ORGANIZACIJA

Journal of Management, Informatics and Human Resources

Volume 58, Issue 4, November 2025

ISSN 1318-5454

Revija za management, informatiko in kadre

ORGANIZACIJA

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:

- organizational theory, management, development, and organizational behaviour;
- human resources management (such as organization & employee development, leadership, value creation through HRM, workplace phenomena etc.);
- managerial and entrepreneurial aspects of education;
- business information systems (such as digital business, decision support systems, business analytics etc.);
- enterprise engineering (e.g., organizational design, business process management, enterprise transformation paradigms etc.);
- papers that analyse and seek to improve organizational performance.

Organizacija (Revija za management, informatiko in človeške vire) je interdisciplinarna recenzirana revija, ki objavlja visoko kakovostne prispevke z vseh vidikov, ki so pomembni za organizacijske procese in strukture.

Revija je zasnovana tako, da spodbuja zanimanje za različne vidike v zvezi z organizacijskimi vedami in je namenjena tako akademski kot strokovni skupnosti. Revija objavlja izvirne članke, ki spodbujajo empirično, teoretično in metodološko razumevanje teorij in konceptov managementa in organizacije. Pozdravljamo tudi prispevke iz drugih znanstvenih disciplin, ki spodbujajo nove koncepte v organizacijski teoriji in praksi. Objavljamo članke, ki analizirajo organiziranost z različnih vidikov, so usmerjeni na organizacije različnih velikosti in iz različnih sektorjev, na enote, ki sestavljajo organizacije, in na mreže, v katere so organizacije vpete.

Teme so pokrivajo predvsem naslednja področja:

- organizacijska teorija, upravljanje, razvoj in organizacijsko vedenje;
- management človeških virov (kot so organizacija in razvoj zaposlenih, vodenje, ustvarjanje vrednosti s pomočjo človeških virov, organizacijski pojavi na delovnem mestu itd.);
- vodstveni in podjetniški vidiki izobraževanja;
- poslovni informacijski sistemi (kot so digitalno poslovanje, sistemi za podporo odločanju, poslovna analitika itd.);
- podjetniški inženiring (npr. organizacijsko oblikovanje, upravljanje poslovnih procesov, paradigme preoblikovanja podjetij itd.);
- članki, ki analizirajo organizacijsko uspešnost in prizadevanja za izboljšanje le-te.

Organizacija, Volume 58, Issue 4
November 2025

Contents 4/2025

Editorial office: University of Maribor, Faculty of Organizational Sciences, Založba Moderna Organizacija, Kidriceva 55a, 4000 Kranj, Slovenia

Tel.: +386-4-2374297, E-mail: organizacija.fov@um.si, URL: https://organizacija.fov.um.si. Organizacija is co-sponsored by the Slovenian Research Agency.

Published quarterly. Full texts of articles are available at https://sciendo.com/journal/ORGA.

Papers for publication in Organizacija can be submitted via journal website at https://organizacija.fov.um.si/submissions/.

Before submission authors should consult. Guidelines available at https://sciendo.com/journal/ORGA, tab “for Authors”. You can contact the editorial via e-mail: organizacija.fov@um.si or maja.mesko@um.si

Articles are currently abstracted/indexed in: Cabell’s Directory, CEJSH (The Central European Journal of Social Sciences and Humanities), Celdes, Clarivate Analytics - Emerging Sources Citation Index (ESCI), CNPIEC, Die Elektronische Zeitschriftenbibliothek, DOAJ, EBSCO - TOC Premier, EBSCO Discovery Service, ECONIS, Ergonomics Abstracts, ERIH PLUS, Google Scholar, Inspec, International Abstracts in Operations Research, J-Gate, Microsoft Academic Search, Naviga (Softweco), Primo Central (ExLibris), ProQuest - Advanced Pol mers Abstracts, ProQuest - Aluminium Industry Abstracts, ProQuest - Ceramic Abstracts/World Ceramics Abstracts, ProQuest - Composites Industry Abstracts, ProQuest - Computer and Information Systems Abstracts, ProQuest - Corrosion Abstracts, ProQuest - Electronics and Co mmunications Abstracts, ProQuest - Engineered Materials Abstracts, ProQuest - Mechanical & Transportation Engineering Abstracts, ProQuest - METADEX (Me tals Abstracts), ProQuest - Sociological Abstracts, ProQuest - Solid State and Superconductivity Abstracts, Research Papers in Economics (RePEc), SCOPUS, Summon (Serials Solutions/ProQuest), TDOne (TDNet), TEMA Technik und Management, WorldCat (OCLC).

DOI: 10.2478/orga-2025-0019

Understanding the Impact of Burnout on Decision-Making Styles

Matea CVJETKOVIĆ[1], Dinko PRIMORAC[2], Katerina FOTOVA ČIKOVIĆ[2]

[1] Institute of Public Finance, Zagreb, Croatia, matea.cvjetkovic@ijf.hr

[2] University of North, Koprivnica, Croatia, dprimorac@unin.hr, kcikovic@unin.hr

Background and purpose: This study aimed to fill a gap in the literature by identifying how employee burnout shapes decision-making styles in the post-COVID-19 business environment. The main goal was to examine the impact of three dimensions of burnout—exhaustion, cynicism, and professional efficacy—on four conflict-related decision-making styles: vigilance, buck-passing, procrastination, and hypervigilance.
Design/Methodology/Approach: A total of 567 employees from various companies in Croatia participated in the online survey conducted in March 2023. Multiple regression analysis examined the impact of exhaustion, cynicism, and professional efficacy on decision-making styles under conflict.
Results: The results of the multiple regression analysis revealed that professional efficacy leads to a vigilant decision-making style, while simultaneously diminishing procrastination, buck-passing, and hypervigilance. Cynicism, in contrast, was a positive predictor of procrastination, buck-passing, and hypervigilant decision-making. Finally, exhaustion was found to have a positive impact on hypervigilance.
Conclusion: The study is significant because it contributes to the body of knowledge on the impact of burnout dimensions on professional decision-making styles in organisational settings, and it also offers practical implications of considerable importance.

Keywords: *Employee burnout, Decision-making style, Work-related stress, Croatian companies, Post-COVID-19 period*

1 Introduction

Stress and work-related burnout are prevalent in modern business organisations, with repercussions at individual, organisational, and societal levels (Miller et al., 1990). Workplace pressures, accompanied by the COVID-19 pandemic, have worsened problems concerning employee well-being, particularly mental health, resulting in an increase in burnout-related symptoms on a global scale (Brasey et al., 2022; Khawaja et al., 2025). On average, one in four employees experiences symptoms of burnout, according to a survey conducted by the McKinsey Health Institute (Brasey et al., 2022). However, many organisations still underestimate burnout and face serious consequences when they neglect workplace factors that contribute to it, particularly in knowledge-intensive sectors (Jerman et al., 2020; Pejić Bach et al., 2020). Record-high levels of employee turnover, a global phenomenon often referred to as Great Attrition, are just the tip of the iceberg, or the visible part of the problem, and the associated costs. Hidden, and very often unaccountable costs, include absenteeism (Dyrbye et al., 2019), withdrawal or social isolation (Tavella & Parker, 2020), reduced job performance and motivation (Rahim & Cosby, 2016; Dyrbye et al., 2019), reduced commitment and satisfaction (Nagar,

Received: 12th March 2025; 25thAugust 2025

2012; Tosun & Ulusoy, 2017), or decreased productivity (Dewa et al., 2014).

Much research has focused on the determinants of burnout, which are linked to occupational, individual, and organisational factors (Chen et al., 2012). Among these, individual workplace antecedents have been widely examined in scientific studies (Toppinen-Tanner, 2011). As such, the effects of personality traits (Hudek-Knežević et al., 2011), specific personal features (Skodová & Lajčíková, 2013), or demographic variables (such as gender, age, marital status, and education) have been examined (Kusumadewi et al., 2023). Organisational characteristics, including work structure and operational procedures, have also been identified as important contributors to burnout (Chen et al., 2012). Prior studies in this area have examined aspects concerning organisational size (Dekker & Barling, 1995) and internal policies (Huang et al., 2003).

However, research observing the effects of burnout on professional decision-making style is lacking (Michailidis & Banks, 2016). Previous studies have suggested that burnout may primarily affect decision-making in chronic cases, potentially leading to decisional avoidance or premature decision-making (McGee, 1989). Additionally, burnout has been found to negatively correlate with the rational decision-making style (Michailidis & Banks, 2016). Nevertheless, research on how chronic stress or burnout influences decision-making remains limited, particularly in the post-COVID-19 era.

The pandemic, which began in 2020, had a significant impact on the safety and health of many employees worldwide (European Agency for Safety and Health at Work, 2022). The spread of the virus posed a genuine threat to many employees, who began to perceive their workplaces as potential sources of infection (Qureshi et al., 2024). Forced lockdowns, combined with increased workload, gradually took their toll. A post-COVID employee survey conducted in April 2022 by the European Agency for Safety and Health at Work (EU-OSHA) showed that across the EU the most common issue experienced at work is overall fatigue (37 %), followed by headaches and eye issues (34 %), problems with muscles, bones, or joints (30 %) and stress, depression, and anxiety (27 %) (European Agency for Safety and Health at Work, 2022).

For many workers, the problems did not end with the end of the pandemic but were further aggravated. The volatility of customer demand, supply chain disruptions, economic recession, and numerous other issues have affected many organisations. In a very short time and under extreme market pressures, they had to coordinate and plan new initiatives to build resilient workplaces of the future (Pedersen & Ritter, 2020). For many businesses, managing uncertainty requires making numerous decisions, sometimes in urgent situations (Humphreys & Trotman, 2022). Relying on previous experience was often not possible, as many employees had not found themselves in a similar situation, especially not in an environment of such considerable ambiguity. Moreover, work settings have also evolved, leading to new forms of communication and interaction in online contexts. As a result, many employees had to accelerate their decision-making processes while simultaneously improving productivity and embracing innovation by learning to use novel technologies (De Smet et al., 2020). Numerous organisations have indeed achieved challenging goals and attained success in remarkably short timeframes. Yet, as many companies continue to adopt new ways of working at high speed, the question remains: how do these altered work practices influence employees' well-being in the long term, and what implications does this have for their decision-making styles?

In light of the above, this study aims to examine the decision-making style under the influence of different dimensions of burnout syndrome in the post-COVID-19 era. Previous research on burnout-decision-making relationships may not apply to the new post-pandemic context, as the pandemic has led to multiple paradigm shifts across organisations that employees still need to fully adapt to (Howe et al., 2021). The "new normal" environment required "new normal" behaviours, styles, processes, organisational climate, and culture that employees have had to acquire. A previous investigation into decision-making styles among Croatian companies (Morić Milovanović & Cvjetković, 2024) found that burnout is associated with poorer decision-making processes. It also highlighted the importance of identifying which specific burnout dimensions influence particular decision-making styles.

The model proposed for this study is based on Maslach, Jackson, and Leiter's classification of burnout for non-human service workers, who observe burnout through three sub-dimensions: exhaustion, professional efficacy, and cynicism (Maslach et al., 1996). The decision-making style is observed based on the typology developed by Mann et al. (1977), who distinguished between four different decision-making styles manifested in conflict situations: vigilance, buck-passing, procrastination, and hypervigilance. The study is set in companies operating in Croatia, a country with characteristics of a developing economy. Like many other EU member states, Croatia faces numerous labour market challenges, often related to high youth unemployment and unfavourable demographic trends, particularly an ageing population. Absenteeism is another common problem for employers and is often linked to employees' health issues, including mental health problems (WHO Regional Office for Europe, 2019). This poses a financial burden on both the Croatian healthcare system and employers. In 2015, for example, financial support for work-related illnesses in Croatia amounted to €80.2 million from employers, more than twice the amount provided by the government (€39.4 million). The causes may be linked to inadequate working conditions, such as inconsistent work hours, lower salaries, insecure jobs, and increased workloads (WHO Regional Office for Europe, 2019).

The indicated situation provides a solid foundation for addressing burnout-related issues and exploring their consequences. This study, therefore, empirically tests the influence of each burnout dimension on different decision-making styles to gain deeper insights into their relationship and to understand how employees' varying mental and physical states can impact their responses to specific situations. Such responses can have both short- and long-term consequences for employees as well as for organisations, since effective decision-making is crucial for organisational success. The identified relationships are examined in companies operating in a developing country during the post-COVID-19 era. Accordingly, this paper focuses on burnout-related decision-making outcomes at the individual level within an organisational context.

Following the introduction, the literature review elaborates on burnout and decision-making styles, presenting the hypotheses that will be tested. The methodology section provides details on the operationalisation of variables, the research sample and the data collection process. The results section reports the outcomes of the hypothesis testing. In the discussion, the findings are examined in greater depth, in regard to theory contribution and with additional emphasis on practical implications. The paper concludes with a summary of findings, limitations of the study, and recommendations for future research.

2 Literature Review and Hypotheses

2.1 The Burnout Phenomenon

Burnout is defined as an emotional, physical, and mental state characterised by exhaustion, cynicism, and professional inefficacy that develops due to workplace-related stressors (Maslach & Leiter, 2017). It is an index of a discrepancy between what people are capable of doing and what is required of them (Leiter et al., 2015). As such, it presents a negative experience for employees, encompassing the difficulties and anxieties that individuals encounter in the workplace (Maslach & Leiter, 2017). The syndrome develops slowly and gradually over time, causing severe depletion of physical and mental resources. Although it primarily develops in the job-related context, research suggests that burnout symptoms can persist even after retirement (Bartol et al., 2024).

Freudenberger (1975) was the first to define and use the term "burnout" to describe a specific type of work-related exhaustion. He observed the emotional depletion of healthcare workers and used the term burnout to describe a rigid worker, closed to new inputs, inflexible in thinking, stubborn, and resistant to change. The same expression of burnout was used by Maslach (1976) to describe the symptoms of exhaustion and depersonalization displayed by healthcare professionals as well. Over time, studies have shown that burnout manifests in various other helping professions, including education, the military, and similar service vocations, as well as in clerical and managerial job positions (Leiter et al., 2015). Today, from a scientific perspective, burnout is understood as a multidimensional construct that reflects the collective effects of prolonged work-related stress (Miller et al., 1990). It incorporates several psychological and behavioural components and is recognised as a phenomenon affecting all occupations worldwide.

This study is based on the widely accepted three-dimensional model of burnout developed by Maslach, Jackson, and Leiter (1996), which conceptualises burnout through the dimensions of exhaustion, cynicism, and professional efficacy. In this framework, burnout is indicated by elevated levels of exhaustion and cynicism, accompanied by a reduced sense of professional efficacy. Among these, exhaustion is considered the core element of the syndrome and is the most frequently reported symptom among individuals experiencing burnout (Leiter et al., 2015). Very often, it is accompanied by feelings of low energy and motivation, as well as general fatigue, which is mainly caused by increased demands at work (Leiter & Maslach, 1999) and often leads to frequent absenteeism (Bang & Reio Jr., 2017). Cynicism and professional inefficacy develop due to the lack of job resources. The cynicism often forms as a defence mechanism against the negative aspects of the job and is reflected in a behaviour in which individuals distance themselves from their work (Maslach et al., 1996). Cynicism can negatively impact performance and social connections at work, leading to interpersonal and intrapersonal conflicts (Stanley et al., 2005). The inefficacy dimension of burnout is based on self-image and is reflected as a feeling of incompetence in performing a work task. It comprises social and non-social occupational accomplishments and work expectations (Maslach et al., 1996).

The symptoms of burnout are manifested in physical, emotional, or mental spheres (Chen et al., 2012). Physically, individuals may experience fatigue, sleep disturbances, headaches, fluctuations in appetite and weight, and immune system deficiencies (Arches, 1991). On the emotional side, feelings of detachment, dissatisfaction, agitation, mood fluctuations, and decreased motivation can occur. Cognitive symptoms include memory problems (Bayes et al., 2021), poor concentration, and impaired decision-making (Masiero et al., 2018). Moreover, individuals show other behavioural symptoms such as isolation and avoidance of colleagues and friends, delays in starting or completing tasks, and increased substance use (Chambers, 1992). The costs are extensive at the organisational level as well, as the loss of employee focus and concentration can impact overall productivity, organisational success, and financial performance (Bakker et al., 2023).

2.2 Professional decision-making and decision-making styles

Decision-making refers to the ability to select among multiple options by evaluating their potential outcomes (Michailidis & Banks, 2016). It is a highly relevant constituent of business success, particularly in management practices (Turulja et al., 2025). Most professional decisions are made within a specific context (Michailidis & Banks, 2016) and are shaped by values, subjective characteristics, and expected rewards (Morgado et al., 2014). The process is further modified by environmental factors, such as uncertainty, cost, interruptions, delays, or social pressure (Morgado et al., 2014). Thus, decision-making behaviour and style are not shaped in a social vacuum and do not depend solely on the choices made by the individual, but rather depend on the organisation's policies and hierarchies, as well as numerous other relational frameworks within which a decision is made (Sutcliffe & McNamara, 2001). At times, decision-making takes place in contexts where the exact outcomes of each alternative are known. However, in business settings, decisions are often made without precise information about their consequences (Hsu et al., 2005). That is why decision-makers often use decisional heuristics or cognitive cutoffs to decide, which can impact the outcome (Sutcliffe & McNamara, 2001).

Three main elements determine the way people make decisions in uncertain situations: knowledge of all the risks embedded within each alternative, anticipation that the best alternative will be chosen, and the fact that there is sufficient time to think through the entire process (Cotrena et al., 2017). The lack of each of the factors results in the manifestation of different decision-making styles, which form the basis of a conflict theory of decision-making developed by Janis and Mann (1976). Stressful situations often cause hesitation and uncertainty, especially when the decision is important and a wrong choice could lead to serious consequences (Bouckenooghe et al., 2007). Janis and Mann identified five coping styles that influence decision-making: (1) vigilance – making thoughtful, well-informed decisions; (2) unconflicted adherence – ignoring possible risks and sticking to the current option; (3) unconflicted change – quickly accepting the most obvious or suggested choice without much thought; (4) defensive avoidance – delaying the decision or shifting responsibility to someone else; and (5) hypervigilance – making rushed, panicked decisions (Bouckenooghe et al., 2007).

Mann et al. (1997) tested Janis and Mann's (1976) conflict theory of decision-making in six countries and, based on the results, refined the model by narrowing it down to four decision-making styles: (1) vigilance, (2) hypervigilance, (3) buck-passing, and (4) procrastination. Similar to the Janis and Mann typology, the vigilant style is associated with a well-considered decision-making process, characterised by the careful examination of available alternatives (Mann et al., 1997). Vigilant decision-makers are competent and confident when making a choice and can select appropriate strategies in the decision-making process (Filipe et al., 2020). They thoroughly analyse the available options and assess the costs and risks associated with each to determine the most suitable choice, which is why vigilance is considered the most effective decision-making style (Filipe et al., 2020). In contrast, procrastination and buck-passing are maladaptive behaviours linked to defensive avoidance, which reflects pessimism about the possibility of selecting an appropriate alternative (Phillips & Reddie, 2007). Procrastinators tend to delay decisions even after an option has been chosen, while those adopting a buck-passing style avoid responsibility by shifting the decision to others. Time constraints and lack of resources often trigger a hypervigilant approach (Phillips & Reddie, 2007). Hypervigilance is characterised by a panicked and anxious decision-making process, in which individuals often choose the first available option without adequately considering potential negative consequences (Cardona Isaza et al., 2021).

2.3 Relationship between burnout dimensions and decision-making styles

Exposure to chronic stress disrupts cognitive functions and negatively affects memory systems, behaviours, anxiety, mood, and habits (Morgado et al., 2014). Since these functions are important for efficient decision-making, several studies have been conducted to understand their impact on the decision-making process and decision-making styles. Decision-makers under stress tend to make riskier decisions, are prone to stereotyping, and often overlook the situational context in which a decision is being made. According to Vine et al. (2016), when experiencing acute stress, an individual's attention narrows, resulting in a slower response rate to new information and poorer task performance. Moreover, stress reduces the possibility of considering all the alternatives to the rising problems (Phillips-Wren & Adya, 2020). Other possible responses could manifest in avoidance of making decisions, inflexibility, or reliance on past solutions that might not be applicable in new situations (McGee, 1989). A study conducted among public sector leaders—such as government officials, department heads, and branch managers—showed that higher workloads were linked to less use of vigilant decision-making and more frequent use of avoidant styles, including buck-passing, procrastination, and hypervigilance (Narangerel & Semerci, 2020). The same research showed that employees with higher levels of control over their work were more likely to engage in vigilant decision-making.

Similar to stress, burnout weakens a person's ability to concentrate and focus, and negatively affects complex thinking processes and problem-solving procedures (McGee, 1989). Recent studies show that 2–13% of workers experience severe burnout. However, burnout symptoms can vary from day to day or week to week, meaning that at some point, all employees may experience exhaustion, cynicism, or reduced effectiveness at work (Bakker et al., 2023). These feelings can impact decision-making styles and capacities. Similar findings were reported by Michailidis and Banks (2016), who demonstrated that all dimensions of burnout were positively related to avoidant decision-making styles. Among the burnout dimensions, exhaustion showed the strongest correlation with avoidance.

Evidence from the literature suggests that the relationship between burnout dimensions and decision-making styles in the business context has received little empirical attention. Thus, this research aims to fill the gaps identified in the aforementioned studies by providing additional theoretical and practical contributions for companies operating in developing countries during the post-pandemic period. Since burnout arises from prolonged exposure to chronic stress, it is reasonable to assume that it also impairs decision-making abilities. It can lead to difficulties such as reduced mental clarity, impaired judgment, decreased motivation, and greater risk aversion (Tavella & Parker, 2020). Burnout can also affect the ability to gather, process, or retrieve information correctly (Potter et al., 2021). In this state, individuals are more susceptible to cognitive biases, such as confirmation bias or anchoring bias, and tend to rely on the first piece of information they hear. This can result in a slower decision-making process, impacting decision-making flexibility and accuracy (Bailey, 2007).

