, referring to the extent to which users find AI-generated interactions useful, efficient, and valuable in their daily tasks (Zeithaml, 1988). Users expect AI to provide quick, relevant, and insightful responses that add value to their interactions. When users perceive AI as helpful, they are more likely to integrate it into their workflows, leading to higher engagement and long-term adoption (Uren & Edwards, 2023). The perceived usefulness of AI varies depending on the context; for example, in customer service, users value AI's ability to provide instant responses and resolve issues efficiently, while in content creation, users appreciate AI's capacity to generate high-quality text with minimal effort. However, if AI-generated content lacks depth, coherence, or originality, users may perceive it as redundant or unreliable, reducing satisfaction (Heskett et al., 1997).

Empirical research on AI satisfaction suggests that multiple factors contribute to the user experience, including ease of use, cognitive effort, and the system's ability to handle complex queries effectively (Adeiza et al., 2022). User experience (UX) research has shown that frustration arises when AI systems fail to understand user intent or generate responses that are irrelevant or misleading. To improve user satisfaction, AI developers must continuously refine models to enhance accuracy, contextual awareness, and conversational fluency. Ethical considerations, including AI fairness, transparency, and adaptability, also play a role in shaping user perceptions of AI reliability and usefulness (Singh, 2023).

As AI technology advances, organisations leveraging AI-driven services must prioritise improving user experience by optimising model performance, addressing ethical concerns, and ensuring responsible AI deployment. Future AI developments should focus on reducing algorithmic bias, enhancing personalisation capabilities, and providing clear explanations for AI-generated decisions. The ongoing refinement of AI-based language models will contribute to more effective, trustworthy, and engaging interactions, ultimately driving greater user satisfaction and adoption.

2.3 Relationship between age and attitude towards artificial intelligence

Numerous studies support the relationship between age and attitudes towards artificial intelligence (AI), demonstrating how age influences perceptions, acceptance, and willingness to embrace AI technologies (Pejić Bach & Marić, 2025). However, most of these studies have been conducted in relation to health care and medical research. Generally, younger individuals tend to exhibit more favourable attitudes towards AI compared to older generations.

Research indicates that younger respondents often have higher trust levels in AI systems, which correlates with their familiarity and comfort with new technologies (Ongena et al., 2021; York et al., 2020). In contrast, older demographics frequently display scepticism and apprehension towards AI applications, especially in healthcare settings where concerns about decision-making and precision in AI capabilities arise (Fritsch et al., 2022).

Furthermore, attitudes towards AI vary significantly across different age groups due to generational differences in technology exposure and inherent learning curves. Yiğitcanlar et al. highlight how individual factors such as age and knowledge about AI significantly shape public perception, with older individuals generally being less informed about AI developments Middle-aged populations have shown mixed responses, exhibiting scepticism towards adopting AI, particularly chatbots and similar technologies, due to perceived complexities and usability challenges (Wang et al., 2024).

While educational attainment plays a role in shaping attitudes towards AI, with higher education levels correlating with greater acceptance and trust, age often serves as a primary barrier. Shevtsova et al. noted that older participants (aged 40-60 and above) exhibited awareness of and positive attitudes towards AI technologies; however, this was not uniform across all older individuals, with some demonstrating reluctance (Shevtsova et al., 2024). Additionally, factors such as gender, experience with technology, and anxiety about AI modulate these attitudes (Sindermann et al., 2022; Alkhalifah et al., 2024). Research by Sindermann et al. illustrates that personal characteristics and previous interactions with AI systems create a reciprocal influence, complicating the dynamics of acceptance among varying age groups (Sindermann et al., 2022).

In summary, understanding the relationship between age and attitudes toward AI requires a multifaceted examination of demographic variables, personal experiences, and educational background. As age increases, the inclination to trust and accept AI technologies often diminishes, influenced by individual experiences and societal perceptions regarding technology and its intersection with daily life (Kauttonen et al., 2025; Zhang et al., 2023).

3 Methodology

3.1 Research questions and hypotheses

Guided by the aim of explaining why Croatian users embrace Chatgpt, the study poses two overarching research questions. RQ1 asks: Which experiential beliefs most strongly predict overall satisfaction with ChatGPT? Building on the Technology Acceptance Model and service quality theory, we propose that two beliefs—perceived ease of use and perceived reliability—serve as the primary antecedents. Accordingly, we advance H1: Perceived ease of use exerts a positive influence on satisfaction, and H2: Perceived reliability exerts a positive influence on satisfaction. RQ2 asks: Do these relationships differ across generations that have grown up with distinct digital habits? Drawing on generational theory, we expect younger “digital natives” to weigh usability and reliability more evenly, whereas older “digital adapters” may lean more heavily on reliability once basic usability is assured. Hence we specify H1a and H1b—replicating H1 and H2, respectively, for Generation Z (18–25 years)—and H2a and H2b for Generation Y (26–35 years). Specifically, we predict that both paths will be significant among Generation Z, but among Generation Y, only the reliability path will remain significant. Testing this hypothesis set allows us to isolate the universal drivers of satisfaction while detecting demographic nuances that can inform tailored design and outreach strategies.

3.2 Research instrument

After an introductory greeting, respondents were briefly informed about the purpose of the study and notified that completing the questionnaire would take about five minutes. It was also emphasised that participation in the research was entirely voluntary and anonymous, and that the collected data would be presented exclusively in an aggregated format. An elimination question was included to determine whether the respondent had ever used ChatGPT, with further participation allowed only for those who answered affirmatively. The research instrument was a survey questionnaire composed of 11 closed-ended questions divided into three sections (Table 1). All 11 items employ a five-point Likert format ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

Table 1: Research instrument

Latent variable	Code	Items
Perceived ease of use (PEOU)	PEOU1	I appreciate the ability to start interacting with ChatGPT regardless of location and time.
	PEOU2	ChatGPT saves me time by providing quick access to information.
	PEOU3	Interacting with ChatGPT justifies the time and effort spent to get the information I want.
	PEOU4	I find ChatGPT easy to use.
Reliability (REL)	REL1	ChatGPT has provided a wide range of information related to my questions, including detailed explanations and relevant examples.
	REL2	ChatGPT service offers greater efficiency in finding information compared to using other tools.
	REL3	ChatGPT provides me with exactly the level of service and quality of information that I expected.
	REL4	ChatGPT helps me to complete many tasks and efficiently.
Satisfaction (SAT)	SAT1	I am satisfied with the overall experience of using ChatGPT.
	SAT2	I plan to continue using ChatGPT in the future.
	SAT3	I would recommend others to use ChatGPT.

Source: Authors' work

Perceived ease of use (PEOU) is gauged using four items that prompt respondents to judge, first, how effortlessly they can initiate a ChatGPT session regardless of time or place and, second, whether the system demonstrably saves them time by delivering information rapidly. Two additional statements ask participants to weigh the overall cost-benefit of the interaction and give a direct appraisal of how easy the tool is to handle. Reliability (REL) is likewise assessed with four indicators. Respondents reflect on the breadth and depth of explanations received, the comparative efficiency of ChatGPT vis-à-vis alternative information sources, the extent to which the service meets their prior expectations of quality, and its usefulness in completing everyday tasks with minimal friction. User satisfaction (SAT) is measured by three items: a global affective evaluation of the experience, an intention to continue using the system, and a willingness to recommend it to others. At the end of the questionnaire, sociodemographic data of respondents were collected.

3.3 Sample and data collection

The overall sample consisted of 357 respondents who had at least used ChatGPT once. A total of 357 people completed the survey. Roughly two-thirds of them were women, while a little over one-third were men. The group was quite young overall: about seven out of every ten respondents were between 18 and 25 years old, and the remaining three out of ten were 26 to 35; no one older than 35 took part. Educational backgrounds ranged from secondary to postgraduate levels. Just under half of the participants had finished high school without yet earning a university degree. Around one quarter held a bachelor's degree, and almost the same proportion had completed a master's programme. Only one respondent reported having a PhD. In sum, the sample represents a predominantly young, female-leaning population with education spanning from high school through master's studies.

3.4 Statistical analysis

To examine the hypothesised relationships among perceived ease of use, reliability and user satisfaction, we applied structural-equation modelling (SEM) in JASP 0.18, which relies on the Lavaan package for maximum-likelihood estimation. Screening showed no extreme multivariate outliers (Mahalanobis distance, $p > .001$). Univariate skewness and kurtosis fell within ± 2, allowing the use of (robust) ML estimation; nonetheless, we adopted the Satorra–Bentler correction to guard against any residual non-normality.

All eleven survey items were specified as reflective indicators of their respective latent constructs. A confirmatory factor analysis (CFA) was first run on the pooled sample to verify factorial validity. Internal consistency was judged with both Cronbach's α and composite reliability (CR); values ≥ 0.70 were deemed acceptable. Convergent validity was inspected through standardised factor load-

Table 2: Sample structure and demographics

Characteristic	Modalities	n	%	Cumulative %
Gender	Female	224	62.7/	62.7
	Male	133	37.3%	100.0
Age	18-25	248	69.5	69.5
	26-35	109	30.5	100.0
Education	High School	173	48.5	48.5
	Bachelor	96	26.9	75.4
	Master	87	24.4	99.7
	PhD	1	0.3	100.0
	Total	357	100.0	

Source: Authors' work

Table 3: The main purpose of using ChatGPT

	Total	18-25	26-35	Chi-square
Purpose	n=357	n=248	n=109	59.648**
Help with learning/education	44.5%	56.5%	17.4%	
Writing/editing text	28.3%	23.4%	39.4%	
Translation/language support	7.6%	4.4%	14.7%	
Seeking information relevant to work	3.9%	2.0%	8.3%	
Health advice/therapeutic purposes	0.6%	0.4%	0.9%	
For asking simple questions (e.g., "What time is it?", "What is the capital of Italy?", etc.)	2.5%	2.0%	3.7%	
Entertainment/chatting	5.3%	4.8%	6.4%	
Analysis of large amounts of data	3.9%	3.6%	4.6%	
Recommendations (books, movies, restaurants, etc.)	2.5%	2.8%	1.8%	
Other purposes	0.8%	0.0%	2.8%	
Total	100.0%	100.0%	100.0%	

Note: *** statistically significant at 1%
Source: Authors' work

ings (target ≥ 0.70) and average variance extracted (AVE ≥ 0.50). After psychometric adequacy was confirmed, we proceeded to the structural step.

The posited paths from perceived ease of use and reliability to satisfaction were estimated simultaneously. Model-level fit was evaluated with multiple indices to offset the limitations of any single statistic: the comparative fit index (CFI ≥ 0.90 for good fit), the Tucker–Lewis index (TLI ≥ 0.90), the root-mean-square error of approximation (RMSEA ≤ 0.06, 90 % CI reported) and the standardised root-mean-square residual (SRMR ≤ 0.08). Predictive power was gauged with the squared coefficient of determination (R^2) for satisfaction as the endogenous construct. Given the age split in the sample, we tested the structural model separately for the 18–25 and 26–35 cohorts, using the multigroup approach.

JASP's Network Analysis module was used to estimate a Gaussian Graphical Model by applying the graphical LASSO to the research items of variables PEOU, SAT and REL. The procedure decreases small partial correlations to zero and chooses the optimal amount of regularisation with the EBIC (engl. Extended Bayesian Information Criterion) tuning rule. The resulting graph displays only those conditional associations that survive this penalisation.

4 Results

4.1 Attitudes towards ChatGPT among Generation Z and Generation Y

Results presented in Table 1 indicate that most respondents say they turn to ChatGPT for study-related tasks: overall 45 % use it primarily to support learning, and this motive dominates in the 18-to-25 cohort (57 %) but drops sharply among 26-to-35-year-olds (17 %). In contrast, older users rely on the tool mainly for writing or editing text (39 % versus 23 % in the younger group) and are more likely to seek translation help or job-related information. Smaller shares across both ages mention casual queries, entertainment, data analysis or recommendations, and only a handful cite health advice or "other" reasons. The chi-square value ($\chi^2 = 59.65$, $p < .01$) confirms that the pattern of purposes differs significantly between the two age brackets.

Roughly one user in four opens ChatGPT only occasionally: 28 % of the total sample report logging in less than once a month, with no great age difference at that lowest tier of engagement (Table 4). Beyond that point, however, the two cohorts diverge. Younger respondents (18–25) are in the mid-range: they are more likely to say they use the tool "once a month" or "several times a month," and fewer reach the higher-frequency categories. Older respondents (26–35) lean in the opposite direction: a fifth of them enter ChatGPT several times a week, and one in six does so many times a day—more than double the proportion seen in the younger group. These contrasting usage patterns yield a chi-square of 16.58 ($p < .01$), confirming that frequency of interaction with ChatGPT varies significantly by age.

About three-quarters of all respondents—77 %—say they regard ChatGPT as an intelligent system, while roughly one in four do not (Table 5). This perception is virtually identical in both age groups (77.4 % among 18- to 25-year-olds versus 77.1 % among 26- to 35-year-olds). The very small, non-significant chi-square value (χ^2 = 0.014) confirms that age makes no observable difference to this judgement.

Table 4: Frequency of ChatGPT use

Usage frequency	Total n=357	18-25 n=248	26-35 n=109	Chi-square
Rarely (less than once a month)	27.5%	28.6%	24.8%	16.583**
Once a month	7.0%	9.3%	1.8%	
Several times a month	24.6%	26.6%	20.2%	
Weekly	9.8%	9.3%	11.0%	
Several times a week	18.5%	16.9%	22.0%	
Once a day	2.8%	2.4%	3.7%	
Multiple times a day	9.8%	6.9%	16.5%	
Total	100.0%	100.0%	100.0%	

Note: *** statistically significant at 1%
Source: Authors' work

Table 5: Considering ChatGPT as intelligent

Consider ChatGPT intelligent	Total n=357	18-25 n=248	26-35 n=109	Chi-square
No	22.7%	22.6%	22.9%	0.014†
Yes	77.3%	77.4%	77.1%	
Total	100.0%	100.0%	100.0%	

Note: † not statistically significant
Source: Authors' work

Table 6: Level of LLM knowledge

Knowledge LLM	Total n=357	18-25 n=248	26-35 n=109	Chi-square
Yes	30.0%	27.0%	36.7%	3.381†
No	70.0%	73.0%	63.3%	
Total	100.0%	100.0%	100.0%	

Note: † not statistically significant
Source: Authors' work

Table 7: Relationship between the level of LLM knowledge and considering ChatGPT as intelligent

Knowledge LLM	Consider ChatGPT intelligent			Chi-square
	No	Yes	Total	
Yes	39,5%	26,9%	29,8%	4.749*
No	60,5%	73,1%	70,2%	
Total	100,0%	100,0%	100,0%	

Note: * statistically significant at 5%
Source: Authors' work

Table 8: Chi-Square test

Model	X^2	df	p
Baseline model	2548.617	55	
Factor model	144.264	41	< .001

Source: Authors' work

Table 9: Fit indices

Fit indices	Value
Comparative Fit Index (CFI)	0.959
Tucker-Lewis Index (TLI)	0.944
Root mean square error of approximation (RMSEA)	0.084
Standardised root mean square residual (SRMR)	0.039
Goodness of fit index (GFI)	0.988

Source: Authors' work

Only three out of ten respondents say they already know what a large-language model (LLM) is, while the remaining seven out of ten admit they do not (Table 6). Self-reported familiarity is somewhat higher among the 26- to 35-year-olds (37 %) than among the 18- to 25-year-olds (27 %), but the gap is small, and the chi-square test (χ^2 = 3.38) shows it is not statistically reliable. In other words, most users interact with ChatGPT without being able to describe the underlying technology, and this lack of technical knowledge is shared across both age groups.

A user's grasp of what a large-language model is shapes the way they judge Chatgpt's intelligence, as indicated by Table 7. Among participants who say they understand LLMs, only about 27 % call the system intelligent, whereas the figure rises to 73 % for those who lack that technical knowledge. Conversely, knowledgeable users make up a larger share of the "not intelligent" camp. The association is modest but statistically reliable (χ^2 = 4.75, $p < .05$), indicating that deeper familiarity with the technology tends to temper perceptions of ChatGPT's intelligence.

4.2 Measurement model

The chi-square test pits the hypothesised three-factor solution against an independence (baseline) model in which all items are assumed uncorrelated (Table 8). The baseline model shows an enormous misfit (χ^2 = 2,548.62, df = 55), whereas the factor model cuts the discrepancy to χ^2 = 144.26 with 41 degrees of freedom. Although the χ^2 statistic for the factor model is still significant (reflecting its sensitivity to sample size), the reduction of more than 2,400 chi square units demonstrates that the latent variable structure explains the observed covariances far better than a null model.

Most descriptive indices meet or exceed conventional benchmarks (Table 9). The CFI (.959) and GFI (.988) signal a very good fit (≥ .95), and the TLI (.944) is just below the same threshold, still considered acceptable. Residual-based measures are also favourable: the SRMR (.039) is comfortably under the .08 criterion, while the RMSEA (.084) is in the "reasonable fit" band (.05–.08) but slightly above the ideal .06 cutoff, suggesting mild room for improvement in model parsimony.

All 11 indicators load strongly and significantly on their intended factors; standardised loadings range from .685 (REL3) to .879 (SAT2), well above the 0.70 rule of thumb (Table 10), which confirms that each item is a reliable reflection of its latent construct.

Coefficient ω and Cronbach's α exceed .84 for every scale, indicating high reliability (Table 11). Average variance extracted (AVE) surpasses .50 for PEOU (.621), REL (.592) and SAT (.728), confirming that, within each construct, the indicators share more variance with the latent factor than with measurement error.

All heterotrait-monotrait (HTMT) ratios fall below the conservative .85 threshold (largest = .806 between SAT and PEOU). Thus, the three constructs are statistically distinguishable despite being moderately correlated (Table 12).

Taken together, the chi-square comparison, fit indices, strong loadings, high reliability, adequate AVE, and satisfactory HTMT ratios provide a coherent body of evidence that the three-factor measurement model is reliable and valid for capturing perceived ease of use, reliability, and satisfaction with ChatGPT.

Table 10: Factor loadings

Factor	Indicator	Estimate	Std. Error	z-value	p	Std. Est. (all)
PEOU	PEOU1	0.746	0.046	16.091	< .001	0.755
	PEOU2	0.808	0.042	19.292	< .001	0.854
	PEOU3	0.723	0.043	16.835	< .001	0.780
	PEOU4	0.684	0.042	16.227	< .001	0.761
REL	REL1	0.750	0.044	17.157	< .001	0.792
	REL2	0.800	0.049	16.476	< .001	0.769
	REL3	0.704	0.050	14.034	< .001	0.685
	REL4	0.846	0.046	18.311	< .001	0.828
SAT	SAT1	0.730	0.041	18.007	< .001	0.812
	SAT2	0.792	0.039	20.416	< .001	0.879
	SAT3	0.805	0.040	19.924	< .001	0.865

Source: Authors' work

Table 11: Reliability and average variance extracted

	Coefficient ω	Coefficient α	AVE
PEOU	0.869	0.866	0.621
REL	0.849	0.853	0.592
SAT	0.892	0.886	0.728
Total	0.942	0.926	

Source: Authors' work

Table 12: Heterotrait-monotrait ratio

	PEOU	REL	SAT
PEOU	0.788		
REL	0.734	0.769	
SAT	0.806	0.800	0.853

Source: Authors' work

Table 13: SEM results for the total sample and Gen Z vs. Gen Y

Group	Outcome	Predictor	Estimate	Std. Error	z-value	R-squared	Hypothesis
Total	SAT	PEOU	0.424	0.072	5.871**	0.716	H1 ✓ (+1%)
		REL	0.457	0.072	6.321**		H2 ✓ (+1%)
18-25	SAT	PEOU	0.435	0.082	5.297**	0.722	H1a ✓ (+1%)
		REL	0.469	0.080	5.872**		H1b ✓ (+1%)
26-35		PEOU	0.262	0.178	1.469†	0.715	H2a Ø
		REL	0.522	0.171	3.057**		H2b ✓ (+1%)

Note: ** statistically significant at 1%; † not statistically significant
Source: Authors' work

4.3 Structural equation modelling

The structural-equation results in [Table 13] show that, in the full sample, both perceived ease of use (PEOU) and perceived reliability (REL) make sizable, statistically significant contributions to satisfaction with ChatGPT (β = 0.42 and 0.46, respectively). Together, they explain about 72 % of the variance in satisfaction.

When the analysis is split by generation, the pattern diverges slightly. For the Gen Z cohort (18–25 years), both paths remain strong and significant ($\beta \approx 0.44$ for PEOU and 0.47 for REL), again accounting for roughly 72 % of satisfaction. For the Gen Y group (26–35 years), reliability is still a significant driver ($\beta = 0.52$). However, ease of use drops to a weaker, non-significant role ($\beta = 0.26$, $p > .05$). Thus, older respondents appear to base their satisfaction chiefly on how dependable ChatGPT's answers are. In contrast, younger users weigh usability and reliability almost equally. Overall, hypotheses H1, H2, H1a and H1b are supported, while H2a is not, and H2b is confirmed.

4.4 Network analysis

Figure 1 visualises the partial-correlation network among the eleven survey items for the whole sample. Each node represents one questionnaire statement, coloured by its latent construct (pink = Perceived Ease of Use, green = Reliability, blue = Satisfaction). Lines indicate regularised partial correlations that remain after controlling for all other items: thicker, darker blue lines mark stronger positive linkages, whereas the virtual absence of red lines means no appreciable negative associations survived the graphical LASSO penalty.

Three observations stand out. First, nodes cluster almost perfectly by their theoretical section, confirming that items within the same construct share stronger conditional ties with each other than with items from other constructs. Second, the densest within-cluster edges appear in the Satisfaction trio—especially between “continue using” (SAT2) and “recommend to others” (SAT3)—highlighting their conceptual closeness. Third, two cross-cluster bridges emerge: PEOU2 (“saves me time”) connects to REL2 (“more efficient than other tools”), and REL4 (“helps me complete tasks”) links to SAT1 (“overall satisfied”). These bridges reflect the pathways later captured in the SEM: ease of use and reliability channel their influence into satisfaction via efficiency and task accomplishment.

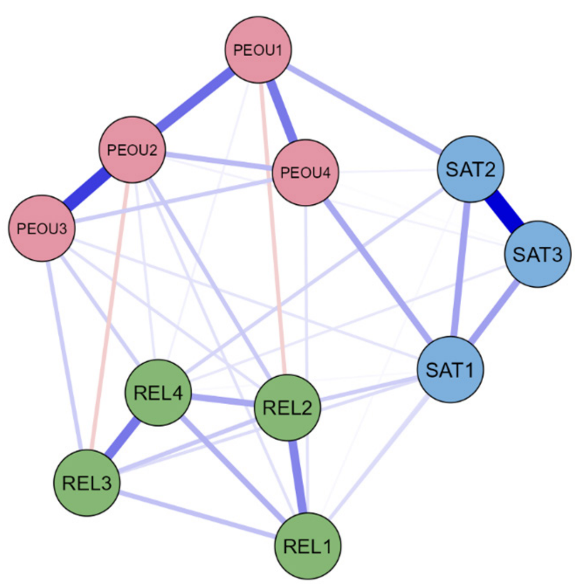
Centrality analysis (strength) shows SAT2 and REL4 as the most influential nodes in the network, suggesting that intentions to keep using the service and perceptions of task efficiency play pivotal roles in holding the entire attitude system together.

To complement the multigroup SEM, Gaussian graphical models were estimated separately for the 18–25-year-old respondents (Generation Z) and the 26–35-year-old respondents (Generation Y).

In each subsample, the eleven manifest variables were treated as continuous, and the networks were obtained with the graphical LASSO, selecting the optimal tuning parameter by the EBIC rule (γ = 0.50). The resulting graphs, depicted in Figure 2, visualise regularised partial correlations: edge width conveys absolute strength, blue hues denote positive relations, and the sparse red lines indicate residual negative associations that survived regularisation. Nodes are colour-coded by their theoretical domain—pink for perceived ease of use (PEOU1-4), green for reliability (REL1-4) and blue for satisfaction (SAT1-3).

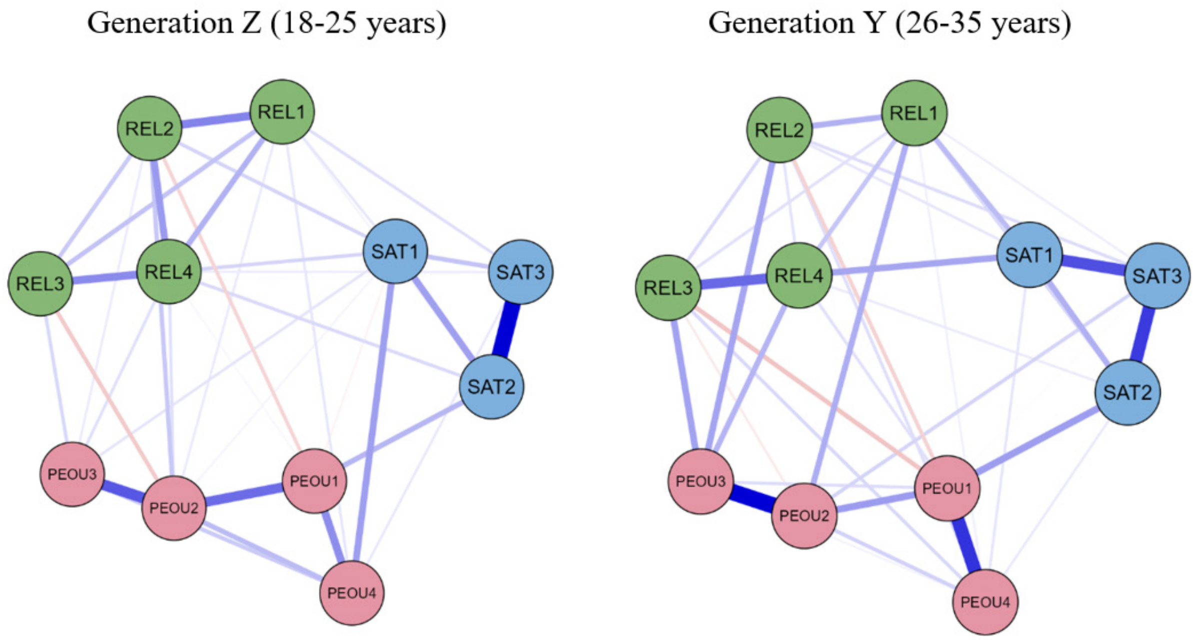
For Generation Z, the topology is highly interwoven. Although the three construct clusters are still discernible, several medium-to-strong bridges link the ease-of-use nodes directly to the satisfaction cluster. The most prominent of these connects the “time-saving” item PEOU2 to both SAT1 (overall experience) and SAT2 (intention to continue). Centrality indices corroborate the visual impression: SAT2 and PEOU2 show the highest strength centrality, indicating that usability cues and future-use intentions form the main hubs through which information flows in the younger cohort. This pattern aligns with the SEM finding that, for Gen Z, perceived ease of use contributes to satisfaction almost as strongly as perceived reliability.

By contrast, Generation Y’s network is more compartmentalised. Most cross-construct connections are weak or absent after regularisation, and the reliability items form the densest sub-graph. REL4 (“helps me complete tasks”) emerges as the key bridge to satisfaction, maintaining a thick edge to SAT1; links emanating from ease-of-use items are much thinner. Consequently, strength centrality ranks REL4 and SAT3 well above the usability nodes,



Source: Authors’ work

Figure 1: Network analysis of a total sample



Source: Authors' work

Figure 2: Network analyses of Generation Z and Generation Y

mirroring the SEM result in which reliability, but not ease of use, significantly predicts satisfaction among older respondents.

Taken together, the generation-specific networks reinforce the multigroup SEM conclusions. Where Gen Z's perceptions of ChatGPT resemble a highly integrated attitude system in which usability and reliability jointly feed into satisfaction, Gen Y's perceptions resemble a modular system whose satisfaction component is supplied chiefly by reliability cues. These structural differences suggest that design and communication strategies aimed at younger users should emphasise both frictionless interaction and dependable output. In contrast, strategies for slightly older users may generate greater returns by foregrounding the system's trustworthiness and task efficacy.

5 Conclusion

This study set out to answer two questions: RQ1, which experiential beliefs drive satisfaction with Chatgpt, and RQ2, whether those drivers differ across generations, and to test the associated hypotheses (H1–H2b). The evidence affirms that perceived ease of use and perceived reliability are the principal antecedents of satisfaction, thereby supporting H1 and H2 for the total sample. However, the multi-group analysis reveals a generational inflexion. Among Generation Z (18–25 years), both ease of use and reliability significantly shape satisfaction, validating H1a and H1b. Among Generation Y (26–35 years), only reliability retains explanatory power, leading to the acceptance of H2b and the rejection of H2a.

These findings are best understood against the backdrop of generational digital literacy. Gen Z has grown up with ubiquitous, intuitive technology; for them, the enjoyment of an AI assistant is tightly linked to how engaging the interface feels. Gen Y is equally tech-savvy but has accumulated more professional experience; accordingly, it places greater weight on the trustworthiness and consistency of information. Designers targeting Gen Z should prioritise interactive, visually rich and highly personalised features, while for Gen Y, marketing messages and product roadmaps should foreground data security and transparent sourcing.

The results also speak to product-development strategy. Segmenting the user base by generation and tailoring feature sets to the specific expectations of each cohort can raise adoption and retention rates. Further research that probes the psychological reasons behind these generational preferences would help refine such segmentation. Finally, user-education programmes should mirror these needs: Gen Z may benefit from tutorials that showcase creative prompt engineering and playful use cases. Gen Y may prefer guidance on evaluating output quality, integrating citations and enforcing ethical safeguards.

These patterns carry several practical implications. Developers hoping to retain younger audiences must continue to streamline prompts, reduce latency and integrate conversational cues that signal effortlessness, while also safeguarding output quality. For older, professionally focused users, investments in source transparency, factual accuracy and task-specific guidance are likely to yield greater returns. Educators, meanwhile, should recognise that most students still lack a working knowledge of LLM technology and thus need structured training not only in prompt engineering but also in critical appraisal and ethical deployment of generative AI.

The study also expands the empirical reach of technology-acceptance research, which has so far concentrated on clinical contexts, by demonstrating that the same constructs operate—and operate differently—among future managers and entrepreneurs. Methodologically, it shows the value of coupling covariance-based SEM with graphical LASSO networks to obtain both confirmatory and exploratory insight.

Future work should replicate the model in organisational field studies, track longitudinal adoption trajectories and probe additional moderators such as task complexity or domain expertise. Additionally, it would be interesting to investigate whether the ChatGPT tool is more useful for natural science or social science professional users, and what the differences are between these two groups of users. Limitations remain and should be considered when taking into account the results of this research. The convenience sample, reliance on self-report and cross-sectional design restrict generalisability and causal inference. Even so, the present findings offer a grounded starting point for designing, teaching and governing conversational AI in the management arena.

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Vpliv uporabnosti in zanesljivosti na zadovoljstvo z orodjem ChatGPT med generacijo Z in generacijo Y

Ozadje/Namen: Hitro širjenje ChatGPT-ja je tehnologijo velikih jezikovnih modelov (LLM) iz specializiranega orodja preobrazilo v splošno dostopnega pomočnika za učenje in delo. Kljub temu je empiričnih dokazov o dejavnikih, ki vplivajo na zadovoljstvo uporabnikov zunaj medicinskega okolja, še vedno malo. Študija se osredotoča na prihodnje poslovne in managerske strokovnjake na Hrvaškem ter raziskuje, kako zaznana enostavnost uporabe in zaznana zanesljivost vplivata na zadovoljstvo z uporabo ChatGPT ter ali se ti vplivi razlikujejo med generacijo Z (18–25 let) in generacijo Y (26–35 let).
Metodologija: V spletni anketi, izvedeni avgusta 2024, je bilo zbranih 357 veljavnih odgovorov. Merilni model je dosegel visoke standarde zanesljivosti in veljavnosti (CFI = 0,96, SRMR = 0,04).
Rezultati: Modeliranje strukturnih enačb je pokazalo, da sta zaznana enostavnost uporabe (β = 0,42) in zanesljivost (β = 0,46) skupaj pojasnili 72 % zadovoljstva v celotnem vzorcu. Analiza po skupinah je pokazala generacijsko razliko: oba dejavnika sta bila pomembna za generacijo Z, medtem ko je bila za generacijo Y pomembna le zanesljivost. Gaussovi grafični modeli so potrdili te ugotovitve – pri mlajših uporabnikih se je oblikovalo gosto prepleteno omrežje stališč, medtem ko je bilo pri starejših osredotočeno predvsem na zanesljivost.
Zaključek: Študija razširja raziskave o sprejemanju tehnologij na področje managementa, poudarja vpliv generacije kot moderirajočega dejavnika in prikazuje vrednost kombiniranja SEM in mrežne analitike. Ugotovitve ponujajo uporabne vpoglede za oblikovalce in pedagoge, ki želijo spodbujati premišljeno, odgovorno in zadovoljivo uporabo generativne umetne inteligence.

Ključne besede: *Umetna inteligenca, Veliki jezikovni modeli (LLM), Marketing, Zadovoljstvo uporabnikov, Hrvaška, ChatGPT*

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Evaluating Attitudes Toward Microchip Implants: A Comparative Study of five Eastern European Countries

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Conflicts of interest: All authors declare that they have no conflicts of interest.
Ethics statement: All procedures performed in this study involving human participants were in accordance with the ethical standards of the University of Maribor, Faculty of Organizational Sciences research committee (decision no. 514/5/2021/1/902-DJ) and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.
Background and purpose: Technology acceptance has been researched for decades. While some technologies are widely accepted, others are perceived as a threat, such as microchip implants. In this study, a two-step structural equation modeling approach was used to evaluate a new research model on microchip implant acceptance.
Methodology: A structural equation modeling model was developed to identify what influences the perceived acceptance of microchip implants. To determine differences in attitudes toward microchip implants, the study was conducted in five Eastern European countries.
Results: The results show that the influence of the factors does not differ significantly across the countries studied. Age, trust, and perceived usefulness affected the overall intention to use microchip implants, while ease of use was significant in only one country. Differences were found in perceptions of the right to privacy and conspiracy theories. The usefulness of microchip implants in pandemic was significant in all countries.
Conclusion: Small differences in attitudes towards microchip implants suggest that a general model of microchip implant acceptance could be constructed based on the data collected. In addition to these findings, our study noted the lack of legislation for microchip implants in the region and a lack of knowledge about this technology.