2.4 Hypothesis development

Drawing on the three-dimensional model of burnout (exhaustion, cynicism, and professional efficacy) and the conflict theory of decision-making (Janis & Mann, 1976; Mann et al., 1997), a set of hypotheses is developed that link each burnout dimension to four decision-making styles: vigilance (careful, systematic choice), buck-passing (shifting responsibility), procrastination (delaying choice), and hypervigilance (panicked, hasty choice).

Exhaustion represents the core of the burnout experience, draining the mental energy needed for sustained attention, information search, and analytical reasoning (Leiter et al., 2015). Individuals who are depleted are less able to engage in the deliberate, data-driven processing that underpins a vigilant style (Mann et al., 1997). Instead, they are more likely to adopt defensive coping strategies, such as passing decisions to others (buck-passing) or repeatedly postponing them (procrastination), to conserve scarce cognitive resources (Phillips & Reddie, 2007). Under time pressure, the same depletion can trigger hypervigilance, in which the first acceptable option is seized without weighing consequences (Cardona Isaza et al., 2021). Therefore, the first hypothesis, with a sub-hypothesis, has been developed:

- H1. Exhaustion will impact the decision-making style
  - o H1a. Exhaustion will reduce the use of a vigi lant decision-making style.
  - o H1b. Exhaustion will increase reliance on a buck-passing style.
  - o H1c. Exhaustion will increase reliance on a procrastination style.
  - o H1d. Exhaustion will increase reliance on a hy pervigilant style.

Cynicism acts as a psychological buffer that allows employees to distance themselves from demanding work (Maslach et al., 1996). This disengagement reduces motivation for careful analysis and weakens vigilance. It also encourages shifting responsibility (buck-passing) or delaying decisions (procrastination), since the work is seen as unworthy of full effort (Narangerel & Semerci, 2020; Michailidis & Banks, 2016). In addition, the negative emotions linked to cynicism can trigger hypervigilant "get-it-over-with" choices under pressure (Phillips & Reddie, 2007). This leads to the second hypothesis and its sub-hypothesis:

- H2. Cynicism will impact the decision-making style.
  - o H2a. Cynicism will decrease the use of a vigi lant decision-making style.
  - o H2b. Cynicism will increase reliance on a buck-passing style.
  - o H2c. Cynicism will increase reliance on a pro crastination style.
  - o H2d. Cynicism will increase reliance on a hypervigilant style.

Professional efficacy is an employee's belief in their ability to perform tasks successfully (Maslach et al., 1996). When efficacy is high, employees feel confident and capable of carefully evaluating options, which supports vigilant decision-making (Filipe et al., 2020). Confident employees are also less likely to pass responsibility to others or postpone decisions, which reduces buck-passing and procrastination (Narangerel & Semerci, 2020). In addition, a strong sense of competence lowers anxiety and makes hasty hypervigilant decisions under stress less likely (Cardona Isaza et al., 2021). Based on this, the third hypothesis and sub-hypothesis are proposed:

- H3. Professional efficacy will impact the decision-making style.
  - o H3a. Professional efficacy will increase the use of a vigilant decision-making style.
  - o H3b. Professional efficacy will decrease reli

ance on a buck-passing style.
o H3c. Professional efficacy will decrease reli ance on a procrastination style.
o H3d. Professional efficacy will decrease reli ance on a hypervigilant style.

In summary, theory and prior evidence suggest a systematic pattern: the resource-depleting facets of burnout, exhaustion, and cynicism are expected to lead professionals toward avoidant or impulsive decision-making strategies, whereas the resource-enhancing facet, professional efficacy, is expected to promote vigilant, well-considered decisions.

3 Methodology

This study investigated the impact of various aspects of burnout on the decision-making processes of employees in Croatian companies. To achieve this, survey data were collected and analysed at the individual employee level.

3.1 Research Instrument

The research instrument was an online questionnaire composed of validated scales measuring burnout and decision-making styles. The first section of the questionnaire comprised demographic and occupational characteristics of respondents (e.g., gender, age, education, industry, and job position), while the second section included questions measuring the main constructs of the study.

Burnout was assessed following the questionnaire reported by Bang and Reio Jr. (2017), which was based on the Maslach Burnout Inventory–General Survey (MBI-GS; Maslach et al., 1996). The original MBI-GS is a 16-item self-report instrument developed for non-human service settings, comprising three subscales: Exhaustion, Cynicism, and Professional Efficacy. In this study, 15 items were used, with each subscale consisting of five items rated on a 7-point Likert scale. The instrument measures respondents' perceptions of their job on a continuum ranging from engagement—an energetic and confident state at work—to burnout, characterised by exhaustion, cynicism, and reduced professional efficacy. Cronbach's α for exhaustion is 0.93, cynicism 0.89, and professional efficacy 0.77.

Decision-making style was measured using items from the Melbourne Decision-Making Questionnaire, which is designed to assess how individuals cope with decision-related conflict (Mann et al., 1997). This instrument considers personality traits and emotional factors, making it suitable for evaluating individual decision-making inclinations (Filipe et al., 2020). The questionnaire includes four subscales: Vigilance, Buck-Passing, Procrastination, and Hypervigilance. Each subscale was measured with five items, using a 3-point Likert scale. Internal consistency (Cronbach's α) was 0.68 for vigilance, 0.83 for buck-passing, 0.84 for procrastination, and 0.83 for hypervigilance.

3.2 Data

To select participants, a random sample of Croatian companies was drawn from the Finiinfo business directory (El koncept d.o.o., 2023), ensuring representation across various industry sectors based on official statistics (Croatian Bureau of Statistics, 2023). In March 2023, the questionnaire was sent to approximately 3,000 company email addresses, obtained either from the Finiinfo database or from official company websites. Given that all questions in the questionnaire were marked as mandatory, 100 % of all completed questionnaires were considered valid. To mitigate the potential for standard method bias (CMB), an ex ante approach was employed by informing participants about the research purpose and ensuring the anonymity of their responses (Chang et al., 2020).

Data collection lasted approximately four weeks and resulted in 567 completed questionnaires, constituting a response rate of 18.9%. The sample consists of 59.3% women and 40.7% men. A majority of respondents (70%) are between 31 and 51 years of age, and over 80% hold a higher education degree. Participants are employed across various departments and represent companies from a wide range of industries, including manufacturing (19.8%), construction (8.3%), trade (16.8%), energy (1.6%), logistics (3%), and service sectors such as information and communication (10.4%), financial services (8.1%), and hospitality (4.4%). The data also show that over 65% of participants typically work 8 to 9 hours each day. Most participants hold managerial positions (38.6%), followed by administrative positions (37.7%), business owners (12.4%), and executive positions (11.3%).

3.3 Statistical methods

The process started with calculating descriptive statistics, after which a Pearson correlation matrix was generated to explore the direction and strength of relationships between independent and dependent variables. These preliminary analyses provided an overview of the data and indicated whether associations were in line with the proposed hypotheses. Hypotheses were then tested using multiple linear regression analysis. Multiple regression was chosen because it allows estimation of the unique contribution of each burnout dimension while simultaneously controlling for the other independent variables, which reduces the risk of bias from overlapping influences (Hair et al., 2019).

Four separate models were specified, each with one decision-making style as the dependent variable: vigilance

(Model 1), buck-passing (Model 2), procrastination (Model 3), and hypervigilance (Model 4). Independent variables across all models included exhaustion, professional efficacy, and cynicism. IBM SPSS software, ver. 26, was used for all analyses.

To confirm the validity of the regression models, several key assumptions were tested, including the normal distribution of residuals, equal variance of errors (homoscedasticity), and a linear relationship between variables. Additionally, diagnostic tests were conducted, including the Durbin–Watson statistic, Cook's distance, and Variance Inflation Factors (VIF). The Durbin–Watson values were close to 2, indicating no autocorrelation: Model 1 (1.956), Model 2 (2.000), Model 3 (1.989), and Model 4 (1.968). Maximum Cook's distance values were low, ranging from 0.026 to 0.046, suggesting the absence of influential outliers. VIF values were all below 3, confirming that multicollinearity was not a concern (Rutledge & Barros, 2002). These diagnostic results indicate that all necessary regression assumptions were met, supporting the validity of the models and allowing for further statistical analysis and hypothesis testing (Eberly, 2007).

4 Results

4.1 Descriptive and correlation analysis

Table 1 displays the means and standard deviations of all variables included in the study. On the 1–7 Likert scale measuring burnout dimensions, respondents expressed moderate levels of exhaustion (M = 4.21, SD = 1.57) and cynicism (M = 3.47, SD = 1.61), but relatively high levels of professional efficacy (M = 5.26, SD = 1.36). For decision-making styles, measured on a 1–3 scale, vigilance showed the highest mean (M = 2.69, SD = 0.36), indicating that a careful and systematic approach was the most common. Avoidant styles were less frequent, with buck-passing (M = 1.51, SD = 0.49), procrastination (M = 1.46, SD = 0.50), and hypervigilance (M = 1.62, SD = 0.54), all clustering near the lower end of the scale.

Table 1: Means and standard deviations for burnout dimensions and decision-making styles (n=567)

Variable	Mean	Standard deviations
Burnout dimensions (scale 1-7)		
Exhaustion (5 items)	4.21	1.57
Professional Efficacy (5 items)	5.26	1.36
Cynicism (5 items)	3.47	1.61
Decision-making styles (scale 1-3)		
Decision-making styles (scale 1-3)	2.69	0.36
Buck-passing (5 items)	1.51	0.49
Procrastination (5 items)	1.46	0.50
Hypervigilance (5 items)	1.62	0.54

Source: Authors, 2025

Table 2: Correlations between burnout dimensions and decision-making styles, (n=567)

	Vigilance	Buck-passing	Procrastination	Hypervigilance
Exhaustion	-0.185*	0.169*	0.258*	0.393*
Professional Efficacy	0.317*	-0.272*	-0.382*	-0.435*
Cynicism	-0.237*	0.309*	0.340*	0.423*

Note*: Correlation is significant at the 0.01 level (2-tailed).
Source: Authors, 2025

Table 3: Results of multiple regression analysis (n=567)

	Vigilance (M1)		Buck passing (M2)		Procrastination (M3)		Hypervigilance (M4)	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Exhaustion (H1)	-0.002	0.012	-0.017	0.016	0.008	0.016	0.059**	0.117
Professional Efficacy (H2)	0.290**	0.015	-0.046*	0.020	-0.101**	0.020	-0.094**	0.021
Cynicism (H3)	-0.034	0.014	0.078**	0.018	0.042*	0.018	0.055**	0.019
R-squared (R^2)	0.101		0.104		0.158		0.235	
Adjusted R^2	0.096		0.100		0.153		0.231	

Note: *p<0.05; **p<0.01; EXH= Exhaustion; P.E. = Professional Efficacy, CYN = Cynicism
Source: Authors, 2025

The results of the correlation analysis, presented in Table 2, indicate statistically significant relationships among all observed variables. Exhaustion is negatively correlated with the vigilant decision-making style (r = –0.185), and positively correlated with buck-passing (r = 0.169), procrastination (r = 0.258), and hypervigilance (r = 0.393). The strength of these correlations ranges from weak to moderate. Regarding professional efficacy, the results show a positive moderate correlation with vigilance (r = 0.317), a weak negative correlation with buck-passing (r = –0.272), and a moderate negative correlation with procrastination (r = –0.382). It is also moderately and negatively correlated with hypervigilance (r = –0.435). Cynicism has a weak negative correlation with vigilance (r = –0.237), but weak positive correlations with buck-passing (r = 0.309) and procrastination (r = 0.340), and a moderate positive correlation with hypervigilance (r = 0.432). A positive correlation indicates that both variables increase together, while a negative correlation means that as one increases, the other decreases (Schober et al., 2018).

4.2 Regression analysis

The results of the multiple regression analysis are presented in Table 3. It gives details for Models 1, 2, 3, and 4, where the dimensions of burnout are independent variables, and each decision-making style is presented as a dependent variable.

As shown in the table, exhaustion has a positive impact on the development of a hypervigilant decision–making style (β = 0.059, p=0.000 < 0.01), confirming H1d. Cynicism dimension of burnout leads to buck-passing (β= 0.078, p=0.000 <0.01), procrastination (β=0.042, p= 0.019 <0.05), and hypervigilant decision-making style (β=0.055, p=0.004 <0.05), which confirms the H2b, H2c, and H2d. Professional efficacy leads to a vigilant decision-making style (β=0.290; p=0.000 <0.01), and reduces buck- passing (β=-0.046, p=0.024<0.05), procrastination (β= -0.101, p=0.000 <0.01), and hypervigilance (β=-0.094, p=0.000 <0.01) decision-making styles, thus confirming hypothesis H3a, H3b, H3c, H3d.

5 Discussion

5.1 Summary

Organisational processes and their outcomes are only as effective as the individuals responsible for implementing them (Miller, 2001). Even the best-designed programs or ideas are unlikely to succeed if employees lack the necessary capability or motivation. The same applies to the decision-making process (Miller, 2001). It depends on the capabilities, work, intelligence, proactivity, and dedication of employees. Only when an organisation can build a cadre of proficient and independent decision-makers will it be able to reap the benefits of a successful decision-making process. This is ultimately reflected in its financial performance and overall success. However, such outcomes are unlikely if employees are experiencing burnout. In a state of exhaustion, professional inefficacy, or cynicism, employees are unable to make informed decisions, as they use additional mental and physical resources to overcome their constraints (Hobfoll et al., 2018). This triggers additional stress (Michailidis & Banks, 2016) and creates an unfavourable context in which individuals are often required to make important and critical decisions, very often in uncertain situations (Morgado et al., 2014). This study tested several hypotheses to understand the impact of three burnout dimensions (exhaustion, professional efficacy, and cynicism) on four different decision-making styles (vigilance, buck-passing, procrastination, and hypervigilance).

A survey was conducted among employees in Croatian companies, addressing the identified research gap in this sector (Morić Milovanović & Cvjetković, 2024).

5.2 Theoretical contributions

The study reveals that the exhaustion dimension of burnout is associated with a hypervigilant decision-making style ($\beta = 0.059$, $p < 0.01$), confirming Hypothesis 1d. This indicates that in a state of exhaustion, employees often make decisions hastily by typically accepting the first available alternative. This could be linked to the fact that exhausted employees lack the strength or energy to consider all available alternatives or process them effectively (Ceschi et al., 2017). As information processing increases and more decisions are required, users can reach the limits of their cognitive capabilities, which undermines their ability to make informed decisions. This could explain why they choose the first available option, so as not to overload themselves with more work. Employees who are already exhausted lack the energy to engage actively in the decision-making process. They accept whatever solution is available. A study conducted by Michailidis and Banks (2016) demonstrated that exhaustion also correlates with an avoidance decision-making style. This study on Croatian employees also revealed significant correlations between the indicated styles. Hypothesis testing revealed a positive, albeit non-statistically significant, influence of exhaustion on any of the avoidant decision-making styles, suggesting that hypotheses 1a, 1b, and 1c could not be confirmed. Possible reasons could lie in the fact that the levels of exhaustion reported by participants were not severe enough to activate avoidant decision-making mechanisms, which may only emerge under higher or prolonged stress conditions.

When it comes to cynicism, as a second burnout dimension, the results show that it statistically and positively affects buck-passing ($\beta= 0.078$, $p=0.000 <0.01$), procrastination ($\beta=0.042$, $p= 0.019 <0.05$), and hypervigilant decision-making style ($\beta=0.055$, $p=0.004 <0.05$), thus confirming hypotheses 2 b, 2c and 2d. The results also showed a negative relationship with vigilant style, but it did not prove to be statistically significant, meaning that hypothesis 2a could not be confirmed. As cynicism is a state in which employees feel indifferent towards their work environment and work tasks, the parallel can easily be drawn to the fact that when found in such conditions, employees do not care about finding the right solution and making the right decision. They will most likely delay their decisions or engage in other activities that distract them from making a decision (Phillips & Reddie, 2007), a pattern also confirmed in a previous study (Michailidis & Banks, 2016), where the cynicism dimension correlated significantly with an avoidant decision-making style. This could also be connected to the changes in the motivational system when employees perceive that the amount of energy invested in performing tasks outweighs the potential rewards and positive outcomes (Boksem & Tops, 2008), resulting in their lack of enthusiasm for investing additional effort in an efficient decision-making process.

The results of this study showed that only professional efficacy leads to a vigilant decision-making style ($\beta = 0.290$, $p < 0.01$), thus confirming Hypothesis 3a. When employees are engaged at work, they feel confident and capable of handling their daily responsibilities (Maslach & Leiter, 2016). As a result, this sense of competence and stability is also reflected in the way they make decisions, leading to a vigilant decision-making style that is characterised by care and analysis (Filipe et al., 2020). Efficient employees express confidence and control over the situation, which is why they are further motivated to invest additional effort in making the right decision (Michailidis & Banks, 2016). This was also confirmed in this study, as professional efficacy diminished the other three decision-making styles: buck-passing ($\beta = -0.046$, $p = 0.024 < 0.05$), procrastination ($\beta = -0.101$, $p = 0.000 < 0.01$), and hypervigilance ($\beta = -0.094$, $p = 0.000 < 0.01$), which confirms hypotheses 3a, b, c, and d. Similar findings were reported in a study by Michailids and Banks (2016), who found that employees with low levels of professional efficacy are more likely to choose a riskier alternative, as they are unable to accurately estimate the severity of the consequences. These findings, thus, underscore how professional efficacy not only enhances vigilant decision-making but also provides a protective buffer against maladaptive decision styles.

This study is among the few that have investigated the relationship between burnout dimensions and decision-making styles in the organisational context of a developing country, making a significant contribution to both theoretical and practical understanding. On the theoretical side, it broadens the findings for decision-making conflict models (Janis & Mann, 1977; Mann et al., 1997), which suggest that decision-makers behave irrationally in conflict and stressful situations, thereby influencing their decision-making styles. This study has shown that when employees experience exhaustion, they tend to exhibit a hypervigilant decision-making style. In a state of energy depletion and resource scarcity, they will not engage in the decision-making process but will make decisions hastily, often by accepting the first available option.

Employees who are cynical and indifferent towards their work will exhibit the same behaviour; however, they will also tend to postpone making decisions or leave it to others to decide. Although exhaustion is considered a core component of burnout, the findings in this study suggest that cynicism, manifested as employees distancing themselves from work and feeling indifferent, may be even more detrimental to today's organisations in the decision-making context. When employees do not care about outcomes, this apathy can lead them toward any of the three maladaptive decision-making styles. These results not only demonstrate consistency with the stated theories but also provide empirical support, thereby adding to the existing body of knowledge. On the other hand, confident and efficient employees feel valued and can see that their work contributes to the organisation's overall goal. In turn, they will approach the decision-making process carefully to make the best possible decision.

5.3 Practical contributions

This study also makes important practical contributions, considering the importance of making informed decisions in organisational settings. Understanding how burnout affects decision-making can help managers and CEOs design work environments that better support their teams. This is especially crucial in the post-COVID-19 era, where fast and creative thinking is essential, however, not at the expense of the employee's health. If employees must adapt to a new post-pandemic work context, companies must also change accordingly. This involves investing in targeted training and education, adjusting initiatives, and offering reward programs that recognise the hard work of employees (De Smet et al., 2020). Many forward-thinking businesses are flattening their work structures, prioritising all levels of employees, and engaging them in their organisational culture. In this process, effective communication and empathy play a key role in mitigating the adverse effects of demanding work conditions (Antić et al., 2024). Additionally, the negative effects of burnout can also be alleviated through lifelong education, which helps employees build resilience and adaptability (Vrdoljak, 2024).

To encourage motivation and engagement, employers should cultivate in employees a sense of belonging and care for the organisation. Organisations need employees who can continually learn, up-skill, and adapt (De Smet, 2020). Investing in employees will pay off for an organisation in the long run. This research has shown that only professionally efficient employees, who are happy at their workplaces and see that their work contributes to the organisation's success, manifest a vigilant decision-making style. Only those employees who engage in a deep-thinking decision-making process will be able to make good decisions, which in turn lead to a successful organisation.

6 Conclusion

Although burnout syndrome in Croatia has been studied for over 30 years, research on its implications for individuals in the context of business organisations is scarce and fragmented. As companies, especially in developed countries, struggle to cope with increasingly turbulent economic, technological, political, environmental, and social environments, they depend on their employees to adapt and embrace all the changes that new, modern societies hold. Each employee will react differently to these changes, which was especially visible during the COVID-19 pandemic. The "new normal" post-pandemic environment, accompanied by additional crises, still presents a burden for many workers who struggle with the workload but are required to make professional decisions daily. With this in mind, this study aimed to explore which aspects of burnout impact decision-making styles among employees in Croatian companies, making it one of the first of its kind in Croatia. The results showed that the exhaustion leads to a hypervigilant decision-making style, while the cynicism dimension leads to buck-passing, procrastination, and hypervigilant decision-making style. On the other hand, professional efficacy leads to a vigilant decision-making style, reducing buck-passing, procrastination, and hypervigilance.

The study has several limitations, the main one being its cross-sectional nature, which makes it challenging to establish the causal relationship between the variables. The fact that the questionnaire was based on self-report data also represents a limitation, as the respondents' emotional state might have influenced the answers at the time of completing the questionnaire. Future studies are encouraged to adopt a longitudinal approach to get deeper insights. The online questionnaire also has its limitations, as it relies on technology and requires a certain level of digital literacy from respondents. The study has tested only four decision-making styles, excluding other possible decision-making manifestations, such as spontaneous decision-making or decision-making confidence, which are also recommended for inclusion in future studies. Future studies could test mediators and moderator variables, such as coping strategies, organisational culture and climate, management support, and include demographic characteristics to determine whether there are any significant differences based on gender, age, education, or employee position. Despite the limitations, this study highlights the importance of understanding how burnout dimensions influence decision-making styles, providing insights that can inform targeted interventions and support systems to enhance employee effectiveness and well-being.