Keywords: *Microchip implant, Near field communication, Behavioural intentions, Structural equation model, Technology acceptance model*

1 Introduction

Since the first decade of the 21st century, the use of microchips in living organisms has been increasingly reported in the literature. Initially, aspects of the implementation of microchip implants (MIs) dominated as a tool for the identification of animals, particularly dogs and cats (Garcia et al., 2020; Turoń et al., 2015). Subsequent reports on

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the use of MIs can generally be divided into two groups: medical and non-medical use.

In the medical field, MIs have been used to access medical records and vaccination (Rotter et al., 2008), to detect patients with changes in mental status (Fram et al., 2020), to monitor patients' heart, blood glucose levels, and general health (Sundaresan et al., 2015), for drug delivery systems (Barbone et al., 2019; Magnusson & Mörner, 2021; Suhail et al., 2021), for visual organs, and smart dentures (Madrid et al., 2012). They have been used for birth control (Shafeie et al., 2022), surgical treatments (Suhail et al., 2021) or to support treatment such as activation of damaged brain parts (Łaszczyca, 2017). In addition to healthcare applications, MIs have also been used to identify the deceased after natural disasters (Meyer et al., 2006).

Alongside medical applications, there are numerous studies in the literature on the use of MIs in non-medical settings. MIs have been used for personal identification (K. Michael et al., 2017; Rotter et al., 2008), purchases and contactless payments (K. Michael & Michael, 2010), access to secured doors, workplaces or smart homes (Carr, 2020; Rotter et al., 2008) and even cryptocurrency transactions (K. Michael, 2016), tracking people indoors, monitoring employee activity (Banafa, 2022; Rodriguez, 2019), and launching applications (Heffernan et al., 2016; Rohei et al., 2021; Siibak & Otsus, 2020) or enhancing innate abilities (Heffernan et al., 2017).

Despite the abundance and diversity of microchip implant (MI) applications, they are treated as a controversial advanced technology, and the benefits of their use in daily life must be balanced with privacy (Carr, 2020), ethical considerations (Moosavi et al., 2014), health risks due to animal test results (Albrecht, 2010; Sapierzyński, 2017), security (Huo, 2014), and legal issues (Graveling et al., 2018).

Another issue that is raised just as frequently in the literature is the possibility of people being controlled by the government or criminal organizations (Gagliardone et al., 2021; Gu et al., 2021). The introduction of microchips in everyday devices has also raised concern among users. These concerns include widely accepted privacy (or loss thereof) and ease of fraud (Graveling et al., 2018).

During the COVID-19 pandemic, the MI technology and the diversity of its uses received additional attention for and against its use. In any case, it is evident that the need for identification of individuals is increasing not only in healthcare but also in society. Despite a considerable number of reports on the use of MIs and discussions for and against their use, research on the acceptance of MIs by individuals is limited and mainly restricted to a specific group or smaller samples of potential users. Moreover, differences or similarities in the acceptance of MIs by the country of origin have not been explored in any of the cases presented.

The first study on the acceptance of MIs found in the literature was conducted by Smith (2008) and included only students. A few years later, Achille et al. (2012) and Perakslis & Michael (2012) conducted a study on the acceptance of MIs, but it was limited to a specific age group, whereas the studies presented by K. Michael et al. (2017) and Perakslis et al. (2014) were limited to small business owners. In addition, the research by Mohamed (2020) was limited to a sample of people with various disabilities. The research by Pettersson (2017) and Boella et al. (2019) used interviews to understand the reasons for using MIs, thus both studies included smaller samples. To gain insight into personal perspectives on the adoption of MIs, Shafeie et al. (2022) included open-ended questions in their survey. The resulting model for behavioral intention to use MIs is very thorough, but the sample size was limited and statistical significance of differences in demographic characteristics was not possible.

The study presented by Pelegrín-Borondo et al. (2017) included a large and diverse sample in terms of basic characteristics. Their acceptance model explained over 73% of the intentions to use MIs. However, the study was limited to the Spanish population. In contrast, the study by Olarte-Pascual et al. (2021) included a large international sample, but it was not large enough to identify cross-cultural differences.

The study presented by Gangadharbatla (2020) included a larger and more representative sample, but the results were evaluated using only basic statistics, which limits the conclusions that can be drawn from the findings. Although Chebolu (2021) included a smaller sample of students in the study, an attempt was made to identify differences in the use of MIs based on demographic characteristics. The results indicated that gender, religion, education, and race/ethnicity were not significant factors in the use of MIs. The report on changing perceptions of biometric technologies by Franks & Smith (2021) revealed a slight increase in willingness to use MIs compared to the previous year. Furthermore, the study concluded with a general understanding among the 99 interviewers in Australia that MIs are an inevitable part of the future. As the overview indicates, existing technology acceptance models do not fully capture distinctive factors that shape the acceptance of MIs. Up to this point, it was not clear how factors such as age, trust, perceived usefulness, ease of use, privacy concerns and conspiracy theories affect the acceptance of MIs.

The research team at the Faculty of Organizational Sciences, University of Maribor has been studying attitudes toward MIs since 2014 (Werber et al., 2018). In the meantime, MI technology has evolved and attitudes toward technology have also changed due to the recent pandemic. Carr (2020) even believes that MI can be a solution to reduce contacts and risks after pandemic outbreaks. Due to the changes in attitudes toward MIs, described above, the research model presented in Werber et al. (2018) and Žnidaršič, Baggia, et al. (2021) was updated and the study was expanded to include a sample from a larger geographic region. Furthermore, given the paucity of knowledge regarding the variation in attitudes towards MI across different countries, an international cross-sectional study was conducted in five countries within the Eastern European region. To date, no research has been conducted on a large, heterogeneous sample that would allow for the identification of differences or similarities in the adoption of MIs according to country of origin. The objective of this research is to address the aforementioned research gap by including a large and diverse sample of participants from different countries and assessing potential differences in their perceptions of MIs following the outbreak of the COVID-19 pandemic. Aligned with this, the dearth of research on the perceived usefulness of MI in the context of pandemics was addressed. Differences in the acceptability of MIs after the pandemic outbreak of COVID-19 were assessed using the two-stage Structural Equation Modeling (SEM) approach. The object examined in this study is an MI the size of a grain of rice (2 × 12 mm) that cannot be tracked from a distance and serves as an identification device using the Near Field Communication (NFC) standard and radio frequency identification device (RFID).

The remainder of the paper is organized as follows: First, the literature on the adoption of MIs is discussed. Second, the theoretical framework for the construction of the research model is presented, followed by the presentation of the research model, the data collection procedure, and the description of the statistical methods used in this research. The third section on the results includes the descriptive statistics of the questionnaire items, the evaluation of the measurement model, the multigroup analyses, the tests, and the results of the structural model. It also discusses the results, including theoretical and practical implications, limitations, and directions for future research. At the end, the conclusions of the study are presented.

2 Review of research studies in the field of microchip implants

The wave of the COVID-19 pandemic, particularly the prospect of vaccination, triggered a period of heightened concern about microchipping (Ullah et al., 2021). In addition, unspecified organizations were accused of trying to take over the world (Gu et al., 2021; Kozik, 2021). There were conspiracy theories that pointed to the faked triggering of a pandemic in order to implant microchips in people (Moscadelli et al., 2020) and thus to the absolute and unlimited possibility of state surveillance of society (Gagliardone et al., 2021).

It should be noted, however, that fears related to the implantation of microchips in humans did not arise with the outbreak of a pandemic. Since the beginning of the 21st century, the literature has pointed to efforts by various governments to control citizens (which microchipping was intended to enable). Some of the long-standing accusations likely came directly from science fiction literature and questioned trust in public authorities (Gagliardone et al., 2021). For example, the literature pointed to the possibility of replacing human intelligence with easily controlled implanted microchips (Foster & Jaeger, 2007). Microchip implantation could become a common practice that allows the government to monitor citizens (Gu et al., 2021) – first in children (Gasson & Koops, 2013) and later gradually in the monitoring of prisoners and workers (K. Michael et al., 2017; Milanovicz, 2012). Eventually, people even invoked religion and referred to the chip as a mark of the beast (Heffernan et al., 2017; Mohamed, 2020).

Despite these beliefs, MI technology has evolved over the years, especially with regard to security issues (Masyuk, 2019). People use MIs on a voluntary basis (Oberhaus, 2018), some even due to the requirements of their employers (K. Michael et al., 2017). Technological development and the use of insertion aids have increased significantly (Sabogal-Alfaro et al., 2021). At the same time, the social stigma associated with these devices has decreased and the general willingness to use MIs is slowly increasing (Franks & Smith, 2021; Gangadharbatla, 2020; Perakslis et al., 2014). The increased knowledge about non-technological objects inserted into the human body, such as piercings and contraceptives, has contributed to the rise and widespread acceptance of the use of technological injectables (Heffernan et al., 2017).

The use of MI enables various benefits, from storage, rapid scanning and processing of large amounts of data, to saving time or consolidating processes (Adhiarna et al., 2013). According to Paaske et al. (2017), organizations can benefit from MIs by saving time and money through real-time traceability, identification, communication, and other data.

Although such technologies have already been adopted by the market and by individuals, research on the willingness of individuals to adopt MI is either lacking or inconclusive (Mohamed, 2020), depending on the application area (Sabogal-Alfaro et al., 2021), or on a specific age group (Perakslis & Michael, 2012).

Nevertheless, some insights into the acceptability of MIs were obtained. Despite the small sample, Chebolu (2021) found that trust in technology and motivation correlate with the use of MIs. In relation to motivation factor, Franks & Smith (2020) found that recent identity crime victims were more than twice as willing to use MIs than non-victims. Based on the interviews conducted, both Boella et al. (2019) and Pettersson (2017) identified health concerns as well as privacy and safety issues as factors inhibiting the use of MIs. In addition, Pettersson (2017) identified lack of knowledge about the technology as a reason for skepticism about MI. Similarly, Franks & Smith (2021) reported that additional information about MIs was deemed necessary before participants would consider MIs.

Gangadharbatla (2020) investigated the factors that influence the adoption of embedded technologies and proposed a model based on the Technology Acceptance Model (TAM) with several additional factors. The results show, among other things, that male and younger respondents are more likely to have positive attitudes toward embedded technologies. Although the results are interesting, Gangadharbatla (2020) used only basic statistics in his study. Pelegrín-Borondo et al. (2017) examined the factors influencing intention to use MIs in Spain using a causal model based on a modified version of TAM. Their results suggest that affective and normative factors, such as positive emotions and social norms, should be considered when promoting MIs. According to a study by Olarte-Pascual et al. (2021) on the acceptance of wearable and implantable technologies, ethical judgment has a high explanatory power for the intention to use in the digital natives group. In particular, for implantable solutions, egoism has the highest explanatory power for intention to use.

Sabogal-Alfaro et al. (2021) identified the determinants of intention to use non-medical insertable digital devices in Chile and Colombia using the Unified Theory of Acceptance and Use of Technology (UTAUT2) model as the framework for their study. Their results suggest that known predictors of intention have less impact than predictors such as habit and hedonic motivation. Concerns and expectations about MIs were examined by Shafeie et al. (2022). As in previous research, Shafeie et al. (2022) used a survey to assess the acceptability of MIs with an extension of TAM. However, they also included open-ended questions to collect participants' personal views. Different determinants of acceptance were identified and categorized into concerns and expectations. Werber et al. (2018) analyzed the perceptions of microchip implants in one country, and later expanded their study to three countries (Žnidaršič, Baggia, et al., 2021). However, because most of the studies presented were conducted before the outbreak of the COVID-19 pandemic, the results of these studies may be slightly outdated.

The studies presented examined the willingness to adopt MIs, whereas Siibak & Otsus (2020) interviewed fourteen employees who already use MIs. The analysis revealed that the social environment plays a major role in the adoption of MIs. Specifically, employees who used MI were seen as more loyal and committed to the company than their colleagues who declined to use MI.

3 Research model and methods

3.1 Theoretical framework

In this study, the extended model based on TAM was used as the basis for developing questionnaires to investigate the attitudes and factors influencing the use of MIs in different countries of the Eastern European region during the COVID-19 pandemic.

The extended model includes all the basic components of TAM (Venkatesh & Davis, 2000): Perceived Ease of Use (PEU), Perceived Usefulness (PU), Behavioral Intention to Use (BIU), and adds the personal factor of Perceived Trust (PT). In addition, age and variables that include the specifics of the MI technology were added as predictors: Privacy Right (PR), Privacy Threat (PTh), Technology Safety (TS), Health Concerns (HC), and Painful Procedure (PP).

PEU was originally proposed by (Davis, 1989) and defined as the extent to which a person believes that the use of technology is possible without effort. From the original 14 measurement items for PEU proposed by Davis (1989), (Venkatesh & Davis, 2000) reduced the number of measurement items to four, whereas Venkatesh et al. (2012) reformulated this construct into Effort Expectancy, which is measured with four items. Since MI technology is not yet widely used, the pilot study conducted by Werber et al. (2018) showed that survey respondents have difficulties in determining ease of use. On the other hand, using MI is quite easy after the initial process of implantation. Therefore, the measurement items for PEU in the present study were formulated slightly differently than in previous research by Davis (1989), Venkatesh et al., (2012) and Venkatesh & Davis (2000). We defined PEU as the degree of constant availability of the multiple functions of MI, which cannot be lost. Similar to Davis (1989), PU was used to describe people adopting a new technology because they expect to benefit from it or because they find it useful. The BIU construct included items about whether respondents would use MIs for various purposes.

PT refers to individuals' confidence that government, banks, and health care systems will be able to provide certain standards of technology safety (TS), security against threads (PTh), and human rights protection (PR) in the areas of identification, tracking, and archiving of personal information, financial transactions, and patient data.

HC refers to four possible threats from the use of MI: the possibility of movements in the body (Graveling et al., 2018), health threats from possible allergies (Gillenson, 2019), effects on emotional behavior, or other types of health threats (Rotter et al., 2008; van der Togt et al., 2011). In addition, the implementation of MI is painful for some people (M. G. Michael & Michael, 2010), which raises even more health concerns. Age must also be considered when discussing technology acceptance, as younger people are more likely to adopt new technologies (Burton-Jones & Hubona, 2006; Morris & Venkatesh, 2000).

After the outbreak of COVID-19, three additional variables, hypothesized to influence the decision to accept MI, were identified: 1) usefulness of Microchips in Pandemic (MP), 2) Conspiracy Theory (CT) and 3) Fake News (FN).

Indeed, the pandemic situation has revived conspiracy theories and fake news. Some of the conspiracy theories are related to MIs and may influence the credibility of fake news (Halpern et al., 2019) or even vaccination refusal (Ullah et al., 2021). In general, conspiracy mentality reduces trust in official sources and thus increases perceived threats to privacy (Imhoff et al., 2018). CT and FN were therefore added as predictors for the variable PT.

Perceived fear of COVID-19 (Al-Maroof et al., 2020) and perceived COVID-19 risk (Aji et al., 2020) were found to influence the PEU and PU of technology. Therefore, the variable MP is included in the study.

3.2 Research model

Based on the literature review and the theoretical framework presented, a research model with fourteen research hypotheses is proposed, as shown in Figure 1. Nine variables were adopted from the 2017 international cross-sectional study (Žnidaršič, Baggia, et al., 2021). Six variables were added to the three basic components of TAM (PEU, PU and BIU): PT, HC, PP, TS, PTh, PR, and age. Three variables were also added due to lifestyle changes in recent years: CT, FN, and MP.

There are two types of variables included in the model. A construct or latent variable is a variable that is indirectly measured with measured variables. An item or measured variable is a variable that is measured directly with questionnaire items. In Figure 1, constructs are represented by ellipses, while items are represented as rectangles. In addition to contextual differences, statistical analyses (e.g., Confirmatory Factor Analysis (CFA) and the first step of SEM) conducted by Werber et al. (2018), Žnidaršič, Baggia, et al. (2021) and Žnidaršič, Werber, et al. (2021) have shown that the items TS, PP, and MP cannot be considered as one of the measured variables included in specific constructs, but must be included in the model as individual measured variables.

Table 1 shows the constructs and items, the scales used, and the corresponding references that determine the construct or item.

Table 1: Variables of the proposed research model with rating scale and references

<table>
<tr><th>Variable</th><th>Rating scale</th><th>References</th></tr>
<tr><td>Painful Procedure (PP)</td><td rowspan="10">5–point scale of agreement:

1 – strongly disagree
2 – disagree
3 – neither agree nor disagree
4 – agree
5 – strongly agree</td><td>M. G. Michael & Michael, 2010</td></tr>
<tr><td>Privacy Threat (PTh)</td><td>Bansal et al., 2015</td></tr>
<tr><td>Fake News (FN)</td><td>Halpern et al., 2019; Ullah et al., 2021</td></tr>
<tr><td>Microchips in Pandemic (MP)</td><td>Aji et al., 2020; Al-Maroof et al., 2020</td></tr>
<tr><td>Health Concerns (HC)</td><td>Albrecht, 2010; Foster & Jaeger, 2007; Gillenson, 2019; Graveling et al., 2018; Katz & Rice, 2009; Rotter et al., 2008; van der Togt et al., 2011</td></tr>
<tr><td>Privacy Right (PR)</td><td>Graveling et al., 2018; Lockton & Rosenberg, 2005</td></tr>
<tr><td>Conspiracy Theory (CT)</td><td>Gagliardone et al., 2021; Gu et al., 2021; Halpern et al., 2019; Imhoff et al., 2018; Ullah et al., 2021</td></tr>
<tr><td>Technology Safety (TS)</td><td>Perakslis et al., 2014</td></tr>
<tr><td>Perceived Ease of Use (PEU)</td><td>Davis, 1989; Venkatesh et al., 2012; Venkatesh & Davis, 2000; Werber et al., 2018</td></tr>
<tr><td>Perceived Trust (PT)</td><td>Graveling et al., 2018; Smith, 2008</td></tr>
<tr><td>Perceived Usefulness (PU)</td><td>1 – very bad idea
2 – bad idea
3 – neither bad nor good idea
4 – good idea
5 – very good idea</td><td>Davis, 1989; Katz & Rice, 2009</td></tr>
<tr><td>Behavioral Intention to Use (BIU)</td><td>No. of different potential MI uses</td><td>Davis, 1989; Venkatesh et al., 2012; Venkatesh & Davis, 2000</td></tr>
</table>

As shown in Table 1, most of the measured variables in the model were assessed based on the level of agreement with a particular statement. PU was also measured on a five-point Likert type scale, but here only an opinion about the idea was assessed. The BIU variable was derived from the number of different potential uses of MIs. The PP variable was measured by agreement with pain caused by MI implantation. PTh included statements about threats from various organizations and agencies, computer use, and general privacy concerns. FN was assessed by agreement with two examples of COVID-19 fake news, whereas MP was measured by a general opinion about the usefulness of MIs during the pandemic. HC included statements about possible movements in the body, impact on emotional behavior, allergies, and the nervous system. The variable PR was assessed using statements about collecting personal information without consent and the right to control personal information. Following recent research, the variable CT was assessed by the difference in beliefs about COVID-19 vaccines, government plans for surveillance and monitoring and 5G technology. Agreement with the safety of the technology was used to measure the variable TS, whereas PEU was assessed based on MI availability, multifunctionality, and inability to be lost. Possible uses of MIs were used to evaluate the variable PU, such as health monitoring, warning of health problems, storing medical information, storing organ donation information and saving lives in the form of a medical device. Opinions about the government, banks, and the healthcare system and their efforts to ensure security were used to evaluate PT.

Following the basic TAM theory (Davis, 1989), the impact of PEU and PU on BIU was hypothesized (H9b and H10). According to TAM, PU is influenced by PEU (Venkatesh & Davis, 2000), which is hypothesized in H9a. Based on previous research by Burton-Jones & Hubona (2006) and Morris & Venkatesh (2000), age has a significant influence on the adoption of new technologies. This impact is presented as H12. Werber et al. (2018) and Žnidaršič et al. (2021) identified and confirmed the existence of hypotheses H1, H2, H5, H6, and H8, as well as H11a and H11b in previous research on adoption of MIs. It is important to note that a negative impact between HC and PU is hypothesized (H5).

In accordance with the presented researches by Al-Maroof et al. (2020) and Aji et al. (2020), hypothesis H4 was made, indicating the impact of MP on PU. In addition, the negative impact of CT on PT and the correlation between FN and CT identified by Žnidaršič et al. (2021) were included in the model.

Based on the model from previous studies (Werber et al., 2018; Žnidaršič, Baggia, et al., 2021), we formulated fourteen hypotheses describing the variety of factors that

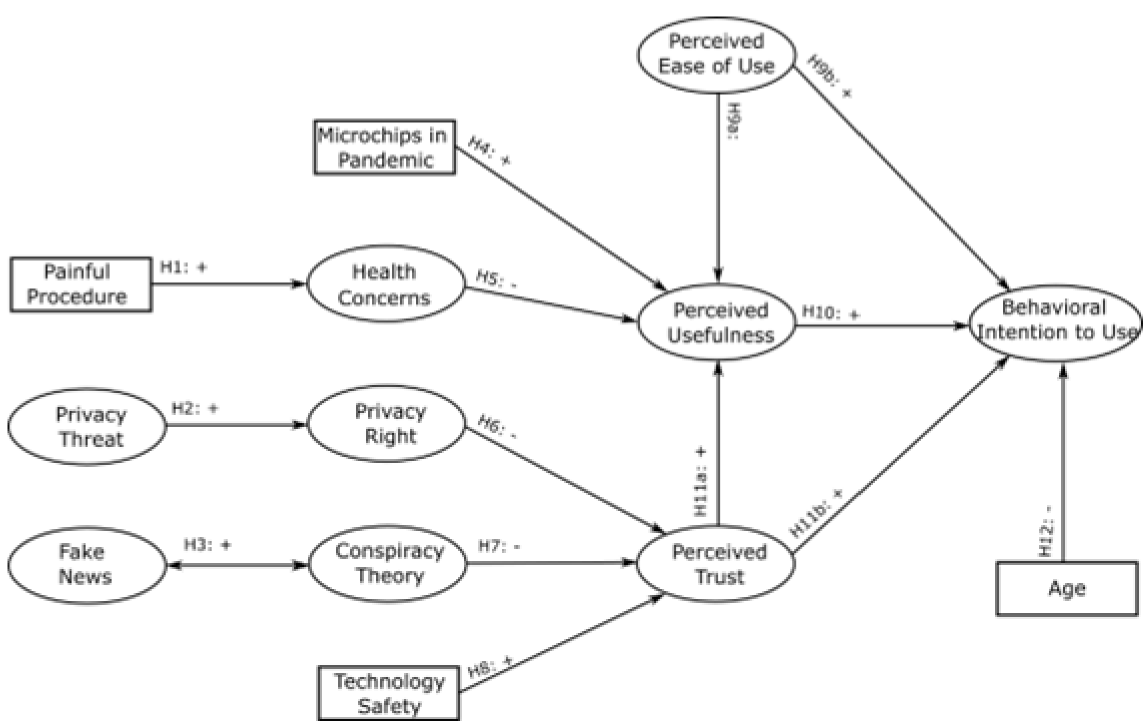

Figure 1: The proposed research model for microchip implant acceptance

influence behavioral intention to use MIs:

H1: Painful Procedure (PP) has a positive impact on Health Concerns (HC).

H2: Privacy Threat (PTh) has a positive impact on Privacy Right (PR).

H3: Fake News (FN) is positively correlated with Conspiracy Theory (CT).

H4: Microchips in Pandemic (MP) have a positive impact on Perceived Usefulness (PU).

H5: Health Concerns (HC) have a positive impact on Perceived Usefulness (PU).

H6: Privacy Right (PR) has a positive impact on Perceived Trust (PT).

H7: Conspiracy Theory (CT) has a positive impact on Perceived Trust (PT).

H8: Technology Safety (TS) has a positive impact on Perceived Trust (PT).

H9a: Perceived Ease of Use (PEU) has a positive impact on Perceived Usefulness (PU).

H9b: Perceived Ease of Use (PEU) has a positive impact on Behavioral Intention to Use (BIU).

H10: Perceived Usefulness (PU) has a positive impact on Behavioral Intention to Use (BIU).

H11a: Perceived Trust (PT) has a positive impact on Behavioral Intention to Use (BIU).

H11b: Perceived Trust (PT) has a positive impact on Perceived Usefulness (PU).

H12: Age has a negative impact on Behavioral Intention to Use (BIU).

Figure 1 graphically represents the hypotheses as relationships between variables in the research model.

The proposed model may have several limitations. The first possible limitation is the complexity of the model. To test the model and make the comparison between countries, the subsample in each country must meet the minimum sample size criteria for SEM. To validate the model, a multigroup CFA and SEM approach must be performed. At each step, all criteria must be met in order to proceed to the next step and confirm the adequacy of the model. A detailed description of the statistical methods and the process of model validation are given in the following section.

3.3 Data collection and statistical methods

Convenience sampling was used to study the acceptability of MIs. After receiving approximately half of the targeted number of responses, the age distribution was analyzed to determine if it matched Eurostat data for specific countries. If necessary, the sampling was then concentrated on specific age groups. The survey was conducted online in the spring 2021 in five countries: Poland (PL), Croatia (HR), Slovenia (SI), Ukraine (UA) and Russia (RU). Both complete and partially submitted responses to questionnaire items were used for analysis: 514 (25.76%) from Poland, 369 (18.50%) from Croatia, 405 (20.30%) from Slovenia, 401 (20.10%) from Ukraine, and 306 (15.34%) from Russia.

The research model presented in Figure 1 describes the relationships between the variables in the model. The survey data were analysed using the SEM approach (Beaujean, 2014; Kline, 2011). Each subgroup's sample size surpasses the recommended 250 cases needed to prevent model rejection according to the combined fit index criteria (Hu & Bentler, 1999).

The analysis followed the standard two-step SEM approach (Schumacker & Lomax, 2010). Firstly, a Confirmatory Factor Analysis (CFA) was conducted in order to validate the measurement model. This was followed by testing the structural relationships between the latent variables.

In the CFA, the construct validity of the measurement model was assessed using convergent validity and discriminant validity. To test the convergent validity of the measurement model, we ensured that the standardized factor loadings were not above 0.5, that the Composite Reliability (CR) for each latent variable was above 0.7, and that the Average Variance Extracted (AVE) for each latent variable was above 0.5 (Fornell & Larcker, 1981; Koufteros, 1999).

During the SEM stage, unstandardized B was computed, along with standardized path coefficients (β) for the relationships between latent variables, z-values, and the level of significance. A coefficient of determination (R^2) was calculated for each endogenous latent variable, representing the percentage of variance explained for the variable by its predictors.

The fit of both the measurement and structural models was evaluated using a range of the most commonly used fit indices. The comparative fit index (CFI) value must be at least 0.9 (Koufteros 1999), and the root mean square error of approximation (RMSEA) must be between 0.06 and 0.08 to be considered mediocre (MacCallum et al., 1996). The SRMR (standardized root mean square residual) value must be below 0.08 (Hu and Bentler 1999). While some goodness-of-fit indices (GFI), such as the CFI, are affected by model complexity, whereas the RMSEA is not (Cheung & Rensvold, 2002) Consequently, the widely-used threshold for complex models (e.g., CFI = 0.90) should be viewed with caution.

In order to complete the two-step approach outlined above, we employed MultiGroup Confirmatory Factor Analysis (MG-CFA) and MultiGroup Structural Equation Modeling (MG-SEM). These techniques were required due to the inclusion of data from five different countries in the sample. The utilization of MG-CFA and MG-SEM, enabled the assessment of measurement invariance (MInv), a pivotal step in the comparison of the same measurement model across groups defined by the selected categorical variable (Miceli & Brabaranelli, 2016).

To ensure effective cross-group comparisons of survey results, it is essential to guarantee that respondents from different countries assign comparable importance to questionnaire items (Cheung & Lau, 2011). MInv assesses the psychometric equivalence of a construct across groups (Putnick & Bornstein, 2016), whereas non-invariance indicates different structures and/or meanings attributed to the construct by respondents from different groups. The standard order for testing MInv is configural, weak, and strong invariance, with strict invariance being the final optional step (Beaujean, 2014).

We explain the results for each invariance test by examining a number of alternative fit indices (AFI), given that in large samples, the χ^2 statistics is highly sensitive to minor, insignificant deviations from a perfect model (Chen, 2007; Cheung & Rensvold, 2002). Accordingly, it is essential to examine the changes in CFI (ΔCFI), SRMR (ΔSRMR), and RMSEA (ΔRMSEA). Chen (2007) posited that a ΔCFI of -0.01 should be accompanied by a ΔRMSEA of 0.015 and an SRMR of 0.030 for metric invariance, or 0.015 for scalar or residual invariance.

All the analyses, including CFA, MInv, and SEM were conducted using the R packages lavaan (Rosseel, 2021) and semTools (Jorgensen et al., 2020). The subsequent section presents the results in accordance with the aforementioned analysis procedure.

4 Results

A representative sample of the general population was surveyed using a questionnaire. A total of 1,995 respondents who had completed at least some of the questionnaires were included in the subsequent analyses. The inclusion of partial responses permitted the consideration of the contributions of all respondents, thereby reducing bias due to controversy over the topic (e.g., some respondents may have dropped out of the survey because they disagreed with microchipping or because of their beliefs).

The composition of the sample is outlined in Section 3.3 (Data collection and statistical methods), which sets out the methodology employed in the data collection process. The mean age of the Polish sample was 33.7 years (SD = 16.24), that of the Croatian sample 27.8 years (SD = 14.09), that of the Slovenian sample 43.4 years (SD = 16.58), that of the Ukrainian sample 44.4 years (SD = 16.23), while the mean age of the Russian sample was 40.9 years (SD =12.91).

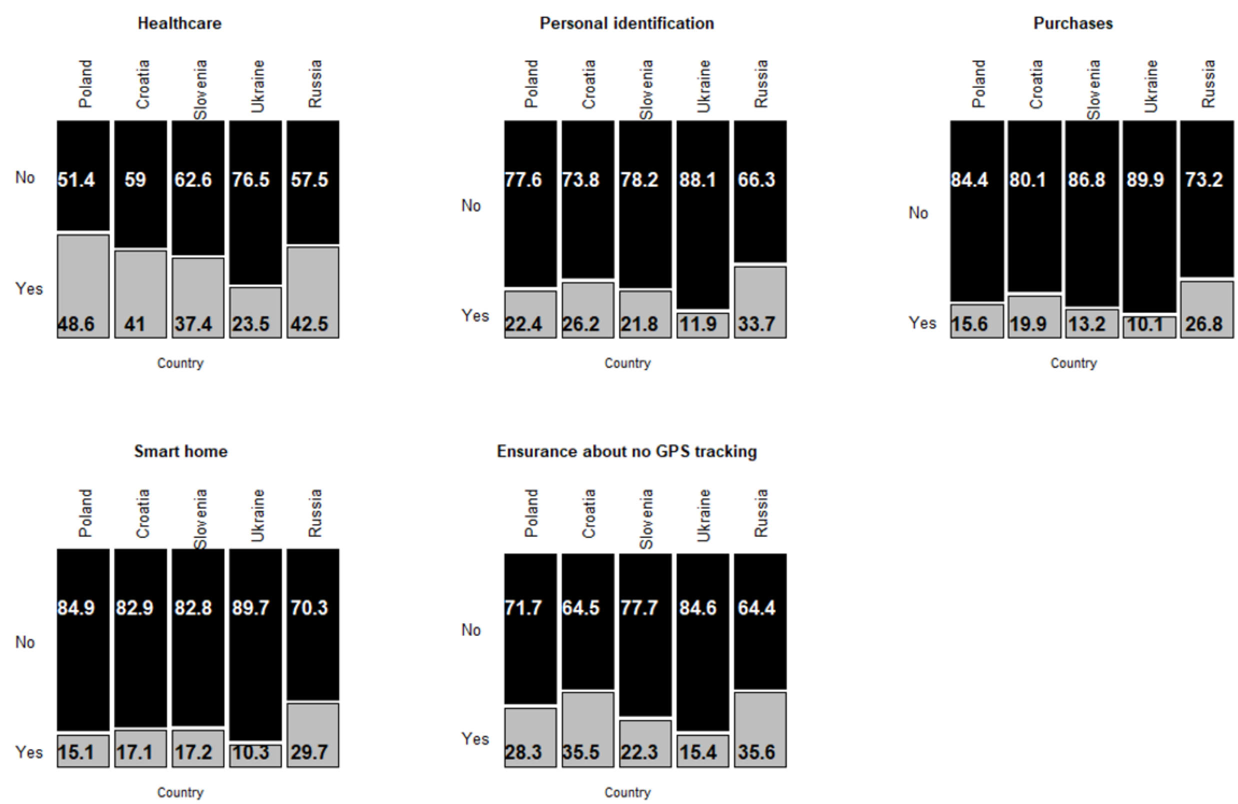

Figure 2: Percentage of respondents willing to use MI for various purposes

4.1 Descriptive statistics of the questionnaire items

As illustrated in Figure 2, a considerable proportion of respondents indicate willingness to use MIs for a range of purposes, with the highest percentage expressing a preference for their use in healthcare. This figure ranges from 23.5% in Ukraine to 48.6% in Poland. Conversely, the lowest percentage of respondents indicated that they would utilise MI for shopping and payment, as well as for smart home applications.

The number of potential MI uses was calculated as the sum of five dichotomous variables representing different uses of MI (see Figure 2). The mean values are indicated by an asterisk (*M) and are presented in boxplots in Figure 3. The mean value for the number of potential MI uses is highest in Russia (M = 1.68), followed by Croatia (M=1.39), Poland (M=1.29), Slovenia (M=1.12), and Ukraine (M=0.72).

Descriptive statistics for the questionnaire items included in the model can be found in Appendix A.

4.2 Evaluation of the measurement model

The construct validity of the set of measured items was examined to ensure that they accurately reflect the underlying theoretical variable. The construct validity was evaluated through an examination of both convergent and discriminant validity. The assessment of the overall measurement model (M1) for the entire sample was the initial step. Table 2 shows the evolution of the measurement model and the associated fit indices.