References

Antić, M., Globočnik Žunac, A., & Križanec Cvitković, M. (2024). Exploring the Link between Empathy and Assertive Communication in Healthcare Settings. ENTRENOVA-*ENTerprise REsearch InNOVAtion, 10*(1), 44-52. https://doi.org/10.54820/entrenova-2024-0005

Arches, J. (1991). Social structure, burnout, and job satisfaction. *Social work, 36(*3), 202-206. https://doi.org/10.1093/sw/36.3.202

Bailey, C. E. (2007). Cognitive Accuracy and Intelligent Executive Function in the Brain and in Business. *Annals of the New York Academy of Sciences, 1118*(1), 122–141. doi:10.1196/annals.1412.011

Bakker, A. B., Xanthopoulou, D., & Demerouti, E. (2023). How does chronic burnout affect dealing with weekly job demands? A test of central propositions in JD-R and COR-theories. *Applied Psychology, 72*(1), 389-410. https://doi.org/10.1111/apps.12382

Bang, H., & Reio Jr, T. G. (2017). Examining the role of cynicism in the relationships between burnout and employee behavior. *Revista de Psicología del Trabajo y de las Organizaciones, 33*(3), 217-227. https://doi.org/10.1016/j.rpto.2017.07.002

Bartol, A., & Grah, B. (2024). Aging and Work-Related Identity Loss Due to Retirement. *ENTRENOVA-ENTerprise REsearch InNOVAtion, 10*(1), 204-220.

Bayes, A., Tavella, G., & Parker, G. (2021). The biology of burnout: Causes and consequences. *The World Journal of Biological Psychiatry*, 1–13. doi:10.1080/15622975.2021.1907713

Boksem, M. A., & Tops, M. (2008). Mental fatigue: costs and benefits. *Brain research reviews, 59*(1), 125-139. https://doi.org/10.1016/j.brainresrev.2008.07.001

Bouckenooghe, D., Vanderheyden, K., Mestdagh, S., & van Laethem, S. (2007). Cognitive Motivation Correlates of Coping Style in Decisional Conflict. *The Journal of Psychology, 141*(6), 605–626. doi:10.3200/jrlp.141.6.605-626

Brassey, J., Coe, E., Dewhurst, M., Enomoto, K., Giarola, R., Herbig, B., & Jeffery, B. (2022). Addressing employee burnout: Are you solving the right problem? *McKinsey & Company*. https://www.mckinsey.com/mhi/our-insights/addressing-employee-burnout-are-you-solving-the-right-problem

Cardona Isaza, A. D. J., Chulia, A. T., González Barrón, R., & Montoya Castilla, I. (2021). Analysis of the psychometric properties of the Melbourne Decision Making Questionnaire in Colombian adolescents. *Revista Latinoamericana de Psicología*, *53*, 47-55. https://doi.org/10.14349/rlp.2021.v53.6

Ceschi, A., Demerouti, E., Sartori, R., & Weller, J. (2017). Decision-making processes in the workplace: How exhaustion, lack of resources and job demands impair them and affect performance. *Frontiers in Psychology, 8,* Article 313. https://doi.org/10.3389/fpsyg.2017.00313

Chambers, R. (1993). Avoiding burnout in general practice. *The British Journal of General Practice*, *43*(376), 442.

Chang, S. J., Witteloostuijn, A. V., and Eden, L. (2020). Common method variance in international business research. *Research methods in international business,* 385-398. https://doi.org/10.1007/978-3-030-22113-3_20

Chen, H., Wu, P., and Wei, W. (2012). New Perspective on Job Burnout: Exploring the Root Cause beyond General Antecedents Analysis. *Psychological Reports, 110*(3), 801–819. https://doi.org/10.2466/01.09.13.PR0.110.3.801-819

Cotrena, C., Branco, L. D., & Fonseca, R. P. (2017). Adaptation and validation of the Melbourne decision making questionnaire to Brazilian Portuguese. *Trends in Psychiatry and Psychotherapy*, *40*, 29-37. https://doi.org/10.1590/2237-6089-2017-0062

Croatian Bureau of Statistics (2023). *Persons in paid employment, by activities,* https://podaci.dzs.hr/2023/en/57988 (April 4, 2023).

De Smet A., Pacthod, D., Relyea, C., & Sternfels, B. (2021). *Ready, set, go: Reinventing the organization for speed in the post-COVID-19 era*. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/ready-set-go-reinventing-the-organization-for-speed-in-the-post-covid-19-era

Dekker, I., & Barling, J. (1995). Workforce size and work-related role stress. *Work & Stress, 9*(1), 45-54. https://doi.org/10.1080/02678379508251584

Dewa, C. S., Loong, D., Bonato, S., Thanh, N. X., & Jacobs, P. (2014). How does burnout affect physician productivity? A systematic literature review. *BMC health services research, 14*(1), 1-10. https://doi.org/10.1186/1472-6963-14-325

Dyrbye, L. N., Shanafelt, T. D., Johnson, P. O., Johnson, L. A., Satele, D., & West, C. P. (2019). A cross-sectional study exploring the relationship between burnout, absenteeism, and job performance among American nurses. *BMC nursing, 18*(1), 1-8. https://doi.org/10.1186/s12912-019-0382-7

Eberly, L. E. (2007). Multiple linear regression. In W. T. Ambrosius (Ed.), *Topics in Biostatistics* (Vol. 404, pp. 165–187). Humana Press. https://doi.org/10.1007/978-1-59745-530-5_9

El koncept d.o.o. (2023). *Finiinfo.* https://www.fininfo.hr/

European Agency for Safety and Health at Work. (2022). *OSH Pulse - Occupational safety and health in post-pandemic workplaces - Flash Eurobarometer – Summary*. https://osha.europa.eu/en/publications/summary-osh-pulse-occupational-safety-and-health-post-pandemic-workplaces

Filipe, L., Alvarez, M. J., Roberto, M. S., & Ferreira, J. A. (2020). Validation and invariance across age and gender for the Melbourne Decision-Making Questionnaire in a sample of Portuguese adults. *Judgment and Decision Making, 15*(1), 135-148. https://doi.org/10.1017/S1930297500006951

Freudenberger, H. J. (1975). The staff burn-out syndrome in alternative institutions. *Psychotherapy: Theory, Research & Practice, 12*(1), 73. https://doi.org/10.1037/h0086411

Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2019). *Multivariate data analysis*. Cengage Learning. Hampshire, United Kingdom.

Hobfoll, S. E., Halbesleben, J., Neveu, J. P., & Westman, M. (2018). Conservation of resources in the organizational context: The reality of resources and their consequences. *Annual review of organizational psychology and organizational behavior,* 5, 103-128. https://doi.org/10.1146/annurev-orgpsych-032117-104640

Howe, D. C., Chauhan, R. S., Soderberg, A. T., & Buckley, M. R. (2021). *Paradigm shifts caused by the COVID-19 pandemic. Organizational dynamics, 50*(4), 100804. 10.1016/j.orgdyn.2020.100804

Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., & Camerer, C. F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science, 310*(5754), 1680-1683. DOI: 10.1126/science.1115327

Huang, I. C., Chuang, C. H. J., & Lin, H. C. (2003). The role of burnout in the relationship between perceptions off organizational politics and turnover intentions. *Public Personnel Management, 32*(4), 519-531. https://doi.org/10.1177/009102600303200404

Hudek-Knežević, J., Kalebić Maglica, B. i Krapić, N. (2011). Personality, organizational stress, and attitudes toward work as prospective predictors of professional burnout in hospital nurses. *Croatian Medical Journal, 52* (4), 538-549.

Humphreys, K. A., & Trotman, K. T. (2022). Judgment and decision making research on CSR reporting in the COVID-19 pandemic environment. *Accounting & Finance, 62*(1), 739-765. https://doi.org/10.1111/acfi.12805

Janis, I. L., & Mann, L. (1976). Coping with decisional conflict: An analysis of how stress affects decision-making suggests interventions to improve the process. *American Scientist, 64*(6), 657-667. https://www.jstor.org/stable/27847557

Jerman, A., Pejić Bach, M., & Aleksić, A. (2020). Transformation towards smart factory system: Examining new job profiles and competencies. *Systems Research and Behavioral Science, 37*(2), 388-402. https://doi.org/10.1002/sres.2657

Khawaja, S., Sokić, K., Qureshi, F. H., & Miloloža, I. (2025). Impact of Personality and Psychopathy on Deviant Workplace Behaviour: Systemic Approach. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy, 16*(1), 23-39. https://doi.org/https://doi.org/10.2478/bsrj-2025-0002

Kusumadewi, F. A., Paskarini, I., & Khairunnisa, A. M. (2023). Demographic Characteristics and Locus of Control Associated with Employee Burnout. *The Indonesian Journal of Occupational Safety and Health, 12*(1), 74-83. Doi:10.20473/ijosh.v12i1.2023.74-83

Leiter, M. P., & Maslach, C. (1999). Six areas of worklife: a model of the organizational context of burnout. *Journal of health and Human Services administration*, 472-489. https://www.jstor.org/stable/25780925

Leiter, M. P., Maslach, C., & Frame, K. (2015). Burnout. In *The Encyclopedia of Clinical Psychology* (pp. 1–7). https://doi.org/10.1002/9781118625392.wbecp14

Linden, D. V. D., Keijsers, G. P., Eling, P., & Schaijk, R. V. (2005). Work stress and attentional difficulties: An initial study on burnout and cognitive failures. *Work & Stress, 19*(1), 23-36. https://doi.org/10.1080/02678370500065275

Mann, L., Burnett, P., Radford, M., & Ford, S. (1997). The Melbourne Decision Making Questionnaire: An instrument for measuring patterns for coping with decisional conflict. *Journal of Behavioral Decision Making, 10*(1), 1-19. https://doi.org/10.1002/(SICI)1099-0771(199703)10:1<1::AID-BDM242>3.0.CO;2-X

Masiero, M., Cutica, I., Russo, S., Mazzocco, K., & Pravettoni, G. (2018). Psycho-cognitive predictors of burnout in healthcare professionals working in emergency departments. *Journal of clinical nursing, 27*(13-14), 2691-2698. https://doi.org/10.1111/jocn.14376

Maslach, C. (1976). Burned-out. *Human Behaviour, 5*, 16-22.

Maslach, C., & Jackson, S. E. (1984). Burnout in organizational settings. *Applied Social Psychology Annual, 5,* 133–153.

Maslach, C., & Leiter, M. P. (2016). Understanding the burnout experience: recent research and its implications for psychiatry. *World Psychiatry, 15*(2), 103–111. doi:10.1002/wps.20311

Maslach, C., & Leiter, M. P. (2017). *Understanding Burnout*. The Handbook of Stress and Health, 36–56. doi:10.1002/9781118993811.ch3

Maslach, C., Jackson, S. E., & Leiter, M. P. (1996). *Maslach burnout inventory manual* (3rd ed.). Palo Alto, CA: Consulting Psychologists Press. Now published by Mind Garden.

McGee, R. A. (1989). Burnout and professional decision making: An analogue study. *Journal of Counseling Psychology, 36*(3), 345–351. doi:10.1037/0022-0167.36.3.345

Michailidis, E., & Banks, A. P. (2016). The relationship between burnout and risk-taking in workplace decision-making and decision-making style. *Work & Stress, 30*(3), 278–292. doi:10.1080/02678373.2016.1213773

Miller, D. (2001). The people make the process: commitment to employees, decision making, and performance. *Journal of Management, 27*(2), 163–189. doi:10.1016/s0149-2063(00)00094-5

Miller, K. I., Ellis, B. H., Zook, E. G., & Lyles, J. S. (1990). An integrated model of communication, stress, and burnout in the workplace. *Communication Research, 17*(3), 300–326. Doi:10.1177/009365090017003002

Morgado, P., Sousa, N., & Cerqueira, J. J. (2014). The impact of stress in decision making in the context of uncertainty. *Journal of Neuroscience Research, 93*(6), 839–847. doi:10.1002/jnr.23521

Morić Milovanović, B. & Cvjetković, M. (2024). Analysis of antecedents and consequences of workplace-related burnout among Croatian employees in the post-COVID-19 era. *Business: Theory and Practice, 25*(1), 108-118. https://doi.org/10.3846/btp.2024.19320

Nagar, K. (2012). Organizational commitment and job satisfaction among teachers during times of burnout. *Vikalpa, 37*(2), 43-60. https://doi.org/10.1177/0256090920120205

Narangerel, E. O., & Semerci, A. B. (2020). The Effects of Workload, Work Control and Self-Efficacy in Decision Making on Decision Making Styles. *Journal of Behavior Studies in Organizations, 3*, 22-32. http://dx.doi.org/10.32038/JBSO.2020.03.04

Pedersen, C. L., & Ritter, T. (2020). *Preparing your business for a post-pandemic world*. Harvard Business Review. https://hbr.org/2020/04/preparing-your-business-for-a-post-pandemic-world

Pejic-Bach, M., Bertoncel, T., Meško, M., & Krstić, Ž. (2020). Text mining of industry 4.0 job advertisements. *International journal of information management, 50*, 416-431. https://doi.org/10.1016/j.ijinfomgt.2019.07.014

Phillips, J. G., & Reddie, L. (2007). Decisional style and self-reported Email use in the workplace. *Computers in Human Behavior, 23*(5), 2414–2428. doi:10.1016/j.chb.2006.03.016

Phillips-Wren, G., & Adya, M. (2020). Decision making under stress: the role of information overload, time pressure, complexity, and uncertainty. Journal of Decision Systems, 1–13. doi:10.1080/12460125.2020.1768680

Potter, G., Hatch, D., Hagy, H., Radüntz, T., Gajewski, P., Falkenstein, M., & Freude, G. (2021). Slower information processing speed is associated with persistent burnout symptoms but not depression symptoms in nursing workers. *Journal of Clinical and Experimental Neuropsychology, 43*(1), 33–45. doi:10.1080/13803395.2020.1863340

Qureshi, F., Khawaja, S., Pejić Bach, M., & Meško, M. (2024). Slovenian higher education in a post-pandemic world: trends and transformations. *Systems, 12*(4), 132. https://doi.org/10.3390/systems12040132

Rahim, A., & Cosby, D. M. (2016). A model of workplace incivility, job burnout, turnover intentions, and job performance. *Journal of Management Development, 35*(10), 1255-1265. https://doi.org/10.1108/JMD-09-2015-0138

Rutledge, D. N., and Barros, A. S. (2002). Durbin–Watson statistic as a morphological estimator of information content. *Analytica Chimica Acta, 454*(2), 277–295. https://doi.org/10.1016/S0003-2670(01)01555-0

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. *Anesthesia & analgesia, 126*(5), 1763-1768. DOI: 10.1213/ANE.0000000000002864

Skodova, Z., & Lajciakova, P. (2013). The effect of personality traits and psychosocial training on burnout syndrome among healthcare students. *Nurse education today, 33*(11), 1311-1315. https://doi.org/10.1016/j.nedt.2013.02.023

Stanley, D. J., Meyer, J. P., & Topolnytsky, L. (2005). Employee cynicism and resistance to organizational change. *Journal of business and psychology, 19*, 429-459. https://doi.org/10.1007/s10869-005-4518-2

Sutcliffe, K. M., & McNamara, G. (2001). Controlling Decision-Making Practice in Organizations. *Organization Science, 12*(4), 484–501. doi:10.1287/orsc.12.4.484.10634

Tavella, G., & Parker, G. (2020). A Qualitative Reexamination of the Key Features of Burnout. *Journal of Nervous & Mental Disease, 208*(6), 452–458. doi:10.1097/nmd.0000000000001155

Toppinen-Tanner, S. (2011). *Process of burnout: structure, antecedents, and consequences.* Doctoral dissertation (article-based). University of Helsinki, Faculty of Behavioural Sciences, Institute of Behavioural Sciences, Finland.

Tosun, N., & Ulusoy, H. (2017). The relationship of organizational commitment, job satisfaction and burnout on physicians and nurses?. *Journal of Economics & Management, 28*, 90-111. https://doi.org/10.22367/jem.2017.28.06

Turulja, L., Smajlović, S., & Šimičević, V. (2025). Business Model Innovation: Impact of Entrepreneurial Competencies to New Value Proposition. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy, 16*(1), 40-59. : https://doi.org/10.2478/bsrj-2025-0003

Vine, S. J., Moore, L. J., & Wilson, M. R. (2016). An integrative framework of stress, attention, and visuomotor performance. *Frontiers in Psychology, 7*, 1671. https://doi.org/10.3389/fpsyg.2016.01671

Vrdoljak, I. (2024). The Importance of Lifelong Education in Modern Economy. *ENTRENOVA-Enterprise Research Innovation, 10*(1), 601-617. https://doi.org/10.54820/entrenova-2024-0018

WHO Regional Office for Europe. (2019). *Croatia: health and employment.* Copenhagen, Denmark. https://iris.who.int/bitstream/handle/10665/324928/9789289054034-eng.pdf?sequence=1

Matea Cvjetković is employed at the Institute of Public Finance, where she conducts research in public sector economics, entrepreneurship, and innovation and takes part in scientific research projects in these fields. Her research interests also include internal communication, organizational change, and selected aspects of behavioral economics. She earned her PhD from the University North. She also holds a master's degree in international relations and diplomacy from Libertas International University, an MSc in Global Management from Neoma Business School (France), and a bachelor's degree in economics from the Rochester Institute of Technology (Croatia). She has published several scientific and professional papers and has presented her work at various international academic conferences.

Katerina Fotova Čiković, MBA, PhD, is an Assistant Professor at the University North in Croatia. She holds a PhD in Economics and has a strong academic and professional background in finance, banking, and marketing. She has authored over 100 scientific papers, received multiple awards, and actively participates in international conferences. She speaks Macedonian, English, and German fluently. Her primary areas of academic and research interest include Finance, Banking, Marketing, Digital Marketing, Branding, and Mathematical Programming (specifically DEA – Data Envelopment Analysis). She has received several prestigious awards for her academic and scientific contributions, including Best Paper Awards at international conferences (EMAN 2021, ToSEE 2023, ISCBE 2025) and a Teaching Excellence Award for the 2022/2023 academic year.

Dinko Primorac is a Croatian scientist, university professor and entrepreneur. He was born in 1982 in Mostar (BiH). He received his undergraduate education at Webster University, graduated from the Faculty of Economics in Zagreb, and received his PhD from Megatrend University. As a professor, he teaches at several Croatian and international universities. He has published numerous scientific and professional articles, as well as university textbooks. He has participated in numerous international scientific conferences, and as a reviewer, he contributes to professional and scientific journals. As a scientist, he participates in several domestic and international economic scientific projects. His specialities are entrepreneurship and macroeconomics. He is a member of several supervisory boards of renowned Croatian companies.

Razumevanje vpliva poklicne izgorelosti na stile odločanja

Ozadje in namen: Namen raziskave je bil zapolniti vrzel v literaturi z opredelitvijo, kako izgorelost zaposlenih vpliva na stile odločanja v poslovnem okolju po obdobju COVID-19. Osrednji cilj je bil proučiti vpliv treh dimenzij izgorelosti – izčrpanosti, cinizma in občutka poklicne učinkovitosti – na štiri z odločanjem v konfliktnih situacijah povezane stile: budno odločanje, prelaganje odgovornosti, odlašanje in pretirano budnost.
Metodologija: V raziskavi je sodelovalo 567 zaposlenih iz različnih podjetij na Hrvaškem, ki so marca 2023 izpolnili spletni vprašalnik. Vpliv izčrpanosti, cinizma in poklicne učinkovitosti na stile odločanja v konfliktnih situacijah je bil analiziran z multiplo regresijsko analizo.
Rezultati: Rezultati multiple regresijske analize so pokazali, da občutek poklicne učinkovitosti spodbuja buden stil odločanja ter hkrati zmanjšuje verjetnost odlašanja, prelaganja odgovornosti in pretirane budnosti. Cinizem se je izkazal kot pozitiven napovednik odlašanja, prelaganja odgovornosti in pretirano budnega odločanja. Izčrpanost pa je imela pozitiven vpliv na pretirano budnost.
Sklep: Raziskava je pomembna, ker prispeva k razumevanju vpliva dimenzij izgorelosti na profesionalne stile odločanja v organizacijskem okolju, hkrati pa ponuja tudi praktične implikacije, ki so za podjetja in strokovnjake s področja managementa velikega pomena.

Ključne besede: *Izgorelost zaposlenih, Stil odločanja, Stres, povezan z delom, Hrvaška podjetja, Obdobje po COVID-19*

DOI: 10.2478/orga-2025-0020

Perceptions of Employer Attractiveness across Employee Cohorts in Slovakia

Lukáš SMEREK[1], Cecília OLEXOVÁ[2], Lívia KNECHTOVÁ[3]

[1] Matej Bel University in Banská Bystrica, Faculty of Economics, Banská Bystrica, Slovak Republic, lukas.smerek@umb.sk

[2] Bratislava University of Economics and Business, Faculty of Business Economics with seat in Košice, Košice, Slovak Republic, cecilia.olexova@euba.sk

[3] Ernst and Young in Bratislava, Slovak Republic, lknechtova@gmail.com

Background/Purpose: This paper investigates employer attractiveness from the perspective of different employee cohorts in Slovakia. The study aims to identify which employer attributes are perceived as most important and to investigate how these perceptions vary across different generational and educational segments. The research addresses current labour market challenges, including shortages of both highly and moderately skilled labour, further exacerbated by demographic ageing.
Methods: A quantitative research design was applied, using a questionnaire survey with a final sample of 481 respondents. A two-step cluster analysis using SPSS software was employed to group respondents with similar preferences.
Results: The results reveal that younger cohorts prioritise opportunities for development and reputation, while older generations emphasise salary and job security. Differences in perception were also observed across education levels. The findings highlight the need for a segmented approach in employer branding strategies, tailored to demographic and regional labour market specifics.
Conclusions: The study contributes to the literature by contextualising employer branding within the Slovak labour market and providing practical insights for organisations seeking to attract and retain diverse talent. These findings are relevant for both academics and HR practitioners aiming to develop more effective employer value propositions.

Keywords: *Employer attractiveness, Employer branding, Attributes, Clusters, Intergeneration differences*

1 Introduction

Employer branding is a growing trend in the field of human resource management (hereinafter referred to as HRM), particularly in response to the shortage of qualified labour across many countries, including Slovakia. It represents a strategic mismatch between employer expectations and labour market realities, driven by demographic, economic and technological shifts. Among these, the rise of AI-driven automation has contributed to the decline of middle-skilled positions, further intensifying competition for qualified talent and reinforcing the need for targeted employer branding strategies. In Slovakia, employers face difficulties in hiring both highly qualified technical staff and lower-skilled workers in the manufacturing sector. The healthcare is also affected, with a notable shortage of medical staff. The creation of new jobs with new requirements for employees, high demands on people’s skills or retirements can be considered the main reasons. Problems can escalate in connection with population ageing, espe-

Received: 21st July 2025; Accepted: 2nd September 2025

cially the gradual ageing of strong population cohorts born between 1970 and 1989 and their subsequent retirement, which reduces the number of working-age population. According to the National Active Ageing Programme report for 2021-2030 (Slovak Republic 2021), the burden of the working-age population (aged 20-64) by the senior (aged 65 and over) will pick up from the current approximately 25 people to 36 in 2030 and 63-67 per 100 people at working age in 2060. In terms of the ageing and labour cost index, Slovakia will rank among the EU countries with the highest percentage of seniors and the highest burden on the working-age population. The forecasts are consistent across OECD countries. Slovakia is among the fastest-ageing OECD countries, and it is expected that the ratio of the population in post-reproductive age to the working-age population will increase from 24% to 54% between 2020 and 2050 (Dujava & Pécsyová, 2020). These labour market and demographic challenges create an increasing need for companies to differentiate themselves as attractive employers and develop targeted employer branding strategies.

Therefore, the primary goal of companies is to attract high-quality job applicants and retain their current employees. Several studies have addressed the topic of employer branding, including publications that attempt to cover the concept comprehensively due to its inherently multidisciplinary nature. However, the approach of employers operating in Slovakia is not sufficiently discussed in the literature. Partial problems of employer branding were mentioned by Fratričová & Kirchmayer (2017). More scientists have addressed this topic only marginally within related fields (Hitka et al., 2019; Kucharčíková et al., 2019; Vetráková et al., 2020; Hitka et al., 2021). However, the growing interest and importance of employer branding can be seen, thanks to the mapping of this area by HR agencies (Deloitte, 2023; Universum, 2023). Universum (2023) states that most companies – the world's most attractive employers (78%) consider employer branding a top priority. There is also increasing interest from companies and organisations in participating in the survey for The Most Attractive Employer of The Year, which has been announced in Slovakia for more than ten years and is gaining prestige year by year. The results of the survey are based not only on the decision of the general public, but also on the opinions of employees, and gradually, employers from various sectors are being added (Profesia, 2023). While existing literature confirms the relevance of employer branding as a strategic HR tool, there is still limited understanding of how its specific attributes are perceived across different demographic and cultural settings. The preferences of different groups of potential job seekers are a specific area of interest due to the meeting of different generations in the labour market. Does it make sense for employers to target their activities at different generations of employees, and also depending on the level of education achieved? In this context, environmental awareness and green skills, such as sustainability thinking or resource efficiency, are emerging as increasingly relevant values, especially for younger generations seeking purpose-driven work. These expectations may shape the way employer branding is perceived and communicated.

Ultimately, the literature lacks consensus regarding the specific audience for employer branding (Theurer et al., 2018), particularly in terms of differences between demographic groups (Sarabdeen et al., 2023). The generational perspective has become increasingly important in the context of workforce diversification; yet, few studies systematically explore how various age cohorts in post-transition economies, such as Slovakia, perceive employer branding.

Therefore, this paper aims to identify the key attributes of building an employer brand that are important for employees of different generations in Slovakia to perceive as attractive, thereby contributing to theoretical knowledge that takes into account the local context and offers practical conclusions applicable to companies operating in Slovakia.

The paper adopts a context-specific approach to employer branding, examining how national labour market conditions and demographic structures shape perceptions of employer attractiveness. This perspective aims to complement international literature and provide theory-driven insights into generational employer preferences.

To achieve the goal, the paper is structured as follows: firstly, a review of the literature on employer branding, including intergenerational differences, is presented. Subsequently, the aim, methodology and sample are defined. In the following sections, the significant results of the research are presented. In the discussion, the focus is put on the essential elements of the employer brand in terms of generational differences and differences resulting from the level of education. In conclusion, the implications of our results, as well as further research directions and limitations, are discussed.

2 Literature review

2.1 Building the Employer Brand

An employer brand exists in every organisation, whether consciously managed or not. Without active shaping, prospective and current employees will form their own opinions (Daley, 2022). A strong employer brand engages current employees and attracts new candidates, making the employer a preferred choice (Rampl, 2014), serving as a long-term competitive advantage. The concept is increasingly tied to employee engagement and organisational embeddedness, where employer branding reinforces perceived organisational support and employee identification (Allen & Shanock, 2013). This brand perception is linked to customer views, with stronger business brands attracting higher-quality talent. Companies with better reputations tend to have more satisfied employees, and a positive applicant experience also boosts retention. Retaining valuable employees is crucial for sustaining a competitive advantage (Gelencsér et al., 2023).

Employer attractiveness, crucial for recruiting and retaining professionals, has received substantial scholarly attention (Berthon et al., 2005; Pingle & Sodhi, 2011). While attractiveness defines key elements, employer branding focuses on the communication that enhances this appeal. This distinction is grounded in signalling theory, which explains how employers' signals (such as branding) influence perceptions under conditions of imperfect information (Backhaus & Tikoo, 2004). Recent studies have also linked employer branding to psychological contract theory and social exchange theory, highlighting how trust and perceived fairness mediate employer-employee relationships (Allen & Shanock, 2013; Kucherov & Zayvalova, 2012). Even consumer-targeted communication impacts employees (Batt et al., 2021). Therefore, the employer branding process should be systematic (Stacho et al., 2022).

Employer branding borrows from product branding by using storytelling and emotion-based messaging to differentiate the company in the labour market (Rampl, 2014). The employer does not make a specific job offer, but instead builds continuous visibility and relevance. Unlike transactional staffing, employer branding represents a long-term strategy to position the company as an employer of choice (Reis & Braga, 2016). This facilitates talent acquisition and enhances internal engagement.

Employer branding also supports retaining employees by promoting internal values and consistency between promises and experience (Vetráková et al., 2020). This requires alignment of internal and external communication. The process of generating value for employees begins with expressing this value, continues with its measurement, and is then transformed into financial and non-financial indicators. It concludes by determining the activities that generate this value (Kucharčíková et al., 2019). From the perspective of psychological contract theory, this alignment is critical, as discrepancies between communicated promises and the actual work environment can erode trust and retention. In this regard, recent findings emphasise that not only psychological but also physical aspects of the workplace matter. Yasin et al. (2025) demonstrate that a green work environment, fostered through green human resource management practices, strengthens employer branding. They demonstrate that employees perceive sustainable and safe physical conditions as part of fulfilling the implicit contract with their employer. A company is considered attractive when potential employees proactively pursue job opportunities with it (Reis & Braga, 2016). Company culture is a key medium through which employer branding becomes credible. It is characterised by fairness, honesty, respect, and employee trust in the employer's actions. Consistency in upholding company values is also crucial (Fonseca, 2022). These soft factors are increasingly important in knowledge-intensive industries, where cultural fit and employer ethics significantly influence employee decisions (Allen & Shanock, 2013).

Brand building involves identifying what makes an employer unique and defining its core values. The "employee value proposition (EVP)" represents the value offered to employees, which Minchington (2006) described as a "set of associations and offerings provided by an organisation in return for the skills, capabilities and experience an employee brings to the organisation."

Several approaches to measuring employer branding are presented in the literature; however, no consensus has been established (Sarabdeen et al., 2023). Some scholars have proposed multidimensional models, such as Srivastava, Bhatnagar, and Arora (2017), who validated an 11-item second-order construct comprising "reputation, perceived culture, and HR systems and processes". Berthon et al. (2005) measured employer attractiveness using five primary values, i.e., attractiveness attributes, a similar approach followed by Lassleben and Hofmann (2023), who added work-life balance. These differing frameworks reflect the complexity of employer branding as a multidimensional phenomenon, requiring a contextual and flexible approach. Robust constructs and a comprehensive measurement model for employer branding were published by Sarabdeen et al. (2023).

Ambler and Barrow (1996) originally defined employer branding as the package of functional, economic and psychological benefits provided by employment. They emphasised its dual relevance for both attracting new talent and retaining existing employees. They conceptualised employer branding as the application of marketing principles to HRM, highlighting that consistent communication of these benefits is key to aligning employer identity and reputation.

EVP is increasingly seen as the strategic core of employer branding and requires adaptation to demographic and cultural expectations. According to Ambler and Barrow (1996), EVP functions as a psychological contract that aligns the mutual expectations of the employer and employee. EVP includes elements such as compensation, trust, work-life balance, and growth opportunities. According to economic migration theories summarised by Přívara et al. (2023), labour mobility is influenced not only by wage differentials but also by labour market segmentation and perceived opportunity structures. These theoretical frameworks support the notion that younger generations and educated talent are more sensitive to perceived employer value propositions.

Employer values can be determined through employee surveys, public opinion, internal analysis, or benchmarking against competitors. Ranking like Slovakia's Best Employer (organised by Profesia) also supports brand visibility by validating employer image through comparative evaluation criteria (management's approach, employer branding strategies, communication, performance management, employee development, benefits, and corporate social responsibility).

2.2 Attributes of employer attractiveness in terms of intergenerational differences

A LinkedIn survey of 18,000 employees from 26 countries, published in the 2014 Talent Trends study, revealed that more than half of job seekers (56%) consider a company's reputation as a great place to work to be a decisive factor in choosing a job. Other influencing factors included the reputation for quality products/services (20%), the reputation of the people employed in the company (17%), and the company's prestige (7%). These findings underscore the importance of clearly articulating organisational values, workplace culture, and expectations in external employer branding strategies. This highlights the strategic role of employer branding in shaping external perceptions.

Reis and Braga (2016) noted that different generations have distinct preferences, mirroring findings from motivation research, which suggest that motivation factors vary significantly with age (e.g., Hitka et al., 2021). Consequently, developing an employer brand that resonates across generational cohorts presents a growing challenge. This challenge is particularly acute in Slovakia, where employers often lack experience in strategic brand communication and segmentation, especially when targeting different generations. Contemporary workplaces commonly comprise three generational groups: Generation X (born 1961 –1981), Generation Y (born 1982 –2000), and Generation Z (born 2000 –2012). This generational framework draws on Strauss and Howe's (1991) theory, which suggests shared historical and social experiences shape each cohort. Generation X is typically characterised by confidence and independence, stronger loyalty to career progression than to employers, and a preference for skill development and work-life balance over hierarchical status. They value opportunities for professional growth paired with competitive compensation, especially in environments that foster diversity and creativity.

Generation Y tend to prioritise personal fulfilment, novelty and continual stimulation through change and challenges. They value flexibility, quality of life, recognition, and continuous feedback, as well as collaborative workplace relationships (Cavazotte et al., 2012). They are also more likely to share experiences and engage in leisure pursuits (Wiścicka & Misiak-Kwit, 2017). Although they may place less emphasis on work itself, they prioritise an attractive compensation package, personal growth, and a positive work environment. Millennials are particularly interested in rapid career advancement and technological innovation, shaped by their formative years during the internet boom (Twenge, 2010).

Generation Z, also known as Gen Z, is the successor cohort to millennials. In contrast, older cohorts may experience greater barriers to digital interaction. Seberini et al. (2022) note that older adults are particularly at risk of internet-related social exclusion, since they tend to use the Internet less than younger adults. They are considered the first true digital natives, having grown up with widespread use of technology. The COVID-19 pandemic accelerated the digital transformation across all age groups, including those previously less engaged with digital tools. The COVID-19 pandemic helped public administration to reduce the digital divide and increase digital citizenship without citizens even realising it (Tokovska et al., 2023). They bring advanced digital skills to the workplace, using them extensively for collaboration. However, their career outlook tends to be more cautious, shaped by exposure to recent global economic recessions. Aligning with their independence, entrepreneurial motivation, and outcome orientation, they place high value on workplace autonomy, including non-traditional employment arrangements such as teleworking (Weidmer, 2015; Lanier, 2017; Dwivendula et al., 2019).

A LinkedIn global trends survey (2020) found cross-generational agreement on top work values (listed as a percentage of people who listed selected factors as the most important when deciding on a new job): adequate compensation and benefits, work-life balance, and a positive work culture, possibly also an inspirational colleague and culture. Purpose-driven work was most valued by Boomers (32%) and least by Gen Z (18%). On the contrary, 36% of Generation Z considered education highly important compared to only 20% of Generation X.

Current research is increasingly targeting the preferences of Generation Z as they transition into employment. Ružić and Benazić (2023), studying Generation Z in Croatia, identified six key attributes based on Berthon et al.'s (2005) methodology: "organisation's market orientation, acceptance and good relationships with colleagues, informal workplace characteristics, potential for gaining experience and career advancement, salary and material benefits, and a sense of belonging to the organisation." Their findings also stressed the impact of economic volatility and labour shortage on shaping these generational preferences. Vieira et al. (2024), based on a literature review, identified key attributes for a Generation Z workplace as social responsibility, salary, and the company's reputation. Ružić and Benazić (2023) noted that cultural context and specific conditions may explain deviations from the original framework proposed by Berthon et al. (2005). Kapuściński et al. (2023) examined Generation Z in the hospitality sector. They recommended tailored employer strategies, including empowering employees through additional responsibilities, supporting development via mentorship programs, and recognising achievements by sharing success stories on social media. However, empirical evidence from Central and Eastern Europe remains scarce, and insights on how employers adapt their branding and EVP strategies to accommodate generational diversity are largely missing. Our research addresses this gap by examining how different generational cohorts in Slovakia perceive employer attractiveness and how these insights can inform employer branding strategies. Specifically, we argue that employer branding must be tailored to intergenerational preferences through differentiated Employee Value Propositions (EVPs), communication channels, and management approaches. For example, digital fluency and autonomy may be central to Gen Z messaging. At the same time, opportunities for personal development and work-life balance are more relevant to Gen Y. These findings provide actionable guidance for HR professionals in designing more effective recruitment and retention strategies that align with the needs of this generation.

3 Objective, Materials and Methods of Research

While the most common selection criteria for employees include technical ability and experience (Poór et al., 2017), age and level of education of candidates are also among the five main factors affecting the selection of employees in Slovak companies (Smerek & Kováčiková, 2019). Therefore, this paper aims to identify the characteristics of an attractive employer and the differences in perception of their importance among various categories of respondents in Slovakia, specifically among different generations of respondents and among respondents with varying levels of education.

Research questions were formulated as follows:

RQ1: What are the most commonly perceived attributes of an attractive employer?

RQ2: Does the perception of attributes of an attractive employer depend on age and education?

Data collection was conducted through a questionnaire survey from October 2024 to February 2025. An electronic questionnaire was created on the Google Docs platform. Respondents were approached either personally or by email (400 people) and through social networks, specifically Facebook and LinkedIn (reaching 2,128 people). This approach represents a form of convenience sampling, which was chosen due to its flexibility and ease of access to a large number of respondents. The sample consists of 481 respondents completing the entire questionnaire. The response rate of the questionnaire was 19.03%. The representativeness of the sample was verified using the Chi-square test of goodness of fit, based on two sorting attributes: gender and age.

Because recruitment relied in part on Facebook and LinkedIn, our sample may reflect platform- and topic-specific self-selection. Recent experiments have shown that subtle changes in the design of social media ads (e.g., explicit cues or themes) can influence who clicks and responds, which in turn can impact composition and estimates (Neundorf & Öztürk, 2025). Studies of surveys conducted via Facebook further suggest that the topic and presentation can subtly alter responses, although not always consistently (Donzowa et al., 2025). Furthermore, platform dynamics (e.g., LinkedIn profile verification practices and age bias) may underrepresent older or less digitally active workers (Schellaert et al., 2024). We minimised this risk through multi-channel outreach and subsequent age and education representativeness checks; however, generalising results beyond active social media users requires caution.

Table 1: Representativeness of the sample in terms of age

Age					
	Observed N	%	Expected N	Expected %	Residual
< 25	160	33.26	151.5	31.50	8.5
25 – 40	134	27.86	121.1	25.18	12.9
40 – 64	187	38.88	208.4	43.32	-21.4
Total	481	100.0	481	100.0	
Null Hypothesis		Chi-Square	df	Asymp. Sig	Decision
The categories of age occur with the specified probabilities		4.037[a]	2	0.133	Retain the null hypothesis

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 121.1.
Source: Own processing, 2025

Table 2: Representativeness of the sample in terms of the level of education achieved

Education					
	Observed N	%	Expected N	Expected %	Residual
Primary	78	16.22	76.5	15.90	1.5
Secondary	219	45.53	234.7	48.79	-15.7
Higher	184	38.25	169.8	35.30	14.2
Total	481	100.0	481	100.00	
Null Hypothesis		Chi-Square	df	Asymp. Sig	Decision
The categories of gender occur with the specified probabilities		2.257[a]	2	0.324	Retain the null hypothesis

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 76.5.
Source: Own processing, 2025

For the identification of the basic set, we utilised data from the Statistical Office of the Slovak Republic, specifically the STATdat database, as of 31 December 2023. The age groups in the mentioned database are shifted by approximately two years compared to the theoretical definition of Generations X, Y and Z. However, the definition of generations is given as indicative in all sources. For statistical testing, an exactly defined age in the database of the statistical office was used. For the purposes of evaluating the results, respondents aged 40 – 64 years were considered Generation X, respondents aged 25 – 40 years Generation Y and respondents aged up to 25 years Generation Z. Although generational theory (Strauss & Howe, 1991) defines cohorts by shared cultural experiences, the present study operationalises them through age categories due to data availability, following an approximate alignment with theoretical generation boundaries. For assessing the representativeness of the sample based on educational attainment, the active population aged 15 and above was considered. The testing was conducted at a significance level of $\alpha = 0.05$, with the results presented in Tables 1 and 2.

In our survey, we were inspired by the individual values and attributes that contribute to employer attractiveness. Respondents were also allowed to add attributes to better identify the specifics of the Slovak labour market. The questionnaire items were derived from established studies (Berthon et al., 2005; Sarabdeen et al., 2023). Unlike most existing studies that focus on global patterns or single generational cohorts, this paper contributes to the literature by comparing generational and educational differences in the Slovak context.

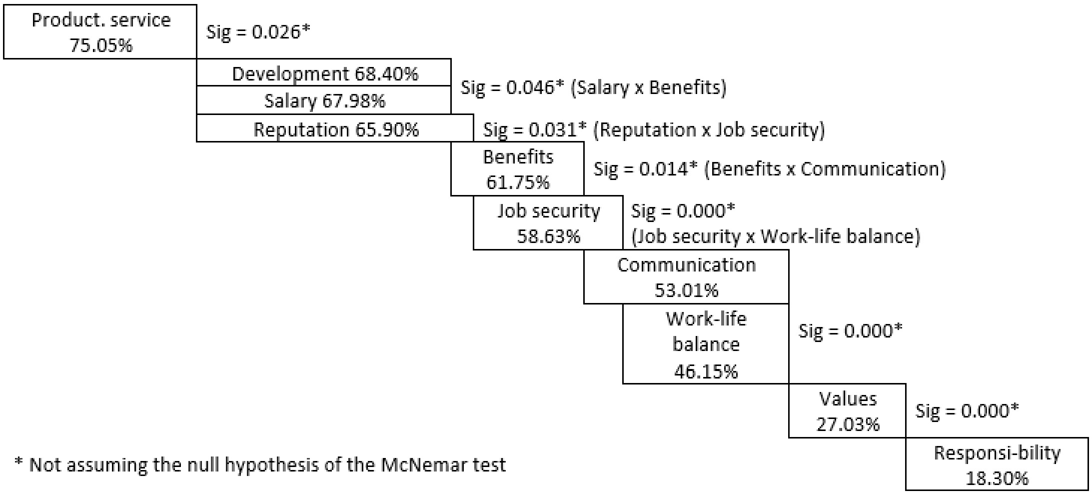
In addition to providing identification data, respondents were asked to identify which attributes of an attractive employer they considered relevant and preferred. To compare differences in the identification of these attributes, the McNemar test was applied. This test is appropriate for comparing two binary variables, assuming the null hypothesis that the distribution across categories is equal. To assess differences in the perceived importance of employer attributes, the Wilcoxon Signed Ranks Test was used, which is suitable for ordinal variables. The null hypothesis assumes that the median difference in the paired data is zero. The testing of the significance of differences between individual groups of respondents at the level $\alpha = 0.05$ was carried out. Finally, to identify groups of respondents with similar preferences, a two-step cluster analysis was conducted using SPSS software. Although findings are statistically significant at $\alpha = 0.05$, their practical relevance is discussed with caution, particularly in the context of designing HR strategies tailored to generational needs.