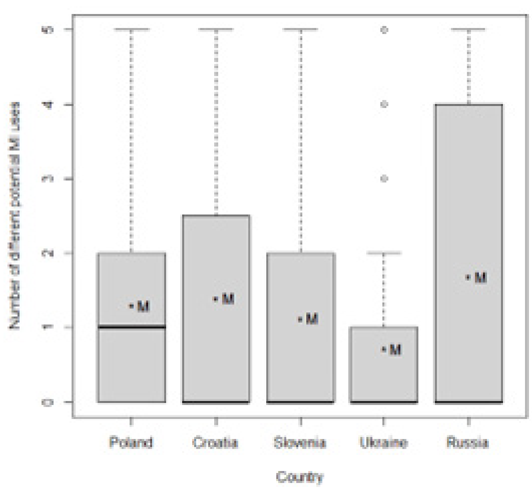

Figure 3: Boxplots for the number of different uses of MI in each country

Table 2: Measurement model development results and model fit indices

Model	χ^2	df	CFI	SRMR	RMSEA	RMSEA 90% CI
M1 – overall model	90% CI	247	0.969	0.034	0.038	0.036; 0.041
Model for each country						
MPL - Poland	567.893	247	0.946	0.049	0.050	0.045; 0.055
MHR - Croatia	461.024	247	0.949	0.045	0.048	0.042; 0.055
MSI – Slovenia	469.613	247	0.962	0.036	0.047	0.041; 0.053
MUA - Ukraine	443.751	247	0.960	0.036	0.045	0.039; 0.050
MRU - Russia	397.703	247	0.960	0.049	0.045	0.037; 0.052

Table 3: Cronbach's Alpha, Composite reliability (CR), average variance extracted (AVE), square root of AVE and correlations between constructs

	Cron. Alpha	CR	AVE	Correlations												
				PP[a]	PTh	FN	MP[a]	HC	PR	CT	TS[a]	PEU	PU	PTh	BIU[a]	Age[a]
PP[a]	/	/	/	/												
PTh	0.802	0.805	0.580	0.149	0.761											
FN	0.657	0.679	0.522	0.197	0.041	0.723										
MP[a]	/	/	/	-0.150	-0.154	0.003	/									
HC	0.898	0.900	0.693	0.604	0.313	0.292	-0.303	0.833								
PR	0.862	0.864	0.761	0.103	0.544	-0.169	-0.049	0.159	0.872							
CT	0.850	0.851	0.656	0.318	0.251	0.698	-0.184	0.530	0.020	0.810						
TS[a]	/	/	/	-0.316	-0.229	-0.107	0.401	-0.587	-0.086	-0.355	/					
PEU	0.804	0.804	0.578	-0.189	0.035	-0.236	0.337	-0.345	0.149	-0.319	0.393	0.760				
PU	0.950	0.950	0.792	-0.226	-0.131	-0.120	0.479	-0.436	0.051	-0.376	0.531	0.538	0.890			
PTh	0.891	0.892	0.734	-0.120	-0.274	0.055	0.447	-0.316	-0.107	-0.209	0.419	0.397	0.576	0.857		
BIU[a]	/	/	/	-0.161	-0.208	-0.060	0.400	-0.371	-0.008	-0.250	0.455	0.338	0.539	0.445	/	
Age[a]	/	/	/	-0.007	0.021	-0.010	-0.030	0.005	-0.111	-0.023	-0.050	0.066	-0.144	-0.074	-0.222	/

[a]The measured variables PP, MP, TS, BIU, and Age are included in the table only to compare the square root of AVE of a construct with correlations to other constructs and items. Cronbach's Alpha, CR, and AVE are not applicable for the measured variables

Table 4: Testing the measurement invariance between countries

Model (Model comparison)	χ^2 (Δχ^2)	df	CFI (ΔCFI)	SRMR (ΔSRMR)	RMSEA (ΔRMSEA)	RMSEA 90% CI
M2 – configural invariance	2335.17	1235	0.955	0.043	0.047	0.045; 0.050
M3 – weak invariance (M2)	2463.25 (128.08)	1303 (68)	0.953 (-0.002)	0.047 (0.004)	0.047 (0.000)	0.045; 0.050
M4 – strong invariance (M3)	3031.55 (568,30)	1371 (68)	0.934 (-0.019)	0.052 (0.005)	0.055 (0.008)	0.053; 0.058
M4a – partial strong invariance (M3)	2903.34 (440,09)	1367 (64)	0.939 (-0.014)	0.051 (0.004)	0.053 (0.006)	0.051; 0.056
M4b – partial strong invari-ance (M3)	2832.12 (368.87)	1363 (60)	0.940 (-0.013)	0.050 (0.003)	0.052 (0.005)	0.049; 0.055
M4c – partial strong invariance (M3)	2792,36 (329.11)	1359 (56)	0.942 (-0.011)	0.049 (0.002)	0.051 (0.004)	0.049; 0.054
M4d – partial strong invari-ance (M3)	2723.35 (260,10)	1355 (52)	0.944 (-0.009)	0.049 (0.002)	0.050 (0.003)	0.048; 0.053
M5 – strict invariance (M4d)	3137.06 (413.71)	1451 (96)	0.931 (-0.013)	0.051 (0.002)	0.054 (0.004)	0.052; 0.056

The study proceeded with an examination of the standardized factor loadings, AVE, and CR for each item in the overall measurement model (M1). The lowest value of AVE is 0.522 for the construct FN and the highest is 0.792 for the construct PU. The lowest value of CR is 0.679 for the FN construct, while the highest value (0.950) is observed for the PU construct. All three indicators exceeded the 0.5 threshold (Table 3), confirming a strong relationship between the observed variables and the underlying latent factor. The convergent validity of the latent variables is thus established, and the discriminant validity of M1 is also corroborated by the square root of the AVE for each factor in comparison with its correlations with other latent variables.

The high internal reliability is determined by Cronbach's alpha coefficients, which range from 0.802 to 0.950 for PTh and PU, respectively (Table 3). The Cronbach alpha coefficient for FN is marginally lower, yet nevertheless acceptable (α=0.657).

The overall fit of the measurement model (M1) was evaluated using the fit indices presented in Table 2. The values of the CFI (0.969), SRMR (0.034),RMSEA (0.038) along with the respective upper bounds of the 90% confidence interval (0.036,0.041) demonstrate that the model exhibits and excellent fit to the data (MacCallum et al., 1996). Based on the aforementioned results, it can be concluded that the overall measurement model fits the data well.

4.3 Testing for measurement invariance across countries (multigroup analysis)

To examine the understanding of the model variables among respondents from different countries and the fit of the model in each country, tests for measurement invariance were conducted using the hierarchical ordering of nested models (Putnick & Bornstein, 2016): configural, weak, strong, and strict invariance were assessed (Table 5).

First, it is necessary to assess whether the proposed model fits the data of each country. According to the fit indices presented in Table 2 (SRMR,RMSEA,CFI) the model fits well with all five subsamples, so our research model is confirmed in all five groups. In the next step, we move to MG-CFA and test whether the proposed model structure is the same in all countries. All fit indices, CFI and SRMR, indicate good model fit (Table 4). The supported configural invariance indicates that the factor structure of the constructs is the same in all five countries.

Furthermore, to assess weak invariance, factor loadings were constrained across groups in order to ensure comparability. The differences between the alternative fit indices of the configural and weak models provide evidence in favour of weak invariance (see Table 4).

In addition to the constrained factor loadings, the next step was to set the intercepts equal across groups (Table 4) in order to test for strong invariance. The results clearly show that the ΔCFI is above the prescribed threshold, indicating unambiguously that the intercepts are not completely invariant across the five countries. As demonstrated in the four consecutive steps (models M4a to M4d), the freely estimated intercepts of the measured items PEU1, PTh3, PTh2, and CT2 across groups were determined, as well as the partial strong variance (of model M4d).

In the next step, the error variances were set across groups. There was a significant difference in CFI between the partial strong model (M4d) and the strict model (M5), indicating a lack of fit of the M5 model. Therefore, the strong measurement invariance was not confirmed. However, as Putnick & Bornstein (2016) note, this is not a mandatory requirement and we proceeded to evaluate the structural model.

4.4 Testing the structural model

According to our research model (see Figure 1), guided by the proposed hypotheses, four measurement variables (PP, MP, TS, and age), represented as rectangles, and 14 structural paths were added to the nine variables. After evaluating the overall model, the invariance of the structural paths was assessed.

The criteria (χ^2=3871.58, df=385, CFI=0.94, and RMSEA=0.061) showed that the fit of the overall structural model was good. The research hypotheses were supported by the overall model. However, it is not clear whether these hypotheses hold true in different countries. For example, would the influence of PEU on BIU remain significant for all five countries?

Table 5: Test of the measurement invariance of the structural coefficients between countries

Structural model (SM)	χ^2	df	p	CFI	SRMR	RMSEA	RMSEA
(Model comparison)	($\Delta\chi^2$)	(Δdf)		(ΔCFI)	($\Delta SRMR$)	($\Delta RMSEA$)	90% CI
SM1 – partial strong invariance	5896.94	2049	/	0.865	0.155	0.069	0.067; 0.071
SM2 – structural coefficients	6020.47	2101	0.0000	0.863	0.157	0.068	0.066; 0.070
(SM2)	(54.33)	(52)		(-0.002)	(0.002)	(-0.001)	
Constrained individual paths to be equal across groups:							
SM1a: PP → HC	5,901.34	2053	0.2519	0.865	0.155	0.069	0.067; 0.070
(SM1)	(4.4)	(4)		(0.000)	(0.000)	(0.000)	
SM1b: PTh -> PR	5,892.44	2053	0.3677	0.866	0.155	0.068	0.067; 0.070
(SM1)	(-4.5)	(4)		(0.001)	(0.000)	(-0.001)	
SM1c: FN ↔ CT	5,912.43	2053	0.0038	0.865	0.155	0.069	0.067; 0.071
(SM1)	(15.49)	(4)		(0.000)	(0.000)	(0.000)	
SM1d: MP → PU	5,901.83	2053	0.1882	0.865	0.155	0.069	0.067; 0.070
(SM1)	(4.89)	(4)		(0.000)	(0.000)	(0.000)	
SM1e: HC → PU	5,907.12	2053	0.0338	0.865	0.155	0.069	0.067; 0.071
(SM1)	(10.18)	(4)		(0.000)	(0.000)	(0.000)	
SM1f: PR -> PT	5,912.56	2053	0.0031	0.865	0.156	0.069	0.067; 0.071
(SM1)	(15.62)	(4)		(0.000)	(0.001)	(0.000)	
SM1g: CT → PT	5,906.00	2053	0.0488	0.865	0.155	0.069	0.067; 0.071
(SM1)	(9.06)	(4)		(0.000)	(0.000)	(0.000)	
SM1h: TS -> PT	5,901.93	2053	0.2405	0.865	0.155	0.069	0.067; 0.070
(SM1)	(4.99)	(4)		(0.000)	(0.000)	(0.000)	
SM1i: PEU → PU	5,896.74	2053	0.5196	0.865	0.155	0.069	0.067; 0.071
(SM1)	(-0.20)	(4)		(0.000)	(0.000)	(0.000)	
SM1j: PEU → BIU	5,907.11	2053	0.0406	0.865	0.155	0.069	0.067; 0.071
(SM1)	(10.17)	(4)		(0.000)	(0.000)	(0.000)	
SM1k: PU → BIU	5,902.45	2053	0.2846	0.865	0.155	0.069	0.067; 0.070
(SM1)	(5.51)	(4)		(0.000)	(0.000)	(0.000)	
SM1l: PT → PU	5,908.58	2053	0.0205	0.865	0.155	0.069	0.067; 0.071
(SM1)	(11.64)	(4)		(0.000)	(0.000)	(0.000)	
SM1m: PT → BIU	5,909.79	2053	0.0126	0.865	0.155	0.069	0.067; 0.071
(SM1)	(12.85)	(4)		(0.000)	(0.000)	(0.000)	
SM1n: Age → BIU	5,910.00	2053	0.9911	0.865	0.155	0.069	0.067; 0.070
(SM1)	(13.06)	(4)		(0.000)	(0.000)	(0.000)	
SM3 – final model	5917.27	2077	0.2873	0.866	0.155	0.068	0.066; 0.070
(SM1)	(20.33)	(28)		(0.001)	(0.000)	(-0.001)	

Table 6: Summary of hypothesis tests for the cross-country structural model

Hypothesis & Path	Expected Sign (Constrained across groups.)	Country	*B*	*β*	z	p	Confirmed?
H1 PP → HC	+ (Yes)	PL	0.538	0.585	23.162***	0.000	Yes
		HR		0.607			
		SI		0.547			
		UA		0.640			
		RU		0.613			
H2 PTh → PR	+ (Yes)	PL	0.498	0.537	14.096***	0.000	Yes
		HR		0.502			
		SI		0.568			
		UA		0.454			
		RU		0.689			
H3[a] FN ↔ CT	+ (No)	PL	0.482	0.790	9.588***	0.000	Yes
		HR	0.432	0.514	6.960***	0.000	Yes
		SI	0.343	0.516	7.078***	0.000	Yes
		UA	0.482	0.694	10.710***	0.000	Yes
		RU	0.708	0.814	7.758***	0.000	Yes
H4 MP → PU	+ (Yes)	PL	0.188	0.223	8.590***	0.000	Yes
		HR		0.218			
		SI		0.229			
		UA		0.216			
		RU		0.236			
H5 HC → PU	- (No)	PL	-0.125	-0.111	-2.230*	0.026	Yes
		HR	-0.204	-0.206	-3.284**	0.001	Yes
		SI	-0.223	-0.226	-3.884***	0.000	Yes
		UA	-0.372	-0.369	-7.684***	0.000	Yes
		RU	-0.213	-0.228	-4.151***	0.000	Yes
H6 PR → PT	- (No)	PL	-0.328	-0.216	-4.007***	0.000	Yes
		HR	0.006	0.005	0.090	0.928	No
		SI	0.007	0.004	0.071	0.944	No
		UA	-0.074	-0.058	-1.002	0.316	No
		RU	-0.354	-0.174	-2.633*	0.008	Yes
H7 CT → PT	- (No)	PL	-0.103	-0.111	-2.177***	0.029	Yes
		HR	-0.055	-0.064	-0.979	0.328	No
		SI	-0.241	-0.243	-4.412***	0.000	Yes
		UA	-0.109	-0.108	-1.756	0.079	No
		RU	0.036	0.035	0.482	0.630	No

Table 6: Summary of hypothesis tests for the cross-country structural model (continues)

Hypothesis & Path	Expected Sign (Constrained across groups.)	Country	*B*	*β*	z	p	Confirmed?
H8 TS → PT	+ (Yes)	PL	0.348	0.401	14.889***	0.000	Yes
		HR		0.396			
		SI		0.394			
		UA		0.407			
		RU		0.426			
H9a PEU → PU	+ (No)	PL	0.412	0.252	8.954***	0.000	Yes
		HR		0.278			
		SI		0.335			
		UA		0.315			
		RU		0.377			
H9b PEU → BIU	+ (No)	PL	0.208	0.081	1.651	0.099	No
		HR	0.460	0.169	3.478**	0.001	Yes
		SI	0.029	0.015	0.301	0.763	No
		UA	0.082	0.045	0.999	0.318	No
		RU	-0.002	-0.001	-0.024	0.981	No
H10 PU→BIU	+ (Yes)	PL	0.551	0.352	14.162***	0.000	Yes
		HR		0.300		0.000	
		SI		0.350		0.000	
		UA		0.396		0.000	
		RU		0.276		0.000	
H11a PT → PU	+ (No)	PL	0.574	0.492	9.272***	0.000	Yes
		HR	0.437	0.403	6.179***	0.000	Yes
		SI	0.384	0.374	6.960***	0.000	Yes
		UA	0.261	0.256	4.486***	0.000	Yes
		RU	0.317	0.325	5.884***	0.000	Yes
H11b PT → BIU	+ (No)	PL	0.424	0.233	5.668***	0.000	Yes
		HR	0.355	0.178	5.089***	0.000	Yes
		SI	0.388	0.240	5.744***	0.000	Yes
		UA	0.138	0.097	2.077*	0.038	Yes
		RU	0.757	0.388	8.496***	0.000	Yes
H12 Age → BIU	- (Yes)	PL	-0.016	-0.169	-8.601***	0.000	Yes
		HR		-0.135			
		SI		-0.169			
		UA		-0.199			
		RU		-0.107			

[a] Correlation coefficient are reported for the hypothesis H3

The invariance of the structural model should be determined to see if the structural relationships are invariant. As shown in Table 5, the fit of the partial strong invariance model (SM1) was good. The fit of the structural model (SM2) also required that the structural coefficients are the same in all groups. The χ^2-test (p=0.000) of the two nested models indicates that the SM1 and SM2 models are significantly different at the 5% significance level, suggesting that some structural coefficients or paths vary between countries.

In successive steps, each structural coefficient was constrained to be the same across groups, and the nested models were compared. Seven paths, listed below, differ between groups at a 5% significance level:

FN ↔ CT (SM1c),
HC → PU (SM1e),
PR → PT (SM1f),
CT → PT (SM1g),
PEU→ BIU (SM1j),
PT → PU (SM1l),
PT → BIU (SM1m).

The listed path coefficients were freely estimated across five groups in the final structural model (SM3). The results are presented in the following subsection.

4.5 The final structural model

The fit of the final model was good (Table 5). Table 6 shows the results for the unstandardized (B) and standardized coefficients (β) along with the corresponding z-values.

Coefficients of determination (R^2) were reported for each endogenous construct (Table 7).

Table 7: Coefficients of determination

Construct	PO	CR	SI	UA	RU
HC	0.343	0.369	0.299	0.41	0.375
PR	0.289	0.252	0.323	0.206	0.475
PU	0.428	0.377	0.422	0.412	0.406
PT	0.224	0.161	0.214	0.182	0.211
BI	0.322	0.253	0.293	0.235	0.328

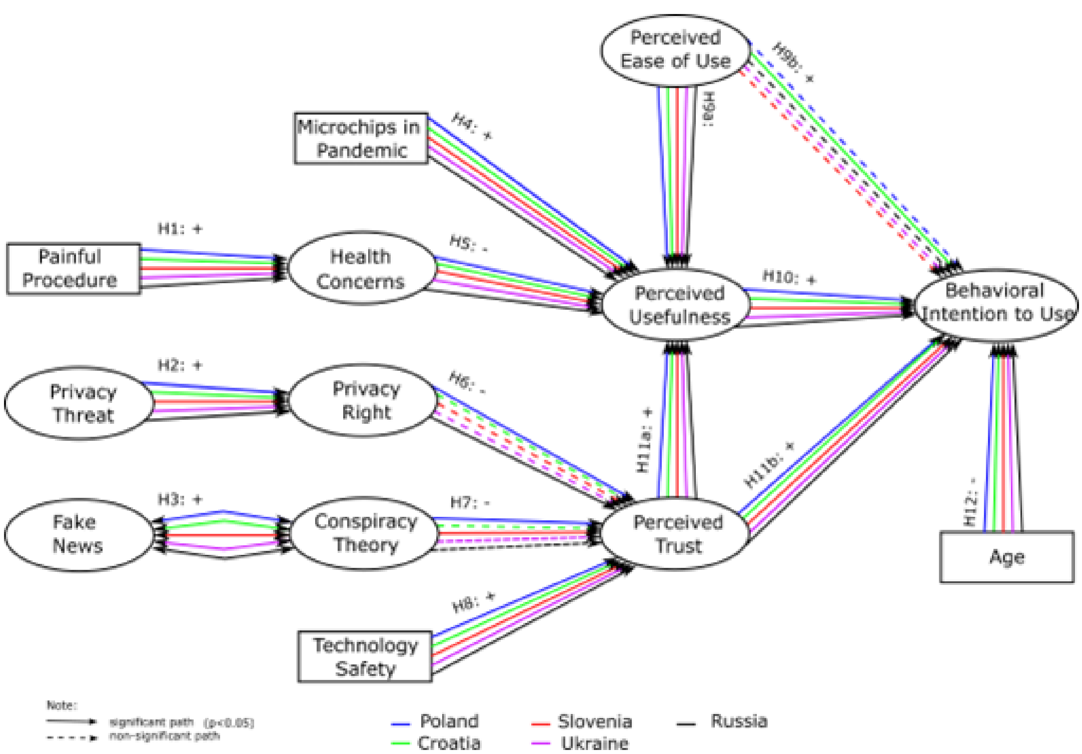

Figure 4: The results of the research model for the behavioral intention to adopt microchip implant

A graphical overview of the confirmed (solid lines) and unconfirmed hypotheses (dashed lines) is shown in Figure 4. The detailed results are discussed in the following section.

5 Discussion

Changes in the way of life are inevitable due to the different situations in the world. It is worth noting that technology plays an important role in these changes. Nevertheless, the acceptance of technology is not always positive. Despite their many benefits, MIs have not been universally adopted and are associated with health issues and privacy concerns. While there have been scattered studies on perceptions of MIs, these were conducted prior to the outbreak of the COVID-19 pandemic, which significantly changed the relationship with technology. According to Gangadharbatla (2020), future studies of embedded technologies should use a more thorough and comprehensive list of predictors of adoption and employ more sophisticated statistical methods such as SEM to examine predictors of embedded technologies adoption and use. In line with this proposal, in this paper we used the two-stage SEM approach to test the research model and identify the differences in attitudes towards MI technology in five countries of the Eastern European region. Unlike previous studies (Boella et al., 2019; Chebolu, 2021; Olarte-Pascual et al., 2021; Pelegrín-Borondo et al., 2017; Pettersson, 2017; Shafeie et al., 2022), the sample size in the present study was large enough to allow the comparison of attitudes toward MIs in different countries.

The theory of TAM (Davis, 1989) suggests that there are two positive effects of Perceived Ease of Use and Perceived Usefulness on Behavioral Intention to Use (hypotheses H9b and H10). The results show that hypothesis H10 about the impact of Perceived Usefulness is confirmed in all countries at a 5% significance level. Hypothesis H9b which assumes a positive impact of Perceived Ease of Use on Behavioral Intention to Use was confirmed only in Croatia (β=0.169) at the 5% significance level. This is in line with the results of the studies by Hidayat-ur-Rehman et al. (2022) and Gangadharbatla (2020), who also found no statistically significant influence of Perceived Ease of Use on the willingness to use smart wearable payments or MIs.

Another relationship commonly predicted in TAM applications is the positive impact of Perceived Ease of Use on Perceived Usefulness (Venkatesh & Davis, 2000), presented in this research as hypothesis H9a. This effect was confirmed in all five countries at a 5% significance level (and the magnitude did not differ statistically significantly between countries).

Of the 14 hypotheses, seven were confirmed to the same extent in all five countries at a 5% significance level, namely H1, H2, H4, H8, H9a, H10, and H12. Similar to Gangadharbatla (2020), we identified age as a significant factor influencing intention to use MIs. The hypotheses for which differences in significance or magnitude of effect were found are described in the following lines.

Shafeie et al. (2022) presented a comprehensive model of intention to use MIs, in which they defined the determinants, hopes, and concerns that influence adoption of MIs. However, their model did not include variables representing the impact of the recent COVID-19 pandemic on attitudes toward MIs. In this study, the usefulness of microchips in a pandemic and the impact of fake news and conspiracy theories were included in the model. Given the variety of sources on the relationship between fake news and conspiracy theories, we found a bidirectional relationship between these constructs. Fake News is positively related to Conspiracy Theories in all countries at a 5% significance level (H3). However, the magnitude of the effect varies and is lowest in Croatia (β=0.514) and highest in Russia (β=0.814). We found a negative impact of Health Concerns on Perceived Usefulness (H5) at a 5% significance level in all countries, but the magnitude of the impact varies and is highest in Ukraine (β=-0.369) and lowest in Poland (β=-0.111). Perceived Trust has a positive impact on Perceived Usefulness (H11a) in all countries at a 5% significance level. The magnitude of the impact in the case of H11a varies from the lowest value in Ukraine (β=0.261) to the highest value in Poland (β=0.574). Similarly, Perceived Trust has a positive effect on Behavioural Intention to Use (H11b) in all countries at a 5% significance level, although the magnitudes vary and are lowest in Ukraine (β=0.097) and highest in Russia (β=0.388).

Privacy Right has a positive impact on Perceived Trust only in Poland and Russia at a 5% significance level (H6), while the impact is not significant in the other three countries. Moreover, Conspiracy Theories have a negative impact on Perceived Trust (H7) in Poland and Slovenia at a 5% significance level, while the impact has not been confirmed in Croatia, Ukraine and Russia.

Based on economic and digital indicators, we assumed large differences in the responses of the countries studied. Ukraine and Russia, for example, are classified in different groups than other countries according to the Networked Readiness Index (NRI) (Dutta et al., 2020), indicating lower use of mobile banking and lower trust in high-tech devices. In contrast to these differences, we did not find major differences among the countries studied in attitudes toward adoption of MIs. Only three of the 14 hypotheses proved to be statistically significantly different at the 5% confidence level.

5.1 Theoretical implications

This study has several theoretical implications. First, by including five different countries in the study, we have shown that the proposed model can be used to study the characteristics and beliefs of potential MI users in different settings. Second, we have successfully implemented the proposed methodology to test and evaluate the proposed model. In this way, other researchers can use similar approaches to test and evaluate their research models. They can use the same procedure to evaluate the measurement model, conduct multigroup analyses and test the structural model. Third, our research has also shown that the proposed methodology can be used to identify differences in specific groups of participants if the sample size is large enough (e.g., by country of origin). Therefore, researchers can use this methodology to identify differences in samples when conducting SEM. Most importantly, we outlined the issues for further research on technology acceptance, specifically MIs, identifying the factors that influence acceptance and the differences or similarities in these factors across countries. Since most hypotheses were confirmed as statistically significant in all countries, we can conclude that these impacts can be studied regardless of country of origin. Instead of focusing research on differences between countries, researchers can now focus on other demographic characteristics, such as gender, education level, or employment status. In addition, further research on the acceptance of MIs can focus on identifying different perspectives on perceived ease of use, privacy rights and conspiracy theories. In addition, our results have shown that appropriate methods and approaches need to be found to reduce concerns about MI technology while increasing trust in technology.

5.2 Practical implications

In general, MIs are perceived as a controversial technology that generates debates about its advantages and disadvantages. Therefore, government agencies and society could benefit from this study by gaining insight into how to deal with the phenomenon of MI acceptance. This study confirms that perceived usefulness has an impact on the acceptance of MIs. It also implies that MI acceptance depends on age and perceived confidence. We can conclude that younger people who perceive technology as trustworthy and useful are more willing to use MIs, whereas ease of use does not play an important role in the acceptance of MIs. Therefore, to increase awareness of the use of MI and its usefulness, older people who have less confidence in technology should be targeted with various awareness activities in their lifelong education. From the responses collected, it appears that the participants in this study are not aware that MI does not provide location tracking or that it cannot move in the body. People should therefore be educated about existing forms of tracking our activities with biometric IDs, mobile or wearable devices, which are not significantly different from MIs. Government agencies should also address these concerns and better inform the public about the use of MIs, its benefits, reported uses, potential risks, problems, and advances in MI technology. Furthermore, despite some initiatives (Graveling et al., 2018) and strict bans by individual states (Coggeshall, 2021), legislation on the use of MIs is lacking. With proper legislation, society in general would have better insight into MI technology and individuals could make better decisions when considering the use of MIs. Ethical principles should be included in legislation to prevent individuals from being forced to chip by employers or legal bodies (Nicholls, 2017). Last but not least, the framework for safe use must be ensured if the adoption of MIs is to continue to grow as expected.

Consistent with the case of a Swedish company that developed MIs to carry COVID-19 passports (Teh, 2021), participants in this study consider MIs useful in the event of pandemic, although they still consider health issues with MIs. Therefore, MI developers should consider how to further improve the technology to avoid health concerns and trust issues, or even consider switching from insertable to a wearable technology to avoid the impact of these factors.

5.3 Limitations and future research

This study has several limitations. First, the data were collected in only five Eastern European countries, making our results less generalizable. Further research should therefore include a broader sample from other regions or even continents. Second, because of the extensive model and large number of questions, some demographic data, such as race or religion, were not included in the questionnaire. To gain deeper insight into the factors that influence adoption of MIs, more demographic data should be collected in future studies. Third, the model presented only identifies the factors that have a significant impact on the acceptance of MIs. This study does not address the reasons why people do or do not adopt MIs. Fourth, based on research published after the development of our model and data collection, some additional variables not included in our model should probably be considered important (e.g., social impact or monetary aspects). In addition, the inclusion of actual users of MIs in the survey would greatly contribute to the usability of the proposed model.

Our study included data from two countries that, unfortunately, have changed significantly since the study was conducted due to military conflict. It is likely that these changes will have a major impact on the future acceptance of MIs in these countries.

Because of the minor differences in the model presented, future research should create and test a common model that shows the overall importance of acceptance factors. The data collected could also be analyzed using other methods and tools to find the links between the issues that are not apparent from the model presented.

6 Conclusions

Microchip implants (MIs) are no longer just a topic of science fiction literature. Over the past thirty years, the use of MIs has evolved from single experiments (K. Michael, 2016) to broader use in organizations (Rodriguez, 2019; Siibak & Otsus, 2020). Although several studies have examined the adoption of MIs over the past decade (e.g., Boella et al., 2019; Gangadharbatla, 2020; Perakslis & Michael, 2012; Pettersson, 2017; Shafeie et al., 2022)), none of them were conducted after the COVID-19 pandemic, which significantly changed our perceptions of news and conspiracy theories (Moscadelli et al., 2020; Ullah et al., 2021). In this study, we examined the differences in attitudes and acceptance of MIs after the outbreak of the COVID-19 pandemic. The research was conducted in five countries in the Eastern European region.

It is most likely that people would use MIs for healthcare purposes, while they would mainly be unwilling to use it for shopping, payment and smart home use. Due to the large sample size, we were able to compare attitudes towards MIs in different countries, confirming the applicability of the proposed research model in different settings.

The results show many similarities in the perceptions of the participants from all countries considered. Perceived ease of use does not significantly influence the intention to use MIs (except in Croatia), but it does affect perceived usefulness. Age is a significant predictor of intention to use MIs. Younger respondents are more likely to use MIs. Safety of technology affects perceived confidence, which in turn affects perceived usefulness and intention to use. In all countries surveyed, painful procedures, health concerns, and the usefulness of microchips in pandemic have a significant impact on perceived usefulness. The reciprocal influence of fake news and conspiracy theories is significant, but they do not influence perceived trust in all countries studied.

We found some differences in the impact of privacy rights, the influence of conspiracy theories, and perceived usefulness. While only in Russia and Poland privacy rights have a significant impact on perceived trust, conspiracy theories influence perceived trust in Poland and Slovenia. Only Croatians believe that usability has a significant influence on the intention to use MIs.

In light of the findings presented, it is clear that the attitudes towards and acceptance of MIs are broadly similar in the Eastern European countries under study. Therefore, it might be interesting to extend the presented research to other regions and continents in the future.

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Ocenjevanje odnosa do podkožnih mikročipov: Primerjalna študija petih vzhodnoevropskih držav

Ozadje in namen: Sprejemanje tehnologije se raziskuje že desetletja. Nekatere tehnologije so splošno sprejete, druge pa se dojemajo kot grožnja, kot na primer podkožni mikročipi. V raziskavi smo uporabili dvostopenjski pristop strukturnega modeliranja za oceno novega raziskovalnega modela o sprejemanju podkožnih mikročipov.
Metodologija: Za oceno razvitega raziskovalnega modela je bil uporabljen pristop strukturnega modeliranja, da bi ugotovili, kaj vpliva na zaznano sprejemanje podkožnih mikročipov. Z namenom ugotavljanja razlik v odnosu do podkožnih mikročipov je bila študija izvedena v petih vzhodnoevropskih državah.
Rezultati: Rezultati kažejo, da se vpliv dejavnikov ne razlikuje bistveno v proučevanih državah. Starost, zaupanje in zaznana uporabnost vplivajo na namero za uporabo podkožnih mikročipov v vseh državah, medtem ko je bila enostavnost uporabe pomembna le v eni državi. Razlike so bile ugotovljene pri dojemanju pravice do zasebnosti in teorijah zarote. Uporabnost podkožnih mikročipov v pandemiji je bila značilna v vseh državah.
Zaključek: Majhne razlike v odnosu do podkožnih mikročipov kažejo, da bi lahko na podlagi zbranih podatkov oblikovali splošni model sprejemanja podkožnih mikročipov. Poleg teh ugotovitev je naša študija opozorila na pomanjkljivo zakonodajo o podkožnih mikročipih v regiji in na pomanjkljivo znanje o tej tehnologiji.

Ključne besede: *Podkožni mikročip, Komunikacija kratkega dosega, Vedenjske namere, Strukturno modeliranje, Model sprejemanja tehnologije*

Appendix A: Descriptive statistics for questionnaire items

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How Workplace Friendships Impact Burnout among Social Care Leaders: A Job Demands-Resources Framework Analysis

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Background and purpose: The purpose of this study, guided by the Job Demands-Resources Model, is to investigate the role of workplace friendships in mitigating burnout. This research is notable for its unique focus on a relatively rare sample: social care leaders. These individuals play a crucial role in shaping and influencing social services, making their insights invaluable for understanding the challenges and opportunities within this sector.
Methods: Using a cross-sectional and quantitative design, data were collected from a convenience sample of Hungarian social care leaders, including sociodemographic information, the Copenhagen Psychosocial Questionnaire (COPSOQ II), and professional core discussion network (pCDN) questions.
The analysis of 449 Hungarian social care leaders employs a saturated model of moderated mediation (controlling for age and gender) to examine how stress mediates the relationship between quantitative demands and burnout and how workplace friendships moderate this mediation effect.
Results: The results indicate that stress significantly mediates the relationship between quantitative demands and burnout, with workplace friendships acting as a buffer under moderate stress levels. Having at least one workplace friend reduces the impact of stress on burnout; however, this protective effect diminishes under higher stress intensities.
Conclusions: These findings underscore the importance of fostering quality and balanced workplace friendships rather than merely increasing the number of supportive relationships. Given the systemic challenges in Hungarian social care, these insights are particularly relevant for leaders seeking to improve workforce resilience and well-being.