4 Results

In evaluating the perception of attractive employer attributes, respondents had the opportunity to select any number of attributes from the list or add their own. They were then to express their importance on a scale from 1 (low importance) to 5 (high importance). If a respondent did not mention a particular attribute in the response, it was assigned an importance of 0 (no importance). Subsequently, the order of the ten most frequently appearing attributes of an attractive employer, according to the percentage of respondents who noticed them (Table 3), was compiled. For each attribute, its average importance was determined (Table 4).

By applying McNemar's test, groups with statistically significant differences between them in the identification of attractive employer attributes were created. Furthermore, using the Wilcoxon Signed Ranks Test, groups of attributes were created and statistically significant differences in the perception of their importance were identified.

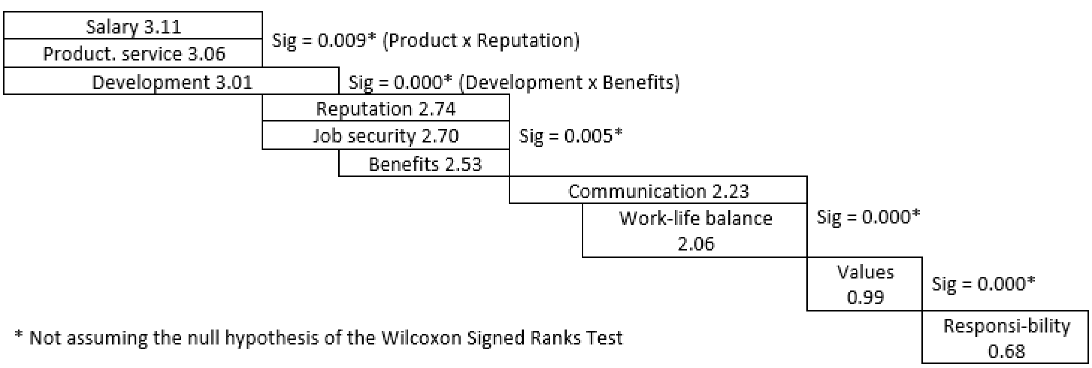
Table 3: Difference in identification of attractive employer attributes



* Not assuming the null hypothesis of the McNemar test

Source: Own processing, 2025

Table 4: The difference in perception of the importance of attractive employer attributes



* Not assuming the null hypothesis of the Wilcoxon Signed Ranks Test

Source: Own processing, 2025

Figure 1: Cluster Model Summary

Source: Own processing, 2025

To identify specific patterns of perception of an attractive employer's attributes that are valid for individual groups of potential employees, a two-step cluster analysis was employed. The attributes mentioned by at least 50% of respondents were considered to create clusters. Therefore, the first 7 of the 10 most frequently perceived attributes – customer satisfaction with the company's product/service, career and personal growth, salary, overall company reputation, benefits offered, job security offered, and good company communication were used. Generally, salary is among the most significant factors in determining an employer's attractiveness. For example, Saini et al. (2015) stated that, although multiple factors are important for job seekers, salary still has the greatest impact on their work decisions. Surprisingly, fewer respondents mentioned work-life balance, as it is often in the centre of attention in society; however, this was also found by Sarabdeen et al. (2023) and Saini et al. (2015). The age of the respondents and their education were investigated as the essential variables. These can be relevant for companies when searching for new employees and can impact the candidate's suitability for performing specific work activities, or can positively influence the work team structure.

Figure 1 shows the appropriateness of the chosen methodology. Considering the data used, the quality of the identified clusters is not the best, but it is satisfactory for us to draw relevant conclusions and recommendations.

When comparing respondents' answers, 8 relevant clusters were created (Table 5–7). Tables 5–7 provide a detailed overview of these clusters, demonstrating how age and education interact to shape preferences for employer attributes. Their analysis enables us to identify distinct patterns for Generations Z, Y, and X, providing the basis for the subsequent graphical model (Figure 2).

Table 5 breaks down Generation Z respondents by education level. The results show that growth and reputation were particularly important to respondents with a college degree. At the same time, those with only primary or secondary education placed a greater emphasis on compensation and benefits. These results highlight that even among the youngest cohorts, education level has a strong influence on perceptions of employer attractiveness.

Table 6 presents the clusters for Generation Y. Respondents in this age group showed a balanced perception of various employer attributes. While compensation and job security remained important, respondents with higher education placed greater emphasis on product/service quality and professional development. This suggests that Generation Y tends to evaluate employer attractiveness more differentially than Generation Z.

Table 7 summarises the clusters for Generation X. Within this age group, compensation and product/service quality are consistently prioritised across all education levels. Compared to younger generations, Generation X respondents value stability and tangible outcomes from their work experiences. These perceptions explain why compensation and job security are the top priorities in their employer brand preferences.

It means that within the group of respondents under 25 (Generation Z) and over 40 (Generation X), differences in the perception of the importance of an attractive employer's attributes by respondents in terms of education can be observed. In the case of the 25- to 40-year-old age group (Generation Y), respondents with primary education exhibited some of the characteristics of respondents with higher or lower levels of education. This is also a limitation of our research. Overall, however, conclusions can be drawn in response to RQ2.

In HR processes, such as job analysis and subsequent recruiting, it is quite common for human resource man-

Table 5: Clusters of age under 25

Cluster	**Primary Z**			**Secondary Z**			**Higher Z**		
Size	5.2% (25)			14.3% (69)			13.7% (66)		
Education	100%			100%			100%		
Age	100%			100%			100%		
	Mean	**St. dev**	**Med**	**Mean**	**St. dev**	**Med**	**Mean**	**St. dev**	**Med**
Salary	2.00	2.33	0	2.75	2.22	4	2.68	2.22	4
Product/Service	3.20	1.73	4	2.65	1.98	4	2.52	1.97	3
Job security	2.04	2.37	0	2.19	2.26	0	2.21	2.33	0
Benefits	1.76	2.07	0	2.54	2.14	3	3.20	1.95	4
Reputation	2.04	2.09	3	2.81	2.01	4	3.15	1.97	4
Communication	1.76	2.11	0	2.01	2.18	0	2.32	2.28	3
Development	3.32	2.17	4	2.83	2.11	4	3.32	2.20	5

Source: Own processing, 2025

agers and other HR specialists to create preferred groups of employees suitable for a specific job position. Depending on the nature of the activities performed and the job requirements, the most common determinant is the level of education completed. To maintain a desirable corporate culture, the continuity of the workforce structure and succession planning are crucial. The age of recruited employees is a frequent determinant in this regard. For the practical application of our findings, a graphic model (Figure 2) was created. The attributes of an attractive employer with an average importance higher than 3 were considered.

In Figure 2, the colours distinguish the educational groups of respondents to provide better clarity of the model. Green indicates respondents with a university education, blue indicates respondents with a secondary education, and red indicates respondents with a primary education. This visual coding allows for easier comparison of how different levels of education within each generation perceive the importance of employer attributes.

This model can serve as an aid to company management in setting the employer's branding strategy regarding the mentioned determinants. The features not connected to the respondents' categories in the model showed an average importance of less than 3, indicating that their influence on the perception of the attractiveness of the employer's brand has minimal added value for the company. Interestingly, respondents with higher education showed greater consistency, which enabled us to identify more significantly essential factors. Generation Y members with primary and secondary education could not agree on a single significant factor. For this generation, it is therefore necessary to strike a balance between following all the signs of an attractive employer.

Table 6: Clusters of age between 25 and 40

Cluster	Secondary Y			Higher Y		
Size	13.1% (63)			11.0% (53)		
Education	100%			98.1%		
Age	100%			100%		
	Mean	St. dev	Med	Mean	St. dev	Med
Salary	2.52	2.26	4	3.00	2.31	4
Product/Service	2.46	2.18	3	3.26	2.15	4
Job security	2.83	2.30	4	3.32	2.24	5
Benefits	2.46	2.04	4	2.60	1.93	3
Reputation	2.44	2.15	3	2.26	2.31	2
Communication	1.76	2.18	0	2.17	2.29	2
Development	2.95	2.05	4	2.70	2.28	4

Source: Own processing, 2025

Table 7: Clusters of age between 40 and 64

Cluster	Primary X			Secondary X			Higher X		
Size	10.8% (52)			18.1% (87)			13.7% (66)		
Education	100%			100%			100%		
Age	65.4%			100%			100%		
	Mean	St. dev	Med	Mean	St. dev	Med	Mean	St. dev	Med
Salary	3.60	1.97	5	3.78	1.90	5	3.70	2.07	5
Product/Service	3.42	1.66	4	3.59	1.59	4	3.44	1.76	4
Job security	3.12	2.18	4	2.92	2.29	4	2.71	2.38	4
Benefits	2.52	2.18	3	2.25	2.21	3	2.55	2.21	3
Reputation	2.81	2.07	4	2.79	2.01	4	3.05	1.90	4
Communication	2.38	2.32	3	2.79	2.08	3	2.17	2.10	3
Development	2.92	2.13	4	3.10	2.04	4	3.00	2.13	4

Source: Own processing, 2025

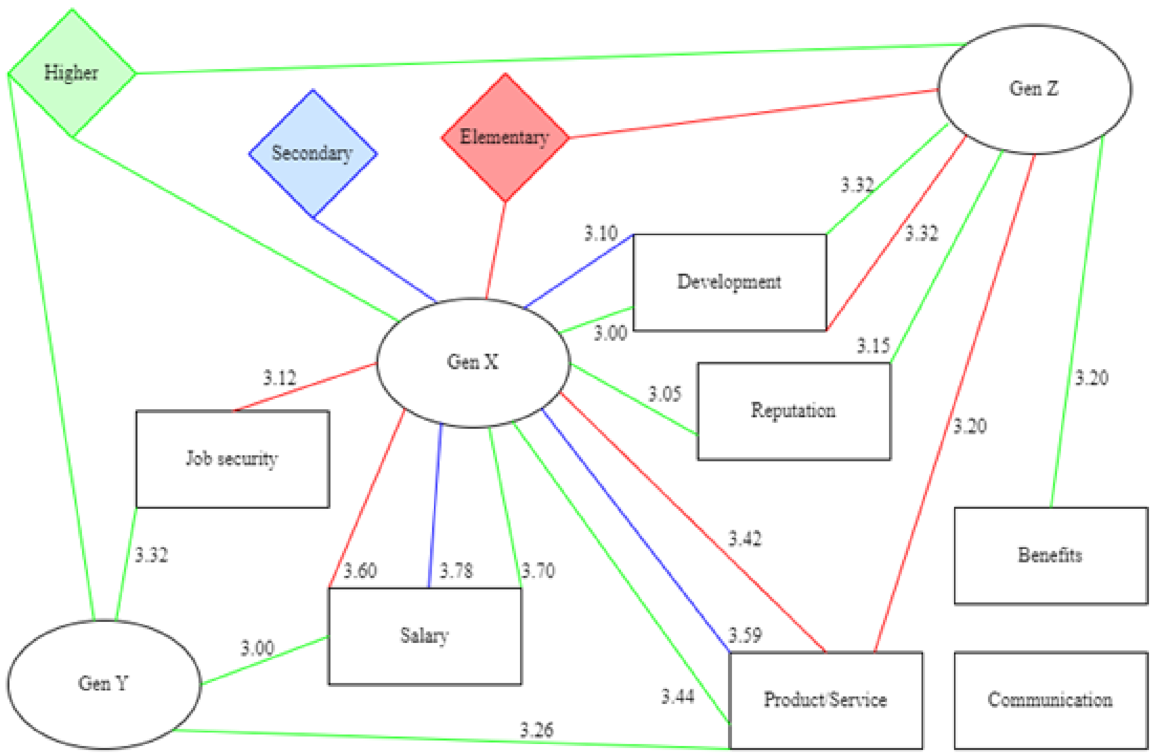


Figure 2: Influence of the characteristics of an attractive employer on different groups of respondents

Source: Own processing, 2025

5 Discussion

The most significant attributes of an employer attractiveness are logical. Regardless of education, development is the most important feature for the age category under 25, i.e., young people are aware of the importance of education for further practice. Similar to our study, Grigore et al. (2023) also examined how age and education influence the perception of employer attractiveness in the context of Eastern Europe, specifically Romania. Their findings underscore the importance of demographic segmentation in designing employer branding strategies for post-transition economies. Sarabdeen et al. (2023) likewise argue that junior employees, or those at the beginning of their careers, are interested in training and perceive development opportunities as "a value-added attribute". Similar conclusions were also reported in the research conducted by Kapuściński et al. (2023) among Generation Z in the UK hospitality industry. Based on this, they emphasised the need to offer people the possibility of career development by providing training or work opportunities in other locations, respectively, in other countries. Dwivedula and Singh (2020) also state that growth opportunities are among the essential factors for Generation Z. According to a Deloitte survey (2023) of Generation Z and Millennials, these groups of people would like employers to offer better career opportunities for part-time employees in this regard. Stiglbauer et al. (2022) dealt with intergenerational differences in a sample of the German online population. However, they concluded their findings by saying that there are no considerable differences in the fundamental characteristics of attractiveness between Generations.

Nevertheless, they only pointed to some, e.g., that Generation Z, compared to Generation X, places greater emphasis on development (like our case) but also on relating (in the sense of placing great emphasis on good social relationships). Compared to other age groups, salary did not appear among the most significant attributes of attractiveness – here we can see a similarity with the results of a survey of motivation factors (Hitka et al., 2019), which presents statistically significant differences between age and salary when younger age groups are aware of their limits in skills and experience and the need to acquire relevant experience for their career development. Similarly, Gallo et al. (2023) state that this is also the case in the example of Generation X social workers. Financial remuneration and upskilling are significant motivators for them. At the same time, career growth is more important for Generation Y, along with interesting work, a friendly work environment, feedback, and a good work-life balance. The findings must be interpreted within the context of the Slovak labour market, characterised by ongoing demographic ageing, emigration of young, skilled labour, and regional disparities. These factors may shape how generations perceive employer attractiveness and how employers respond through tailored branding strategies. This aligns with empirical findings by Přívara et al. (2023), who demonstrated that immigration in V4 countries has a significant and negative effect on unemployment, particularly in the short run, which supports the potential of targeted labour mobility as a solution for less developed regions such as Prešov and Košice. In addition, our results empirically support the dual-process model of EB proposed by Backhaus and Tikoo (2004). In addition to the dual-process perspective, two complementary models help explain why cohorts in our data weigh employer attributes differently. First, signalling theory (Thang & Trang, 2024) posits that under conditions of information asymmetry, job seekers rely on observable signals to infer implicit employment terms. Gen Z, who are more digitally embedded, is particularly vulnerable to employer signals disseminated through social media; thus, they appear to respond more strongly to online signals about advancement and reputation. Second, psychological contract research suggests that cohorts entering the labour market have different sets of expectations regarding reciprocity. Data from recent cohort-moderated models show that younger workers exhibit lower psychological contract fulfilment compared to older cohorts (Ellethiey et al., 2024), which may increase their sensitivity to tangible advancement opportunities and transparent communication. Together, these mechanisms fit our pattern – Gen Z emphasises growth/reputation, Gen Y emphasises job security, and Gen X emphasises reward – and suggest that tailoring EVP signals to cohort-specific expectations can increase employer attractiveness.

Respondents aged 25–40 with secondary education mentioned development as the most important feature. For university-educated people of Generation Y, other attributes of employer attractiveness are more important, as they want to apply their education and experience. It is completely different for the group of people aged 40 to 64. They showed the salary as the most important factor, which is not surprising. There can be several explanations. Firstly, the fact that employees at this age already want to materialise the results of their work experience, and at the same time, it is pragmatism because the salary will later affect their retirement income. In addition, the salary in Slovakia is relatively low, including differences in terms of the highest level of education completed, and the salary mainly serves to cover basic needs, which may be another explanation for the emphasis on salary compared to the results of Stiglbauer et al. (2022), where all generations placed less emphasis on money.

When examining the other features of employer attractiveness, diversity is evident in the differences between age and educational levels. In general, regardless of education, a company's reputation is important to Generation Z. We can rely on the findings of Wilden et al. (2010), which indicate that the credibility of information also contributes to employer attractiveness. The importance of reputation, especially for inexperienced respondents, which in our case means Generation Z, is explained by Wilden et al. (2010). The main reason is that these people want an employer with a strong brand name on their CVs. Generation Y, currently at a productive age, also considers job security and salary. Generation X agrees, regardless of the level of education, that customer satisfaction with the company products and services is also an important attribute for this generation, which can be explained by the fact that for this generation it is essential to experience the meaningfulness of work and the awareness of the close connection between customers' satisfaction and the success of the company, reflected in the amount of pay. They also attach relatively high importance to education, which is currently a prerequisite for maintaining work skills due to the constantly increasing demands on employees.

Deloitte survey results (2023) also found that 49% of Generation Z and 62% of Millennials say work is central to their identity. However, they place great emphasis on work-life balance – a distinctive trait they admire in their peers and the main criterion when choosing an employer. Similarly, work-life balance is also evident in the results reported by Ada et al. (2023) and Rozsa and Machová (2020). However, it was not confirmed by our data. A general explanation could be that nowadays, especially in the post-pandemic period, it is taken for granted, not something that makes the employer unique and different from others (see Universum, 2023), or this may also be a matter of different culture (Baum & Kabst, 2013; Bábiková & Bucek, 2019). We believe, following the situation in Slovakia, that it may be a locally specific issue, with low salaries and less attractive job opportunities in individual regions of Slovakia. This is also stated by Habánik et al. (2019), who note that Slovak employers tend to focus more on low-wage employees due to Slovakia's emphasis on industry. For these reasons, the salary and other values mentioned are on the first rungs of the decisive attributes.

Based on the findings, employer branding strategies should highlight professional development opportunities and reputation for Gen Z, job security and career progression for Gen Y, and fair compensation and meaningful work for Gen X. Tailoring communication on platforms relevant to each group (e.g. social media for Gen Z, LinkedIn and internal communication for Gen Y/X) can further enhance employer appeal. In this respect, Ghorbanzadeh et al. (2025) provide empirical support by showing that social media characteristics, particularly social presence and informativeness, significantly shape employer brand attractiveness and person–organisation fit. From a signalling theory perspective, these online cues serve as important signals of organisational values, reinforcing the importance of carefully crafted digital content (Suprawan et al., 2025) as a key driver of recruitment outcomes.

In line with global sustainability agendas and shifting generational values, recent research confirms that all generational cohorts are increasingly responsive to employers' environmental and societal commitments. Generation X shows the most favourable attitude toward sustainability, followed by Generation Z, which highlights the need for organisations to communicate their sustainability efforts effectively to attract these groups (Verčič & Verčič, 2025). Green employer labels in recruitment ads enhance person–organisation fit and employer attractiveness, especially among environmentally oriented applicants (Pfiffelmann et al., 2025). Although not directly captured in our survey items, attributes related to sustainability and environmental responsibility may be indirectly reflected in preferences for development, innovation, and employer reputation. Future employer branding strategies may need to explicitly articulate their commitments in this area to maintain competitiveness among emerging generations of talent. This supports the theoretical proposition that employer brand associations (e.g. development, reputation, security) influence the employer brand image, which in turn affects employer attractiveness (Backhaus & Tikoo, 2004). Our findings support the view that such brand associations contribute to better person–organisation value matching, especially when tailored to generational expectations.

6 Conclusions

The topic of building an employer's brand is not new in Slovakia, but it gained practical importance only in connection with the labour market's shortage of employees. Even though the rate of registered unemployment in Slovakia is not enormously high (3.81% in December 2024), employers face growing challenges in attracting and retaining qualified human resources, especially in less developed regions (such as Prešov and Košice). The paper contributes to its results by identifying attributes of employer attractiveness, which can help employers in Slovakia retain talent and attract new ones. Creating an employer brand must be systematic and responsive to generational differences in employee values. The results show that while core values are shared, their relative importance differs by age and education. Employers should segment EVP communication to match generational expectations and consistently deliver on these promises. Practically, this implies fostering intergenerational inclusivity, strengthening a culture of feedback, and investing in the growth of younger cohorts to enhance engagement and loyalty. Satisfied and engaged employees can thus become powerful brand ambassadors, shaping external perceptions through authentic advocacy. The conducted research also has its limitations. This study is limited by potential self-selection bias due to convenience sampling and the inability to isolate employer branding effects from broader organisational variables.

Specifically, social-media recruitment can introduce coverage and algorithmic delivery effects, as well as cohort-specific non-response (e.g., lower propensity among older workers) (Schellaert et al., 2024). Future work should pre-register ad variants, log recruitment creatives, and, where feasible, triangulate samples from offline frames or probability-based panels to improve external validity (Neundorf & Öztürk, 2025; Donzowa et al., 2025). Subsequent studies might incorporate longitudinal or experimental designs to assess causality.

Upcoming research agendas should also address the role of the sectoral differences, company size, and regional labour market disparities in shaping employer brand preferences.

In addition, future research should explicitly include elements of corporate social responsibility (CSR) and sustainability commitments, given the growing body of evidence that younger generations – particularly Generation Z – value employers' commitment to environmental and social issues (Sengupta et al., 2024; Gintale et al., 2024; Mas-Manchón et al., 2024). Recommended elements include externally verified ESG reports and emissions targets, investment in green skills training, ethical supply chain policies, community engagement and volunteering opportunities, and transparent sustainability communications. Incorporating these elements would enable testing whether Generation Z clusters demonstrate a stronger response to CSR-related signals than older generations and whether CSR enhances value alignment between individuals and organisations beyond basic attributes, such as development and compensation. CSR can, within the framework of signalling theory, act as a strong signal of an organisation's authenticity and value orientation. Empirical findings by Vázquez-Rodríguez et al. (2025) further show that companies with a stronger CSR orientation not only develop soft skills more intensively but also engage their managers more actively in community activities, thereby signaling to applicants that CSR is an integral part of the organisational culture rather than merely a symbolic tool with comparative studies across countries or industries helping to establish broader generalisability.

Overall, this paper contributes to the theoretical understanding of intergenerational employer brand perception and delivers practical implications for strategic HRM and EVP design. It also highlights avenues for future research in a rapidly evolving labour market.

Acknowledgements

This work was supported by the Ministry of Education, Research, Development and Youth of the Slovak Republic under project KEGA 020EU-4/2025 The Development of a Model for an Innovative Didactic Concept to Enhance Green Skills of Students at Economics-focused Universities with an Emphasis on Ecosystem Sustainability.

This work was supported by the Scientific Grant Agency of the Ministry of Education, Research, Development and Youth of the Slovak Republic under project VEGA 1/0029/25 Specifics of human resource management in Slovak companies related to Industry 4.0.

References

Ada, N., Korolchuk, M., & Yunyk, I. (2023). The Role of Employer Branding Practices on Management of Employee Attraction and Retention. *Economics Ecology Socium*, 7(1), 46–60. https://doi.org/10.31520/2616-7107/2023.7.1-5

Allen, D. G., & Shanock, L. R. (2013). Perceived Organisational Support and Embeddedness as Key Mechanisms Connecting Socialisation Tactics to Commitment and Turnover Among New Employees. *Journal of Organizational Behavior*, 34(3), 350–369. DOI: 10.1002/job.1805

Ambler, T., & Barrow, S. (1996). The employer brand. *Journal of Brand Management*, 4(3), 185–206.

Bábikova, K., & Bucek, J. (2019). A Model Replication with an Extension of Students' Perception of Prospective Employer Attractiveness. *Journal of Competitiveness*, 11(2), 5-21. https://doi.org/10.7441/joc.2019.02.01

Backhaus, K., & Tikoo, S. (2004). Conceptualising and researching employer branding. *Career Development International*, 9(5), 501–517. https://doi.org/10.1108/13620430410550754

Batt, V., Holzer, M., Bruhn, M., & Tuzovic, S. (2021). Effects of sponsorship quality and quantity on employee brand behavior. *Journal of Brand Management*, 28, 495–509. https://doi.org/10.1057/s41262-021-00242-w

Baum, M., & Kabst, R. (2013). How to attract applicants in the Atlantic versus the Asia-Pacific region? A cross-national analysis of China, India, Germany, and Hungary. *Journal of World Business,* 48, 175–185. https://doi.org/10.1016/j.jwb.2012.07.002

Berthon, P., Ewing, M., & Hah, L.L. (2005). Captivating company: dimensions of attractiveness in employer branding. *International Journal of Advertising*, 24(2), 151–172. https://doi.org/10.1080/02650487.2005.11072912

Cavazotte, F., Lemos, H.C., & Viana, M.D. (2012). Relações de trabalho contemporâneas e as novas gerações produtivas: renovadas ou antigos ideais? Cadernos EBAPE. *Encontro Nacional da ANPAD*, 10(1), 162–180. ISSN 2177-2576. https://doi.org/10.1590/S1679-39512012000100011

Deloitte (2023). 2023 Gen Z and Millennial Survey: Waves of change: acknowledging progress, confronting setbacks.

Donzowa, J., Perrotta, D., Zagheni, E. (2025). Assessing self-selection biases in Facebook-recruited surveys: Evidence from the COVID-19 Health Behavior Survey. *PLOS ONE*, 20(7), 0326884. https://doi.org/10.1371/journal.pone.0326884

Dujava, D. & Pécsyová, M. (2020). Slovenský trh práce počas prichádzajúcich demografických zmien. *Inštitút finančnej politiky*, https://www.mfsr.sk/files/archiv/48/dujava_pecsyova-trh_prace_demo_zmeny.pdf, accessed 10 August 2023.

Dwivedula, R., & Singh, P. (2020). What motivates Gen Z at work? An empirical analysis. *Journal of Human Resource Management*, XXIII(2), 40–53.

Dwivedula, R., Singh, P., & Azaran, M. (2019). Gen Z: Where are we now, and future pathways. *Journal of Human Resource Management*, 22(2), 28–40.

Ellethiey, N. S., Ashour, H. M. A. A., & Awad, N. H. A. (2024). Talent management in volatility, uncertainty, complexity, and ambiguity (VUCA) health environment, nurses' psychological contract fulfillment, cordial relation and generation: moderation-mediation model. *BMC Nursing*, 23, 883. https://doi.org/10.1186/s12912-024-02506-7

Gallo, P., Mihalcova, B., Balogova, B. (2023). Work Motivation of Social Workers in the Context of Management Innovations. *Marketing and Management of Innovations*, 1, 55-63. https://doi.org/10.21272/mmi.2023.1-05

Gelencsér, M., Szabó-Szentgróti, G., Kőmüves, Z. S., & Hollósy-Vadász, G. (2023). The Holistic Model of Labour Retention: The Impact of Workplace Wellbeing Factors on Employee Retention. *Administrative Sciences*, 13(5), 121. https://doi.org/10.3390/admsci13050121

Gintale, G., Correia, R., Venciute, D., & Lapinskiene, R. (2024). Sustainability and beyond: decoding the influences of corporate social responsibility on employer brand attractiveness. *Cogent Business & Management*, 11(1), 2429799. https://doi.org/10.1080/23311975.2024.2429799

Ghorbanzadeh, D., Radhakrishnan, L. C., Prasad, K., Alkhayet, A., Yajid, M. S. A., & Dhaliwal, A. S. (2025). Enhancing intentions to apply for job through social media: the mediating role of employer attractiveness and person-organisation fit. *Asia-Pacific Journal of Business Administration*. https://doi.org/10.1108/APJ-

BA-11-2024-0619

Grigore, G., Chapleo, C., Homberg, F., Alniacik, U., & Stancu, A. (2023). Employer branding dimensions: An adapted scale for Eastern Europe. *Journal of Strategic Marketing*. https://doi.org/10.1080/0965254X.2023.2241460

Habánik, J., Grenčíková, A., & Krajčo, K. (2019). The Impact of New Technology on Sustainable Development. *Engineering Economics*, 30 (1), 41-49. https://doi.org/10.5755/j01.ee.30.1.20776

Hitka, M., Lorincová, S., Potkány, M., Balážová, Ž., & Caha, Z. (2021). Differentiated approach to employee motivation in terms of finance. *Journal of business economics and management*, 22(1), 118-134. https://doi.org/10.3846/jbem.2020.13702

Hitka, M., Rózsa, Z., Potkány, M., & Ližbetinová, L. (2019). Factors forming employee motivation influenced by regional and age-related differences. *Journal of Business Economics and Management*, 20(4), 674-693. https://doi.org/10.3846/jbem.2019.6586

Howe, N., & Strauss, W.(1991). Generations: The History of America's Future, 1584 to 2069, William Morrow & Co., New York.

Kapuściński, G., Zhang, N., & Wang, R. (2023). What makes hospitality employers attractive to Gen Z? A means-end-chain perspective. *Journal of Vacation Marketing*, 29(4), 602-616. https://doi.org/10.1177/13567667221110234

Kucharčíková, A., Miciak, M., Malichova, E., Durisova, M., & Tokarcikova, E. (2019). The Motivation of Students at Universities as a Prerequisite of the Education's Sustainability within the Business Value Generation Context. *Sustainability*, 11(20), 5577. https://doi.org/10.3390/su11205577

Kucherov, D., & Zavyalova, E. (2012). HRD practices and talent management in the companies with the employer brand. *European Journal of Training and Development*, 36(1), 86-104. http://dx.doi.org/10.1108/03090591211192647

Lanier, K. (2017). 5 things HR professionals need to know about Generation Z. *Strategic HR Review*, 16(6), 288–290. https://doi.org/10.1108/SHR-08-2017-0051

Lassleben, H., & Hofmann, L. (2023). Attracting Gen Z talents. Do expectations towards employers vary by gender?. *Gender in Management: An International Journal*, 38(4), 545-560. https://doi.org/10.1108/GM-08-2021-0247

LinkedIn (2020). 2020 Global Talent Trends, https://business.linkedin.com/content/dam/me/business/en-us/talent-solutions/resources/pdfs/linkedin-2020-global-talent-trends-report.pdf, accessed 3 October 2023.

LinkedIn Corporation (2014). Talent Trends 2014: What's on the minds of the professional workforce, https://business.linkedin.com/content/dam/business/talent-solutions/global/en_US/c/pdfs/linkedin-talent-trends-2014-en-us.pdf, accessed 5 November 2023.

Mas-Manchón, L., Fernández-Cavia, J., Estanyol, E., & Van-Bergen, P. (2024). Differences Across Generations in the Perception of the Ethical, Social, Environmental, and Labor Responsibilities of the Most Reputed Spanish Organizations. *Profesional de la Información*, 33(3), e330302. https://doi.org/10.3145/epi.2024.0302

Minchington, B. (2006). Your Employer Brand: Attract, Engage, Retain. Collective Learning Australia.

Neundorf, A., & Öztürk, A. (2025). Advertising online surveys on social media: How your advertisements affect your study. *Public Opinion Quarterly*, 89(2), 335–360. https://doi.org/10.1093/poq/nfaf018

Pfiffelmann, J., De Pelsmacker, P., Guillot-Soulez, C., & Soulez, S. (2025). Do green employer labels matter? A study of the impact of advertising environmental responsibility on recruitment. *International Journal of Advertising*, 44(6), 985–1016. https://doi.org/10.1080/02650487.2025.2511352

Pingle, S., & Sodhi, H.K. (2011). What Makes an Attractive Employer: Significant Factors from Employee Perspective?. *Anvesha,* 4(2), 18–25. ISSN 0974-5467.

Poór, J., Engle, D. A., Blštáková, J., & Joniaková, Z. (2017). Internationalisation of Human Resource Management: Focus on Central and Eastern Europe. New York: Nova Science Publishers. ISBN 978-1-53612-632-7.

Přívara, A., Gavurová, B., Rievajová, E., & Štofková, Z. (2023). Labour Market and Immigration Nexus in V4 Countries: Using Panel Data Analysis for the Period of 2000-2020. *Migration Letters,* 20(3), 465-476. DOI: https://doi.org/10.47059/ml.v20i3.2909

Profesia (2023). Najatraktívnejší zamestnávateľ 2023, https://www.najzamestnavatel.sk/, accessed 5 January 2024.

Rampl, L. V. (2014). How to become an employer of choice: transforming employer brand associations into employer first-choice brands. *Journal of Marketing Management*, 30(13-14), 1486–1504. https://doi.org/10.1080/0267257X.2014.934903

Reis, G. G., & Braga, B. M. (2016). Employer attractiveness from a generational perspective: Implications for employer branding. *Revista de Administração*, 51(1), 103-116. https://doi.org/10.5700/rausp1226

Rozsa, Z., & Machova, V. (2020). Factors Affecting Job Announcement Competitiveness on Job Listing Websites. *Journal of Competitiveness*, 12(4), 109-126. https://doi.org/10.7441/joc.2020.04.07

Ružić, E., & Benazić, D. (2023). Dimensions of attractiveness in employer branding and the value proposition framework for young employees. *Ekonomski Vjesnik / Econviews – Review of Contemporary Entrepreneurship, Business, and Economic Issues*, 36(1), 89–100. https://doi.org/10.51680/ev.36.1.7

Saini, K. G., Gopal, A., & Kumari, N. (2015). Employer Brand and Job Application Decisions: Insights from the Best Employers. *Management and Labour Studies*, 40(1 & 2), 34–51. https://doi.org/10.1177/0258042X15601532

Sarabdeen, J., Balasubramanian, S., Lindsay, V., Chanchaichujit, J., & Sreejith, S. (2023). Employer branding: Confirmation of a measurement model and its implication for managing the workforce. *Journal of General Management*, 48(2), 153–170. https://doi.org/10.1177/03063070221079574

Schellaert, M., Oostrom, J. K., & Derous, E. (2024). Ageism on LinkedIn: Discrimination towards older applicants during LinkedIn screening. *Computers in Human Behavior*, 162, 108430. https://doi.org/10.1016/j.chb.2024.108430

Seberini, A., Nour, M. M., & Tokovska, M. (2022). From digital divide to technostress during the COVID-19 pandemic: A scoping review. Organizacija, 55(2), 98–108. https://doi.org/10.2478/orga-2022-0007

Sengupta, D., Mathews, M., Bridges, L., D'Costa, R., & Bastian, B. L. (2024). Sustainability orientation of Generation Z and its role in their choice of employer – A comparative Qualitative Inquiry of India and United States. *Administrative Sciences*, 14(10), 249. https://doi.org/10.3390/admsci14100249

Slovenská republika. (2021). Národný program aktívneho starnutia na roky 2021-2030, https://slovak.statistics.sk/wps/wcm/connect/cb469301-9175-489d-8ab6-e5ff77c2faf3/Narodny-program-aktivneho-starnutia-roky-2021-2030.pdf?MOD=AJPERES&CVID=oNAzSxD&CVID=oNAzSxD, accessed 5 December 2024.

Smerek, L., & Kováčiková, V. (2019). University as a Factor in the Employee Selection Process in Slovak Enterprises. Proceedings of the 33rd IBIMA Conference: Education Excellence and Innovation Management through Vision 2020. ISBN 978-0-9998551-2-6.

Srivastava, P., Bhatnagar, J., & Arora, A.P. (2017). A multidimensional scale for measuring employer brand. *Indian Journal of Industrial Relations*, 52(4), 659–674.

Stacho, Z., Lizbetinova, L., Stachova, K., & Starecek, A. (2022). The Application of Progressive HR Tools in the Environment of Slovak Enterprises. *Journal of Competitiveness*, 14(3), 173-190. https://doi.org/10.7441/joc.2022.03.10

Stiglbauer, B., Penz, M., & Batinic, B. (2022). Work values across generations: Development of the New Work Values Scale (NWVS) and examination of generational differences. *Frontiers in Psychology*, 13. https://doi.org/10.3389/fpsyg.2022.1028072

Suprawan, L., Suengkamolpisut, W., & Singhatong, S. (2025). The impact of social media characteristics on young job applicants' intentions: mediating roles of employer brand attractiveness and person-organisation fit. *International Studies of Management & Organization*, 1–19. https://doi.org/10.1080/00208825.2025.2500831

Thang, N. N., & Trang, P. T. (2024). Employer branding, organisation's image and reputation, and intention to apply: the moderating role of the availability of organisational information on social media. *Frontiers in Sociology*, 9. https://doi.org/10.3389/fsoc.2024.1256733

Theurer, C.P., Tumasjan, A., Welpe, I.M., & Lievens, F. (2018). Employer Branding: A Brand Equity-based Literature Review and Research Agenda. *International Journal of Management Reviews,* 20, 155-179. https://doi.org/10.1111/ijmr.12121

Tokovska, M., Ferreira, V. N., Vallušová, A., & Seberíni, A. (2023). E-Government—The inclusive way for the future of digital citizenship. Societies, 13(6), 141. https://doi.org/10.3390/soc13060141

Twenge, J. (2010). A review of the empirical evidence on generational differences in work attitudes. *Journal of Business and Psychology*, 25(2), 201-210. https://doi.org/10.1007/s10869-010-9165-6

Universum (2023). Employer Branding Now 2023: A survey of over 1,700 talent leaders – focused on how companies compete in a world of talent shortages and the specific strategies used by the World's Most Attractive Employers.

Vázquez-Rodríguez, A., Quiroga-Carrillo, A., García-Álvarez, J., & Sáez-Gambín, D. (2025). Soft skills and the corporate social dimension: the perspective of university graduate employers. *Educational Research for Policy and Practice*. Published online. https://doi.org/10.1007/s10671-025-09395-w

Verčič, A. T., & Verčič, D., 2025. Attitudes toward sustainable development and employer brands: comparing generations X, Y and Z in two countries. *Corporate Communications: An International Journal*, 30 (2), 355-371. https://doi.org/10.1108/CCIJ-11-2023-0161

Vetráková, M., Šimočková, I., Kubaľa, J., & Malachovský, A. (2020). How to establish talented employees in Slovak companies. *Periodica Polytechnica Social and Management Sciences,* 28(1), 29-37. https://doi.org/10.3311/PPso.13269

Vieira, J., Gomes da Costa, C., & Santos, V. (2024). Talent Management and Generation Z: A Systematic Literature Review through the Lens of Employer Branding. *Administrative Sciences*, 14(3), 49. https://doi.org/10.3390/admsci14030049

Wiedmer, T. (2015). Generations do differ: Best practices in leading traditionalists, boomers, and generations X, Y, and Z. *Delta Kappa Gamma Bulletin*, 82(1), 51.

Wilden, R., Gudergan, S., & Lings, I. (2010). Employer branding: strategic implications for staff recruitment. *Journal of Marketing Management*, 26(1-2), 56–73. https://doi.org/10.1080/02672570903577091

Wiścicka, M., Misiak-Kwit, S. (2017). Building relations between a company and consumers through cocreation: Polish and Chinese context. *Kelaniya Journal of Management*, 6(1), 32-46. https://doi.org/10.4038/kjm.v6i1.7525

Yasin, R., Bataineh, M. S., Atif, M., & Hossain, M. T. B. (2025). Green HRM and employer branding: corporate environmental sustainability and organisational safety climate mediating role and moderating role of job experience. *Benchmarking: An International Journal*. https://doi.org/10.1108/BIJ-01-2022-0052

Lukáš Smerek, Associate Professor. In his research activity, he has previously devoted himself to the diagnosis of Organisational Culture. Currently, he focuses mainly on Human Resource Management in companies of the V4 countries, comparing HR processes across companies, HRD, and increasing the competitiveness of companies through the application of modern HR and Green HRM. He is an active member of several associations, such as the European Marketing and Management Association (EUMASS), the Slovak Academic Association for People Management (SAAPM), and the Association of Lecturers and Career Counsellors (ALKP). ORCID: 0000-0003-0008-282X.

Cecília Olexová, Associate Professor, deals with the issue of human resource management in relation to the efficiency of organisations, both in teaching and research. She prefers a multidisciplinary approach to management, considering legal and tax aspects. She is significantly involved in developing views on the financial aspects of HRM, as well as on green HRM. She is a member of the Slovak Academic Association for People Management (SAAPM) and an ambassador for diversity and inclusion. ORCID: 0000-0003-2154-9564.

Lívia Knechtová is a graduate with a Bachelor's degree in Business Economics and Management and a Master's degree in Economics and Management of Small and Medium Enterprises from the Faculty of Economics at Matej Bel University in Banská Bystrica. During her studies, she primarily focused on identifying supporters of crowdfunding campaigns and, later on, the determinants of attractive employers in Slovakia. She currently works at Ernst & Young in Bratislava as a junior specialist in the financial department.

Percepcije privlačnosti delodajalcev med različnimi skupinami zaposlenih na Slovaškem

Namen in izhodišča: Prispevek obravnava zaznavanje privlačnosti delodajalcev med različnimi skupinami zaposlenih na Slovaškem. Cilj raziskave je bil prepoznati ključne atribute delodajalcev, ki jih zaposleni ocenjujejo kot najpomembnejše, ter analizirati razlike v teh zaznavah med generacijskimi in izobrazbenimi skupinami. Raziskava odgovarja na aktualne izzive trga dela, med katerimi posebej izstopa pomanjkanje tako visoko kot tudi srednje usposobljene delovne sile, dodatno poglobljeno z demografskim staranjem prebivalstva.
Metodologija: Raziskava temelji na kvantitativnem pristopu, izvedena je bila z anketnim vprašalnikom, ki ga je izpolnilo 481 respondentov. Za oblikovanje skupin znotraj vzorca na podlagi podobnih preferenc je bila uporabljena dvofazna klastrska analiza s programom SPSS.
Rezultati: Rezultati kažejo, da mlajše generacije zaposlenih največji pomen pripisujejo možnostim za karierni razvoj in ugledu podjetja, medtem ko starejši bolj poudarjajo stabilnost zaposlitve in ustrezno plačilo. Razlike so bile zaznane tudi glede na doseženo izobrazbeno raven. Rezultati kažejo na potrebo po segmentiranem pristopu pri strategijah blagovne znamke delodajalca, prilagojenih demografskim in regionalnim posebnostim trga dela.
Sklepne ugotovitve: Raziskava prispeva k literaturi s kontekstualizacijo blagovne znamke delodajalca na slovaškem trgu dela in zagotavlja praktične vpoglede za organizacije, ki želijo pritegniti in obdržati raznoliko delovno silo. Ugotovitve so uporabne tako v akademskem okolju kot tudi za kadrovske strokovnjake pri oblikovanju in izvajanju privlačnejše ponudbe vrednosti delodajalca.

Ključne besede: *Privlačnost delodajalca, Blagovna znamka delodajalca, Atributi delodajalca, Klastrska analiza, Medgeneracijske razlike*

DOI: 10.2478/orga-2025-0021

Exploring the Role of Perceived Benefits and Attitudes Toward Web in Modelling Online Purchase Intentions: A Case of Slovenia

Miha MARIČ[1], Gašper JORDAN[2], Robert LESKOVAR[1]

[1] University of Maribor, Faculty of Organizational Sciences, Kranj, Slovenia, miha.maric@um.si, robert.leskovar@um.si

[2] Independent researcher, gasper.jordan77@gmail.com

Background and Purpose: E-commerce has reshaped consumer behaviour by offering unparalleled convenience, variety and accessibility, while creating new opportunities for businesses to grow revenues. Despite its prominence, there remains a need for parsimonious models that explain online purchase intention in terms of core consumer perceptions. This study aims to develop and test a structural equation model (SEM) in which consumer perceived benefits and attitudes toward the web drive intention to purchase online.
Methods: An online survey was administered to 190 Slovenian consumers. Questionnaire items were drawn from established scales measuring (a) perceived benefits of online shopping, (b) attitude toward the web, and (c) online purchase intention. Internal consistency was assessed via Cronbach's alpha. SEM was then applied using IBM SPSS AMOS to evaluate both measurement and structural components of the model, testing hypotheses that perceived benefits influence both attitude and intention, and that attitude further mediates intention.
Results: The survey instrument demonstrated excellent reliability (Cronbach's $\alpha = 0.92$). The three-construct SEM explained 74 % of the variance in online purchase intention. Fit indices indicated very good model performance (NFI = 0.969, NNFI = 0.970, CFI = 0.979, IFI = 0.979). All hypothesized paths were significant, confirming that higher perceived benefits enhance both positive web attitudes and purchase intentions, and that web attitudes further bolster intention.
Conclusion: This streamlined SEM offers a robust and well-fitting explanation of consumer online purchase intentions. E-commerce platforms can leverage these insights by emphasizing the specific benefits consumers value and cultivating positive web experiences to drive sales. The model offers both practical guidance for online retailers and a foundation for future research, such as incorporating environmental consciousness, to refine our understanding of sustainable e-commerce adoption.