Keywords: Workplace friendship, Burnout, Stress, Quantitative demands, Social care leaders, Social work

1 Introduction

The field of social work stands out as particularly vulnerable to burnout, affecting not only frontline social workers but also leaders in social care services (Giménez-Bertomeu et al., 2024). There is a notable gap in research regarding burnout among social care leaders. This research gap exists primarily because most studies concen-

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trate on frontline social workers (Maddock, 2023; Watson and Begun, 2024; Giménez-Bertomeu et al., 2024). In contrast, research focusing specifically on social care leaders is rare (Kozák et al., 2025; Mahara et al., 2024). This knowledge gap extends to the Hungarian context as well (Győri & Ádám, 2024; Győri & Perpék, 2021; Kopasz et al., 2024), limiting our understanding of how burnout impacts individuals in leadership roles. Effective caregiving systems rely heavily on competent social care leaders who navigate the complexities of managing social institutions, especially under challenging conditions. These leaders are entrusted with the responsibility of fostering the well-being of employees who face heightened exposure to stress and burnout. The effects of burnout in leaders go beyond personal consequences, potentially harming the entire organization and negatively affecting coworkers. Hence, exploring factors that may act as buffers or protective mechanisms against burnout among social care leaders is imperative.

Burnout, stemming from prolonged exposure to high levels of stress, manifests in emotional exhaustion, depersonalization, and diminished personal accomplishment (Maslach & Leiter, 2016). Existing literature suggests that personal resources, such as workplace social support from colleagues or superiors, can mitigate the impact of feelings of isolation and lack of support, both antecedents of burnout (Jenaro et al., 2007; Zeijen et al., 2024). Additionally, job resources like social support and performance feedback could mitigate the adverse effects of job demands, such as cognitive challenges and interpersonal conflicts, on psychological distress and burnout (Bakker & Demerouti, 2024).

Research on post-transition of the political system changes in Hungary revealed a shift in ego network patterns from kin ties to non-kin ties dominating core discussion networks (Albert et al., 2021). Additionally, it emphasized workplace friendships as a primary source of personal relationships in Hungary (Utasi, 1990). This highlights the significance and prevalence of workplace friendships in contemporary Hungarian society, impacting both professional and personal spheres.

Workplace friendships, characterized by affective connections within formal organizational settings, are recognized as a common phenomenon with significant implications for employee performance and organizational outcomes (Methot et al., 2016; Chen et al., 2024). While numerous studies emphasize the benefits of workplace friendships for employees, we posit that the role of workplace friendships among leaders, particularly supportive relationships with colleagues, could significantly mitigate burnout.

This research paper utilizes the Job Demands-Resources (JD-R) framework to examine the interplay between workplace friendships, quantitative demands, stress, and burnout among social care leaders. It aims to contribute to the existing literature on the role of workplace friendships, specifically in social care leadership.

2 Literature Review

This literature review uses the JD-R model as a framework to investigate previous research about workplace friendships, quantitative demands, stress and burnout. Our review highlights how workplace friendships can influence burnout and focuses on the importance of this dynamic for individuals and organizations.

2.1 The Job Demand-Resources Model

The JD-R model is a psychological framework introduced by Bakker and Demerouti in the early 2000s and has since been commonly used in occupational and organizational psychology (Bakker et al., 2024; Schaufeli, 2017). It is a comprehensive conceptual framework ó to measure burnout and subsequently expanded to incorporate work engagement (Schaufeli, 2017). The JD-R Model is based on the idea that every job has specific demands and resources, and the relationship between these demands and resources can significantly impact employees' well-being and job outcomes (Bakker, 2024). The model proposes two main categories of factors in the work environment: job demands, which require effort and can be physically, psychologically, or emotionally taxing for employees, and job resources, which support employees in dealing with job demands and achieving their goals. Job resources can be tangible, such as access to training and equipment, or intangible, such as social support from co-workers and supervisors, autonomy, and opportunities for skill development. Job resources help employees cope with job demands, reduce stress, and enhance their motivation and job satisfaction (Bakker, 2024). The JD-R model suggests two underlying psychological processes initiated by demands and resources: the health impairment process, where job demands exceed job resources, leading to adverse outcomes such as stress, burnout, and health problems, and the motivational process, where sufficient job resources lead to positive outcomes such as increased job performance, well-being, and job satisfaction (Demerouti & Bakker, 2011). The model suggests that high job demands can lead to adverse outcomes unless employees have sufficient resources to cope effectively. Conversely, high job resources may facilitate positive outcomes despite high job demands (Berthelsen et al., 2018). The JD-R model's interaction between demands, resources, and adverse outcomes is widely examined in various settings (Schaufeli, 2017; Bakker et al., 2003; Hu et al., 2011). Several studies compare the positive and negative effects of resources and demands on work outcomes. It is commonly found that resources have a more powerful impact than demands by buffering or reducing work outcomes (Huang et al., 2022). All of this supports the idea that the JD-R model is a well-established theoretical framework for examining the roots of burnout and understanding the relationships between them.

2.2 Quantitative job demands and stress

Increased work pressure is a global phenomenon (Van Veldhoven, 2024). In everyday language, quantitative demands are usually described by several other terms with slightly different associations or connotations, such as work pressure, workload, or speed. To address the lack of clear definitions, Van Veldhoven suggests employing the following working definition for quantitative demands: "Quantitative job demands constitute those elements of the work environment that concern the amount and speed of work to be performed and require physical and/ or psychological effort" (Van Veldhoven, 2013, p.121). Thus, quantitative job demands refer to the specific aspects of a job that can be quantified or measured in terms of the amount of work, effort, or output required from an employee (Van Veldhoven, 2024).

The level of quantitative job demands in a role can vary significantly from one job to another and within different industries. While some degree of quantitative demand is a normal part of most jobs, excessive demands in these areas can lead to stress and burnout if employees do not have the necessary resources and support to cope with them (Mette et al., 2018; Montgomery et al., 2006).

According to Lazarus and Folkman (1984), stress is present when we lack the resources to overcome difficult situations and events. (Demerouti & Bakker, 2011). The conservation of resources theory posits that individuals strive to acquire and maintain valuable resources (Zhang et al., 2019). The theory suggests that people experience stress or threats when faced with these resources' actual or potential loss (Anthony-McMann et al., 2016). Similarly, the World Health Organization defines work-related stress as a response to work demands and pressures that exceed a person's knowledge, skills, or ability to manage effectively (WHO, 2019). It has been suggested that job demands positively impact, while job resources negatively affect work stress (Frank et al., 2017). Additionally, there is a consensus on the positive linkage between stress and burnout, and burnout is considered a severe feature of prolonged stress (Lloyd et al., 2002; Gorgievski & Hobfoll, 2008; Anthony-McMann et al., 2016).

2.3 Burnout

According to the International Classification of Diseases (ICD-11), burnout is an occupational phenomenon caused by chronic stress that has not been effectively managed at the workplace (WHO, 2019). This definition is similar to Maslach's theory (Maslach & Jackson, 1981). It explains that burnout arises when there is a prolonged mismatch between the individual and one or more work dimensions, such as workload, control, rewards, community, fairness, and values (Maslach & Leiter, 2016).

Burnout is one of the most common and severe psychosocial occupational hazards (Schaufeli et al., 2009; Demerouti, 2024). It is generally conceptualized as the result of permanent and chronic occupational stress and failure to cope with it (Guglielmi, 2001). It can range from acute fatigue to chronic exhaustion and associated problems (Edú-Valsania et al., 2022). While burnout is an individual response (Maslach & Leiter, 2016), it also has a detrimental effect at the organisational level (Fernet et al., 2013).

Burnout can have a wide range of consequences. It can lead to various physical health problems, such as type 2 diabetes, chronic fatigue, insomnia, headaches, and gastrointestinal issues. Burnout is also often associated with mental health issues, including depression and anxiety, dissatisfaction with life, low self-esteem, and increased alcohol and tobacco consumption (Edú-Valsania et al., 2022). Individuals experiencing burnout may also develop feelings of helplessness and hopelessness. Additionally, it can decrease job performance, increase absenteeism, and reduce job satisfaction and engagement. Moreover, one adverse outcome of burnout may be increased turnover, with employees choosing to leave their organizations (Edú-Valsania et al., 2022).

Social work is a highly demanding profession (Rantonen et al., 2016), associated with a high risk of burnout (Lloyd et al., 2002; Sánchez-Moreno et al., 2014). While frontline social workers are known to experience burnout (Maddock, 2023; Maslach & Leiter, 2016; Watson and Begun, 2024), research involving only managers is rare (Erera, 1992). Nowadays, the focus is more on the relationship between leadership styles, attitudes, and employee burnout (Kim & Lee, 2009; Maddock, 2023; Padín et al., 2021).

Measuring burnout among leaders in the social care sector can be challenging because they primarily work with employees rather than clients. Nevertheless, they still work with people, just like frontline social workers. In addition, selecting an appropriate measurement tool for burnout also presents a persistent obstacle in academic research, mainly due to the significant variations observed across diverse occupational settings (Kristensen et al., 2005).

The most widely recognized tool for evaluating burnout is the Maslach Burnout Inventory (MBI) (Maslach & Jackson, 1981) and its subsequent versions. Maslach initially identified three dimensions of burnout: emotional exhaustion, depersonalization and reduced personal accomplishment (Maslach & Leiter, 2016). The current format of the measurement tool remains three-dimensional; however, “emotional exhaustion” has been replaced by “exhaustion” and “depersonalization” by “cynicism” to better fit roles without direct human contact. In addition, “personal accomplishment” now measures “professional efficiency,” highlighting the challenges tied to professional competence (Kristensen et al., 2005).

One-dimensional questionnaires such as the Copenhagen Burnout Inventory (Kristensen et al., 2005) or the Shirom Melamed Burnout Measure (Shirom & Melamed, 2006) and the Burnout Measure (Malakh-Pines et al., 1981) narrow the focus by reducing burnout to a single core dimension: exhaustion. Nevertheless, despite the lack of definition and the debate around the construct (Schaufeli et al., 2020), some common threads could be recognized, such as that exhaustion is the crucial and central component of the construct (Kiss et al., 2018).

2.4 The importance of workplace friendships

The workplace is recognized as a social space (Sias et al., 2011), constituting a significant part of individuals’ lives and fostering friendships (Methot et al., 2024). Despite the absence of a precise definition, attributed to the subjective perception influenced by individuals’ value systems (Ibrahim & Dickie, 2010) and the blended nature of workplace settings and personal connections (Zarankin & Kunkel, 2019), various studies have identified key characteristics distinguishing workplace friendships from other forms of workplace relationships (Methot et al., 2024; Nielsen et al., 2000; Zarankin & Kunkel, 2019;; Sias et al., 2003; Colbert et al., 2016).

Workplace friendships, characterised by formal interactions layered with affective relationships, are a common organizational phenomenon that can impact employee performance and organizational outcomes (Methot et al., 2016; Chen et al., 2024).

Defining workplace friendships can be challenging, which is why there is no widely agreed-upon definition of leader workplace friendships. One notable difference between employee and leader networks is the number of professional contacts outside work (Carroll & Teo, 1996). This suggests that leaders’ workplace friendships may transcend the confines of the physical workplace. In our study, we therefore measured the workplace friendships of leaders in a broader framework outside the physical boundaries of the workplace.

While we often cannot choose our colleagues, we can choose our friends (Sias et al., 2003). Research indicates that workplace friendships evolve through informal and voluntary interactions involving genuine personal connections beyond professional relationships (Zarankin & Kunkel, 2019; Rumens, 2016; Sias, 2009), and organizational mechanisms can facilitate their development. Several organizational factors, such as the physical proximity of the workplace and a climate conducive to supervisor support, collaborative behavior, tasks, and employee participation, can nurture workplace friendships (Zarankin & Kunkel, 2019).

Consequently, workplace friendship is recognized as a multifaceted phenomenon (Methot et al., 2024) and is distinct from instrumental relationships, such as those between supervisors or subordinates (Nielsen et al., 2000; Zarankin & Kunkel, 2019; Cao & Zhang, 2020; Dobel, 2001).

Among other things, workplace friendship could positively impact task performance (Methot et al., 2016; Berman et al., 2002; Chen et al., 2024). It could increase well-being, job satisfaction, commitment and involvement, and team performance. It can also reduce stress and turnover intention. Workplace friendship could also positively influence emotions (Zarankin & Kunkel, 2019). Simultaneously, workplace friendship helps individuals to achieve their work goals and find access to potential job resources (Methot et al., 2016), which may also result in positive job outcomes. For example, workplace friendship can enhance instrumental and emotional support among employees, thus leading to higher employee job effectiveness (Yan et al., 2021). In addition, Colbert and co-authors (2016) discovered that friendship exhibited the strongest correlation with positive emotions experienced during work hours among different types of workplace relationships.

Workplace friendship is also associated with high access to resources, a more diverse sources of information, better control in task accomplishment, and supportive interactions, e.g., emotional support, reliable personal feedback, or even career strategizing (Methot et al., 2016). Additionally, it could also aid individuals in managing better work-related problems and stressful situations and nurture positive work attitudes (Yan et al., 2021). Furthermore, workplace friendship results in a stronger sense of belonging at work (Fasbender et al., 2023). Therefore, workplace friendship may be a key determinant of organizational effectiveness (Yan et al., 2021).

However, recent research indicates that workplace friendships may affect outcomes differently depending on their quality and type (Zarankin & Kunkel, 2019; Pillemer & Rothbard, 2018). Developing friendships within the workplace (besides its positive impact) can lead to detrimental outcomes, such as excluding other colleagues and creating tensions with organizational policies. These adverse effects may arise due to the involuntary nature of such relationships and the exchange norms and instrumental goals that may be involved (Pillemer & Rothbard, 2018). A growing number of researchers support that workplace friendship has a dual nature and that the adverse effects of workplace friendship can be harmful to organizations (Methot et al., 2016; Fasbender et al., 2023; Sias et al., 2004; Pillemer & Rothbard, 2018; Choi & Ko, 2020).

According to Methot and colleagues (2016), multiplex research, workplace friendship is a “mixed blessing” as it has both advantageous and detrimental outcomes, and they postulate that an inverted U-shape could depict workplace friendship and performance relationship: “Up to a certain point additional friendships correlate with better performance; but at that point, performance starts to decline due to the emotional labor and possible exhaustion from maintaining all these friendships.” (Zarankin & Kunkel, 2019, p. 52). Nevertheless, despite the opposing sides of friendship (workplace nepotism, gossip, or even disruptive behaviors (Jones & Stout, 2015), friendship has more advantages than disadvantages in the workplace (Song & Olshfski, 2008).

As workplace friendship nurtures positive workplace outcomes inspired by the JD-R model, it could be categorized as a valid social job resource (Yan et al., 2021). Additionally, as it is suggested that friendship and burnout are inversely related (Kruger et al., 1995; Doolittle, 2020), we assume that workplace friendship could impact burnout directly and indirectly through various resources.

2.5 Hypothesis development

Based on the existing literature, our research question is as follows: How do workplace friendships influence the relationship between quantitative job demands, stress, and job-related burnout among leaders? In line with the JD-R framework, we have developed six hypotheses to explore the interactions between workplace friendship, quantitative demands, stress and burnout. In our proposed model, quantitative demands are the predictor variable, stress functions as the mediator, burnout is defined as the outcome, and workplace friendship is identified as a moderator (see Figure 1).

Every job has an optimal level of quantitative demands. When these demands are too high or the recovery time is inadequate, they can adversely affect workers’ health, well-being, and job performance (Van Veldhoven, 2024). Furthermore, excessive job demands can increase stress (Mette et al., 2018; Montgomery et al., 2006), suggesting a clear connection between quantitative demands and stress levels (Frank et al., 2017). Therefore, the first hypothesis is that there is a positive relationship between the quantitative demands placed on leaders and their stress levels (H1) (see Figure 1, path a).

The relationship between stress and job burnout is widely recognized. There is consistent agreement on the positive correlation between stress and burnout, with burnout often seen as a significant consequence of prolonged and chronic stress (Lloyd et al., 2002; Gorgievski & Hobfoll, 2008; Anthony-McMann et al., 2016). Consequently, the second hypothesis proposed that there is a positive relationship between leaders’ stress levels and their job-related burnout (H2) (refer to Figure 1, path b).

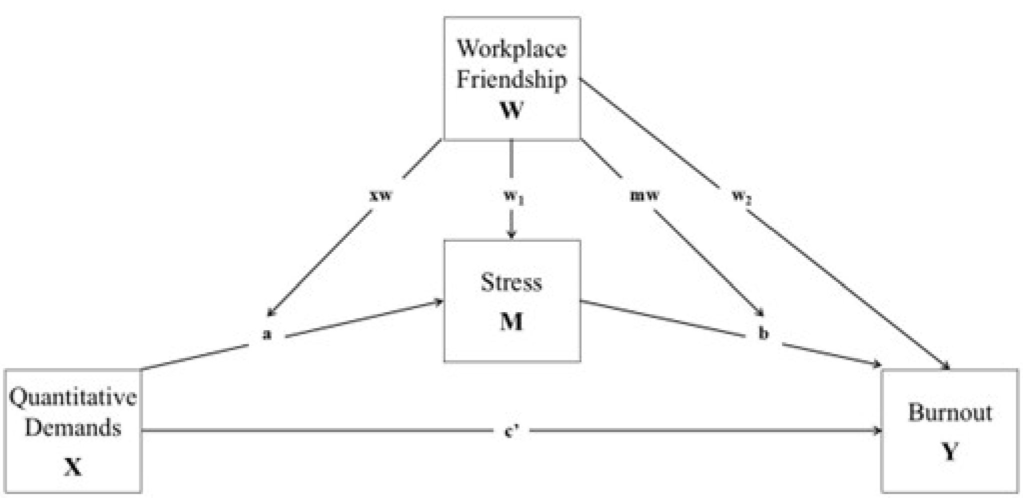


Figure 1: The conceptual model of the moderated mediation between Quantitative Demands and Burnout with Stress as mediator and Workplace Friendship as moderator; Age and Gender were included as control variables in the model

The relationship between quantitative job demands and burnout is assumed to become more nuanced with various mediators, particularly stress, as excessive demands paired with inadequate resources are widely recognized to generate significant stress (Van Veldhoven, 2024), a direct antecedent to burnout (Lloyd et al., 2002). Therefore, the third hypothesis posits that stress mediates the relationship between quantitative job demands and burnout (H3) (see Figure 1, path ab).

Research findings suggest that workplace friendships can buffer stress through social and emotionally supportive aspects and access to valuable resources (Methot et al., 2024; Fasbender et al., 2023). It is also postulated that workplace friendships are key determinants of orgainaziational effectiveness (Yan et al., 2021). This evidence suggests that workplace friendships could ease the pressure of high quantitative demands and prevent high stress levels. Consequently, the fourth hypothesis posits that workplace friendships negatively moderate the relationship between quantitative demands and stress (H4) (see Figure 1, path xw).

Workplace friendship provides numerous advantages to employees, such as increased well-being, job satisfaction, stronger engagement, and improved team performance (Methot et al., 2016; Berman et al., 2002; Zarankin & Kunkel, 2019; Yan et al., 2021). Additionally, an inverse relationship is proposed between work-related burnout and friendships in private life (Kruger et al., 1995; Doolittle, 2020). All this supports the assumption that workplace friendship can be considered a protective factor against burnout. Therefore, the fifth hypothesis proposes that there is a negative relationship between workplace friendships and job-related burnout (H5) (see Figure 1, path w2).

Research also indicates that these friendships could reduce the consequences of stress (Methot et al., 2024; Fasbender et al., 2023), which may moderate the effect of stress on burnout. Given the moderating role of workplace friendship in the relationship between stress and burnout, several questions arise regarding the nature of this effect. Research indicates that the impact of workplace friendship on work-related outcomes varies based on their quality and type (Zarankin & Kunkel, 2019; Pillemer & Rothbard, 2018). Therefore, the sixth hypothesis proposes that workplace friendship moderates the relationship between stress and burnout (H6) (see Figure 1, path mw).

3 Research methodology

3.1 Data collection

Power analysis was performed using Monte Carlo simulation (Zhang & Mai, 2023) to estimate the sample size required for the appropriate statistical power for the moderated mediation analysis with the following settings: $\alpha = .05$, target Power = .80. A moderate strength ($\beta = .30$) was assumed for the regression coefficients included by the indirect path, and the strength of the direct path was considered to be zero. Additionally, moderate ($\beta = .30$) direct effects of the moderator variable and weak interaction terms ($\beta = .15$) were assumed. A sample size of 345 participants was determined to be sufficient to detect the interactions on the indirect pathway.

The questionnaire was distributed to Hungarian social care leaders, who participated in the training of the Semmelweis University Health Services Management Training Centre in 2019 (Bálity et al., 2019; Ethical Approval ID: SE RKEB: 61/2019). All adult participants provided written consent, and participation was voluntary and anonymous.

Data was obtained through paper-based questionnaires among 667 social care leaders, the response rate was 82%. In addition to general demographic data, the questionnaire also included questions regarding organizational operation-related data and a social network name generator. The scales of the (Quantitative demands, Stress and Burnout) Hungarian version of the COPSOQ II questionnaire (Nistor et al., 2015) were applied to measure Quantitative demands, Stress, and Burnout. The questionnaire was anonymous and voluntary.

3.2 Sample

The total sample consisted of 547 Hungarian leaders of social care organizations. However, due to unusable responses (where participants did not mention any confidential professional relationships) and other missing values in relevant variables (considered to be Missing Completely at Random), the final sample size was reduced to 449. The leaders managed organizations with an average of 54.3 (SD = 98.3) employees. The gender ratio of the sample shows female predominance (female = 85.3%; male = 14.7%). 98.4% of the respondents have a higher education degree: 50.3% have a bachelor's degree, 27.8% have a master's degree, 19.8% have a postgraduate degree, and 0.4% have a doctorate. The average age of the leaders is 45.4 years (SD = 7.0, Min = 23, Max = 60), with an average of 21.5 years SD = 8.9) of work experience and 10.2 years (SD = 6.8) of management experience.

3.3 Measures

The psychosocial work factors were measured by the Copenhagen Psychosocial Questionnaire (COPSOQ) II middle version (Pejtersen et al., 2009). The Hungarian version of the questionnaire was validated by Nistor and colleagues (2015). In the current study, we use the scales of Quantitative Demands as the predictor, Burnout as the outcome, and Stress as a mediator variable. Items were measured by a five-point Likert scale (converted to 0-100) (Pejtersen et al., 2009). In our sample, the reliability of all scales was excellent: for Quantitative Demands Cronbach's α = .81 for Stress α = .87; and for Burnout α = .90.

The study regarding the nature of workplace friendships was executed through the utilization of social network tools. Individuals' network data was collected using a social network name generator (Burt et al., 2012). The name generator was recall-based (Pustejovsky & Spillane, 2009) and focused on the personal network's professional, confidential relationship subset (Marin & Hampton, 2007) marked as pCDN. Respondents were asked to record the number of persons with whom they had confidentially discussed their workplace professional problems and conflicts in the last six months, with the alter number limited to five persons (Merluzzi & Burt, 2013). The analysis categorized the indicated persons as professional confidential relationships (pCDN). The name generator was combined with name interpreter (Stark, 2017) questions (recording the gender, age, type of connection, and the type of shared problems to characterize the relationship with the indicated persons). More precisely, the respondents could mark whether they consider the indicated person their friend.

The Workplace Friendship variable (WPF) represents the percentage ratio of friendships among the pCDNs entered in the name generator. 464 of the 547 respondents indicated at least one confidential professional relationship (M = 2.7, SD = 1.3), with an average WPF of 42.1% (SD = 40.3). Respondents without any confidential professional relationship were dropped from further analyses.

3.4 Data analysis

After reviewing the descriptive statistics, Pearson correlation analysis was performed to explore the relationships between the WPF and the COPSOQ II variables. Following this, a moderated mediation analysis was conducted with Quantitative Demands as the predictor variable, Stress as the mediator, and Burnout as the outcome variable. The WPF variable was used as a moderator on paths "a" and "b" (see Figure 1). Age and Gender were included as control variables in the model. The distribution of the variables was found to be suitable for conducting a moderated mediation analysis. For the COPSOQ II variables and age, skewness ranged from -0.30 to 0.25 and kurtosis from -0.21 to 0.11, indicating a fairly normal distribution. The distribution of the WPF variable was slightly platykurtic (K = -1.47), with a skewness of 0.31, which is within acceptable limits. Nonetheless, we chose Maximum Likelihood as parameter estimator and Percentile Bootstrap to make the analysis robust to this slight deviation from the normal distribution. Standardized variables were used for the mediation analysis. All analyses were performed using JASP (0.18.3) (JASP Team, 2023).

4 Results

Participants indicated that on average slightly more than a third of their confidential professional relationships are friendships (Median = 33.33, Mean = 42.10, SD = 40.25), bearing in mind that the distribution of WPF is somewhat flat with 38.5% of the sample reporting the proportion of friends as zero percent, and 24.1% as one hundred percent. They also reported moderate Quantitative Demands, Stress and Burnout (see Table 1).

Pearson correlation was used to examine the correlations between the WPF variable and the COPSOQ II variables. The WPF variable showed a very weak significant negative association with Stress and a weak significant negative association with Burnout. Significant positive correlations were observed between each of the measured COPSOQ II variables (Table 1).

Table 1: Means, Standard deviations and Pearson correlations between WPF, Quantitative Demands, Stress and Burnout, Age, and Gender

Variable	M	SD	1	2	3	4	5
1. WPF	42.10	40.25	—				
2. Quantitative demands	46.88	17.71	.01	—			
2. Stress	42.55	18.99	-.12 *	.25 ***	—		
4. Burnout	49.18	20.83	-.27 ***	.14 **	.45 ***	—	
5. Age	45.43	6.96	-.10 *	.05	-.05	-.03	—
6. Gender	-	-	.05	.05	-.03	-.01	.05

Note. M and SD are used to mean and standard deviation, respectively. Values indicate Pearson correlation coefficients. For Gender 1 = male, 2 = female. * indicates p < .05; ** indicates p < .01; *** indicates p < .001.

Table 2: Results of the moderated mediation model

Path	Variables	β	SE(β)	p	CI_{95}
a	QD → Stress	.25	.05	**<.001*** **	.16; .34
w1	WPF → Stress	-.13	.05	**.005** **	-.22; -.03
xw	QD*WPF → Stress	.02	.04	.633	-.07; .11
c'	QD → Burnout	.04	.04	.345	-.05; .13
b	Stress → Burnout	.42	.04	**<.001*** **	.33; .52
w2	WPF → Burnout	-.23	.04	**<.001*** **	-.31; -.15
mw	Stress*WPF → Burnout	.09	.04	**.031***	-.01; .18
Conditional effect of Stress on Burnout at different values of WPF					
Path	**WPF**	**β**	**SE(β)**	**p**	**CI_{95}**
b^{o}	0%	.33	.06	**<.001*** **	.20; .46
	33.3% (Median)	.40	.04	**<.001*** **	.31; .50
	50%	.44	.04	**<.001*** **	.35; .54
	100%	.55	.08	**<.001*** **	.37; .72
Conditional indirect effect of QD on Burnout through Stress at different values of WPF					
Path	**WPF**	**β**	**SE(β)**	**p**	**CI_{95}**
ab^{o}	0%	.07	.03	**.004** **	.02; .14
	33.3% (Median)	.10	.02	**<.001*** **	.05; 15
	50%	.11	.02	**<.001*** **	.07; .16
	100%	.16	.05	**<.001*** **	.07; .25

Note. QD indicates Quantitative Demands; WPF indicates the ratio of Workplace Friendship. Age and gender were included as covariates with no significant effect. N=449. β indicates the standardized estimate. Standard Errors and 95% Confidence Intervals of the standardized estimates were calculated with Bootstrapping. Values in bold are statistically significant and discussed in text. * indicates $p < .05$; ** indicates $p < .01$; *** indicates $p < .001$.

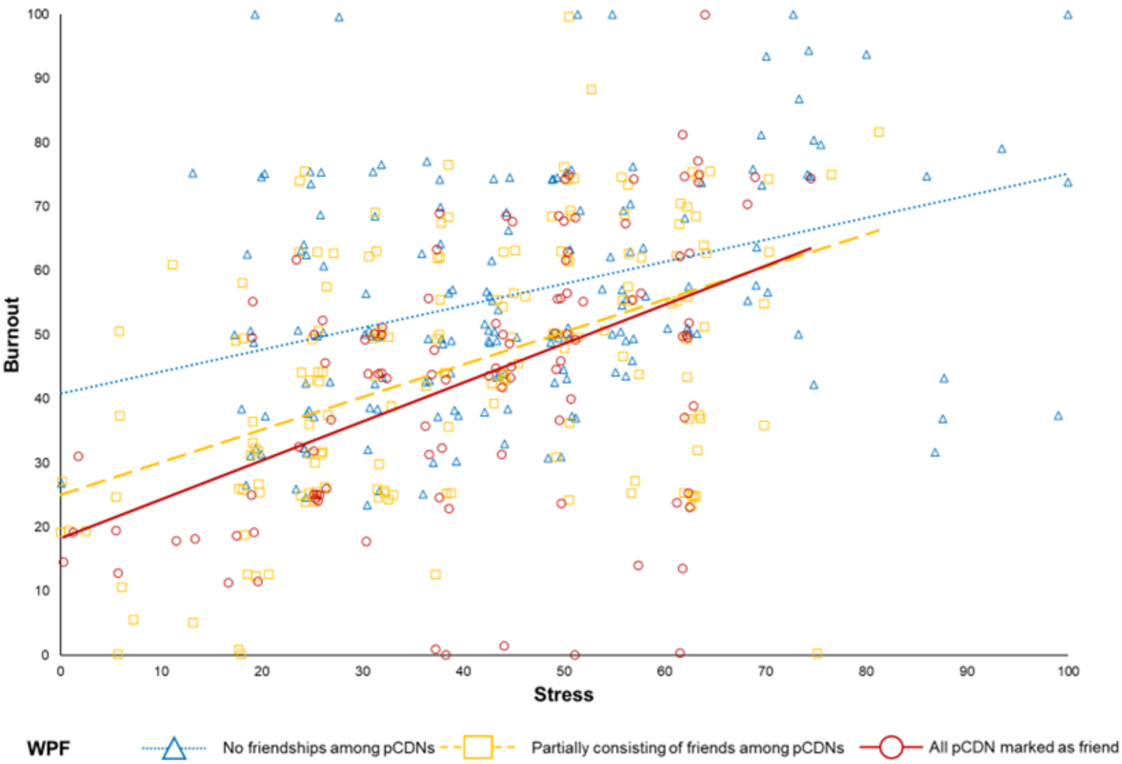
To examine the influence of WPF on the relationship between Quantitative Demands, Stress, and Burnout, a mediation analysis was conducted, with Quantitative Demands as the predictor, Burnout as the outcome, and Stress as the mediator. WPF was incorporated as a moderator on the mediated pathway (Fig. 1). Age and Gender were included as control variables in the model.

In our model (Table 2), it was observed that Quantitative Demands exert a significant positive effect on Stress (see Figure 1, path a). Furthermore, the analysis confirmed that Stress has a significant positive effect on Burnout (see Figure 1, path b).

The direct effect of Quantitative Demands on Burnout, after controlling for Stress, was found to be nonsignificant (see Figure 1, path c'). However, the relationship between Quantitative Demands and Burnout was significantly mediated by Stress (path ab). Additionally, WPF demonstrated a weak yet significant negative effect on Stress (w1), as well as a significant negative effect on Burnout (w2).

Regarding the interaction effects, the analysis revealed that WPF does not have a significant moderating effect on the relationship between Quantitative Demands and Stress (see Figure 1, path xw). However, the analysis revealed that WPF negatively moderates the effect of Stress on Burnout (see Figure 1, path mw).

To examine the significant interaction between WPF and Stress, we calculated the effect of Stress on Burnout at different values of WPF (b^{o}). Examination of these condi-



Note. No friendship among pCDNs indicates 0% WPF; Some Friendship among pCDNs indicates 0<WPF<100%; All pCDN marked as friend indicates 100% WPF. Data is plotted using normally distributed (m = 0; sd = 0.9 point) jitter. N = 449.

Figure 2: Relationship between Stress and Burnout moderated by WPF

tional effects revealed that higher ratio of WPF is associated with a steeper slope. Similarly, higher WPF is associated with a stronger indirect effect (ab^o). The direction of moderation may seem surprising at first, but Fig. 2 clarifies this. It shows that with a low ratio of workplace friends, burnout can occur even at low stress levels, whereas with a higher ratio of workplace friends, burnout only increases when stress is high. However, when stress is high, the protective power of WPF is weakened, and individuals with both low and high WPF are at high risk of burnout.

This evidence challenges the original reasoning behind our hypothesis (H6), which generally assumed that the moderating effect of workplace friendships acts as a buffer against the negative effects of high levels of stress. Instead, the findings suggest a more nuanced relationship: the absence of workplace friendships increases vulnerability to burnout even at low stress levels, while the presence of workplace friendships serves as a protective factor under moderate stress. However, as stress intensifies, the buffering effect of workplace friendships diminishes, leaving individuals with both low and high levels of workplace friendships at increased risk of burnout.

5 Discussions and further directions

5.1 Discussions

Using a saturated model of moderated mediation (controlling for age and gender), this study aimed to explore the role of workplace friendships in the relationship between quantitative demands, stress, and burnout among social care leaders guided by the JD-R framework. The findings offer novel insights into the dynamics of stress and burnout and their implications for leaders in high-demand roles.

According to the results, quantitative demands significantly predict stress, supporting Hypothesis 1 (H1). This aligns with existing literature, emphasizing that high quantitative demands increase pressure and workload, thus increasing stress levels (Van Veldhoven, 2013; Mette et al., 2018; Montgomery et al., 2006; Frank et al., 2017). Furthermore, stress was found to have a significant positive effect on burnout, supporting Hypothesis 2 (H2). This outcome highlights stress's critical role in exacerbating job-related burnout, consistent with the well-established stress-burnout model (Lloyd et al., 2002; Gorgievski & Hobfoll, 2008; Anthony-McMann et al., 2016).

The analysis also revealed that stress fully mediates the relationship between quantitative demands and burnout. The direct effect of quantitative demands on burnout was not significant, but the mediated pathway (quantitative demands → stress → burnout) was significant, supporting Hypothesis 3 (H3). These findings reinforce the importance of addressing stress as a mechanism linking high job demands to burnout (Van Veldhoven, 2013; Lloyd et al., 2002), particularly in leadership roles.

The hypothesized moderating effects of workplace friendships presented an intricate pattern than originally anticipated. Contrary to the expectations outlined in Hypothesis 4 (H4), workplace friendships did not significantly moderate the relationship between quantitative demands and stress. This finding suggests that while workplace friendships are generally associated with stress-reducing benefits (Methot et al., 2016; Fasbender et al., 2023), their protective influence may not extend to stress specifically induced by high quantitative demands. Quantitative demands are characterized by a high volume of tasks and tight deadlines. The pressure of quantitative demands can surpass the alleviating capacity of social support from colleagues. This suggests that coping with quantitative demands may require other forms of organizational support or individual coping strategies that are more directly targeted at workload management.

Workplace friendships demonstrated a weak but significant negative direct effect on stress and burnout (H5). This result highlights that strong interpersonal connections in the workplace might have psychological benefits, and they could reduce stress levels and lower the likelihood of burnout. Prior studies support also emphasize the role of workplace friendships in fostering emotional support, a sense of belonging, and resilience in high-pressure environments (Methot et al., 2016; Berman et al., 2002; Zarankin & Kunkel, 2019; Yan et al., 2021). These direct benefits highlight the critical role of social bonds in mitigating occupational strain.

In addition to their direct effects, workplace friendships significantly moderated the relationship between stress and burnout, supporting Hypothesis 6 (H6). This indicates that workplace friendships act as a buffer, reducing the impact of stress on burnout by providing emotional and social support. These findings support the idea that strong workplace connections enhance coping mechanisms by offering resources such as empathy, advice, and assistance. Thereby, they are fostering a supportive environment that reduces stress and lowers the risk of burnout (Methot et al., 2016; Fasbender et al., 2023).

On the other hand, the analysis revealed that workplace friendships weaken the stress-burnout link, but this protective effect diminishes under high stress levels. While workplace friendships can protect against burnout under moderate stress, their effectiveness as a buffer decline when stress levels become severe. This finding suggests that the protective power of workplace friendships has limits, particularly under high stress. The conditional effects of stress on burnout reveal a selective buffering effect of workplace friendships. In scenarios without workplace friendships, burnout occurs even under low-stress levels, highlighting the importance of social connections in fostering resilience against burnout. Conversely, having even one workplace friend can shield against burnout until stress levels become higher. However, under the high level of stress, the protective effect of workplace friendships diminishes, and individuals with both low and high numbers of workplace friendships experience burnout. These findings challenge our reasoning behind Hypothesis 6 (H6), which assumed that workplace friendships act as a buffer against the negative effects of high levels of stress. Nevertheless, what is important is to have at least one friend, but it is not beneficial to increase the number of friends significantly. In summary, we propose that workplace friendships can only reduce the impact of stress on burnout up to a certain threshold and beyond this threshold, their protective effect diminishes.

Inspired by Methot's U-shaped model (Methot et al., 2016), it can be assumed that the selective protective effect of workplace friendships against burnout is likely related to the quality of these relationships. This aligns with prior research by Zarankin and Kunkel (2019) and Pillemer and Rothbard (2018), highlighting friendship quality's real role in determining its impact on workplace outcomes.

Notably, our findings suggest that having at least one meaningful friendship in the workplace is more advantageous than having a large number of superficial or lower-quality relationships. This indicates that even a single strong workplace friendship is sufficient to protect against stress and provide emotional support, making it a more valuable resource than numerous weaker connections. Together, these findings emphasize the importance of fostering meaningful, high-quality workplace friendships to maximize their protective benefits against stress and burnout.

5.2 Theoretical implications

This study aimed to better understand how workplace friendships, job demands, and burnout are related and to contribute valuable insights to the literature on workplace friendships in the specific context of social care leadership.

Understanding workplace friendships is important because they have a profound impact at both the organizational and individual levels. Promoting workplace friendships through organizational initiatives, such as fostering a supportive and collaborative environment, can yield significant benefits. Employers can make a relatively low-cost investment with complex, far-reaching effects by cultivating a positive workplace climate and shifting attitudes towards interpersonal connections. Zhang and co-authors (2021) provide a notable illustration of this complexity. They discerned the mediating role of workplace friendships in facilitating the relationship between high-commitment work systems and the enhancement of employee well-being.

Furthermore, our study revealed new insights into the relationship between workplace friendships and burnout in Hungarian social care leaders. Notably, it is a recent perspective of its kind in this field. Our research tends to expand the literature on workplace friendship and burnout within the framework of the Job Demand-Resources model.

5.3 Practical implications

Despite the limitations of this study, our analysis offers valuable insights for future research. Our findings highlight the significance of workplace friendship as a crucial job resource in addressing burnout among social care leaders. Drawing inspiration from the JD-R framework, we discovered that stress play a substantial mediating role in the relationship between quantitative demands and burnout. Interestingly, workplace friendship exhibited only a modest correlation with the targeted demands and burnout when considered independently. However, its pivotal role became more apparent when positioned as a moderator. Hungarian social care leaders have been facing ongoing challenges, such as low salary and limited prestige, for decades (HCSO, 2023). These challenges make them particularly vulnerable to disparities between personal motivation and external conditions. In regions where resources for improving the social care system are scarce, fostering supportive resources, including workplace friendship, has important practical implications for HR and the overall well-being of social care professionals.

6 Conclusions

Our study explored the beneficial effects of workplace friendship on burnout among social care leaders within the Job Demand-Resources framework, which incorporates quantitative demands, and stress prerequisites for burnout. Our findings confirm that workplace friendship, viewed as a crucial job resource, has the potential to act as a protective shield against burnout, particularly in the presence of demanding work conditions. In the context of workplace friendship, it is essential to emphasize the significance of genuine relationships over superficial ones. Emphasizing the value of a genuine relationship with a single friend becomes paramount, outweighing the quantity of friendships.

7 Limitations

Our study has several limitations. First, the cross-sectional design may not capture the full dynamics between the investigated phenomena, and we could not analyze reverse or reciprocal relationships. Second, reliance on self-report questionnaires (Network and COPSOQ II) (Podsakoff et al., 2012) may introduce methodological variance bias. Third, the unique characteristics of our sample, including gender, age, and the Hungarian context, might affect the correlation values. Fourth, incorporating additional demands could provide a more nuanced understanding. Fifth, using other specific questionnaires might broaden the scope of our hypotheses, despite our assessment of quantitative demands, stress, and burnout with COPSOQ II.

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Vpliv prijateljskih odnosov na delovnem mestu na izgorelost med vodji na področju socialnega varstva: analiza v okviru modela delovnih zahtev in virov

Ozadje in namen: Namen te raziskave, ki temelji na modelu delovnih zahtev in virov (JD-R), je raziskati vlogo prijateljskih odnosov na delovnem mestu pri zmanjševanju izgorelosti. Posebnost študije je osredotočenost na relativno redko raziskano ciljno skupino – vodje v socialnovarstvenih organizacijah. Ti posamezniki imajo ključno vlogo pri oblikovanju in usmerjanju storitev socialnega varstva, zato so njihovi vpogledi dragoceni za razumevanje izzivov in priložnosti v tem sektorju.
Metodologija: Z uporabo presečnega in kvantitativnega raziskovalnega pristopa so bili zbrani podatki priložnostnega vzorca madžarskih vodij na področju socialnega varstva. Uporabljeni so bili vprašalniki s področja sociodemografije, Köbenhavnski psihosocialni vprašalnik (COPSOQ II) ter vprašanja o osrednji strokovni socialni mreži (pCDN). Analiza podatkov 449 vodij temelji na modelu moderirane mediacije, pri čemer se kontrolirajo vplivi starosti in spola. Raziskuje se, kako stres posreduje razmerje med kvantitativnimi zahtevami in izgorelostjo ter kako prijateljstva na delovnem mestu moderirajo ta mediacijski učinek.
Rezultati: Rezultati kažejo, da stres pomembno posreduje razmerje med kvantitativnimi zahtevami in izgorelostjo. Prijateljstva na delovnem mestu delujejo kot zaščitni dejavnik pri zmernih ravneh stresa, saj že prisotnost vsaj enega prijatelja na delovnem mestu zmanjša vpliv stresa na izgorelost. Vendar se ta zaščitni učinek ob višjih ravneh stresa znatno zmanjša.
Sklep: Ugotovitve poudarjajo pomen kakovostnih in uravnoteženih prijateljskih odnosov v delovnem okolju, ne zgolj povečanja števila podpornih vezi. V kontekstu sistemskih izzivov madžarskega sistema socialnega varstva so ti vpogledi posebej pomembni za vodje, ki si prizadevajo za povečanje odpornosti in dobrega počutja zaposlenih.

Ključne besede: *Prijateljstvo na delovnem mestu, Izgorelost, Stres, Kvantitativne zahteve, Vodje socialnega varstva, Socialno delo*

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Mapping the Evolution of Social Innovation in Scientific Publications: A Topic Modelling and Text Mining Approach

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Objective: To trace how academic discourse on social innovation has evolved from 2000 – mid-2024 in numbers and leading topics by applying a special topic modelling and text mining methodology.
Data & Sources: 4,703 full-text journal articles retrieved from Science Direct.
Methods: Literature review and PDF text extracted with PyPDF2 and pdfplumber; cleaned and tokenised in R; topic modelling performed with Latent Dirichlet Allocation (ldatuning-optimised); temporal and correlation analyses visualised via tidyverse.
Results: The number of publications increased significantly from 16 (in 2000) to 573 (in 2021), stabilizing thereafter. Seven dominant topics emerged: renewable energy, environmental/resource management, smart-city governance, sustainable food systems, corporate strategy, academic-method studies, and social-governance structures. “Social” and “innovation” became the top word pair after 2006; energy-related terms surged after 2016. Surprisingly, topics typically considered ‘social’ have not dominated the social innovation discourse in scientific communities compared to the aforementioned dominant topics.
Discussion: Our results largely confirm existing findings from literature reviews and affirm the interdisciplinary, vague, contested, and still intensively evolving nature of social innovation. Dominant social innovation topics in scientific papers reference to social innovation topics in global political and policy documents, notably from the EU (from 2013 onwards) and the 2015 UN SDGs agenda, also emphasising collaboration between scientific, business, political and non-governmental stakeholders, and can thus serve as scientific, evidence-based advocacy for other stakeholders involved in social innovation processes.
Conclusions: Social innovation research is now an established, systemic, and broadly interdisciplinary field of study, focusing on sustainability, emerging technologies, and governance topics. It is tightly connected with the political and policy agendas of leading international organisations, as well as business and non-governmental ones.
Implications: Findings guide scholars to under-explored social-related content and niches (such as governance and, especially, equity topics) and help policymakers and other stakeholders involved in social innovation processes locate evidence-based approaches and clusters when designing their socially innovative responses, interventions, solutions, and measures.

Keywords: *Social innovation theories, Global policy agenda, Text mining, Topic modelling literature review*

1 Introduction

Today, social innovation is understood within diverse yet interconnected contexts. Definitions of social innovation can thus be found, predictably, in academia, but also, by its very nature, in broader everyday social and political discourse. Due to the very diverse nature of social innovation, there is no single, uniform definition. Moreover, as the concept has developed in both academic and broader socio-political discourse, definitions of social innovation

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have intertwined, complemented each other, or reflected contemporary views shaped by political and wider user discourse (Ayob et al., 2016; Godin, 2016; Logue, 2020). This situation can, on one hand, bring confusion and diminish credibility within the scientific world and for scientific work, while on the other hand, it also helps in understanding the evolution of a newly developing field of scientific interest. Acknowledging the former while seeing potential in the latter.

This paper aims to trace the evolution of academic discourse on social innovation from 2000 to mid-2024 by employing advanced text mining techniques—including PDF text extraction, cleaning, tokenization, and topic modelling with Latent Dirichlet Allocation (LDA)—to analyse a comprehensive dataset of 4,703 full-text journal scientific papers retrieved from the ScienceDirect database.

The text analysis of the volume and prevailing topics in the analysed papers reveals a significant increase in publications on social innovation, from 16 in 2000 to 573 in 2021, followed by a period of stabilization. Seven dominant topics emerged, including renewable energy, environmental/resource management, smart-city governance, sustainable food systems, corporate strategy, academic and methodological studies, and social governance structures. The analysis highlights the interdisciplinary and contested nature of social innovation, mirroring global policy shifts such as the Sustainable Development Goals. The findings guide scholars to understand the prevailing scientific discourse on social innovation across different time periods, correlate this with the general evolution of international political and policy documents and agendas on social innovation, and identify potential for stronger advocacy-related relationships between science and real-world needs in social innovation policy design. The findings also help identify under-explored niches and assist policymakers in locating evidence clusters when designing socially innovative interventions.

The structure of this paper is as follows: Section 2 outlines the theoretical background, followed by Section 3 detailing the methodology. Section 4 presents the text mining analysis and discussion. Finally, Section 5 offers conclusions, limitations, and future research directions.

2 Theoretical background

Despite the fact that various types of innovation can be recognized, each type of innovation has its distinct meaning and scope. Social innovation, however, specifically focuses on developing new responses to pressing societal demands, which influence the process of social interactions. Its primary goal is to enhance human well-being by fostering solutions that are beneficial to both society and individuals, empowering citizens, civil society organizations, local communities, businesses, and public institutions (Godin, 2016).

In the initial period of intensive development of the idea of social innovation in the academic world, there were supposedly 252 different definitions of social innovation, referred to in more than 2,300 scientific publications (Edwards-Schachter & Wallace, 2017), creating a large number of theoretical settings, as well as boundary conditions (Oeij et al., 2019; Van der Have & Rubalcaba, 2016). Summarizing an extensive review of definitions by Solis-Navarrete et al. (2021), the scientific definition of social innovation encompasses interdisciplinary, temporal, and target diversity frameworks, referring to new ideas, solutions, processes, or tools for solving social problems or meeting needs to achieve positive, deep, and long-lasting changes that improve and empower living conditions.

However, the fact that social innovation is contested, conceptually imprecise, and used in ways that may be seen as disagreeable should not dissuade us from engaging with the concept (Ayob et al., 2016). It should be the goal of research to make sense of complex concepts and to understand their evolution over time (Collier et al., 2006). According to an early outline by Gallie (1956), contested concepts, such as social innovation, have five main characteristics: 1) they are appraised as signifying a valued achievement; 2) they are internally complex and so variously interpreted; 3) they are variously describable by different actors; 4) they are open and amenable to change over time; and 5) they are recognized as contested by the stakeholders, meaning that each actor attempts to assert their own authority in defining the concept.

A few years after the intense development of the idea of social innovation in the academic world, the concept also started to receive an intense response in the wider public political sphere. Social innovation has been recognized as one of the central ways to recover from crises and a building block for social, political, and environmental resilience since the end of the global financial crisis after 2009. Sustainable social and environmental development topics were addressed through social innovation discourse in the UN's 2030 Agenda for Sustainable Development, adopted in 2015 (United Nations, 2024). The 2030 Agenda for Sustainable Development outlines specific goals, pinpoints the most pressing issues, and provides a shared blueprint for peace and prosperity for people and the planet, now and into the future. While addressing climate change and working on planet preservation, the Agenda recognizes that ending poverty and other deprivations must go hand-in-hand with strategies that improve health and education, reduce inequality, and spur economic growth (United Nations, 2024). Among these, SDG 9 – Industry, innovation and infrastructure and SDG 12 – Responsible consumption and production, are particularly relevant to social innovation. Spadafora and Rapaccini (2024) explore the intersection of servitization and social innovation, proposing that servitization – a model emphasizing service-oriented solutions – can reshape industrial societies and enhance well-being. Their findings suggest that servitization is not only an economic strategy but also a form of social innovation with the potential to drive societal progress.

Another important concept related to social innovation in the international policy community is global citizenship, which emphasizes shared values and shared responsibility, acknowledging that local events are significantly shaped by global events, and vice-versa. The World Economic Forum (2017) defines global citizens as individuals and organizations – ranging from corporations to civil society actors – who recognize their roles in shaping global developments. Segales et al. (2023) investigated the relationship between social innovation and global citizenship in the case of facilitating sustainable and democratic energy transitions in cities. They suggested five criteria stemming from the intersection of social innovation and global citizenship perspectives: 1) democratic governance; 2) civil empowerment and capacity building; 3) human rights approach; 4) diversity of actors; and 5) sustainability (Segales et al., 2023). Likewise, De Souza Joao-Roland and Granados (2023) postulated that the processes and structures of a collaborative and user-centred approach and participatory organizational culture are positively linked with social innovation performance. Their study encompassing 78 social enterprises from the UK highlights the importance of cooperation with diverse stakeholders, particularly the community, beneficiaries, and universities. Development of solutions based on the community's needs is guaranteed by employing creative tools such as design thinking, and the engagement of people inside the social enterprise who have an entrepreneurial mindset. These efforts result in a positive linear relationship with social innovation and thus successfully drive social innovation.

Against this backdrop, the European Commission as early as 2013 launched the Social Innovation agenda, defined as "the development and implementation of new ideas – whether in the form of products, services and/or models in order to meet social needs and create new social relationships or collaborations. Addressing neglected or inadequately met societal challenges – including environmental, social issues – is central to social innovation" (European Commission, 2013). The European Commission (2013) identifies four key components of the social innovation process: 1) Identification of new/unmet/inadequately met social needs; 2) Development of new solutions in response to these social needs; 3) Evaluation of the effectiveness of new solutions in meeting social needs; and 4) Scaling up of effective social innovations. Given the increasing demand for public services and limited resources, policymakers often promote 'social innovation' as a means to address these tensions and challenges (Purcell et al., 2025). On the other hand, some critics argue that social innovation is merely a 'fashionable concept' or 'buzzword' in public policy discourse, emphasizing the need for further empirical research to improve our understanding of the actors and mechanisms that drive effective social innovations (Purcell et al., 2025).

The concept of social innovation has also recently been explored from different lenses, including open innovation and R&D innovation perspectives. Arvaniti et al. (2024) define open social innovation as a new fast-growing discipline within Open Innovation, where they (re)emphasize the importance of co-creation, collaboration, and co-working under the auspices and shared efforts to tackle societal challenges. Today, many organizations and universities adopting social innovation principles employ open innovation strategies to generate tangible societal benefits (Arvaniti et al.).

By bridging public and market sectors, social innovation also enables the creation of products and services that align with both individual and collective aspirations. However, despite its potential, social-innovation-oriented companies often encounter resource constraints, which can significantly impact their economic or social performance (Lu & Wang, 2024). Lu and Wang (2024) analysed data from 598 social-innovation-oriented firms (period from 2010 to 2020) and found that non-R&D innovation complements R&D innovation, ultimately enhancing both economic and social performance. Their findings also suggest that the long-term impact of social innovation is more significant than its immediate impacts. Conversely, Jeannerat and Lavanchy (2024) pinpoint that traditional innovation policies historically prioritized technological advancements (e.g., traditional and technological innovation), while social innovation has only recently gained recognition, largely due to global challenges such as climate change and social inequalities. Further historical analysis conducted by Hu et al. (2024) traces social innovation back to 1642, demonstrating its role as a mediator between technological advance and economic expansion. They also highlight the Internet-of-Things as a powerful mechanism of social innovation in the sixth Kondratieff wave. As a result, a transformative policy paradigm is emerging, shifting from market-driven competition to a model that acknowledges social innovation as a crucial driver of systemic change (Jeannerat & Lavanchy, 2024). This evolving framework moves beyond the traditional 'triple helix' model—focused on interactions between research institutions, industry, and government. In addition, it involves and engages NGOs, civil society organizations, and individual citizens as key stakeholders in social innovation (Jeannerat & Lavanchy, 2024).

In this section, we have outlined the key dimensions of social innovation, highlighting the link between the academic and the actual social, political, and economic/business user environment, as currently reflected through the aspects of social, sustainability, and more recently digitalisation topics, as well as global governance and citizenship discourse. Social innovation is intertwined with all of the abovementioned terms and is also an active player when addressing not only wider social challenges but also environmental, and broadly speaking, sustainable ones.

One of the most provocative questions relates to the creation of the social innovation discourse: who created what context of social innovation, and for whom? Has the scientific community shaped a broader social understanding of social innovation via its publications, or has the everyday social, environmental, economic, and political community steered science's view on social innovation? What topics and issues constitute social innovation? In seeking answers to these dilemmas, the purpose of this article is to examine how scientific publications have addressed social innovation over time, and how the field has evolved from a research perspective as well as in relation to the broader social agenda of the time. This is addressed by analysing the volume and variety of prevailing topics in leading academic work and international political documents from the pivotal year 2010 up to mid-2024. Based on existing findings regarding the evolution of social innovation in scientific and wider public discourse, the analytical part of this paper will focus on the following research questions:

RQ1: Has the number of scientific publications on social innovation risen in recent decades, corresponding to increasing interest in the field?

RQ2: Do the main themes in scientific papers on social innovation relate to social, environmental, and sustainability issues, systems of governance, and digitalisation?

RQ3: Does text analysis of scientific papers confirm a linkage between scientific, political, and business discourse on social innovation?

3 Methodology

We focused on scientific research papers and employed Science Direct as a source. We intentionally neglected book chapters, etc., as complete data for these could not be gathered. We focused on both review and research papers published in English. On July 24th, a search for "social innovation" yielded 4,703 papers. We downloaded all of them in their full-text version; six people simultaneously downloaded their respective shares of papers. We covered the time period from 2000 until mid-2024 (published until July 24, 2024). After that, we employed a combination of Python and R programming languages, leveraging their respective strengths in data extraction and statistical analysis.

3.1 Data Collection and Extraction

To efficiently extract textual content from the PDFs, we developed a custom Python script in Python 3.11.9 that utilized the PyPDF2 (Fenniak et al., 2024) and pdfplumber (Singer-Vine et al., 2024) libraries. The script was designed to attempt text extraction using PyPDF2 first, due to its speed and efficiency in handling well-structured PDFs. If PyPDF2 failed to extract text—often the case with scanned documents or those with intricate formatting—the script automatically switched to pdfplumber, which is more robust in handling complex layouts but at the cost of increased processing time. This two-step approach maximized our ability to retrieve textual data while optimizing performance.

After successful extraction, the text from each document was cleaned to remove non-textual elements such as images, tables, and metadata. The cleaned text was then saved into CSV files, with each row representing a single document. This structured format facilitated seamless importation into R for subsequent analysis.

Data Preprocessing in R

Upon importing the extracted data into R version 4.4.1 using RStudio 2024.09.0, we undertook extensive preprocessing to prepare the text for analysis. The preprocessing steps included:

- Tokenization: Splitting the text into individual words or tokens using the tidytext package (Silge & Robinson, 2016).
- Normalization: Converting all text to lowercase to ensure consistency.
- Stop Words Removal: Eliminating common stop words (e.g., "and," "the," "of") that do not contribute meaningful information to the analysis. Besides including stopwords from package, we defined the list of our own stopwords.
- Stemming and Lemmatization: Reducing words to their root forms using the textstem package (Rinker, 2018), which helps in grouping similar terms together.
- Removing Punctuation and Numbers: Excluding non-alphabetic characters to focus on meaningful text.
- Handling Sparse Terms: Removing infrequent terms that appear in a minimal number of documents to reduce dimensionality.

These preprocessing steps resulted in a clean and manageable dataset, from which we constructed a Document-Term Matrix (DTM) using the tm package (Feinerer, Hornik, & Meyer, 2008). The DTM is a mathematical matrix that describes the frequency of terms appearing in a collection of documents, serving as the foundation for text mining and topic modelling.

Parallel Processing

Given the large size of the dataset—comprising [over 400 000 words]—computational efficiency was a priority. We utilized parallel processing techniques to expedite data processing and analysis. By leveraging the doParallel (Microsoft Corporation & Weston, 2022) package, we were able to distribute tasks across 11 cores of a multicore processor. This approach significantly reduced processing times, enabling us to perform complex computations that would otherwise be time-prohibitive.

Topic Modelling

To identify latent themes and patterns within the text data, we employed topic modelling techniques using the topicmodels package (Grün & Hornik, 2011). Specifically, we implemented Latent Dirichlet Allocation (LDA), a generative probabilistic model that allows sets of observations to be explained by unobserved groups. The number of topics was determined based on model perplexity and coherence scores, optimizing for interpretability and statistical validity.

We assessed the quality of the topics generated by examining the top terms associated with each topic and their distribution across documents. This analysis provided insights into prevalent research themes and how they have evolved over time.

Data Visualization and Analysis

For data manipulation and visualization, we utilized the tidyverse ecosystem (Wickham et al., 2019), including the dplyr and ggplot2 packages. dplyr facilitated efficient data frame operations such as filtering, summarizing, and joining datasets. ggplot2 allowed us to create high-quality visualizations to represent term frequencies, topic distributions, and temporal trends.

Results Interpretation

The combination of advanced text extraction, comprehensive preprocessing, and robust statistical modelling enabled us to uncover meaningful insights from academic literature. The analysis revealed trends across different periods, contributing to a deeper understanding of the academic landscape.

4 Text mining analysis with discussion

In this section, we will present the number of journal articles and words through years (4.1), keywords by year (4.2), word correlations (4.3), and topic modelling (4.4).

4.1 Number of journal articles and words through years

The bar chart (Figure 1) displays the number of publications per year from 2000 to 2024, highlighting a clear trend of growth over time. In the initial years between 2000 and 2010, the number of publications remained relatively low and stable, fluctuating between single digits and around 30 publications annually. Specifically, there was a slight peak in 2003 with 24 publications, followed by a dip to 9 publications in 2004, and modest growth afterward.

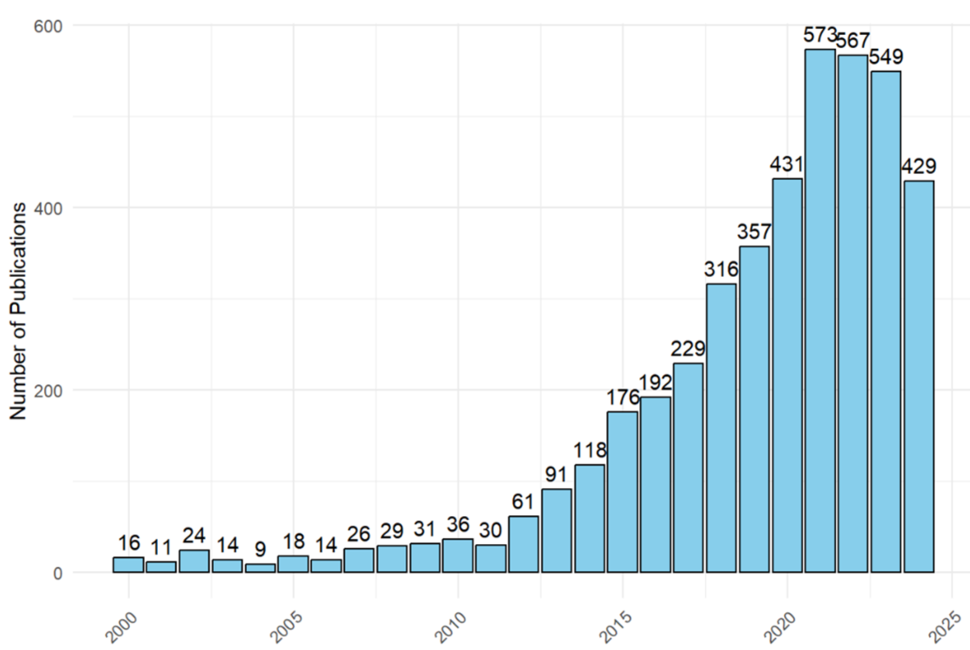

Figure 1: Number of publications per year from 2000 to 2024

From 2011 onward, a steady upward trend emerged, signalling increasing scholarly interest. The growth becomes more pronounced starting in 2015, where the publication count rises sharply from 61 publications in 2012 to 176 in 2015. This upward trajectory continues into the subsequent years, reaching 431 publications by 2020, marking a significant acceleration. We hypothesize that this growth from 2015 onwards is closely related to the 2030 Agenda for Sustainable Development, adopted in 2015 by all United Nations Member States. Especially considering sustainability topics and related pressing issues such as intensive consumption and resource use, social innovation can be seen as part of the solution pertaining to sustainable development goals (SDGs; United Nations, 2024). The period from 2021 to 2023 showcases a peak in publication activity. The highest number of publications occurred in 2021, with 573 publications, followed closely by 567 in 2022. These years demonstrate a sharp increase compared to previous years, possibly reflecting heightened interest or global factors influencing research output.

However, a slight decline is observed from 2023. In 2023, publications dropped to 549, and by mid-2024 (data collected until July 24), the count was 429. Although these numbers remain significantly higher than in earlier years, the 2023 figure suggests a possible stabilization, while the 2024 count reflects partial year data. Overall, the chart reveals a long-term growth trend in the number of publications, particularly accelerating from 2010 onward, peaking around 2021-2022, followed by a minor decline in 2023 and partial data for 2024. This pattern indicates a maturing research field with sustained, albeit with a recent plateau or slight decrease in fully completed years', scholarly output.

Table 1: Total number of words in publications annually between 2000 and 2024

Year	Total Words
2000	55,316
2001	87,017
2002	89,126
2003	57,211
2004	40,446
2005	62,028
2006	62,444
2007	128,238
2008	104,558
2009	151,812
2010	157,590
2011	141,783
2012	227,858
2013	447,530
2014	524,918
2015	759,884
2016	906,218
2017	1,216,992
2018	1,666,712
2019	1,764,112
2020	2,270,012
2021	2,878,006
2022	3,060,713
2023	2,718,392
2024	2,083,199

The dataset reveals a significant growth trend in the total number of words published annually between 2000 and mid-2024 (Table 1). In the early years (2000–2004), word counts remained relatively low, with a minimum of 40,446 words recorded in 2004. This period reflects limited research activity or fewer contributions to the field. From 2007 onward, the total word count increased steadily, surpassing 100,000 words and marking a transition to a more productive phase. By 2012, word counts surged to 227,858, illustrating a pivotal period of growth. The upward trend became exponential after 2015, where the total word count nearly tripled over five years, reaching its peak of 3,060,713 words in 2022. The years 2020–2022 represent the most productive period, coinciding with a global focus on research, possibly influenced by worldwide events like the COVID-19 pandemic that may have spurred academic activity. Post-2022, a slight decline is observed, with 2024 (partial year) recording 2,083,199 words. Despite the reduction, the output remains significantly higher than earlier years. Overall, this progression highlights a maturing research landscape, with a sharp increase in scholarly activity from 2012 onward, solidifying the growing importance and attention toward research topics during this period, and so also confirming our first research question expectation.

4.2 Keywords by year

From the table 2 related to the top 5 most frequent words by year (2000–2024), some key patterns emerge:

- Dominance of "social" and "innovation": Starting from 2006, the word "social" becomes consistently dominant, highlighting its importance in academic discourse. It continues to remain the most frequent word, reflecting a focus on societal themes in research.

Table 2: The top 5 most frequent words by year (2000–2024)

Year	Word 1	Freq 1	Word 2	Freq 2	Word 3	Freq 3	Word 4	Freq 4	Word 5	Freq 5
2000	scenario	419	change	397	energy	366	future	354	environmental	353
2001	future	645	change	500	world	477	development	452	technology	446
2002	innovation	868	future	830	system	821	social	576	change	493
2003	change	624	social	490	process	456	system	369	technology	315
2004	science	330	innovation	267	service	263	social	257	system	228
2005	network	675	future	467	system	426	research	399	study	377
2006	social	695	change	388	future	373	system	371	study	351
2007	university	955	change	797	regional	682	project	660	development	656
2008	social	876	policy	661	change	630	innovation	630	development	622
2009	social	1633	innovation	1061	system	854	research	794	process	769
2010	social	1146	change	964	study	770	policy	718	system	696
2011	social	1359	network	874	research	839	city	791	process	720
2012	innovation	2768	social	1891	research	1553	system	1467	change	1458
2013	innovation	4234	social	3050	change	2846	policy	2747	research	2344
2014	social	5282	innovation	4656	change	3054	research	2941	study	2731
2015	social	7706	innovation	5760	research	3818	system	3798	development	3513
2016	social	9027	innovation	6849	energy	5585	research	4720	system	4572
2017	social	11233	innovation	9590	energy	6863	research	6329	study	5779
2018	social	15753	innovation	12710	energy	10093	development	8622	policy	8618
2019	social	17430	innovation	14943	research	10472	study	9105	system	8251
2020	social	19169	innovation	16683	research	14288	energy	12002	study	11461
2021	social	28943	innovation	22836	research	18937	study	15440	system	12707
2022	social	28171	innovation	26479	research	19894	energy	19752	study	17266
2023	innovation	24097	social	23166	research	18397	study	16562	development	12907
2024	social	17794	innovation	17243	research	13923	study	13235	energy	9622

- Rise of “innovation” and “research”: The word “innovation” gains prominence around 2012, marking its peak in 2013 and maintaining its high frequency thereafter. Similarly, “research” emerges as a frequently recurring term, showcasing an emphasis on scholarly investigation.
- Energy and Climate Themes: Words like “energy” and “change” appear repeatedly, particularly from 2016 onward, which could be attributed to rising concerns around sustainability, renewable energy, and climate change.
- Growth in “development” and “system”: Terms such as “development” and “system” remain consistent across the years, suggesting their central role in discussions related to technological, economic, or societal advancements.

Overall, the shift in word frequency over time reflects evolving priorities in research, from environmental concerns in the early 2000s to innovation, sustainability, and societal themes dominating recent years. Interestingly, this part of the analysis also does not support our expectations related to the increased presence of social-related contents, contents related to different forms of governance, including also non-governmental and civil society communities and, also not more recently, digitalisation-related topics.

4.3 Words correlation

The correlation chart above (Figure 2) visually represents the relationships between words that frequently co-occur across all journal articles. Since the number of articles at the beginning of the examined period was small, the analysis was conducted on the entire dataset to reveal stronger word associations over time. The nodes (blue dots) represent individual words, and the edges (lines) connecting them indicate the level of correlation, where thicker lines signify stronger associations. Several distinct thematic clusters can be observed, reflecting different areas of academic focus in the dataset.