Keywords: *Attitude toward web, Perceived benefits, Online purchase intention, SEM, Consumer behaviour, e-commerce*

1 Introduction

Usage of information and communication technologies in recent decades has affected every aspect of businesses (i.e. business intranets, business-to-business, business-to-government, big data, artificial intelligence) and people's everyday activities (i.e. education, e-banking, entertainment, online gaming) (Cai, Fan & Du, 2017; Park &

Received: 13th May 2025; Accepted: 25th August 2025

Lee, 2011). Rich interactions and opportunities for all generations in an online environment (Blažun Vošner, Bobek, Kokol, & Javornik Krečič, 2016) also boost social media (Zhu, Wang, Wang, & Wan, 2016). E-commerce is bundled with a wide range of marketing tools (i.e. customer relationship management, data analytics, recommendation system) to detect purchase intentions (Lim, Osman, Salahuddin, Romle & Abdullah, 2016).

A change in customer behaviour, especially regarding privacy concerns, has been observed (Fortes & Rita, 2016), and the introduction of smart solutions, both on the part of retailers and customers, has been reported (Gerrikagoitia, Castander, Rebón, & Alzua-Sorzabal, 2015). The growth of e-commerce is not likely to abate (Chen, 2012; Lai, 2014; Liao, Lin, Luo & Chea, 2016; Pei, Paswan & Yan, 2014; Shiau & Luo, 2012; Sin, Nor & Al-Agaga, 2012), because consumers find it more economical and more convenient to shop online (Hong & Cha, 2013).

Limitations of traditional shopping, such as specific times and places, as well as the availability of sellers, are largely removed with the introduction of e-marketplaces (Hsieh & Liao, 2011; Kiang & Shang, 2015). Because online shopping is a process of purchasing a product via the web (Jusoh & Ling, 2012), it is essential to note that attitude towards the web is a crucial factor influencing the behavioural aspects of online consumers. Online shopping is increasing rapidly (Guritno & Siringoringo, 2013); therefore, understanding the impact of perceived benefits, along with attitudes towards the web, on online purchase intention is of great importance.

We have found a lack of research on the impact of perceived benefits on attitudes towards the web and online purchase intention, as well as perceptions of e-commerce, which is the focus of our study. Hypothesized relations will be tested with the use of structural equation modelling.

2 Theoretical Background and Hypothesis Development

This chapter provides insight into the literature review and previous research related to consumer behaviour, perceived benefits, attitude towards the web and online purchase intention.

2.1 eConsumer Behaviour

Online purchasing involves decision-making, and customers typically collect information before making a purchase (Žnidaršič, Marič & Ferjan, 2012). Most frequently, this information includes the acceptable price and quality ratio, preferred brand, delivery and payment conditions (Oliveira-Castro, 2003). This decision-making process depends on the information processing style employed (Zinkhana & Braunsberger, 2004; Bleda & Valente, 2009), where the perceived value of the product plays a crucial role in decision-making.

With the advent of internet consumer behaviour analysis, the field has become interdisciplinary, requiring theoretical foundations from psychology, marketing science, human-computer interfaces, and economics (Foxall, 2003). Customer benefits, expressed as a utility function, are the core of the neoclassical theory of consumer behaviour (Graham & Isaac, 2002). Psychologists and economists ascribe rationality to the consumer; thus, choice itself has been viewed as a cognitive activity (Foxall, 2003).

Consumer choice, translated into a utility function, however, presents a bounded and simplified model of the customer decision-making process. Oliveira-Castro (2003) argues that consumer behaviour is not always induced by optimality and rationality. Baumgartner and Steenkamp (1996) discussed the importance of sensory stimulation by examining the products, and they concluded that purchase intention is also affected by a desire to adjust actual stimulation to the most preferred level.

Fischer and Hanley (2007) analyzed decision behaviour and found two distinguished types: extensive and limited consumer decisions. The characteristics of extensive decisions are strong emotional involvement and a demand for additional information. Limited decisions are taken with less information due to the consumer's prior experience.

The volume of possible information has increased exponentially due to online presence and accessibility, influencing customers' behaviour and choices. Whereas it was almost unimaginable for an individual to purchase goods from the other side of the world, it has become a standard practice nowadays due to the increase in e-commerce and improved infrastructure.

2.2 Perceived Benefits

Online consumer behaviour is widely dependent on the perception of benefits associated with online shopping (Bhatnagar & Ghose, 2004; Garbarino & Strahilevitz, 2004; Huang, Schrank, & Dubinsky, 2004). Consumers perceive online shopping as convenient, offering various selections, low prices, personal attention, and easy access to information (Delafrooz, Paim, Haron, Sidin, & Khatibi, 2009). According to Gutman (1982), the benefits can be physiological, psychological, sociological or material in nature. The perceived benefits in online shopping are the sum of online shopping advantages that meet customers' needs (Pavlou, 2003). Since consumers' buying patterns can differ (Lee, Jackson, Miller-Spillman & Ferrell, 2015; Soopramanien, 2011), purchasing decisions are personal, and often very complex behaviours (Chen, Yan, Fan & Gordon, 2015), but in the end, the consumers make online purchases for both convenience and enjoyment (Childers, Carr, Peck &Carson, 2001).

2.3 Attitude towards Web

Over the past decade, companies have reached customers across the web in various ways (Wu, Chen, Chen, & Cheng, 2014), as people spend increasing amounts of time on social media and the internet. The web has had a significant impact on marketing practices, and most consumers are now comfortable purchasing products online (Poddar, Donthu &Wei, 2009). The reason behind the increase in online shopping is that online shopping enables a huge number of alternatives with immediate access to information of interest (Seock & Norton, 2007).

An attitude is defined as a set of beliefs, feelings, and behavioural tendencies towards socially significant objects, groups, events or symbols (Hogg & Vaughan, 2005), and it is a learned predisposition to behave in a consistently favourable or unfavourable way (Schiffman & Kanuk, 2000). We simplify that the attitude towards the web is an individual's specific behaviour towards the web, together with its attractiveness. Therefore, it is of great importance that potential consumers have a positive attitude towards the web, as it is a crucial starting point for them and e-retailers to make the final step towards purchasing products online.

2.4 Online Purchase Intention

Purchase intention, defined by (Wang & Yang, 2008; Wells, Valacich & Hess, 2011), is "the decision to act or as a mental stage in the decision-making process where the consumer has developed an actual willingness to act towards an object or brand". It is no surprise that understanding customer online purchase intentions drives intensive research efforts in e-marketing and e-retail literature (Kwek, Tan, & Lau, 2015).

Online purchase intention was defined by Kwek, Tan & Lau (2015), Hsu, Chang & Chen (2012), and Wu, Yeh & Hsiao (2011) as the consumer's intention to perform a specified purchasing behaviour. Therefore, it can be utilized as a component of consumers' cognitive behaviour. Online purchase intention is viewed as the situation when a "customer is willing and intends to become involved in an online transaction" (Pavlou, 2003), and it "is led by their emotions" (Ha & Lennon, 2010). As noted by Schiffman & Kanuk (2007), an increase in purchase intention increases the likelihood of purchasing. The final decision to choose or opt out of the offered good or service depends on the consumers' intention (Madahi & Sukati, 2012; Wang & Tsai, 2014).

2.5 Hypotheses Overview

We formulated three hypotheses to determine the significance of the relationships between the constructs "Perceived benefits", "Attitude towards web", and "Online purchase intention". We propose that perceived benefits and a positive attitude have a positive effect on online purchase intention. Proposed hypotheses were tested in the proposed model (Figure 1) as follows:

- *H1: Construct "Perceived benefits" explains a statistically significant part of the variance in construct "Attitude towards web".*
- *H2: Construct "Attitude towards web" explains a statistically significant part of the variance in construct "Online purchase intention".*
- *H3: Construct "Perceived benefits" explains a statistically significant part of the variance in construct "Online purchase intention".*

The assumption is that "Perceived benefits" affect "Attitude toward web" and "Intention of online purchase" while "Attitude toward web" affects "Intention of online purchase".

3 Methodology

This study employs a quantitative approach to test the hypothesized relationships among perceived benefits, attitudes toward the web, and online purchase intention through a structural equation model (SEM). This chapter outlines the research design, data collection, and statistical methods employed, ensuring reliability and validity in the analysis.

3.1 Questionnaire and data collection

An online questionnaire was designed, and invitations for an online survey were sent (considering sampling relevance (Etikan, Abubakar Musa & Sunusi Alkassim, 2016) in winter 2016 via e-mail and social media to participants in Slovenia. After gathering, we stripped incomplete responses. IBM SPSS—Statistical Package for the Social Sciences, version 27, software was used for data analysis.

Attitude towards web was measured on a 5-item scale developed by Küster, Vila and Canales (2016), which was: "ATW1 - This website connects with me. ATW2 - I would like to visit this website again. ATW3 - I feel comfortable navigating this website. ATW4 - This site is a good place to spend my time. ATW5 - I consider this website to be a good site for fashion. The response scale was a 5-point Likert scale ranging from 1 (completely disagree) to 5 (completely agree). The coefficient of reliability (Cronbach's alpha) was 0.92, respectively.

Perceived benefits were measured on a three-item scale developed by Chen et al. (2015), which were: “PB1 - I think online shopping can help me easily find a lower price. PB2 - I think online shopping has the advantage of a wide selection of products. PB3 - I think online shopping is more convenient than bricks-and-mortar shopping.” The response scale was a 5-point Likert scale ranging from 1 (completely disagree) to 5 (completely agree). The coefficient of reliability (Cronbach’s alpha) was 0.87, respectively.

Online purchase intention was measured on a three-item scale developed by Salisbury, Pearson, Pearson and Miller (2001), which consisted of: “OPI1 - I would use the Internet for purchasing a product. OPI2 - Using the Internet for purchasing a product is something I would do. OPI3 - I could see myself using the Internet to buy a product.” The response scale was a 5-point Likert scale ranging from 1 (completely disagree) to 5 (completely agree). The coefficient of reliability (Cronbach’s alpha) was 0.94, respectively.

3.2 Sample Selection and Generalizability

We analyzed complete responses from a total of 190 participants, comprising 98 men (51.6%) and 92 women (48.4%). The marital statuses of the participants were as follows: 60 (31.6%) married, 2 (1.1%) widowed, 5 (2.6%) divorced, 70 (36.8%) single, 19 (10.0%) in life partnerships, and 34 (17.9%) married but living apart. The employment statuses of the respondents were as follows: 74 (38.9%) students, 7 (3.7%) self-employed, 46 (24.2%) employed in the public sector, 59 (31.1%) employed in the private sector, 1 (0.5%) retired, and 3 (1.6%) unemployed.

An educational levels earned by participants were: 1 (0.5%) without primary school, 1 (0.5%) primary school, 2 (1.1%) finished secondary vocational education, 4 (2.1%) finished technical secondary education, 42 (22.1%) high school diploma, 4 (2.1%) finished vocational college, 28 (14.7%) finished professional higher education, 66 (34.7%) bachelor’s degree, 27 (14.2%) master’s degree, and 15 (7.9%) PhD degree.

The geographical location of the 190 respondents was: 69 (36.3%) in the western part of Slovenia and 121 (63.7%) in the eastern part. The average age of respondents was 29.7 years. Participants reported an average shopping experience of 7.7 years, with an average of 10.4 online purchases in the past year.

The selection of a Slovenian sample allows for cultural specificity in understanding consumer behaviour but limits the generalizability of findings to other contexts. While the demographic diversity strengthens the study’s robustness, future research could expand to include participants from

Table 1: Descriptive statistics for research constructs

	n	M	SD	Min	Max
Perceived benefits	190	4.37	0.78	1	5
Attitude towards the web	190	4.14	0.99	1	5
Online purchase intention	190	4.36	0.85	1	5

Notes: n = total number of respondents, M = mean value, SD = standard deviation, Min. = minimum, Max. = maximum.

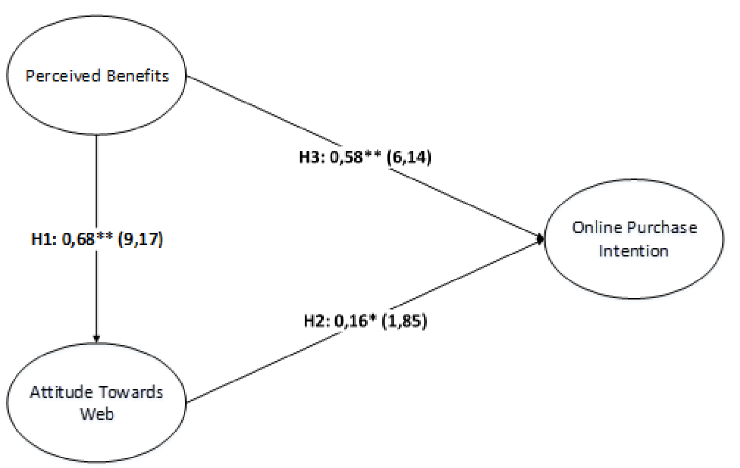


Figure 1: The relationships between SEM constructs and standardized solutions, along with t-values for the hypotheses tested

different regions and levels of technological readiness (Žnidaršič, Marič & Ferjan, 2012; Oliveira-Castro, 2003).

3.3 Results

Table 1 presents descriptive statistics for three groups of questions, which form constructs: perceived benefits, attitude toward the web, and online purchase intention (number of respondents, means, standard deviations, minimums, and maximums). All mean values are above 4, and according to the Likert scale, we interpret them as strong to complete agreement that: online shopping is beneficial (M = 4.37), attitude towards use of the web is positive (M = 4.14), and online purchase intention is strong (M = 4.36).

Structural equation modelling (SEM) (Prajogo & McDermott, 2005) was employed within IBM SPSS AMOS version 27 software to explore the relationships between constructs and test hypothezes of statistically significant relations. SEM combines factor and regression analysis, thereby enabling the evaluation of the significance of hypothezised relations among variables (Diamantopoulos & Siguaw, 2000). Figure 1 depicts the relations between SEM constructs and standardized solutions with t-values for the hypotheses tested.

The data in our sample of questionnaires confirms all three hypotheses for relationships between constructs:

- *H1: Construct "Perceived benefits" explains a statistically significant part of the variance in construct "Attitude towards web" (standardized solution = 0.68, t-test = 9.17).*
- *H2: Construct "Attitude towards web" explains a statistically significant part of the variance in construct "Online purchase intention" (standardized solution = 0.16, t-test = 1.85).*
- *H3: Construct "Perceived benefits" explains a statistically significant part of the variance in construct "Online purchase intention" (standardized solution = 0.58, t-test = 6.14)*

We further examined fit indices, as explained in Hooper, Coughlan & Mullen (2008); Hu & Benter, 1999); and Kenny (2015), including the normed fit index (NFI), non-normed fit index (NNFI), comparative fit index (CFI), and incremental fit index (IFI). Table 2 presents the results of the examination of selected indices and standardized residuals. All indices demonstrated a statistically significant, very good fit according to reference values. (p-value = 0.0000). The χ2 for our model was 87.35 with 32 degrees of freedom.

We can conclude that: a) two constructs ("Perceived benefits" and "Attitude towards web") can explain 74% of the variation in the construct "Online purchase intention", and b) model fit indices show very good fit and statistically significant relations.

4 Discussion

Online purchases are increasing, and consumer behaviour is adapting, but there are still doubts and restraints among potential customers and organizations regarding e-commerce. We have therefore explored perceptions of existing and possible future customers. Perceived benefits and attitudes towards the web are positively related, and both are associated with online purchase intention.

The study provides new insights into the interplay of perceived benefits, attitudes toward the web, and online purchase intention, contributing to the e-commerce and consumer behavior literature. Consistent with previous research, perceived benefits emerged as a significant determinant of both attitudes toward the web and online purchase intention (Bhatnagar & Ghose, 2004; Delafrooz et al., 2009; Chen et al., 2015). These findings validate the utility-driven model of consumer behavior while also emphasizing the role of positive emotional responses (Graham & Isaac, 2002; Poddar et al., 2009).

Table 2: Results of examination of selected indices and standardized residuals

Fit indices	Value for the model	Reference value	Model fit according to individual indices*
χ2/df	2.729	≤ 2 or ≤ 5	Good fit
NFI	0.969	≥ 0.90	Very good fit
NNFI	0.970	≥ 0.95	Very good fit
CFI	0.979	≥ 0.93	Very good fit
IFI	0.979	≥ 0.95	Very good fit
SRMR	0.0465	≤ 0.08	Good fit

Notes: NFI = Normed Fit Index, NNFI = Non-normed Fit Index, CFI = Comparative Fit Index, IFI = Incremental Fit Index.

The findings underscore the significance of perceived benefits and attitudes toward the web in influencing online purchase intentions. Our research confirmed the hypothesis on the relations between constructs in the proposed SEM. The following significant and positive relations were extracted from survey data: a) “Perceived benefits” and “Attitude towards web”, b) “Attitude towards web” and “Online purchase intention” and c) “Perceived benefits” and “Online purchase intention”. These results contribute to the growing body of literature on e-consumer behaviour by demonstrating the interplay between utilitarian and emotional factors in online decision-making (Žnidaršič et al., 2012; Graham & Isaac, 2002; Poddar et al., 2009).

Finding b) specifically confirms and extends the study by Seock and Norton (2007), which was conducted only among US students and suggested that other population groups be considered to generalize the results more widely. Furthermore, the study underscores the potential of e-commerce platforms to integrate sustainability into their offerings, leveraging perceived benefits to encourage eco-friendly purchasing behaviours (Gutman, 1982; Childers et al., 2001).

The limitation of the proposed model is the omission of other determinants that may have implications for actual purchase decisions. However, simple models have one advantage – they can be applied with minimal resources and effort. There are likely constructs with undisclosed relationships that may involve perceived risks, privacy concerns, the fear of identity theft, loyalty to the brand/retailer, and similar factors. Again, as the model becomes larger and more complex, the effort, resources, vulnerability, and mistrust grow exponentially.

Also, the sample was geographically restricted to Slovenia, which may limit generalizability to other cultural contexts. While the demographic diversity strengthens the study’s internal validity, cross-cultural comparisons could provide a more comprehensive understanding of the relationships among the constructs (Žnidaršič et al., 2012; Fischer & Hanley, 2007).

The reliance on self-reported data introduces the possibility of response biases, such as social desirability bias. Furthermore, the cross-sectional design limits the ability to assess dynamic changes in consumer behaviour over time (Etikan et al., 2016). Future research should employ longitudinal designs to capture temporal shifts and investigate additional factors, such as trust, perceived risks, or consumer environmental consciousness (Ha & Lennon, 2010; Schiffman & Kanuk, 2007).

The results of our analysis demonstrate the theoretically backed-up positive relations between the constructs included in the model. Positive perceived benefits positively affect the attitude towards the web, which in turn increases online purchase intention. The theoretical contribution of this study lies in testing and confirming the relationships among the observed constructs.

For practitioners, these findings provide actionable insights into enhancing customer engagement and promoting sustainable consumption practices. E-commerce platforms can highlight perceived benefits such as convenience, cost savings, and access to eco-friendly products to enhance consumer attitudes and purchase intentions. Additionally, integrating features such as green delivery options and eco-certifications can further align online shopping with sustainable consumer values (Bhatnagar & Ghose, 2004; Chen et al., 2015; Schiffman & Kanuk, 2000).

Retailers can also design user-friendly interfaces that foster positive attitudes toward the web by providing personalized recommendations, simplifying navigation, and highlighting sustainability-related features (Poddar et al., 2009; Seock & Norton, 2007). These strategies align with previous findings that positive attitudes have a significant impact on consumer intentions to engage in online transactions (Wu et al., 2014; Schiffman & Kanuk, 2000).

By deepening our understanding of online purchasing, we enable organizations in the e-commerce field to promote perceived benefits, improve attitudes towards the web, and, in turn, increase the online purchase intentions of current and potential customers. Due to the worldwide accessibility and similarity of e-commerce, we believe that these findings will be confirmed in future studies.

Expanding the model to include sustainability-specific constructs, such as environmental consciousness or perceived risks, could also provide richer insights into consumer behaviour (Chen et al., 2015; Ha & Lennon, 2010). Expanding the model to include moderating variables, such as cultural influences or technological readiness, could also deepen understanding of consumer behaviour in diverse contexts (Žnidaršič et al., 2012; Olivera-Castro, 2003). Comparative studies across regions with varying levels of environmental awareness could further refine the model and provide insights into global e-commerce trends.

5 Conclusion

Research efforts on factors, constructs, and situations that stimulate or deter potential buyers from making online purchases are substantial due to their practical value for real businesses. The presented and tested SEM model, along with the examination of fit indices, is encouraging from both theoretical research and practical implementation perspectives. Simple models are not the best-suited solution for every application, but the one proposed and tested seems to have an acceptable ratio between “costs” (effort and resources required to implement) and “benefits” (accuracy and value to the business).