Major Observations and Interpretation

- **Energy and Sustainability Cluster**

A prominent cluster revolves around the term “energy,” which has strong connections to related words like “renewable,” “solar,” “electricity,” and “development.” This cluster highlights a significant focus on renewable

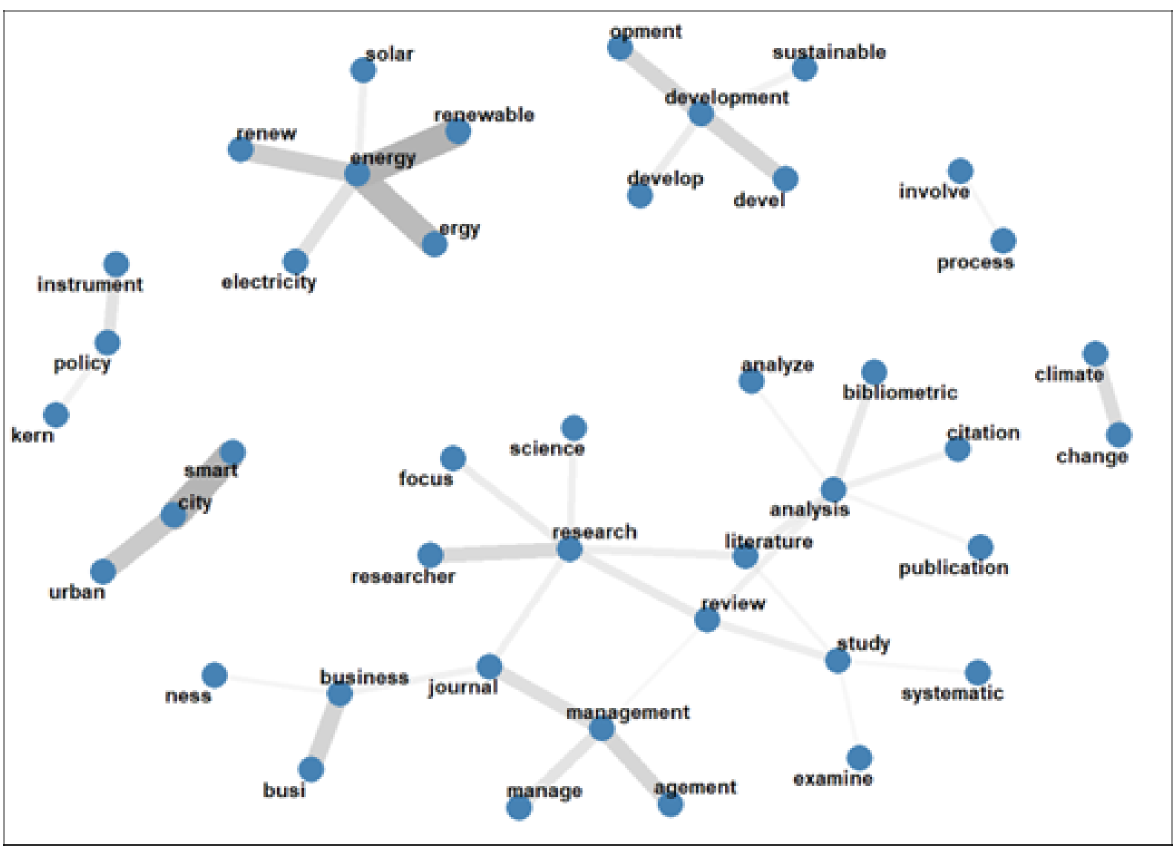

Figure 2: The relationships between words that frequently co-occur across all journal articles

energy and sustainable energy systems, key themes in research during the studied period. The appearance of terms like “solar” and “renewable” suggests increasing interest in clean energy technologies and climate action, aligning with global sustainability goals. Chen et al. (2025) note that sustainability-driven forces are key drivers for social innovations in microbusiness clusters.

- **Research and Analysis Cluster**

At the centre of the chart is the word “research,” which connects to words such as “science,” “focus,” “review,” “literature,” and “analysis.” This central position indicates the overarching importance of research-related activities in academic discourse. Terms like “bibliometric,” “citation,” and “publication” reflect a meta-analysis approach, where research on academic output and scholarly citations has become a subject of study itself. There are many studies conducted including term social innovation, however Daniel and Jenner (2022) highlight that social innovation still raises interest among scholars and policymakers, as a potential panacea for social disenfranchisement and civic dysfunction. What is troubling, according to researchers, is diverse perspectives of social innovation abound, creating inconsistencies in methodological approaches which confound theory development.

- **Urban Development and Smart Cities**

Another noticeable cluster includes terms such as “smart,” “city,” and “urban,” forming a coherent group. The co-occurrence of these words highlights the growing research focus on urbanization, smart city technologies, and sustainable urban development. This trend likely reflects the increasing importance of cities in global policy discussions around sustainability and infrastructure development. Researchers in this topic emphasize that there are present several challenges such as high implementation costs, slow technological adoption, and social equity issues, highlighting the complexity of achieving inclusive and sustainable urban evolution (Oyadeyi & Oyadeyi, 2025). This is related to the social dimension of social innovation, enhancing and providing well-being and equity to all and form of cooperation in resolving and addressing properly these challenges.

- **Management and Business Studies**

A distinct group focuses on “business,” “management,” and related words like “journal” and “busi” (likely stemming from truncation during preprocessing). The inclusion of “manage” and “agement” emphasizes themes surrounding business operations, management processes, and entrepreneurship. This cluster underscores a consistent academic interest in organizational management and corporate strategies over the years. Related to social innovation and entrepreneurship the results of literature review conducted by Grilo and Moreira (2022) reveal that the connection between social innovation and social entrepreneurship is in its take-off phase, but it still is a fragmented field with a huge lack of consensus.

- **Climate Change and Environmental Focus**

A small yet significant cluster features the terms “climate” and “change,” which strongly correlate. This reflects the consistent attention given to climate change research and its implications. The standalone yet connected nature of this cluster suggests that climate change remains a central yet independent topic, tying into broader themes like energy and sustainability. This is in line with the literature review conducted by Kouam and Asongu (2022), who as well emphasized the role of social innovation in achieving sustainable development. From a sustainable development perspective, social innovation plays a crucial role in addressing economic, social, and environmental challenges. In more detail, social innovation drives economic growth by creating jobs, fostering entrepreneurship, promoting sustainable agriculture, and encouraging innovation. It supports the transition to more inclusive and resilient economic systems. From the social dimension point of view, it promotes social cohesion, reduces inequalities, and expands opportunities for all, including women, youth, people with disabilities and the most vulnerable. By fostering inclusive participation, social innovation strengthens communities and promotes equitable development. From the environmental dimension, social innovation tackles environmental challenges by introducing new climate change adaptation and mitigation technologies. It also promotes sustainable consumption patterns and measures resilience, which all together support long-term environmental sustainability. (United Nations, 2024)

- **Process and Involvement Themes**

Words such as “process” and “involve” cluster together, indicating that studies often emphasize processes (methodological, operational, or organizational) and the involvement of stakeholders. This may signify a research focus on collaboration, engagement, or participatory frameworks in various contexts. Li and Bacete (2022) note technology’s role in driving social innovation through direct adoption or indirect engagement in co-design processes.

The correlation analysis reveals that academic research within this dataset has consistently focused on themes of energy sustainability, climate change, urban development, and management processes. The prominence of clusters such as energy-renewable-electricity and research-analysis-bibliometric reflects both domain-specific and methodological concerns. As global priorities shifted toward sustainability and urbanization, these themes have become intertwined with technological and policy-oriented research. Moreover, the interconnectedness of words like “research,” “analysis,” and “publication” signals an increasing interest in bibliometric studies and knowledge dissemination. Meanwhile, the growing focus on smart cities and renewable energy highlights a response to global challenges like climate change and rapid urbanization. This chart (Figure 2) effectively demonstrates how thematic priorities in academic articles are interconnected, reflecting the focus of research in this field. Above all, it clearly supports our research question expectations regarding prevailing topics and the interconnectedness between scientific, political, and business/entrepreneurial social innovation agendas.

4.4 Topic modelling

The initial Document-Term Matrix (DTM) for topic modelling contained 4,347 documents (after removing documents with insufficient text for analysis, if applicable, or state this number is for topic modelling specifically) and 455,065 unique terms. It had 6,230,699 non-sparse entries. The sparsity level was very high, reflecting the common phenomenon of many terms appearing rarely across the document set. The high sparsity was addressed by filtering out words that appeared in fewer than 40 documents, reducing the matrix to 13,428 terms, which significantly improved the efficiency of topic modelling (Table 3).

To determine the optimal number of topics, the log-likelihood curve and multiple topic coherence metrics were evaluated (Figure 3). The ldatuning package (see Figure 4) provided metrics like Griffiths (2004), CaoJuan (2009), Arun (2010), and Deveaud (2014).

Table 3: Document-Term Matrix (DTM) Comparison: Initial vs. Filtered

Matrix Details	**Initial DTM**	**Filtered DTM**
Number of Documents	4347	4347
Number of Terms	455,065	13,428
Non-/Sparse Entries	6,230,699/1.97B	5,049,933/53.3M
Sparsity	100%	91%
Maximal Term Length	19	19
Weighting	Term Frequency	Term Frequency

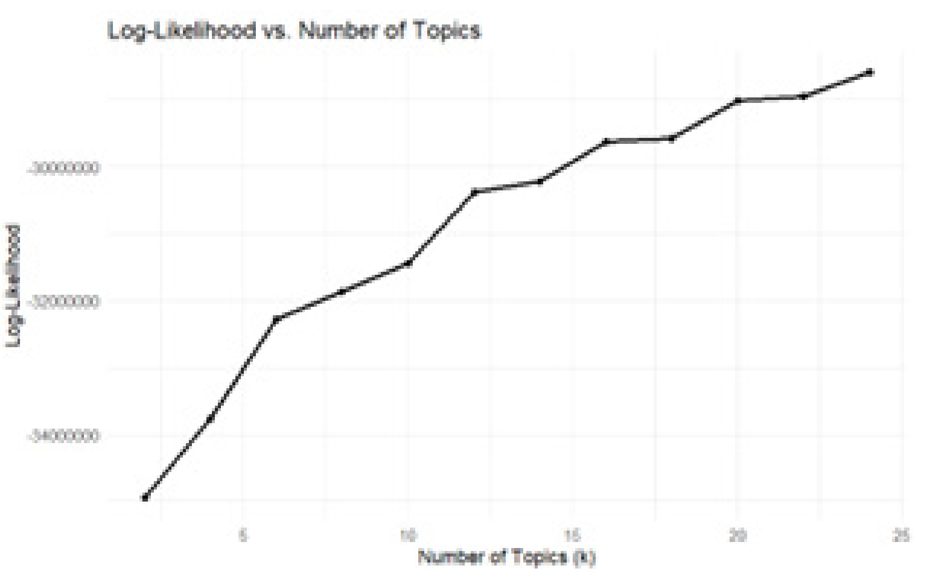

Figure 3: Determining the Optimal Number of Topics: Log-Likelihood vs. Number of Topics in LDA

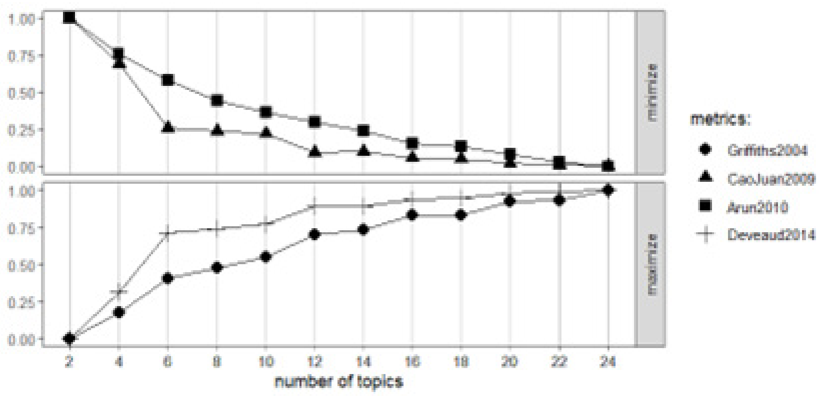

Figure 4: Comparison of Topic Coherence Metrics for LDA

Table 4: Identified Topics with Keywords and Suggested Names

Topic	Top Terms	Proposed Topic Name	Addressed in Policy Documents Discourse
1	supply, water, emission, price, consumption, gas, trade	**Environmental and Resource Management**	**UN, EU, WEF**
2	policy, system, community, local, public, project	**Governance and Social Structures**	**UN, EU, WEF**
3	research, literature, review, study, publication, analysis	**Academic Research and Study Methods**	**UN, EU, WEF**
4	business, management, product, service, innovation	**Corporate Strategy and Entrepreneurship**	**UN, EU, WEF**
5	energy, renewable, electricity, power, transition	**Renewable Energy and Power**	**UN, EU, WEF**
6	city, urban, smart, sustainable, citizen, development	**Smart Cities and Urban Sustainability**	**UN, EU, WEF**
7	food, waste, sustainable, chain, production, consumer	**Sustainable Food Systems and Production**	**UN, EU, WEF**

Note: UN = United Nations; EU = European Union; WEF = World Economic Forum

- The log-likelihood graph showed significant improvement in model fit as the number of topics increased from 2 to 7. Beyond 7 topics, the improvement plateaued, suggesting diminishing returns with additional topics.
- The coherence metrics also pointed to 7 topics as the optimal balance between clarity and complexity.

The Latent Dirichlet Allocation (LDA) and NMF (Non-negative Matrix Factorization) models generated 7 topics (see Table 4), each characterized by a set of words and their weights (β values).

Pertaining to Table 4, the Environmental and Resource Management topic focuses on themes related to resource management, emissions, energy consumption, and waste management. Terms like supply, water, emission, and trade suggest a strong emphasis on sustainability and resource efficiency.

The Governance and Social Structures topic centres around governance, social structures, and public projects, featuring terms such as policy, system, community, and local. It highlights the critical role of governance in societal development and community initiatives. In Academic Research and Study Methods, terms like research, study, literature, review, and analysis indicate a focus on academic methodologies, scholarly publications, and systematic reviews. The Corporate Strategy and Entrepreneurship topic emphasizes business management, entrepreneurship, and product innovation, as shown by words like business, management, service, and product. The Renewable Energy and Power topic highlights renewable energy and electrification, with terms such as energy, renewable, electricity, and power, reflecting global sustainability trends and energy transitions. Addressing urban planning and smart city development, the Smart Cities and Urban Sustainability topic includes terms like city, urban, smart, sustainable, and citizen, reflecting research on sustainable infrastructure and urban innovations. Finally, the Sustainable Food Systems and Production topic focuses on food systems, waste management, and production chains, with terms like food, waste, chain, production, and consumer, emphasizing increasing concerns about sustainable consumption and food security.

Above we can see that social innovation is present in different topics and addresses different dimensions of sustainability. Social innovation is perceived as an independent innovation type but also is seen in inter-dependence with other innovation forms (e.g., technological, product, service, organizational, business, and design-driven innovations). It stems from multi-stakeholder and cross-sectoral cooperation and results in either development or adoption of social innovation between the public and private actors, in collaboration with civil society (Edwards-Schachter, 2018). Moreover, also The Organization for Economic Co-operation and Development (Organisation for Economic Co-operation and Development [OECD], 2025) has extensively addressed social innovation in its policy documents, recognizing its pivotal role in addressing social and environmental challenges. Social innovation is defined by the OECD as the development and implementation of new solutions that improve the quality of life for individuals and communities.

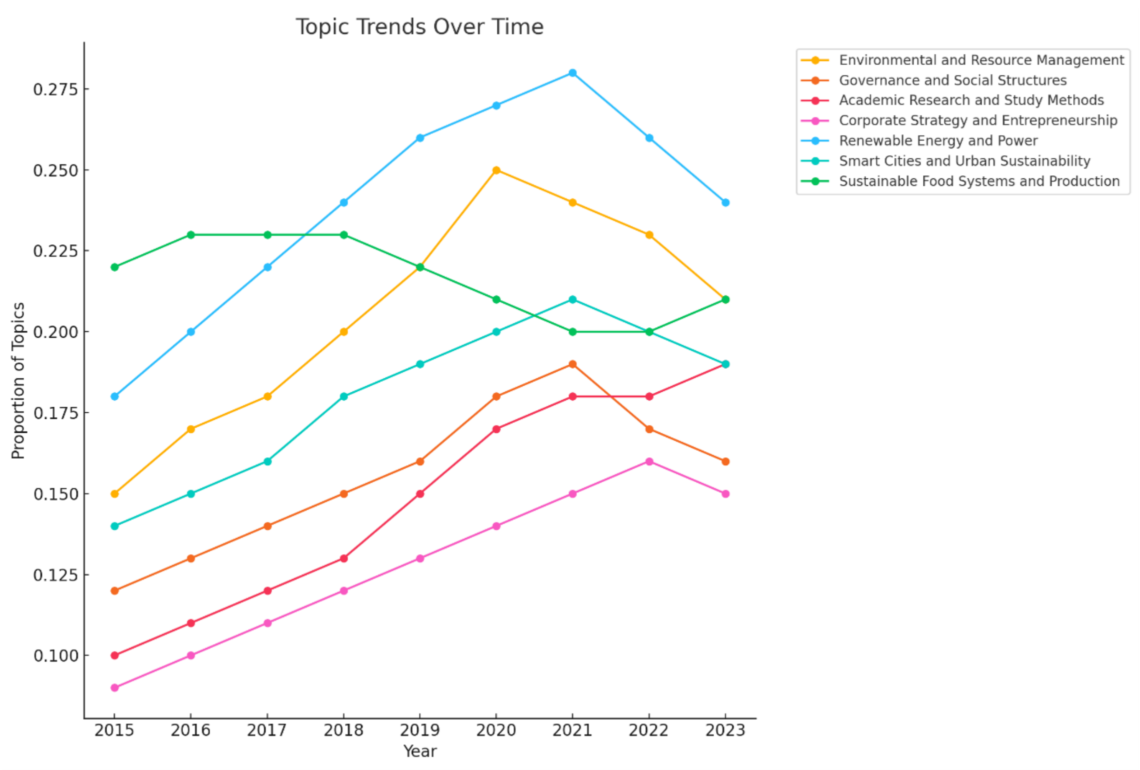

Figure 5: Evolution of Topic Proportions from 2015 to 2023

The visualisation (Figure 5) illustrates the trends of seven key topics identified through topic modelling over the period 2015–2023, with each line representing the proportion of articles addressing a specific topic in a given year. Renewable Energy and Power emerges as the most dominant topic, steadily rising from 2015 and peaking around 2021 before slightly declining in 2022–2023, reflecting growing global interest in sustainability and renewable energy transitions. Similarly, Environmental and Resource Management shows a notable upward trend, particularly between 2015 and 2020, as its share increased from approximately 15% to over 25%, driven by discussions on resource efficiency, emissions control, and energy management. Sustainable Food Systems and Production maintains a consistent presence throughout the years, hovering around 22%–23%, underscoring ongoing research interest in sustainable consumption, food security, and production chains. Meanwhile, Smart Cities and Urban Sustainability exhibits steady growth, peaking at approximately 21% in 2021, highlighting the focus on smart infrastructure and urban innovation. Academic Research and Study Methods demonstrates gradual but steady growth from approximately 10% in 2015 to around 18% in 2023, reflecting the importance of scholarly methodologies and systematic reviews. Corporate Strategy and Entrepreneurship begins at a lower level but steadily increases, reaching its peak around 2021, signalling a growing emphasis on innovation, entrepreneurship, and business management strategies. Although Governance and Social Structures remains among the lower proportion topics overall, it experiences noticeable growth until 2021, emphasizing the role of governance and community-oriented initiatives. Collectively, these trends reveal evolving research priorities over these years, with a pronounced focus on renewable energy, sustainability, and innovation, aligning with global movements toward environmental consciousness and strategic advancements. This part of the text analysis and its interpretation particularly supports our research question expectations regarding the tight interconnectivity between the academic agenda and global political and policy agendas.

5 Conclusion

This paper examined a set of questions related to social innovation content within the scientific community over time. By analysing a large sample of scientific research papers (4,703 articles) from 2000 to mid-2024 and employing a combination of Python and R programming languages, we arrived at several conclusions.

The evolution of scientific interest in social innovation topics has been rising both in volume and content variety within the scientific community over time. Our main operational findings are as follows. First, while in 2000 there were 16 published papers including the term "social innovation," in the first seven months of 2024 alone (data until July 24), 429 papers were published on the topic. Especially since 2011, the results demonstrate increasing interest in social innovation among researchers, with a steady annual increase in publications on the subject, closely followed by the emergence of strategic political and policy documents on social innovation from the EU, UN, World Bank, and OECD.

Second, our findings indicate that "social" and "innovation" have been among the top five most frequent words by year since 2006 (being the core search terms). In 2012, there was a rise in the use of "research" (alongside the search terms), while from 2016 onward, words like "energy" and "change" began to appear more frequently. Additionally, "development" and "system" have remained central terms across all years, as many publications address technological, economic, or social issues.

Third, regarding word correlations, our text mining analysis identified six major clusters: 1) Energy and sustainability, 2) Research and analysis, 3) Urban development and smart cities, 4) Management and business studies, 5) Process and involvement themes, and 6) Governance and Policy.

Fourth, our topic modelling identified seven key topics based on their top terms: 1) Environmental and Resource Management, 2) Governance and Social Structures, 3) Academic Research and Study Methods, 4) Corporate Strategy and Entrepreneurship, 5) Renewable Energy and Power, 6) Smart Cities and Urban Sustainability, and 7) Sustainable Food Systems and Production. These topics highlight the broad scope of social innovation and its potential to bring benefits and improvements across many areas and various sectors of everyday life, fostering better modes of mutual cooperation among diverse stakeholders in society. This part of the analysis has also shown and reinforced that, despite its diversity, social innovation is developing as an important part of academic research and methodology. A major and unexpected finding from the content analysis is the relatively low incidence of specific 'social content' terms (beyond the core search terms 'social' and 'innovation') compared to other thematic contents. This underscores a critical need for the scientific community to more explicitly address diverse social-related aspects within social innovation in future research, not only for academic purposes but also for practical applications and policy impact.

Referring back to the theoretical introduction, we can generally confirm our research questions, which were based on previously gained conclusions about the heterogeneous, diverse, evolving, and intertwined understandings of social innovation within academic and actual everyday social and political discourse. Gallie's (1956) parameters of contested concepts have not only been confirmed but also further reinforced by the assessment that it is these differences that can lead to progressive competition and better quality of arguments over time.

The dominant central themes in academic publications also clearly coincide with actual social, economic, environmental, and political conditions and their global exposure within the context of social innovation. The discourse of social innovation in academia appears to align closely with everyday policy-making and business-run agendas.

Regarding the limitations of our study, one limitation stems from the fact that we examined only scientific research papers. Another one pertains to the method used in this paper, where strengths include a large full-text dataset analysis and robust computational techniques for identifying trends, while weaknesses involve reliance on a single database and the inherent simplifications of automated text processing and topic interpretation. Future research could extend this analysis to other types of literature, such as books, and, in particular, conduct a detailed analysis of leading political and policy documents. Additionally, our study focused on the ScienceDirect database, which covers a significant portion of relevant scientific journal articles; however, future research could incorporate other databases to provide a more comprehensive view and complement these recent findings.

Hence, future research directions could include replicating our study using different publication types or employing different databases. Future research could also explore specific aspects of social innovation or analyse its impact within particular domains. Given the increasing trend in publications pertaining to social innovation and the growing practical interest in the topic, we can conclude that social innovation is gaining well-deserved recognition and merit. This rise may stem from the broader sustainability movement and the acknowledgment that social innovation can be a response to environmental, social, and economic challenges.

Concluding with the thoughts of Minguijon et al. (2024), who emphasize that social services function as a protective system designed to support individuals throughout their lives, while innovation plays a crucial role in addressing contemporary societal challenges and adapting to an ever-evolving world. Ultimately, social innovation plays a crucial role in fostering responsibility and driving positive change in our environment.

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Razvoj družbenih inovacij v znanstvenih publikacijah: pristop tematskega modeliranja in besedilnega rudarjenja

Cilj: S pomočjo posebne metodologije tematskega modeliranja in besedilnega rudarjenja slediti razvoju akademskega diskurza o družbenih inovacijah od leta 2000 do sredine leta 2024 z vidika obsega objav in izpostavljenih vsebinskih vidikov oz. vodilnih tematik.
Podatki in viri: 4.703 polnih besedil znanstvenih člankov, pridobljenih iz zbirke Science Direct.
Metode: Pregled literature; besedilo iz datotek PDF, ekstrahirano s PyPDF2 in pdfplumber; očiščeno in tokenizirano v programskem okolju R; tematsko modeliranje, izvedeno z Latentno Dirichletovo alokacijo (optimizirano z ldatuning); časovne in korelacijske analize, vizualizirane s paketom tidyverse.
Rezultati: Število publikacij se je znatno povečalo s 16 (leta 2000) na 573 (leta 2021), nato pa se je ustalilo. Pojavilo se je sedem prevladujočih tematik: obnovljiva energija, okoljsko upravljanje/upravljanje z viri, upravljanje pametnih mest, trajnostni prehranski sistemi, korporativna strategija, akademsko-metodološke študije in strukture družbenega upravljanja. Besedni par »družbeno« in »inovacija« je postal najpogostejši po letu 2006; izrazi, povezani z energijo so močno narasli po letu 2016. Presenetljivo je, da tematike, ki se običajno štejejo za 'družbene', v znanstvenih skupnostih v diskurzu o družbeni inovaciji v primerjavi z zgoraj navedenimi prevladujočimi tematikami niso prevladovale.
Razprava: Naši rezultati v veliki meri potrjujejo obstoječe ugotovitve iz pregledov literature ter interdisciplinarno, pa tudi nejasno, sporno in še vedno intenzivno razvijajočo se naravo družbenih inovacij v znanstvenem objavljanju. Prevladujoče tematike družbenih inovacij v znanstvenih člankih sovpadajo z diskurzom družbenih inovacij v globalnih političnih in strateških dokumentih, zlasti EU (od leta 2013 naprej) in agende Ciljev trajnostnega razvoja ZN iz leta 2015, pri čemer poudarjajo tudi sodelovanje med znanstvenimi, poslovnimi, političnimi in nevladnimi deležniki. Kot takšne, znanstvene objave o družbenih inovacijah lahko služijo tudi kot znanstveno, na dokazih temelječe zagovorništvo za druge deležnike, vključene v procese, povezane z vsebinami družbenih inovacij.
Zaključki: Raziskovanje družbenih inovacij je danes uveljavljeno, sistemsko in široko interdisciplinarno področje preučevanja, osredotočeno na trajnost, nove tehnologije in teme upravljanja. Tesno je povezano s političnimi in strateškimi agendami vodilnih mednarodnih organizacij, pa tudi poslovnega sveta in nevladnih organizacij.
Priporočila: Ugotovitve usmerjajo raziskovalce k manj raziskanim družbeno relevantnim vsebinam in nišam (kot so upravljanje in zlasti teme pravičnosti) ter pomagajo oblikovalcem politik in drugim deležnikom, vključenim v procese družbenih inovacij, pri iskanju na dokazih temelječih pristopov pri oblikovanju njihovih družbeno inovativnih odzivov, intervencij, rešitev in ukrepov.

Ključne besede: *Teorije družbenih inovacij, Globalna politična agenda, Besedilno rudarjenje, Tematsko modeliranje, Pregled literature*

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Organizational and Individual Antecedents of Resistance to Change: Organizational Climate and Technology Readiness

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Background and purpose: There is interest in barriers to change in organizations. This research discusses factors affecting resistance to change based on employees' technological competencies. This research aims to determine the mediating role of technology readiness in the effect of organizational climate in health institutions on resistance to change.
Methodology: Research data were collected from 389 employees working in the healthcare sector. SPSS Process 2.13 macro was used to analyze the model.
Results: According to the analysis results, organizational climate positively affected technology readiness. Additionally, organizational climate reduced resistance to change. In addition, employees' readiness for technology reduced resistance to change. Finally, the mediating role of technology readiness (motivating and blocking factors) in the effect of organizational climate on resistance to change was significant. Further, a positive organizational climate in healthcare institutions increased employees' readiness for new technologies and significantly reduced employees' resistance to change.
Conclusion: Creating a positive organizational climate can be vital in successfully implementing change processes in the healthcare sector. At the end of the research, theoretical and practical suggestions were presented. The research contributes to the literature by addressing the antecedents of resistance to change from organizational and individual perspectives.

Keywords: *Healthcare workers, Organizational climate, Resistance to change, Technology readiness*

1 Introduction

Change is mandatory for organizations in dynamic environments. Organizations that do not ensure change lose their competitive advantage, and their life cycles end. However, change may require extra effort. Sometimes, employees are against changes and resist them being implemented. Since a change includes uncertainty, it creates stress in individuals and is challenging for them (Burton et al., 2004; Çetinkaya et al., 2019; Goll et al., 2007).

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One of the prominent premises in the literature on preventing resistance to change is the organizational climate (Douglas et al., 2017). Organizational climate refers to the employee's perception of organizational structure, promotion of individual responsibility, solidarity, reward-punishment, risk-taking, and management support (Slimani et al., 2017). A positive organizational climate can reduce the resistance of employees or groups within the organization to change. Research in many sectors has found findings reporting that the positive structure of the organizational climate reduces resistance to change (Van Dam et al., 2008). Change is frequently seen in the healthcare sector, where it is integrated with the sector structure. Continuous developments, procedures, technologies, and treatment methods in the healthcare sector make change mandatory (Mareš, 2018). Change brings uncertainty, and mistakes of healthcare professionals significantly affect human health.

Serious consequences of problems that may occur due to the mistakes of healthcare professionals may cause them to resist change (Fournier et al., 2023). Therefore, organizations with the organizational climate can effectively overcome change barriers in healthcare institutions. The positive structure of the organizational climate may enable healthcare professionals to perceive change positively, participate in the change voluntarily, and take responsibility.

In addition to organizational factors that reduce resistance to change, there are also individual factors. In particular, factors such as adaptation to new technologies, openness to new technologies, and trust (Parasuraman & Colby, 2001) can reduce employees' resistance to change (Mini & Janetuis, 2012; Nov & Ye, 2008). The use of new technologies in the health sector is related to employees' readiness to use technologies. Employees ready to use new technologies or technological innovations (Lin et al., 2015) are less resistant to change (Hsieh, 2015; Kamal et al., 2020). However, employees with low technological competencies or fear of using technologies may resist change because they need to learn how to solve problems.

Previous studies provide evidence on how organizational climate and employees' technological competencies influence resistance to change separately. However, the relevant literature needs sufficient explanations about how organizational climate (organizational level) affects technology readiness (individual level) and how employees' technology readiness affects resistance to change. The lack of understanding of how organizational climate and technology readiness sequentially affect resistance to change limits our knowledge of overcoming resistance barriers in the healthcare sector. It is important to determine how the organizational climate affects the technological competencies of employees and how technological competencies overcome the obstacles to change, as it will increase the effectiveness of healthcare providers and the quality of life of healthcare recipients. Based on this deficiency, this research aims to determine the mediating role of the technology readiness level in the effect of organizational climate in health institutions on resistance to change.

The findings obtained are important in terms of showing how the organizational climate, an indicator of the organizational structure, and the positive and negative views on technologies, which are an indicator of individual competencies, play a role in overcoming the barriers to change. Thus, individual and organizational factors affecting the implementation of change decisions in the health sector can be determined. For example, motivations of healthcare professionals to use technologies and how factors that prevent the use of technologies hinder change can be determined. Knowing factors that prevent change contributes to the easy implementation of change decisions in the health sector, directly affecting human life.

One of the main points that the research aims to achieve is to clearly reveal the effect of organizational climate on technology readiness (H1). In addition, determining the negative effect of organizational climate on resistance to change (H2) was determined as another hypothesis. Examining the direct effect (H3) and mediating effect (H4) of the technology readiness level on resistance to change were expressed as other hypotheses of the study.

The research initially elucidates the concepts of organizational climate, technology readiness, and resistance to change. This study examines the level of technology readiness in two dimensions: as a motivating and a blocking factor. The subsequent section presents the relationships among these concepts and addresses the formulation of hypotheses. The following section provides detailed information about the methodologies employed in the research. Finally, the study concludes by presenting the findings, results, and discussions.

1.1 Conceptual Framework

Economic, social, and technological developments have accelerated organizational changes in structure and processes, especially in the last quarter century. While organizations regulate the organizational relations that come with social changes, they also try to compete in the industrial field by establishing extremely complex productivity relationship brought by technology. One of the most important ways to compete in the globalizing economic system is to produce innovations that meet customer demands and expectations and offer them to the market. Organizational climate is one of the most important catalysts in this environment. It helps organizational change and is a concept that creates the personality of the organization, distinguishes the organization from other organizations, dominates the organization, and can affect the behavior of employees (Bakan et al., 2004: 67).

Thakare at al. (2014) considers organizational climate as a concept based on social perceptions of the working environment to influence the motivation and behavior of working individuals. In this study, organizational climate was considered as the individual perception of the working environment and the characteristics of the business (Slimani et al., 2017: 216). According to the definition, organizational climate can be considered a concept that can affect many different organizational areas, from the quality of the product to innovation efforts, from trust in the individual and the organization to motivation (Burton et al., 2000).

One of the areas directly affected by the organizational climate is organizational change. Organizational change is a structured approach to shift individuals, teams, and organizations from a current state to a desired future state. Therefore, the organizational climate will help employees accept and adopt changes in their current jobs (Slimani et al., 2017: 216). However, it may only sometimes be possible to ensure that organizational members fully embrace and support change activities. Even if the organizational climate creates an environment that supports change, employees may resist change for various reasons (Dinçer, 2008, p. 102).

Organizations are represented by the people within them and if these people do not change, there will be no organizational change. Changes in hierarchy, technology, communication networks, etc. become effective only to the extent that these structural changes are associated with those in the psychology of employees (Schneider, 1996, p. 7). Accordingly, constantly developing technologies can lead to structural changes or differences in business processes that directly affect the organizational climate of the organization.

One way to reduce the possible resistance of organizational employees to change is increasing the technology readiness levels of employees within the organizational climate. Parasuraman and Colby (2015) define technology readiness as individuals' tendency to use new technologies at home and work to achieve goals. In other words, technology readiness is the ability to understand and be prepared to use technology (Lai, 2008; Tsai et al., 2020). This concept can be seen as the individual's mental state resulting from the combination of motivational and blocking factors that determine their predisposition to use new technologies (Jacobs et al., 2019; Lin et al., 2015; Öngel et al., 2022).

Parasuraman (2000) developed a comprehensive framework for technology readiness, focusing on four key dimensions: optimism, innovation, discomfort, and insecurity. Optimism involves individuals' belief in technology's ability to enhance control, efficiency, and flexibility in their lives. Innovation reflects their natural inclination to adopt new technologies and take leadership roles. Both optimism and innovation serve as primary motivators for technology readiness. Conversely, discomfort arises from feelings of inadequate control and confidence in using technology, while insecurity stems from distrust in its reliability. These factors significantly block an individual's readiness to adopt technology (Meng et al., 2009; Öngel et al., 2022).

Improving employee's perception of technology readiness in the organizational climate can help change and minimize resistance. In this environment, instead of eliminating resistance, examining its causes, learning the expectations of employees, and making decisions together in team spirit, if necessary, will increase the chance of success.

1.2 Relationships Between Concepts, and Development of Hypotheses

Studies examining the factors that enable the adoption of technologies or readiness for technologies have found that the organizational structure and management structure affect the adoption of technologies (Chittipaka et al., 2023; Taherdoost, 2022). When organizations provide a learning climate, innovation climate, and top management support, the tendency of employees to adopt new technologies increases (Malik et al., 2021). Supportive structure of the organization accelerates the adoption of new technologies in the company (Hameed et al., 2012; Huang et al., 2011; Nystrom et al., 2002; Ofosu-Ampong & Acheampong, 2022). The negative climate of the organization may negatively affect employees' level of technology adoption and readiness for new technologies. When senior management in healthcare institutions takes actions that will make it easier for employees to adopt new technologies, it will be easier for employees to adopt technologies. The hypotheses created based on the inference are as follows:

H1: Organizational climate affects technology readiness (motivating and Blocking factors).

H1a: Organizational climate positively affects motivating factors.

H1b: Organizational climate negatively affects blocking factors.

Continuous changes in the healthcare sector increase the well-being of patients and make it necessary for healthcare professionals to adapt to change. The resistance of employees in the health sector, which makes great contributions to the country's development and is constantly exposed to technological change, can cause serious problems (Lin et al., 2012). As in various sectors, in the health sector (Aydın & Okar, 2020), the positive structure of the organizational climate reduces employees' resistance to change. The open communication and participatory structure of organizational structures (Schulz-Knappe et al., 2019) reduce employees' resistance. At the same time, senior management's development of supportive and positive relationships, creating a positive organizational climate, reduces employees' resistance to change (Rehman et al., 2021; Srivastava & Agrawal, 2020). In fact, organizational climate in health institutions is seen as a concept that increases the positive behavior of employees (Berberoglu, 2018). The hypothesis created based on these inferences is as follows:

H2: Organizational climate negatively affects resistance to change.

Various technological changes may pave the way for the development of uncertainty and threat perception (Kuo et al., 2013). In this environment, employees may develop resistance to the change they experience (Lin et al., 2012). Resistance to change in the healthcare sector may be more prominent than other negative factors. Healthcare professionals often avoid changing business operations (Fournier et al., 2023). This strong resistance should generally lead senior management to act more carefully. Otherwise, it will be difficult to achieve the set goals (Poon et al., 2004; Rafferty & Jimmieson, 2017). Negative perceptions about technology increase employees' resistance to change (Özdemir-Güngör & Camgöz-Akdağ, 2018; Tsai et al., 2020).

On the other hand, technology readiness increases the relationship between employees' basic and soft skills and makes it easier for employees to adopt new processes (Caputo et al., 2019). It is expected that motivating factors and blocking factors affecting the technology readiness of employees in the healthcare sector will affect resistance to change. The hypothesis created based on these inferences is as follows:

H3: Technology readiness (motivating and blocking factors) affects resistance to change.

H3a: Motivational factors negatively affect resistance to change.

H3b: Blocking factors positively affect resistance to change.

Previous research results provide the inference that organizational climate and organizational structure (Taherdoost, 2022) positively affect the motivating factors that make employees ready for technology. In addition, employees approach technologies negatively when the organizational climate is negative. Employees' positive attitudes toward technology can reduce resistance to change. In addition, employees' negative thoughts about technologies may increase resistance to change (Lin et al., 2012; Özdemir-Güngör & Camgöz-Akdağ, 2018). The hypotheses created based on this inference are as follows:

H4: Technology readiness has a mediating role in the effect of organizational climate on resistance to change.

H4a: Motivational factors have a mediating role in the effect of organizational climate on resistance to change.

H4b: Blocking factors have a mediating role in the effect of organizational climate on resistance to change.

2 Method

2.1 Data collection tools

The Technology Readiness Index (TRI): Developed by Parasuraman and Colby (2015), the TRI is used to measure the technology readiness levels of healthcare professionals. The TRI includes four dimensions (optimism, innovativeness [motivating], discomfort, and insecurity [blocking]) and 16 items. This research us the scale with two main dimensions (motivating and blocking factors).

Resistance to Change Scale: This scale was developed by Brislin et al. (1973); Çalışkan (2019) conducted its Turkish adaptation study. The scale includes 15 items and three dimensions. In the research, the measurement tool was used as a single structure.

The Organizational Climate Scale: This scale was developed by Chen and Huang (2007) using the work of Jaw and Liu (2003). The scale includes five items.

The Survey Form: This form includes questions about the demographic information of healthcare professionals (i.e., age, gender, education, and tenure).

2.2 Sampling method

This research was conducted with a sample of 389 healthcare professionals from private healthcare institutions in Adana, Turkey. Data were collected using online survey forms distributed to participants via email. Reminders were sent until the desired number of responses was achieved. Participants were selected through a simple random sampling technique, ensuring equal opportunity for all healthcare professionals to participate. The sample's representativeness was considered sufficient, surpassing the required sample size of 360 as determined by Hair et al. (2014), who recommend a minimum of 10 respondents per scale item (36 items).

To determine the necessary sample size for regression analysis, a power analysis (Cohen, 1988) was conducted with an expected effect size (Cohen's f2) of 0.50 and a significance level (alpha) of 0.05. Given a population size of 25,000, the power analysis indicated a minimum of 166 participants would be required for regression analysis. Considering both the guidelines provided by Hair et al. (2014) and the results of the power analysis, the sample size of 389 participants was deemed adequate.

Participant demographics were as follows: 53.5% female, 46.5% male, with age distribution: 10.8% below 25, 27.3% aged 25–29, 20.1% aged 30–34, 16.8% aged 35–39, and 25% aged 40 and over. Educational levels included 23.7% with high school/associate degrees, 54% undergraduate graduates, and 22.4% with graduate degrees. Additionally, 56.8% were direct healthcare professionals (nurses, physicians, and midwives), while 43.2% were support staff.

2.3 Analysis Techniques

The data were analyzed using SPSS 25 package program. Additionally, SPSS Process 2.13 macro was used to test the mediation model. Factor and reliability analyses were performed in the analysis process. In evaluating the results of these analyses, Hair et al.'s (2014) and frequently accepted limit values in the literature were taken as basis (Kaiser-Meyer-Olkin [KMO] = > .60/.70, Bartlett's Test = p < .05, Explained variance = > 60%, Cronbach's alpha = > .6/.7). Skewness and kurtosis values were taken as a basis to ensure normal distribution of the data. Skewness and kurtosis values in the range of -2.0 – 2.0 are considered appropriate to assume a normal distribution (George & Mallery, 2010; Tabachnick & Fidell, 2013).

Generally accepted criteria were used in the examination correlation values (0 = no relationship, .01-–.19 = very low relationship, .2–.39 = low relationship, .4–.59= moderate relationship, .6–.79 = high relationship, .8–.99 = very high relationship, and 1 = complete relationship). Model 4, developed by Hayes (2018), was used to implement the mediation analysis. In evaluating the significance of the mediation model findings, p < .05 level was considered and confidence interval (CI) evaluation was performed. The fact that the confidence interval (ULCI-LLCI) does not contain a value of 0 shows that the results are significant. For the mediation findings to be meaningful, the confidence interval values of the indirect effect are checked. The bootstrapping method is used to determine the significance of the indirect effect value. The fact that the confidence interval (BootULCI-BootLLCI) values obtained by the resampling method do not contain 0 shows that the mediation role is realized (Gürbüz, 2019; Hayes, 2018).

The mediation model (4) used in this research is presented in Figure 1.

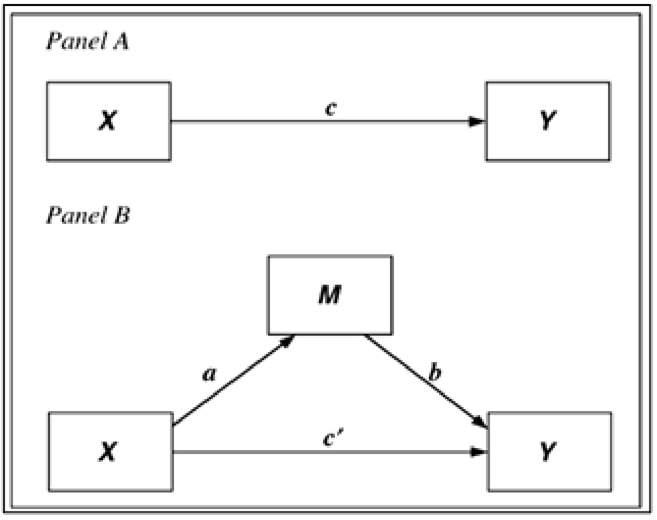

Figure 1: Simple Mediation Model

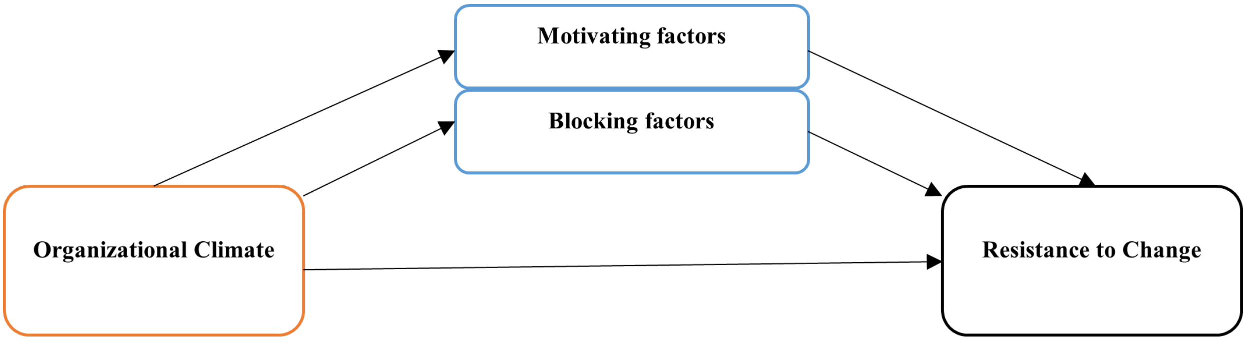

Figure 2: Conceptual Model of the Research

The path a in Figure (Panel B) expresses the direct effect (coefficient) of x on m. The effect of the mediator variable (m) on the dependent variable (y) (the coefficient obtained as a result of testing x, y and m in the same model) refers to the b path. The effect of the independent variable (x) on the dependent variable (y) (total effect; Panel A) is shown via c. Finally, path c' shows the direct effect of the independent variable (x) on the dependent variable (y) (when the coefficient/m obtained as a result of testing x, y and m in the same model is under control). In summary, It is expressed as c = total effect, a.b = indirect effect, c' direct effect, c = c'+ (a.b) (Gürbüz, 2019; Preacher & Hayes, 2004). Consistent with Hayes's (2018) model, the conceptual model created in this research is shown in Figure 2.

Factor and reliability analyses were used to evaluate the suitability of measurement tools. Analysis results are included in Table 1.

According to the factor analysis results, the KMO value of the resistance to change scale was .872, Bartlett's sphericity test was at p < .05 level, the explained variance was 68.45%, Cronbach's alpha coefficient was .890, and the number of items was 15. The KMO value of the measuring tool for the blocking factors of technology readiness was .871, Bartlett's test was at p < .05, the explained variance was 72.19%, Cronbach's alpha coefficient was .882, and the number of items was 8. The KMO value of the motivating factors of the technology readiness measurement tool was .902, Bartlett's sphericity test was at p < .05 level, the total variance explained was 81.30%, Cronbach's alpha coefficient was .926, and the number of items was 7. One item on the motivating factors of technology readiness was removed from the study due to inappropriate loading values. Finally, the KMO value of the organizational climate scale was .889, Bartlett's test was at p < .05 level, the total variance explained was 82.88%, Cronbach's Alpha coefficient was .947, and the number of items was 5. When the analysis findings are evaluated in general, it is possible to state that the resistance to change, technology readiness and organizational climate scales provide appropriate values.

Table 1: Search strategies to select articles

	Resistance to change	**Technology readiness (blocking)**	**Technology readiness (motivating)**	**Organizational climate**
KMO measure of sampling Adequacy.	.872	.871	.902	.889
Bartlett's test of sphericity (*p*)	.000	.000	.000	.000
Total variance explained (%)	68.445	72.189	81.30	82.88
Cronbach's alpha	.890	.882	.926	.947
N of item	15	8	7	5

Table 2: Correlation Analysis

	$\bar{x}$	σ	**Technology readiness (motive)**	**Technology readiness (blocking)**	**Organizational climate**	**Resistance to change**
Technology readiness (motiveting)	3.27	1.12	1			
Technology readiness (blocking)	2.26	.75	**-.622****	1		
Organizational climate	2.80	1.20	**.391****	**-.311****	1	
Resistance to change	3.44	.71	**-.428****	**.539****	**-.329****	1
**. Correlation is significance .01. *N*= 389						

Table 3: The Mediating Effect of Motivating Factors on the Effect of Organizational Climate on Resistance to Change

	R	*R²*	*p*	B	*SD*	*p*	LLCI	ULCI	Hypothesis	
Motivating factors	.3910	.1529	.000	2.2476	.1333	.0000	1.9856	2.5097	H_{1a}	Supported
Organizational climate				.3650	.0437	**.000**	**.2790**	**.4509**		
Resistance to change	.3288	.1081	.000	3.9776	.0858	.000	3.8089	4.1464	H_2	Supported
Organizational climate				-.1927	.0282	**.000**	**-.2480**	**-.1373**		
Resistance to change	.4632	.2145	.000	4.4776	.1063	.000	4.2686	4.6866	H_{3a}	Supported
Motivating factors				-.2224	.0308	**.000**	**-.2830**	**-.1619**		
Organizational climate				-.1115	.0288	**.000**	**-.1680**	**-.0550**		
(m)		Effect	BootSE		BootLLCI		BootULCI		H_{4a}	Supported
Motivating factors		-.0812	.0207		**-.1246**		**-.0442**			

Correlation analysis results are presented in Table 2. The results showed a low and positive relationship between motivating factors and organizational climate, and a moderate and negative relationship between motivating factors and resistance to change. There was a low and negative significant relationship between blocking factors and organizational climate and a moderate and positive significant relationship between blocking factors and resistance to change. A low and negative relationship was found between resistance to change and organizational climate. According to descriptive statistics, employees' motivation to use technologies was at a medium level, and their perception of blocking factors was low. In addition, their perception of organizational climate was low, and their resistance to change was moderate.

The model results, which examine the mediating role of employees' positive approaches to technologies (motivating factors) in the effect of organizational climate on resistance to change, are shown in Table 3. According to the findings, organizational climate affected employees' positive approach to technologies at a level of 15.29% ($p = .000 < .05$). The regression coefficient was positive and significant (B = .3650, ULCI = .279, LLCI = .4509). Organizational climate affected employees' resistance to change at 10.81% ($p = .000 < .05$). The regression coefficient was negative and significant (B = -.1927, ULCI = -.2480, LLCI = -.1373). The level of effects of resistance to change by organizational climate and motivational factors was 21.45% ($p = .000 < .05$). The coefficient of affecting the resistance to change of organizational climate (B = -.1115, ULCI = -.1680, LLCI = -.0550) and the coefficient of affects the resistance of motivating factors to change (B = -.2224, ULCI = -.2830, LLCI = -.1619) was negative and significant. The mediating role of motivational factors in the effect of organizational climate on resistance to change was low (-.0812), negative and (BootLLCI= -.1246, BootULCI= -.0442) significant. Motivational factors had a mediating role in the effect of organizational climate on resistance to change. The mediating effect of motivating factors was low and negative.

When the findings are generally interpreted, it is seen that the positive climate of the organization reduced employees' resistance to change. In addition, the positive climate of the organization increased employees' positive attitudes toward technology. The employees' positive approach to technology was a factor that reduced resistance to change. When the organizational climate was positive, employees' approach to technologies was positive and resistance to change decreased.

The model results, which examine the mediating role of employees' negative approaches to technologies (blocking factors) in the effect of organizational climate on resistance to change, are presented in Table 4. According to the findings, the level of organizational climate explaining the blocking factors related to technology was 9.7% ($p = .000 < .05$). The regression coefficient was negative and significant (B = -.1951, ULCI = -.2547, LLCI = -.1354). The level of explanation of resistance to change by organizational climate and blocking factors was 31.74% (p = .000 < .05). The effect coefficient of the organizational climate's resistance to change (B = -.1050, ULCI= -.1560, LLCI= -.0539) is negative and significant. The coefficient affecting the resistance of blocking factors to change (B = .4496, ULCI = .3682, LLCI = .5309) was positive and significant. The mediating role of blocking factors in the effect of organizational climate on resistance to change was low (-.0877), negative and significant (BootLLCI = -.1337, BootULCI = -.0514). The main findings of this study are presented visually in Figure 3.

Blocking factors had a mediating role in the effect of organizational climate on resistance to change. The mediating effect of blocking factors was low and negative. According to the findings, a positive organizational climate reduced employees' negative attitudes toward technology. When employees had a negative approach toward technology, resistance to change increased. A positive organizational climate reduced employees' negative attitudes toward technology and subsequently reduces resistance to change.

3 Discussion

Important results were obtained in this research, which was conducted to determine the mediating role of technology readiness level in the effect of organizational climate in health institutions on resistance to change. According to the findings, a positive organizational climate in healthcare

Table 4: The Mediating Effect of Blocking Factors on the Effect of Organizational Climate on Resistance to Change

	R	*R²*	*p*	*B*	*SD*	*p*	LLCI	ULCI	Hypothesis	
Blocking factors	.3019	.097	.000	2.8092	.0925	.000	2.6272	2.9911	H_{1b}	Supported
Organizational climate				-.1951	.0303	**.000**	**-.2547**	**-.1354**		
Resistance to change	.5634	.3174	.000 .4496	2.7146	.1384	.000	2.4424	2.9869	H_{3b}	Supported
Blocking factors			-.1050	.4496	.414	**.000**	**.3682**	**.5309**		
Organizational climate				-.1050	.0260	**.001**	**-.1560**	**-.0539**		
(m)		Effect	BootSE		BootLLCI		BootULCI		H_{4b}	Supported
Blocking factors		-.0877	.0211		**-.1337**		**-.0514**			

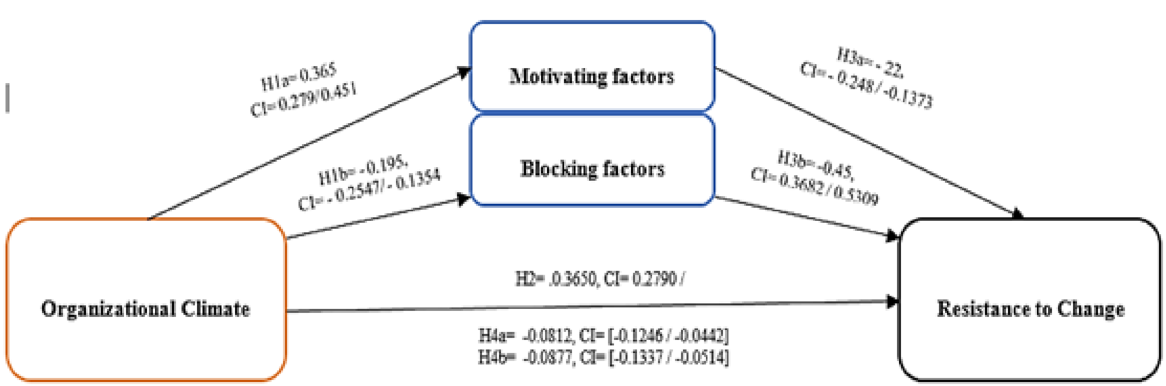

Figure 3: Resulting Model

institutions motivates employees to be ready for technology and reduces the factors that prevent them from being ready for technology. In addition, a positive organizational climate significantly reduces employees' resistance to change. Health workers' positive attitudes to technologies reduce their resistance to change. On the other hand, healthcare professionals' negative attitudes to technologies increase their resistance to change.

The important finding of the research is about the mediating role of technology readiness level. According to the results, while a positive organizational climate in healthcare institutions reduces resistance to change, technology readiness's motivating and blocking factors have mediating roles. In other words, the organizational climate in healthcare institutions motivates employees to be ready for technology and reduces employees' resistance to change. Additionally, organizational climate reduces employees' negative attitudes toward technology (blocking factors) and reduces resistance to change.

Based on all these findings, it may be beneficial for healthcare managers to take the following measures to make their institutions more successful:

Organizations are living organisms where more than one individual comes together to achieve certain goals. The more the goals and objectives in the organization are embraced, the more the sense of unity and solidarity, organizational ownership, commitment and solidarity will develop. It can play a more active role in improving the organizational climate, eliminating its deficiencies, and adopting and implementing goals and strategies. As resistance to change decreases, it can improve employees' readiness for technological changes.

Change is one of the fundamental elements that affects organizations in every field and shapes their future. It manifests itself in competition, innovation, customer expectations and demands, technology and many different areas. It is extremely important for organizations to be prepared for change and to take precautions by anticipating internal and external environmental differences. In this context, managers who can follow technology and allow their employees to assimilate the technology they obtain can achieve their goals faster. In addition, managers who evaluate and manage technological advances together with their employees may encounter less resistance to changes.

The findings obtained from this study are compatible with those of other studies in the literature discussing resistance to change. Previous studies show that organizational climate reduces resistance to change (Aydın & Okar, 2020; Burton et al., 2000; Hon et al., 2014), readiness for technology reduces resistance to change (Abdel-Ghany, 2014; Turan, 2020), and organizational climate reduces resistance to technology. Literature proves it increases the positive approach (Ashraf et al., 2020; Huang et al., 2011; Khasawneh, 2018; Yoo & Wen-Hao, 2012).

The findings obtained from this research are compatible with the previous studies; however, these results have different contributions. Previous studies do not sufficiently examine the technological context of the organizational climate in healthcare institutions and the resistance of healthcare professionals to change; however, this research examines the hindering and motivating factors of technology readiness affecting healthcare workers' resistance to change, which makes it unique. The research contributes to the literature as it is the first study examining the role of technology readiness in the effect of organizational climate on change resistance. In addition, this study constitutes a new agenda by showing the extent to which technological developments in today's health sector and other sectors create resistance in employees and how organizational and individual factors effectively overcome resistance to change.

4 Conclusion

This research has limitations in some aspects, the most important of which was that it examined general technologies. The study was based on no specific technological innovations in a specific health sector. Examining specific technological innovations can effectively show how resistance to change varies in organizations. Additionally, this research was conducted in the Turkish healthcare sector. The technology readiness level of healthcare personnel in developing countries may differ from that of healthcare professionals in developed countries, and different results may be obtained in renewed studies. Another limitation of the research was about the losses of employees in organizational changes. Changes may cause employees to lose their professional practices. These losses can increase stress levels (Fournier et al., 2023). Finally, the skills employees had to change were not addressed within the scope of this research.

It is recommended that future studies on resistance to change be conducted specifically on the technologies used in hospitals. Thus, it can be determined how technology's usefulness, difficulty, and satisfaction affect resistance to change. In addition, actions in the health sector directly affect patients' health. The fact that healthcare professionals' behavior has such a significant impact may cause their skills to come to the fore. For this reason, it is recommended that healthcare professionals' intellectual capital and self-efficacy be associated with resistance to change. Some of the research's recommendations are related to the health sector. Making employees competent in technology reduces resistance to change (Yoo & Wen-Hao, 2012; Kim, 2009;). Therefore, training, technical support and cognitive strengthening should be provided to healthcare professionals. Since the support of top management creates a positive organizational climate in healthcare institutions, it is recommended that senior management create feedback, open communication and a supportive climate in healthcare institutions. In this way, healthcare professionals can easily solve problems and be ready for innovations.

In developed and developing countries, readiness for and resistance to innovations are unique. Numerous studies support this viewpoint (Jones et al., 2005; Rojas-Mendez et. Al., 2017; Alhammadi et al., 2023). The technological infrastructure in developed countries facilitates higher acceptance of technological innovations. Therefore, readiness for new technologies can vary depending on countries and cultures. Hence, future research should explore the impact of culture on technology readiness and resistance to change.

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Organızacıjskı ın ındıvıdulanı dejavnıkı odpora do sprememb: organızacıjska klıma ın prıpravljenost na tehnologıjo

Ozadje in namen: Ovire za spremembe v organizacijah so pogosto predmet raziskav. Ta študija obravnava dejavnike, ki vplivajo na odpor do sprememb, pri čemer se osredotoča na tehnološke kompetence zaposlenih. Namen raziskave je ugotoviti posredniško vlogo pripravljenosti na tehnologijo v vplivu organizacijske klime v zdravstvenih ustanovah na odpor do sprememb.
Metodologija: Podatki so bili zbrani od 389 zaposlenih v zdravstvenem sektorju. Za analizo modela je bil uporabljen SPSS Process 2.13 macro.
Rezultati: Rezultati analize so pokazali, da ima organizacijska klima pozitiven vpliv na pripravljenost na tehnologijo. Poleg tega je ugodna organizacijska klima zmanjšala odpor do sprememb. Prav tako je višja pripravljenost zaposlenih na tehnologijo zmanjšala odpor do sprememb. Ugotovljeno je bilo, da ima pripravljenost na tehnologijo (v smislu motivacijskih in zaviralnih dejavnikov) pomembno posredniško vlogo v vplivu organizacijske klime na odpor do sprememb. Pozitivna organizacijska klima v zdravstvenih ustanovah povečuje pripravljenost zaposlenih na nove tehnologije in bistveno zmanjšuje njihov odpor do sprememb.
Zaključek: Oblikovanje pozitivne organizacijske klime je lahko ključno za uspešno izvajanje sprememb v zdravstvenem sektorju. Na koncu raziskave so podana teoretična in praktična priporočila. Raziskava prispeva k literaturi z obravnavo predhodnikov odpora do sprememb z organizacijskega in individualnega vidika.

Ključne besede: *Zdravstveni delavci, Organizacijska klima, Odpor do sprememb, Pripravljenost na tehnologijo*

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User Evaluation of a Machine Learning-Based Student Performance Prediction Platform

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Background/Purpose: The integration of machine learning in education has opened new possibilities for predicting student performance and enabling early interventions. While most of the work has been focused on prediction algorithms design and evaluations, little work has been done on user-centric evaluations.
Methodology: This study evaluates a web-based platform designed for student performance prediction using various machine learning algorithms. Users, including students, professors, and career counselors, tested the platform and provided feedback on usability, accuracy, and recommendation likelihood.
Results: Results indicate that the platform is user-friendly, requires minimal technical support, and delivers reliable predictions.
Conclusion: Users strongly endorsed its adoption, highlighting its potential to assist educators in identifying at-risk students and improving academic outcomes.

Keywords: *Student performance, Machine learning, System evaluation*

1 Introduction

The application of Machine Learning in various contexts, especially across educational levels from pre-primary to university, represents a transformative and promising approach to enhancing teaching and learning outcomes. As we know, data is the key enabler that allows us to apply various ML and AI algorithms to improve existing results. Among other things, if the data quality is high, the recommendations generated by ML and AI algorithms can be more effectively integrated into efforts to enhance student performance, particularly in critical areas where the education system needs improvement. This also facilitates the early identification of students who may be at risk of failure. Prior research has demonstrated the effectiveness of ML algorithms in forecasting student performance based on various academic and demographic factors (Pallathadka et al., 2023), (Hussain et al., 2024a). Predictive models have been employed to identify at-risk students (Malik et al., 2022), optimize curriculum structures (Ab Rahman et al., 2024), and improve early intervention strategies (Dr Joel Osei-Asiamah et al., 2024). However, while these studies highlight the importance of student performance prediction, they often lack user-centered evaluations of the platforms implementing these models. This research addresses this critical gap by developing and evaluating a user-friendly, web-based student performance prediction platform, integrating supervised ML algorithms including Support Vector Machine, Decision Tree, Random Forest,

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and Neural Networks. Unlike previous works that primarily focus on model accuracy (Binti Baharuddin et al., 2024), (Hoti & Zenuni, 2024), (A. Hoti et al., 2025), this study attempts to assess real-world usability, accessibility, and perceived effectiveness of the platform through comprehensive user feedback and system evaluation. The evaluation framework includes a multi-dimensional analysis encompassing system usability, prediction reliability, and user recommendations.

The key novelty of this study lies in its comprehensive user assessment of an ML-driven prediction platform, offering insights into its practicality for educational institutions. While prior studies (Sopegno et al., 2016), (Jáuregui-Velarde et al., 2023), have explored ML-based prediction models, our research uniquely investigates how end-users interact with and perceive the effectiveness of such a system. The findings are expected to inform the design of more effective, user-friendly educational technologies and guide policymakers and institutions in adopting AI-based solutions for academic support.

The remainder of this paper is organized as follows: Section 2 presents a literature review of related works, Section 3 describes the methodology, Section 4 discusses results and user evaluations, and Section 5 concludes with insights and future improvements.

2 Related Work

The application of machine learning (ML) and artificial intelligence (AI) in education has been widely explored to enhance student performance prediction and support decision-making in academic institutions. Previous studies have demonstrated the effectiveness of ML algorithms in forecasting student success and identifying at-risk students, thereby enabling timely interventions (Pallathadka et al., 2023b), (Hussain et al., 2024b). Several research efforts have focused on the development of ML-based predictive models. For instance, (Hasan et al., 2018), proposed a student performance prediction model utilizing decision trees and support vector machines, achieving high accuracy in predicting academic outcomes. Similarly, (Asselman et al., 2021) applied the XGBoost algorithm to improve prediction accuracy, highlighting the importance of feature selection in enhancing model performance. Other studies have explored deep learning approaches, such as neural networks, for predicting student success based on behavioral and demographic data (Sokkhey & Okazaki, 2020), (Wang & Yu, 2025). While these models exhibit strong predictive capabilities, their practical implementation in real-world educational settings remains underexplored.

Another critical area of research involves the integration and use of various educational platforms that have AI built in. Studies have shown that user engagement and ease of use significantly impact the effectiveness of educational technology (Briz-Ponce et al., 2016), (Chan et al., 2024). Akçapınar and others developed an early warning system for at-risk students, demonstrating that real-time data analysis can enhance retention rates. However, limited research has been conducted on user-centered evaluations of prediction platforms, particularly from the perspective of students, educators, and career counselors (Akçapınar et al., 2019).

Predicting student performance is essential for improving academic outcomes and supporting learners. Many researchers use different data from LMSs' such as Moodle

(Abuzinadah et al., 2023), (Rogers et al., 2025), Canvas (Desai et al., 2021), (Bai, 2024), and Blackboard (Rubio-Arraez, 2022), (Darko, 2021), (Othman, et al., 2024) to analyze data from their input and visualize them for institution needs. Compared to this, the proposed model of our platform is more productive because it offers prediction automatically for each student, using different algorithms and doesn't limit the terms for courses or institutions. Moreover, from the proposed platform each person can upload their data to our platform and predict student performance or with our data experiment with them.

In contrast to prior work, this study introduces a web-based, interactive ML platform designed for student performance prediction and conducts a comprehensive user evaluation to assess usability, adoption potential, and accuracy. This paper investigates how users interact with the system, their perceptions of its predictive capabilities, and its practical applications in academic institutions. The findings contribute to the growing body of research on AI in education by bridging the gap between technical accuracy and real-world usability, ensuring that predictive analytics tools are both effective and accessible.

3 Methodology

The study evaluates a machine learning-based student performance prediction platform by assessing its usability, accuracy, and user perception. The evaluation focuses on how users interact with the platform, their assessment of its predictive capabilities, and their willingness to adopt and recommend it. Key stakeholders in higher education, including students, professors, and career counselors have been involved, to ensure a well-rounded assessment from both end-users and expert evaluators.

The platform was designed as a web-based tool, developed using Streamlit (Inc., 2019) and hosted on GitHub, providing users with an interactive environment for student performance prediction. Participants could upload their datasets or use a built-in dataset, select a machine learning model—such as Decision Tree, Support Vector Machine (SVM), Random Forest, or Neural Networks—and receive a prediction regarding student success or dropout risk.

These interactions allowed users to test the platform's usability, functionality, and effectiveness in an educational setting.

To systematically assess the platform, the study was guided by three research questions:

(RQ1) How do users perceive and evaluate the platform's usability and effectiveness?

(RQ2) Would users recommend the platform, and what factors influence their recommendation?

(RQ3) How accurate do users find the platform's predictions, and what improvements do they suggest? These questions provided a structured approach to understanding user experiences and areas for enhancement.

Data collection for the user evaluation was conducted through a structured three-part survey. The first section measured usability using the System Usability Scale (SUS), where participants rated aspects such as ease of use, navigation, and clarity on a Likert scale (1–5). The second section focused on adoption and recommendation, using the Net Promoter Score (NPS) to assess how likely users were to recommend the platform on a scale from 1–10. Open-ended responses were also collected to understand the reasons behind their ratings. The final section examined perceived accuracy and potential improvements, where users evaluated whether the platform's predictions aligned with real-world student performance and provided suggestions for refinement.

To analyze the collected data, both quantitative and qualitative methods were applied. Likert scale and NPS ratings were processed using descriptive statistics, with results presented in tables and graphs to highlight trends in user perception. Open-ended responses were analyzed through thematic coding, categorizing insights into usability strengths, challenges, and suggestions for improvement. This dual approach allowed for a comprehensive evaluation of the platform, ensuring that both numerical trends and user feedback were incorporated into the study's findings.

4 Results and Discussion

To ensure a comprehensive evaluation of the developed platform before final publication, a structured user assessment was conducted. The evaluation process involved distributing the platform for testing, followed by a survey designed using Google Forms to systematically capture user feedback. The primary objective of this assessment was to analyze user perception from multiple perspectives, including usability, effectiveness, and adoption potential.

The survey was disseminated among students, professors, and career counselors, who represent key stakeholders in higher education as presented in Figure 1. Their insights were crucial in understanding how the platform supports academic decision-making and intervention strategies. Students and faculty members were the primary focus of this study, as the platform aims to assist educators in identifying at-risk students and facilitating timely interventions. Given that career counselors play a significant role in academic and professional guidance, their perspectives were also integrated to evaluate the system's broader applicability.

Additionally, feedback was gathered from individuals outside the educational system, including former students and professionals who have completed or discontinued their studies. These participants provided an external viewpoint on the platform's relevance, drawing from their own experiences in higher education. Their input helped assess whether the tool effectively addresses the challenges associated with student retention and performance prediction.

By incorporating diverse perspectives, this evaluation ensures a holistic understanding of the platform's usability, strengths, and areas for improvement. The following sections present a detailed analysis of user responses, highlighting key trends and implications for future enhancements.

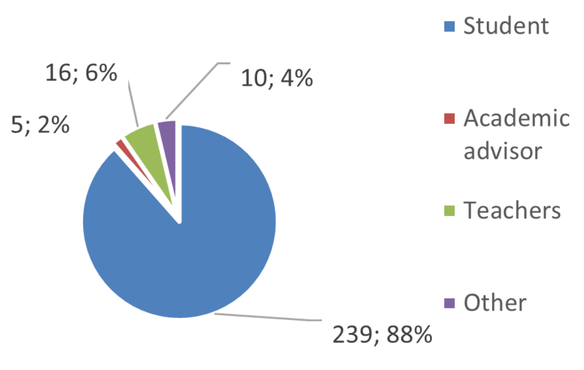

Figure 1: Distribution of the participants

The evaluation of the student performance prediction platform was structured into three key components to ensure a comprehensive assessment of its usability, adoption potential, and predictive accuracy. The first component focused on user perception and evaluation, specifically analyzing the platform's usability, user experience (UX), and interface design. Participants assessed the ease of navigation, intuitiveness, and overall accessibility of the system. These insights were critical in identifying potential usability challenges and determining whether the platform requires additional support mechanisms for users with varying levels of technical expertise.

The second component examined user recommendations and adoption likelihood. Participants were asked whether they would endorse the platform to their peers and what factors influenced their decision. This analysis provided valuable insights into the platform's perceived value, effectiveness, and potential areas for increasing adoption rates within academic institutions.

The third component evaluated the accuracy of the model in predicting student success or attrition. Users tested the system with real or sample datasets to assess its predictive performance. Additionally, this section of the evaluation allowed participants to provide qualitative feedback on what aspects of the platform should be improved or expanded, such as refining algorithm accuracy, incorporating additional predictive factors, or enhancing data visualization.

Following a detailed analysis of user feedback, modifications were implemented to improve the platform's functionality and effectiveness. User-driven enhancements played a crucial role in optimizing system performance, refining the user interface, and increasing the clarity of predictive outputs. These iterative improvements not only strengthened the platform's usability but also ensured that it better aligns with the needs of students, educators, and career counselors.

4.1 Platform Design and Deployment

To develop a robust student performance prediction system, multiple supervised machine learning algorithms were implemented and evaluated. The selected models included Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), Linear Regression (LinR), and Naïve Bayes variants (GaussianNB, MultinomialNB, ComplementNB, BernoulliNB). Additionally, advanced neural network architectures such as the Multilayer Perceptron (MLP) and Kolmogorov-Arnold Networks were integrated to enhance predictive capabilities. The performance of these models was assessed based on accuracy and F1-score, ensuring an optimal balance between precision and recall.

The selection of algorithms was made based on the list of standard algorithms and boosting algorithms, from which the algorithms that were most suitable for our data were selected. To achieve higher accuracy, avoid overfitting, and bias management, all algorithm parameters were carefully tuned rather than using the default settings. The optimal parameter combinations were identified using the RandomizedSearchCV method. For example, the most suitable parameters for the Decision Tree model were: ccp_alpha = 0.0, max_depth = 10, min_samples_leaf = 5, and min_samples_split = 10, and this model was evaluated using 5-fold cross-validation, achieving a mean accuracy of 0.88 [5].

Following model development and validation, the platform was deployed using GitHub for code management and Streamlit for web-based accessibility. Streamlit was selected for its ability to create an interactive and user-friendly interface, enabling seamless experimentation with different machine learning models.

Users could access the platform in real time via std-performance.streamlit.app, where they were provided with multiple functionalities for testing and evaluating student performance predictions as shown in Figure 2. The interface allows users to upload a dataset or utilize the preprocessed dataset provided within the system. To enhance usability, the main menu featured intuitive navigation options, including "Data Exploration" for analyzing input variables and patterns, and an "About" section providing insights into the predictive model's functionality.

This structured approach ensures that users, including students, educators, and career counselors, could efficiently interact with the system, test different predictive models, and assess their applicability in real-world academic settings. The next section presents the findings from the user evaluation, highlighting key insights into platform usability, adoption potential, and predictive accuracy.

Figure 3 presents the prediction menu, which is structured into three distinct sections. The first section, referred to as the "Prediction Section," enables users to generate predictions based on selected input data. Within this section, users have the option to either utilize the default dataset or upload a custom dataset, provided that the uploaded data adheres to the predefined attribute structure. Additionally, users can select the desired machine learning classifier to perform the prediction task.

Upon executing a prediction, the platform automatically evaluates the selected model, generating key performance metrics, including accuracy, F1-score, and confusion matrix values. These outputs facilitate an objective assessment of the model's effectiveness in classifying student performance outcomes, providing users with quantifiable insights into predictive reliability and decision-making accuracy.

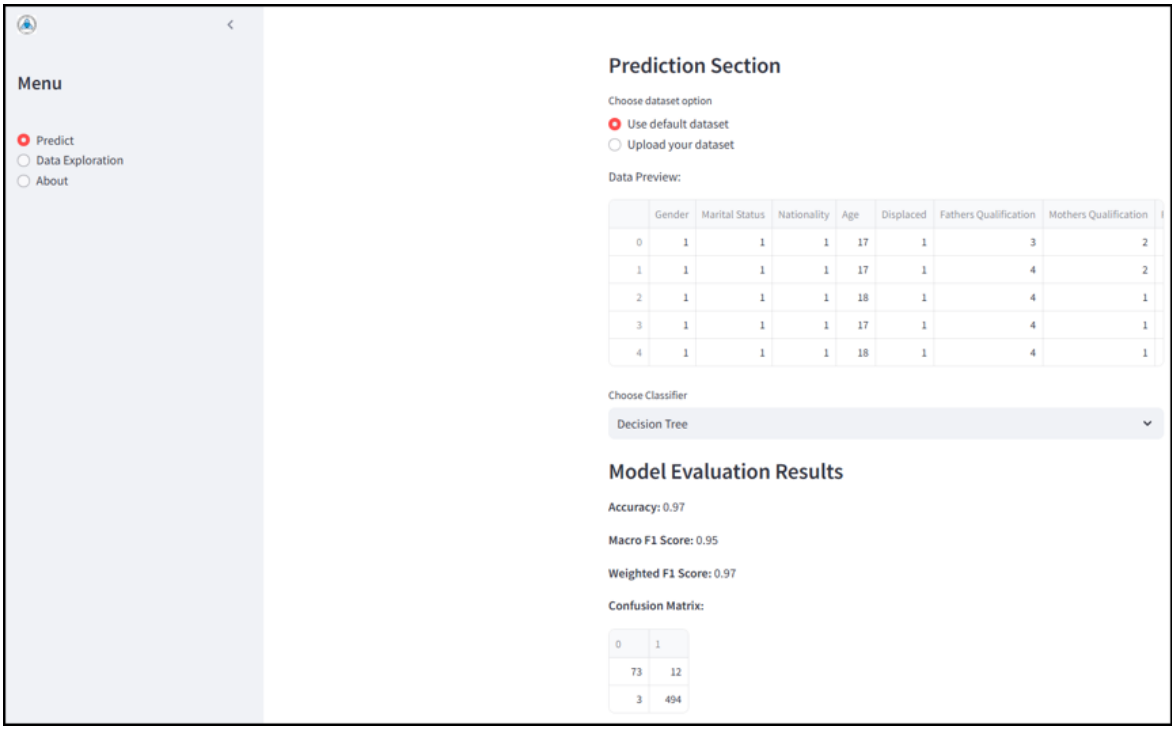

Figure 2: Web app prototype

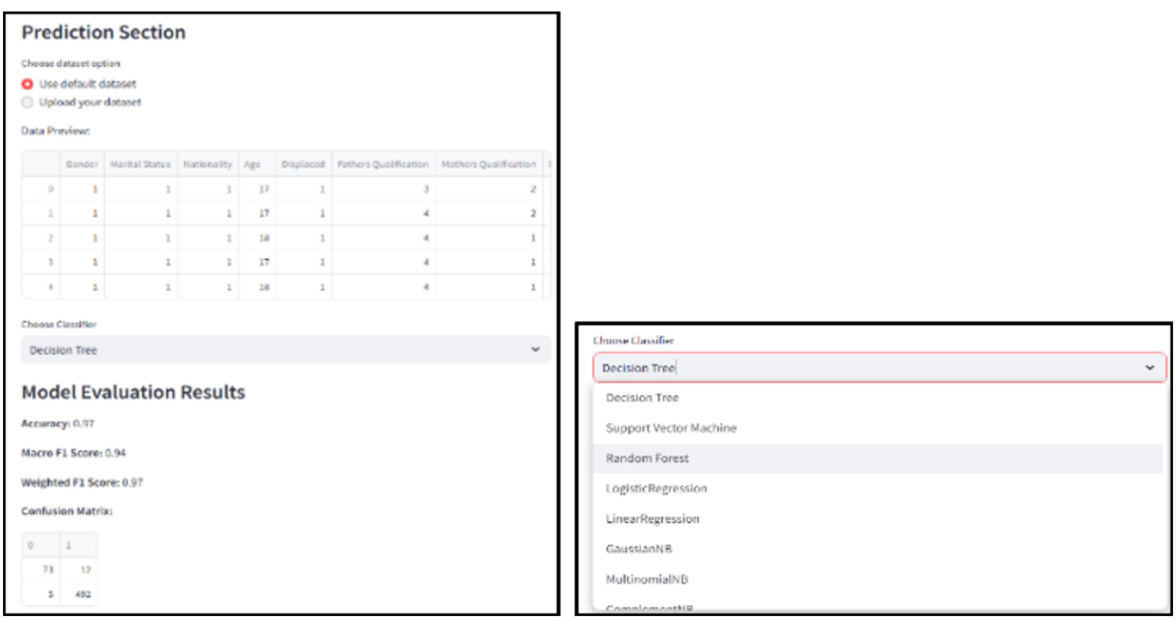

Figure 3: Prediction section

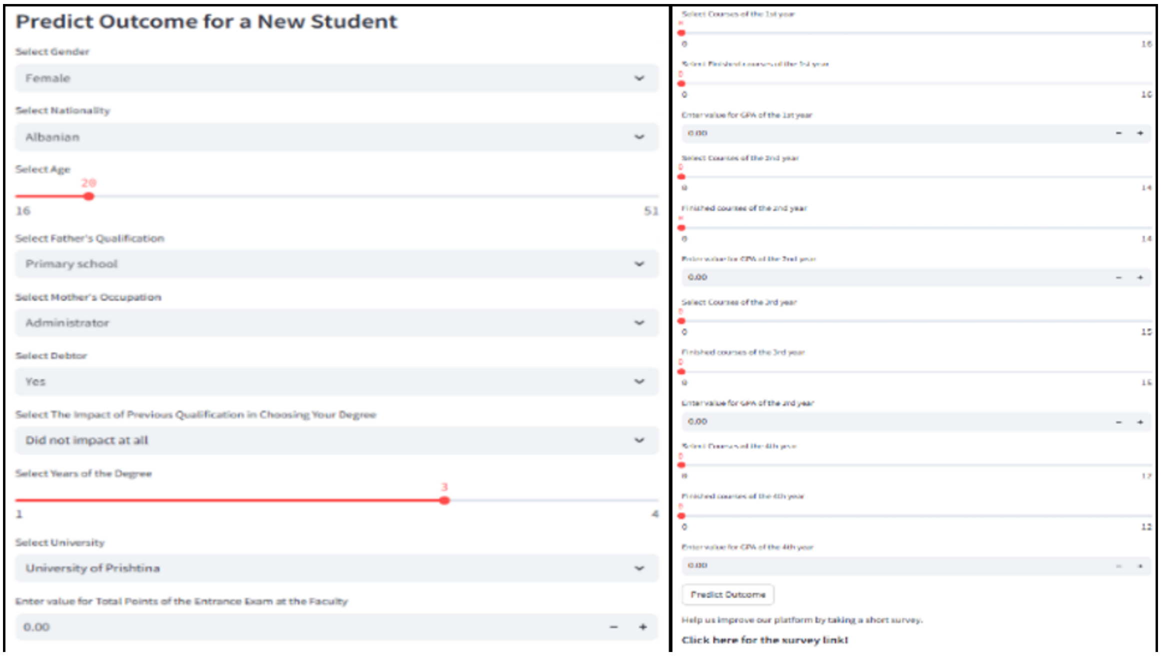

Figure 4: Predict outcome section

Table 1: Results for perception and evaluation of the platform

Description	5-point Likert Scale									
	1	2		3		4		5		
The platform is easy to use?	4	(1.48%)	3	(1.11%)	21	(7.78%)	72	(26.67%)	117	(62.96%)
Were the functions on this platform well integrated?	2	(0.74%)	4	(1.48%)	32	(11.85%)	88	(32.59%)	144	(53.33%)
I need the support of a technical person to be able to use this platform?	223	(82.59%)	23	(8.52%)	13	(4.81%)	7	(2.59%)	4	(1.48%)
I need to learn a lot of things before using this platform?	71	(26.30%)	67	(24.81%)	56	(20.74%)	40	(14.81%)	36	(13.33%)
Was the platform difficult to use?	218	(80.74%)	23	(8.52%)	20	(7.41%)	6	(2.22%)	3	(1.11%)
Will I use this platform in the future?	2	(0.74%)	8	(2.96%)	47	(17.41%)	117	(43.33%)	96	(35.56%)

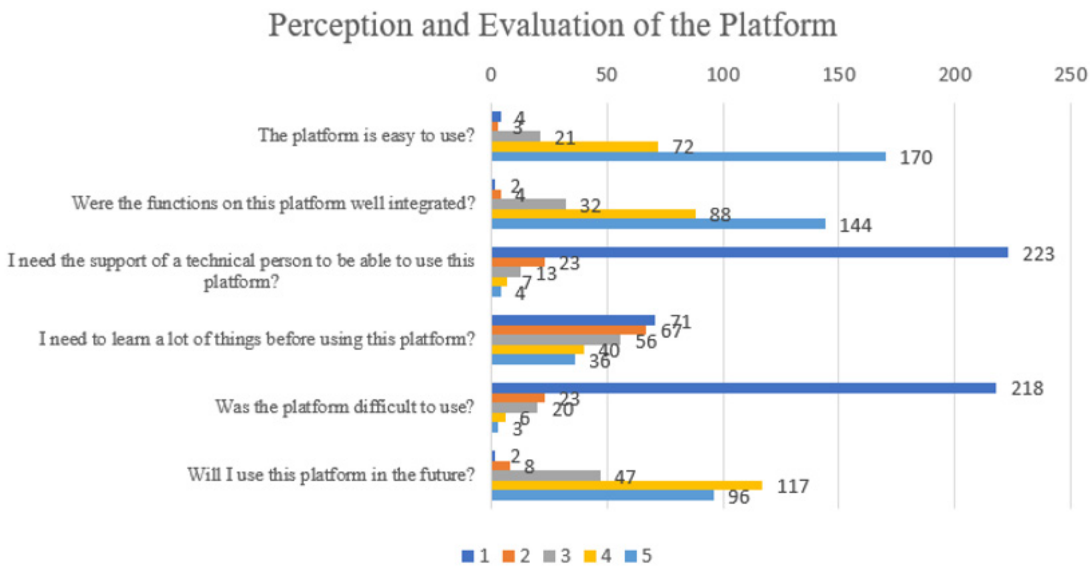

Figure 5: Perception and evaluation of the platform graph

As shown in Figure 4, the second section, "Predict Outcome for a New Student," allows users to input key academic and demographic attributes to generate performance predictions. After submitting the required data, users receive results via the "Predict Outcome" button. The platform ensures unrestricted access to testing while maintaining user privacy and data confidentiality. Following the predictions, users were invited to complete a survey to provide feedback on the platform's usability and effectiveness.

4.2 User Perception and Evaluation of the Platform

To assess user perception of the platform's usability and effectiveness, a structured questionnaire was conducted, evaluating key aspects such as ease of use, integration, and technical support requirements. Responses were recorded on a 5-point Likert scale, ranging from strongly disagree (1) to strongly agree (5).

The results as presented in

Table 1 and Figure 5 indicate a high level of usability, with 62.96% of participants strongly agreeing that the platform is easy to use, while an additional 26.67% agreed, confirming its intuitive design. Similarly, 53.33% of respondents strongly agreed that the platform is well integrated, with 32.59% agreeing, suggesting a well-structured system.

Regarding the need for technical assistance, the majority of users (82.59% strongly disagreed) that external support was necessary, indicating that the platform is accessible to users of varying technical backgrounds. Additionally, 80.74% strongly disagreed that the platform was difficult to use, reinforcing its user-friendly design.

Future adoption trends were also analyzed, with 78.89% of users indicating they would continue using the platform. Only a small fraction expressed uncertainty or reluctance. These findings, visualized in Figure 5, highlight strong user confidence and satisfaction, suggesting that the platform is well-suited for broader academic adoption done.

4.3 Platform Recommendations and User Ratings

To assess the likelihood of user adoption and platform endorsement, participants were asked whether they would recommend the platform to others on a scale from 1 to 10. This evaluation addressed Research Question 2 (RQ2): Would users recommend the platform, and what factors influence their recommendation?

The results, summarized in Table 2 and Figure 6, indicate a high recommendation rate, with an average score of 8.14, suggesting strong user confidence in the platform's utility. Open-ended responses, detailed in Table 3, provide further insight into the rationale behind these ratings, highlighting key factors such as ease of use, predictive accuracy, and potential benefits for students and educators. These findings suggest that user satisfaction plays a crucial role in driving platform adoption, reinforcing its applicability in educational settings.

Table 2: Results from the recommendation platform

Would you recommend this platform to someone else, on a scale of 1 to 10?		
1 - 10 - Rating scale	1	0 (0.00%)
	2	0 (0.00%)
	3	1 (0.37%)
	4	3 (1.11%)
	5	18 (6.67%)
	6	35 (12.96%)
	7	33 (12.22%)
	8	47 (17.41%)
	9	53 (19.63%)
	10	80 (29.63%)
Average Score	8.14	

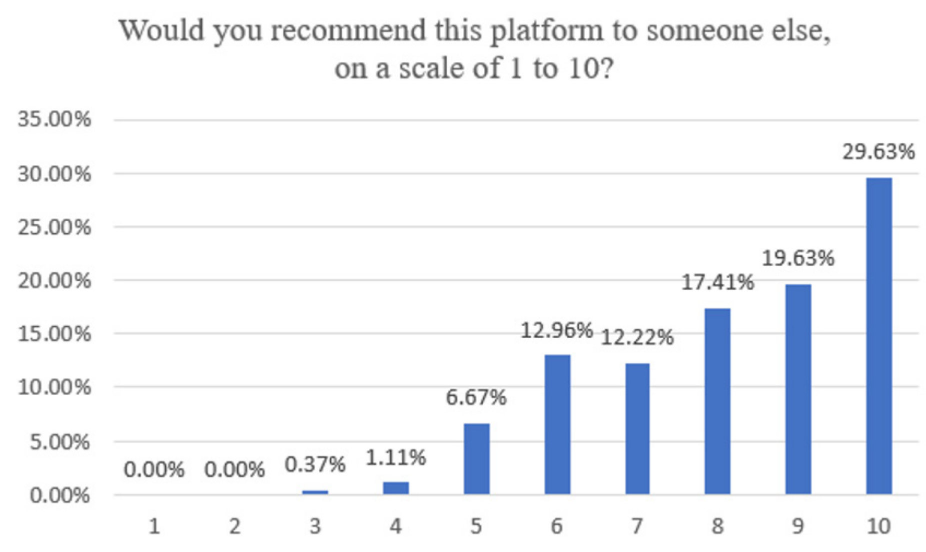

Figure 6: Percentage of the results from the recommendation platform

Table 2 presents the results of the preliminary selection, indicating the respondents' recommendations on a scale of 1 to 10. Among the participants, 29.63% (80) selected a rating of 10, while 19.63% (53) chose a rating of 9. For both ratings of 10 and 9, respondents expressed similar opinions, as detailed in Table 3. Specifically, they recommended the platform due to its ease of use, clarity, engagement, efficiency in predicting student performance, consideration of factors influencing performance, and minimal time required for operation.

A rating of 8 was given by 17.41% (47) of respondents, who also recommended the platform. However, some users noted that the prediction algorithms and the presentation of data in tables were unclear, though they acknowledged that these aspects could enhance the prediction process. For ratings ranging from 1 to 7, the distribution of responses is reflected in Table 2. The open-ended responses from users regarding their evaluations are summarized in Table 3.

Table 3: User's opinions about recommendation platforms

Rating scale	What made you choose this rating? Please share the reasons behind your choice?
10	– *I like it;* – *The platform is easy to use, and has accurate prediction;* – *Forecast performance;* – *The platform was interesting;* – *Because the platform was quite easy to use, and it was efficient;* – *It is very easy and effective;* – *It has easy access, is simple to understand, and does not take much time;* – *Very good and easy to use;* – *Everything directly related to our work is of great help to us, that's why I rated it like this;* – *I have heard about these types of platforms but not for our country, where I would recommend the same to others for use;* – *It is easy to use;* – *Easy, understandable, and simple access for each person;* – *Since it was very easy, and could have a good result;* – *Since the idea is very good, and may have an impact on predicting our success.*
9	– *I chose this assessment because this platform provides valuable insights into student performance factors that are essential for predicting graduation outcomes;* – *Simple to use and easy-to-understand interface;* – *A good data analysis and innovation platform;* – *I chose this assessment because I think these platforms are essential in our country because it is good to see the performance of students;* – *Since it is a new platform and has not been seen so far it is worth recommending to others and the way it works;*
8	– *Easily accessible and very understandable;* – *I found the first part of the platform a little elusive, somehow I didn't understand how the tabular part worked, the question part was fine;* – *Ease during work;* – *Easy access to respond;* – *New method;* – *Since the platform can have a positive impact on its use.*
7	– *To further improve the forecast by taking more cases;* – *Curiosity to try something new.*
6	– *To clarify some of the keywords (such as: Debtor)* – *To integrate hours of study, lab activities;* – *It would be helpful to provide some additional clarification.*
5	– *Print the report after completion and send it to the competent bodies;* – *I was not clear how it works and would need a user manual.*
4	– *The knowledge of the English language affects the academic performance of students and the absence of lectures or exercises.* – *I would recommend it to others, but first, let's clarify how it works.*
3	– *I choose this rating, as I think the platform still needs to be advanced.*
2	– *NA*
1	– *NA*

4.4 Model Predictions and User Feedback on Platform Usage

The primary objective of these surveys was to evaluate the accuracy of the platform's predictions and to gather additional insights from users regarding its functionality across different contexts. To address this, the research question RQ3 was formulated: "How accurate are the predictions of student success, and what additional features should be integrated according to user feedback?" This question aims to assess the accuracy of the results generated by the platform based on tests conducted by various users.

Table 4 presents the survey results on a Likert scale from 1 to 5 (1 = strongly disagree, 5 = strongly agree), indicating participants' perceptions of the model's accuracy. Figure 7 provides a graphical representation of participants' opinions concerning the accuracy and quality of the platform's predictions. According to Table 4, among the 270 respondents, the majority expressed satisfaction with the model's performance: 50.37% (136) strongly agreed that the model was accurate, 31.11% (84) agreed, 11.11% (30) were neutral, 6.30% (17) disagreed, and only 1.11% (3) strongly disagreed with the accuracy of the platform's predictions for their individual cases. These percentages reflect the user feedback, indicating that the platform generally produces reliable results.

Table 5 presents user comments regarding the aspects they liked or felt should be removed from the platform. Several comments also suggest potential improvements and alternatives that could further enhance the platform's precision. For instance, some users proposed adding attributes such as tracking whether students have participated in training during their studies, defining subjects for each academic year, and addressing the inclusion of parental qualifications. While some participants believe the parental qualification attribute should be omitted, others consider it an important factor to incorporate.

Additionally, feedback related to the platform's usability suggests that providing a manual on its operation would facilitate user experience. Users also emphasized the need for more detailed information on their activity levels, such as the amount of time spent on each subject and overall engagement.

Based on the feedback presented in Table 5, the platform appears to have a positive impact. It effectively identifies student performance, highlighting both the best and weakest results, as well as their engagement in systematic evaluations. Moreover, the platform's predictive capabilities could help guide students towards success by enabling comparisons among peers.

Table 4: Results from the accuracy prediction

How satisfied are you with the platform's accuracy and forecast quality?		
5-point Likert Scale	**1**	3 (1.11%)
	2	17 (6.30%)
	3	30 (11.11%)
	4	84 (31.11%)
	5	136 (50.37%)

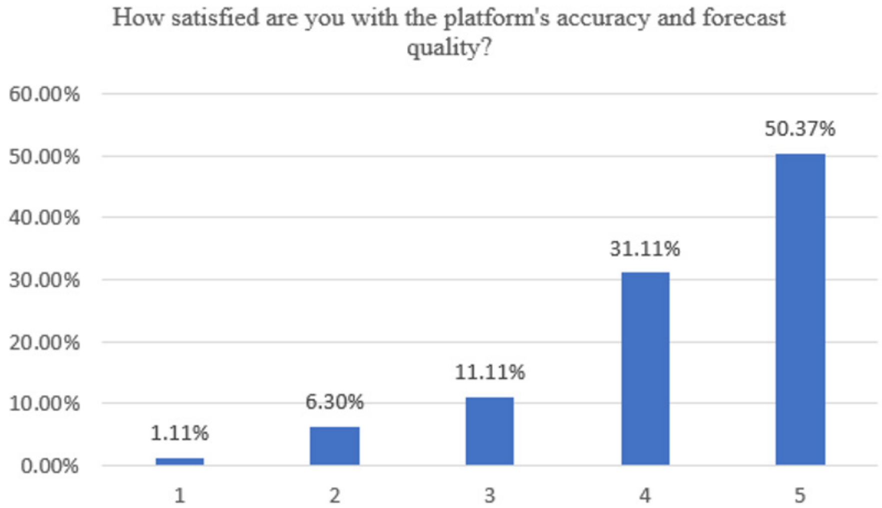

Figure 7: Accuracy of the platform

Table 5: Opinions from the users

Question	What do students think about this question?
What features would you like us to add, improve, or remove from the platform?	– *Improve the platform;* – *To add if we attended or are attending any training;* – *I don't think there is any need for changes;* – *Most of us hardly remember the questions for the entrance exam;* – *I have no idea about removing or adding anything to the platform;* – *I think that's okay;* – *Part of determining the subjects in an academic year;* – *The platform is very light with these features. I don't think features should be added or removed;* – *No features;* – *I would have removed the qualification of the parents;* – *New evaluation method;* – *I believe more questions and some small technical things;* – *All seems clear;* – *To sub-division the application;* – *Dynamic graph that presents in real time what you choose and appears in the result;* – *Student activities;* – *I would improve the prediction part as it was not very accurate in my case;* – *To improve forecasting;* – *The direction I am in should also be added and filled within them, since in some cases we may not know how many subjects we have in the second or third year;* – *I would add preliminary documentation of how the platform functions;* – *Add user manuals;* – *Student activities during lectures and exercises;* – *How much time per day should they study to complete the subjects of each year of studies?*
How do you think the platform can help improve student performance?	– *It could have a positive impact;* – *Positively;* – *It would increase the possibility of faster intervention by professors for students who may drop out of the faculty;* – *It could serve positively;* – *Anyway, it would improve performance;* – *Maybe it makes them more aware;* – *By adding a part of interest to students;* – *I think this assessment would be in the best interest of students;* – *From the assessment they receive from the platform;* – *Maybe the teaching part of the curriculum;* – *The platform can help identify students at risk and improve support for them based on performance factors that affect their graduation;* – *By increasing curiosity to learn new things;* – *By facilitating their plans;* – *In learning and in more effective time;* – *With other questions;* – *A prediction of the next steps in pursuing studies and completing the relevant courses to see how a satisfactory result can be achieved as an outcome, graduate;* – *I am satisfied with that;* – *I think that from this platform students can be well-informed about their academic development;* – *In evaluation;* – *I think this platform will help you a lot;* – *It helps a lot because it presents integrated functions;* – *I think that in general, it is beneficial for students;* – *Students are committed to being evaluated continuously;* – *Depending on the real demands of the situation we have as students;* – *It can have a great impact since it can be intervened earlier;* – *The platform can help teachers find those students who do not have good performance;* – *Students can predict their success;* – *It will enable me to find students who are in the dropout section.*

Table 6: User's opinion about accuracy platform

Question	What do students think about this question?
What features of the platform did you like the most?	– *I don't have;* – *Overall I liked it;* – *All the thinks about this platform;* – *Specification of how many subjects we have, and how many we have passed;* – *Option to choose the university, years of degree etc.;* – *Questions about completed courses;* – *Everything was fine;* – *Part one;* – *The platform can encourage students to stay engaged in their studies by providing them with direct information about their performance;* – *Identification of students who need support;* – *Short answers;* – *GPA;* – *Result part;* – *I liked the „Data Exploration" feature, as it offers the opportunity to analyze and visualize data interactively;* – *Compilation of questions in different versions which does not create monotony;* – *Questions with numbers;* – *Easy and simple use of the platform;* – *Easy and fast access;* – *I liked 90% of the features of this platform;* – *Rating;* – *It differs a lot from other platforms starting from questions, content, and structure;* – *Correctness;* – *Integration of the mother's and father's profession to predict performance;* – *The part of the data you have that is related to the results it provides.* – *I feel like they are my results in terms of accuracy;* – *The part of predicting if a student will drop out or graduate;* – *Integration of each academic year;* – *Integration of the points that we have been accepted to the faculty;* – *The part of academic success;* – *The academic part.*
Do you have any other comments or suggestions about the platform that are not mentioned above?	– *I don't have any comments or suggestions;* – *The enrolled section should also be integrated;* – *It would be useful to provide some additional clarifications;* – *My comment is that I have never heard of this type of platform before. I realize now that I am at the end of my studies;* – *No, I have no other comments or suggestions;* – *The platform was okay except that in the case where students need to know about the average grade for each year in the Faculty, they may not remember it. Maybe another way can be found to measure each year in the Faculty;* – *I hope that this platform continues;* – *Everything is okay;* – *I hope it is used more and has success;* – *Yes, to increase accuracy;* – *Yes, I propose that the subjects be presented automatically when we choose what faculty and direction we are in;* – *Yes, to add a user manual;* – *To add how many subjects we have in the following years, to specify for each direction.*

Table 6 presents the opinions and comments from students regarding the platform, highlighting features such as the ability to track the number of subjects they are enrolled in for each academic year, the number of subjects they have passed, the average grade for each academic year, and the encouragement it provides for students to engage with their academic performance. Additionally, students expressed appreciation for the platform's capability to visually analyze their data through data exploration. One feature mentioned by users is the structuring and incorporation of various factors influencing performance.

Regarding suggestions for improvement, students recommended integrating the average grade for each academic year. However, this was identified as a challenge, as students may not always remember their grades accurately. Another suggestion was to include the attribute specifying the faculty and program of study. For instance, when a student selects a particular university, the platform should automatically display the relevant faculty (e.g., "Education") and program (e.g., "Primary Education"), along with details such as the number of academic years completed and the number of subjects for each academic year. Furthermore, several students noted that this platform represents a novel experience for them, as such an evaluation tool has not been encountered before in their academic journey.

5 Conclusions

The use of web services is increasingly prevalent across various fields, enhancing work efficiency and supporting data-driven decision-making. In this study, a web application was developed to predict student performance in Kosovo, with adaptable data for other countries. The platform enables educational institutions, individuals, and advisors to predict student success, simplifying performance forecasting. By utilizing Machine Learning (ML) and Artificial Intelligence (AI), the platform offers an effective solution for educational sectors, addressing key challenges in academic performance prediction.

Based on research findings, RQ1 shows that 62.96% of participants found the platform easy to use, with 53.33% rated the function placement as highly coherent. This high usability suggests that the platform effectively addresses common design challenges in educational tools. For RQ2, 89% of users would recommend the platform, highlighting its practical value for academic advising and performance monitoring. RQ3 findings show that 50.37% of users rated the platform's prediction accuracy at the highest level, confirming its capability to generate precise insight from preprocessed datasets. Open-ended feedback also emphasized the platform's role in early intervention, raising awareness of academic outcomes, and supporting faster courses completion.

However, a key limitation is the use of data exclusively from Kosovo, which may impact the generalizability of the findings to other regions with different educational systems. This geographic limitation could impact the applicability of the study in other countries, as certain attributes or factors may be specific to Kosovo and may not be present elsewhere.

Future research will consider including data from additional geographical and educational contexts to enhance the generalizability and applicability of the findings. The findings suggest that accurate predictions will encourage broader adoption by students, professors, and educational advisors.

Future work will focus on integrating the platform into university policies and adding attributes such as work experience and training to enhance its predictive capabilities.

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Uporabniška ocena platforme za napovedovanje uspeha študentov na osnovi strojnega učenja

Ozadje/Namen: Integracija strojnega učenja v izobraževanje je odprla nove možnosti za napovedovanje uspeha študentov in omogočanje zgodnjih intervencij. Medtem ko se večina dosedanjih raziskav osredotoča na zasnovo in evalvacijo napovednih algoritmov, je zelo malo pozornosti namenjene uporabniško usmerjenim ocenam.
Metodologija: Študija ocenjuje spletno platformo, zasnovano za napovedovanje študentske uspešnosti z uporabo različnih algoritmov strojnega učenja. Platformo so preizkusili uporabniki – študenti, profesorji in karierni svetovalci – ter podali povratne informacije glede uporabnosti, natančnosti napovedi in verjetnosti priporočila drugim.
Rezultati: Rezultati kažejo, da je platforma enostavna za uporabo, zahteva minimalno tehnično podporo in zagotavlja zanesljive napovedi.
Zaključek: Uporabniki so močno podprli njeno uporabo in poudarili njen potencial pri prepoznavanju študentov z večjim tveganjem neuspeha ter izboljšanju učnih rezultatov.

Ključne besede: *Uspešnost študentov, Strojno učenje, Ocenjevanje sistema*

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