To gain a higher percentage than 74% of explained variation of online purchase intention, new constructs should be introduced, causing a more complex and more “expensive” model. Particularly when considering that the intention of online purchase has the greatest value at the moment of customer entrance into a web shop, the practical implementation must measure intention in real-time, not through surveys. Current research in this field heavily relies on artificial intelligence, big data processing, and past purchasing data.

E-commerce represents a powerful platform for advancing both consumer convenience and sustainable practices. By emphasizing perceived benefits and fostering positive attitudes toward the web, online retailers can increase purchase intentions while aligning with global sustainability objectives. This dual focus on enhancing user experience and promoting eco-friendly behaviour provides a competitive advantage for businesses and contributes to societal well-being.

The findings of this study serve as a roadmap for practitioners and researchers, highlighting the potential of e-commerce to drive both economic growth and sustainable development. Future research can build on this foundation to explore additional factors and strategies, further refining the pathways to sustainable consumer behaviour.

Everything changes over time, and so does customer behaviour in online purchasing. Additionally, customers rely on advanced information and communication technologies, as well as recommendations from friends and relatives, previous experiences, and preferences for specific brands and products. Therefore, we can identify numerous future research challenges in the world of digital marketing.

References

Baumgartner, H., & Steenkamp, J. B. E. M. (1996). Exploratory consumer buying behavior: Conceptualization and measurement. *International Journal of Research in Marketing, 13*, 121–137. https://doi.org/10.1016/0167-8116(95)00037-2

Bhatnagar, A., & Ghose, S. (2004). A latent class segmentation analysis of e-shoppers. *Journal of Business Research, 57*(7), 758–767. https://doi.org/10.1016/S0148-2963(02)00357-0

Blažun Vošner, H., Bobek, S., Kokol, P., & Javornik Krečič, M. (2016). Attitudes of active older Internet users towards online social networking. *Computers in Human Behavior, 55*, 230–241. https://doi.org/10.1016/j.chb.2015.09.014

Bleda, M., & Valente, M. (2009). Graded eco-labels: A demand-oriented approach to reduce pollution. *Technological Forecasting & Social Change, 76*, 512–524. https://doi.org/10.1016/j.techfore.2008.05.003

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education, 105*, 1–13. https://doi.org/10.1016/j.compedu.2016.11.003

Chen, Y. Y. (2012). Why do consumers go internet shopping again? Understanding the antecedents of repurchase intention. *Journal of Organizational Computing and Electronic Commerce, 22*(1), 38–63. https://doi.org/10.1080/10919392.2012.642234

Chen, Y., Yan, X., Fan, W., & Gordon, M. (2015). The joint moderating role of trust propensity and gender on consumers' online shopping behavior. *Computers in Human Behavior, 43*, 272–283. https://doi.org/10.1016/j.chb.2014.10.020

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing, 77*(4), 511–535. https://doi.org/10.1016/S0022-4359(01)00056-2

Delafrooz, N., Paim, L. H., Haron, S. A., Sidin, S. M., & Khatibi, A. (2009). Factors affecting students' attitude toward online shopping. *African Journal of Business Management, 3*(5), 200–209.

Diamantopoulos, A., & Siguaw, J. A. (2000). *Introducing LISREL*. SAGE Publications.

Etikan, I., Abubakar Musa, S., & Sunusi Alkassim, R. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1–4.

Fischer, A., & Hanley, N. (2007). Analyzing decision behaviour in stated preference surveys: A consumer psychological approach. *Ecological Economics, 61*, 303–314. https://doi.org/10.1016/j.ecolecon.2006.02.024

Fortes, N., & Rita, P. (2016). Privacy concerns and online purchasing behaviour: Towards an integrated model. *European Research on Management and Business Economics, 22*(3), 167–176. https://doi.org/10.1016/j.iedeen.2016.04.002

Foxall, G. R. (2003). The behavior analysis of consumer choice: An introduction to the special issue. *Journal of Economic Psychology, 24*, 581–588. https://doi.org/10.1016/S0167-4870(03)00002-3

Garbarino, E., & Strahilevitz, M. (2004). Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation. *Journal of Business Research, 57*(7), 768–775. https://doi.org/10.1016/S0148-2963(02)00363-6

Gerrikagoitia, J. K., Castander, I., Rebón, F., & Alzua-Sorzabal, A. (2015). New trends of intelligent e-marketing based on web mining for e-shops. *Procedia – Social and Behavioral Sciences, 175*, 75–83. https://doi.org/10.1016/j.sbspro.2015.01.1176

Graham, F., & Isaac, A. G. (2002). The behavioral life-cycle theory of consumer behavior: Survey evidence. *Journal of Economic Behavior & Organization, 48*, 391–401. https://doi.org/10.1016/S0167-2681(01)00242-6

Guritno, S., & Siringoringo, H. (2013). Perceived usefulness, ease of use, and attitude towards online shopping usefulness towards online airlines ticket purchase. *Procedia – Social and Behavioral Sciences, 81*, 212–216.

https://doi.org/10.1016/j.sbspro.2013.06.415

Gutman, J. (1982). A means-end chain model based on consumer categorization processes. *Journal of Marketing, 46*(2), 60–72. https://doi.org/10.2307/3203341

Ha, Y., & Lennon, S. J. (2010). Effects of site design on consumer emotions: Role of product involvement. *Journal of Research in Interactive Marketing, 4*(2), 80–96. https://doi.org/10.1108/17505931011051641

Hogg, M., & Vaughan, G. (2005). *Social psychology* (4th ed.). Prentice Hall.

Hong, I. B., & Cha, H. S. (2013). The mediating role of consumer trust in an online merchant in predicting purchase intention. *International Journal of Information Management, 33*(6), 927–939. https://doi.org/10.1016/j.ijinfomgt.2013.08.007

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *The Electronic Journal of Business Research Methods, 6*(1), 53–60.

Hsieh, J. Y., & Liao, P. W. (2011). Antecedents and moderators of online shopping behavior in undergraduate students. *Social Behavior and Personality: An International Journal, 39*(9), 1271–1280. https://doi.org/10.2224/sbp.2011.39.9.1271

Hsu, C. L., Chang, K. C., & Chen, M. C. (2012). The impact of website quality on customer satisfaction and purchase intention: Perceived playfulness and perceived flow as mediators. *Information Systems and e-Business Management, 10*(4), 549–570.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1007/s10257-011-0181-5

Huang, W. Y., Schrank, H., & Dubinsky, A. J. (2004). Effect of brand name on consumers' risk perceptions of online shopping. *Journal of Consumer Behaviour, 4*(1), 40–50. https://doi.org/10.1002/cb.156

Jusoh, Z. M., & Ling, G. H. (2012). Factors influencing consumers' attitude towards e-commerce purchases through online shopping. *International Journal of Humanities and Social Science, 2*(4), 223–230. Retrieved July 21, 2021, from https://pdfs.semanticscholar.org/327f/0ec65bd0e0dabad23c42514d0e2ac8b05a97.pdf

Kenny, D. A. (2015, November 24). Measuring model fit. Retrieved June 23, 2016, from http://davidakenny.net/cm/fit.htm

Kiang, M. Y., & Shang, K. H. (2015). *Online purchase decision and its implication on e-tailing strategies.* In New meanings for marketing in a new millennium (pp. 212–217). Springer.

Küster, I., Vila, N., & Canales, P. (2016). How does the online service level influence consumers' purchase intentions before a transaction? A formative approach. *European Journal of Management and Business Economics, 25*(3), 111–120. https://doi.org/10.1016/j.redeen.2016.04.001

Kwek, C. L., Tan, H. P., & Lau, T. C. (2015). Investigating the shopping orientations on online purchase intention in the e-commerce environment: A Malaysian study. *Journal of Internet Banking and Commerce.* Retrieved July 21, 2021, from http://www.icommercecentral.com/open-access/investigating-the-shopping-orientations-on-online-purchase-intention-in-the-ecommerce-environment-a-malaysian-study-1-21.php?aid=38386

Lai, J. Y. (2014). E-SERVCON and e-commerce success: Applying the DeLone & McLean model. *Journal of Organizational and End User Computing, 26*(3), 1–22. https://doi.org/10.4018/joeuc.2014070101

Lee, M. Y., Jackson, V., Miller-Spillman, K. A., & Ferrell, E. (2015). Female consumers' intention to be involved in fair-trade product consumption in the US: The role of previous experience, product features, and perceived benefits. *Journal of Retailing and Consumer Services, 23*, 91–98. https://doi.org/10.1016/j.jretconser.2014.12.001

Liao, C., Lin, H. N., Luo, M. M., & Chea, S. (2017). Factors influencing online shoppers' repurchase intentions: The roles of satisfaction and regret. *Information & Management, 54*(5), 651–668. https://doi.org/10.1016/j.im.2016.12.005

Lim, Y. J., Osman, A., Salahuddin, S. N., Romle, A. R., & Abdullah, S. (2016). Factors influencing online shopping behavior: The mediating role of purchase intention. *Procedia Economics and Finance, 35*, 401–410. https://doi.org/10.1016/S2212-5671(16)00050-2

Madahi, A., & Sukati, I. (2012). The effect of external factors on purchase intention amongst young generation in Malaysia. *International Business Research, 5*(8), 153–159. https://doi.org/10.5539/ibr.v5n8p153

Oliveira-Castro, J. M. (2003). Effects of base price upon search behavior of consumers in a supermarket: An operant analysis. *Journal of Economic Psychology, 24*, 637–652. https://doi.org/10.1016/S0167-4870(03)00006-0

Park, B. W., & Lee, K. C. (2011). Exploring the value of purchasing online game items. *Computers in Human Behavior, 27*(6), 2178–2185. https://doi.org/10.1016/j.chb.2011.06.013

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134.

Pei, Z., Paswan, A., & Yan, R. (2014). E-tailer's return policy, consumer's perception of return policy fairness and purchase intention. *Journal of Retailing and Consumer Services, 21*(3), 249–257. https://doi.org/10.1016/j.jretconser.2014.01.004

Poddar, A., Donthu, N., & Wei, Y. (2009). Web site customer orientations, Web site quality, and purchase intentions: The role of Web site personality. *Journal of Business Research, 62*(4), 441–450. https://doi.org/10.1016/j.jbusres.2008.01.036

Prajogo, D. I., & McDermott, C. M. (2005). The relationship between total quality management practices and organizational culture. *International Journal of Operations & Production Management, 25*(11), 1101–1122. https://doi.org/10.1108/01443570510626916

Salisbury, W. D., Pearson, R. A., Pearson, A. W., & Miller, D. W. (2001). Perceived security and World Wide Web purchase intention. *Industrial Management & Data Systems, 101*(4), 165–177. https://doi.org/10.1108/02635570110390071

Schiffman, L. G., & Kanuk, L. L. (2000). *Consumer behavior* (7th ed.). Prentice Hall.

Schiffman, L. G., & Kanuk, L. L. (2007). *Consumer behavior* (9th ed.). Prentice Hall.

Seock, Y. K., & Norton, M. (2007). Attitude toward Internet Web sites, online information search, and channel choices for purchasing. *Journal of Fashion Marketing and Management, 11*(4), 571–586. https://doi.org/10.1108/13612020710824616

Shiau, W. L., & Luo, M. M. (2012). Factors affecting online group buying intention and satisfaction: A social exchange theory perspective. *Computers in Human Behavior, 28*(6), 2431–2444. https://doi.org/10.1016/j.chb.2012.07.030

Sin, S. S., Nor, K. M., & Al-Agaga, A. M. (2012). Factors affecting Malaysian young consumers' online purchase intention in social media websites. *Procedia – Social and Behavioral Sciences, 40,* 326–333. https://doi.org/10.1016/j.sbspro.2012.03.195

Soopramanien, D. (2011). Conflicting attitudes and scepticism towards online shopping: The role of experience. *International Journal of Consumer Studies, 35*(3), 338–347. https://doi.org/10.1111/j.1470-6431.2010.00945.x

Wang, X., & Yang, Z. (2008). Does country-of-origin matter in the relationship between brand personality and purchase intention in emerging economies? Evidence from China's auto industry. *International Marketing Review, 25*(4), 458–474. https://doi.org/10.1108/02651330810887495

Wang, Y. H., & Tsai, C. F. (2014). The relationship between brand image and purchase intention: Evidence from award-winning mutual funds. *The International Journal of Business and Finance Research, 8*(2), 27–40.

Wells, J. D., Valacich, J. S., & Hess, T. J. (2011). What signal are you sending? How website quality influences perceptions of product quality and purchase intentions. *MIS Quarterly, 35*(2), 373–396.

Wu, L. Y., Chen, K. Y., Chen, P. Y., & Cheng, S. L. (2014). Perceived value, transaction cost, and repurchase-intention in online shopping: A relational exchange perspective. *Journal of Business Research, 67*(1), 2768–2776. https://doi.org/10.1016/j.jbusres.2012.09.007

Wu, P. C., Yeh, G. Y. Y., & Hsiao, C. R. (2011). The effect of store image and service quality on brand image and purchase intention for private label brands. *Australasian Marketing Journal, 19*(1), 30–39. https://doi.org/10.1016/j.ausmj.2010.11.001

Zhu, Z., Wang, J., Wang, X., & Wan, X. (2016). Exploring factors of users' peer-influence behavior in social media on purchase intention: Evidence from QQ. *Computers in Human Behavior, 63*, 980–987. https://doi.org/10.1016/j.chb.2016.05.037

Zinkhan, G. M., & Braunsberger, K. (2004). The complexity of consumers' cognitive structures and its relevance to consumer behavior. *Journal of Business Research, 57*, 575–582. https://doi.org/10.1016/S0148-2963(02)00396-X

Žnidaršič, J., Marič, M., & Ferjan, M. (2012). The effect of consumer eco-awareness on the use, the buying and the preference of eco-labeled food products. *Advances in Business-Related Scientific Research Journal, 3*(1), 91–103.

Miha Marič, PhD, is a researcher in the field of leadership, management and organizational sciences. He holds a PhD from the Faculty of Economics at the University of Ljubljana. He is currently employed as an associate professor at the University of Maribor's Faculty of Organizational Sciences. His research interests are power, leadership, organizational behaviour, human resource management, organization and management. He is the author of numerous original scientific articles, professional articles, papers presented at scientific conferences, scientific monographs, and an editorial board member, editor, and reviewer, as well as a programme committee member of several international conferences. He also participates in research projects and consulting work.

Gašper Jordan, M.Sc., is an independent researcher who studied in the field of human resource management at the University of Maribor's Faculty of Organizational Sciences. His main interests are human resource management, organizational behaviour and organizational psychology.

Full Professor **Robert Leskovar**, PhD, obtained his PhD at the University of Maribor, where he is habilitated in the field of Quality and Information Systems. His research interests include multiple criteria decision making, modeling and simulation, digital marketing, artificial intelligence, and software engineering. He has published more than forty original scientific articles and is the author or co-author of over twenty chapters in scientific monographs. He serves as the Head of the Department of Informatics at the Faculty of Organizational Sciences, University of Maribor, where he teaches courses at undergraduate, postgraduate, and doctoral levels. As a visiting professor, he has lectured at several international universities, including the Prague University of Economics and Business and RWTH Aachen University, Faculty of Business and Economics. Prof. Leskovar is a member of the Slovenian Society Informatika, the International Society on Multiple Criteria Decision Making, and the Association for Computing Machinery (ACM). In 2022, he was awarded the honorary title Legend of Computing and Informatics for his contributions to the development and promotion of these fields in Slovenia.

Raziskovanje vloge zaznanih koristi in stališč do spleta pri modeliranju namenov spletnega nakupa: primer Slovenije

Ozadje in namen: E-trgovanje je preoblikovalo vedenje potrošnikov, saj ponuja neprimerljivo udobje, raznolikost in dostopnost ter hkrati ustvarja nove priložnosti za rast prihodkov podjetij. Kljub svojemu pomenu ostaja potreba po enostavnih modelih, ki pojasnjujejo namero za spletni nakup na podlagi temeljnih potrošniških zaznav. Namen te študije je razviti in preizkusiti model strukturnih enačb (SEM), v katerem zaznane koristi potrošnikov in odnos do spleta vplivajo na namero za spletni nakup.
Metode: Spletna anketa je bila izvedena med 190 slovenskimi potrošniki. Vprašalnik je temeljil na uveljavljenih lestvicah za merjenje (a) zaznanih koristi spletnega nakupovanja, (b) odnosa do spleta in (c) namere za spletni nakup. Notranja zanesljivost je bila ocenjena s Cronbachovim alfa koeficientom. Na model je bil nato uporabljen SEM s programom IBM SPSS AMOS za oceno merilnega in strukturnega dela modela ter za preverjanje hipotez, da zaznane koristi vplivajo tako na odnos kot na namero, odnos pa dodatno mediira namero.
Rezultati: Merilni instrument je pokazal odlično zanesljivost (Cronbachov α = 0,92). Tridelni SEM je pojasnil 74 % variance v nameri za spletni nakup. Indeksi prileganja so pokazali zelo dobro delovanje modela (NFI = 0,969; NNFI = 0,970; CFI = 0,979; IFI = 0,979). Vse predpostavljene poti so bile statistično značilne, kar potrjuje, da višje zaznane koristi povečujejo tako pozitiven odnos do spleta kot tudi nakupne namere, odnos do spleta pa dodatno krepi namero.
Zaključek: Ta poenostavljen SEM ponuja trdno in dobro prilegajoče se pojasnilo potrošniške namere za spletni nakup. Platforme za e-trgovanje lahko te ugotovitve izkoristijo tako, da poudarijo specifične koristi, ki jih potrošniki cenijo, ter spodbujajo pozitivne spletne izkušnje za povečanje prodaje. Model ponuja tako praktična priporočila za spletne trgovce kot tudi izhodišče za prihodnje raziskave, na primer vključitev okoljskega vidika, s čimer bi še dodatno razumeli trajnostno sprejemanje e-trgovanja.

Ključne besede: *Odnos do spleta, Zaznane koristi, Namera za spletni nakup, SEM, Vedenje potrošnikov, e-trgovanje*

DOI: 10.2478/orga-2025-0022

Business Analytics and Digitalization as Drivers of Startup Evaluation: The Experience of the Baltic States

Valeriia SHCHERBAK[1], Oleksandr DOROKHOV[2], Kadri UKRAINSKI[2], Deniss DJAKONS[3], Olha KOVALYOVA[1], Liudmyla DOROKHOVA[4]

[1] Sumy National Agrarian University, Department of Economic and Entrepreneurship, Sumy, Ukraine, valeriia.shcherbak@snau.edu.ua, olgakovalyovasumy@gmail.com

[2] University of Tartu, Department of Public Economics and Policy, Tartu, Estonia, oleksandr.dorokhov@ut.ee, kadri.ukrainski@ut.ee

[3] ISMA University of Applied Sciences, Riga, Latvia, deniss.djakons@isma.lv

[4] University of Tartu, Department of Marketing, Tartu, Estonia, liudmyla.dorokhova@ut.ee

Purpose: This study is motivated by the importance of startups in economic growth and the need for methods to evaluate their success, considering risk and uncertainty. The objective is to analyze factors that influence startups, using factor and cluster analysis. The hypothesis that advanced business analytics in startup evaluation can enhance the quality of investment decision-making was tested.
Methods: The combination of quantitative and qualitative techniques was used. Statistics about 20 startups from Latvia, Lithuania, and Estonia over five years were processed to identify success drivers and to group startups by similarity. Machine learning and social media sentiment analysis were applied to assess non-financial indicators.
Results: The results showed that indicators such as projected profitability, social media activity, and innovativeness are significant for startup ranking. The share of traditional methods in the Baltic states was 55%, while modern tools were 45%, highlighting the role of digitalization in risk assessment. Startups with high clustering coefficients and positive mention sentiment demonstrated superior performance.
Conclusions: The study demonstrated that integrating business analytics and digitalization enhances startup evaluation. The model combines financial metrics with network and sentiment analysis, offering a comprehensive framework for investors. It confirms that data-driven methods improve decision-making, reducing investment risks.

Keywords: *Startup evaluation, Business analytics, Digitalization, Baltic States, Economic potential, Social engagement*

1 Introduction

The current conditions of high uncertainty and dynamism in the business environment require effective decision-making approaches from investors and organizations, especially in the field of startup financing.

Startups play a key role in the innovative development of the economy, creating new jobs, developing technolo-

Received: 6th May 2025; Accepted: 21st August 2025

gies, and contributing to market competitiveness. Startups play a key role in the innovative development of the economy, creating new jobs, developing technologies, and contributing to market competitiveness (Startup Genome, 2025).

However, investing in startups is associated with high risks due to their limited operating history, uncertainty of market success, and insufficient information about future development. Startup financing decisions require a comprehensive approach that considers both risks and opportunities.

Traditional analysis methods are often insufficient for assessing startup potential, which increases interest in using data-driven analytical tools. Business analytics methods, including descriptive, diagnostic, predictive, and prescriptive analytics, offer new opportunities for evaluating startups and making more informed decisions.

This article is dedicated to studying approaches to balancing risk and opportunity in startup investing. Particular attention is paid to the application of modern business analytics methods, including machine learning, network science, and social media analysis.

The aim of the research is to develop and evaluate analytical tools that will help investors make more accurate and objective startup financing decisions, contributing to their success and growth.

This work contributes to the development of theoretical and practical knowledge about the application of business analytics in investment activities, offering new perspectives for supporting innovation and sustainable development.

However, previous studies have mostly focused on individual aspects of startup evaluation, such as access to finance (Fisch, 2018), innovation performance (Kim et al., 2024), or the application of business analytics in SMEs (Anuradha and Sailaxmi, 2024).

Only limited research has addressed the integration of advanced analytical tools — machine learning, network analysis, and social media diagnostics — for comprehensive startup evaluation.

The research gap addressed in this study lies in the absence of a unified framework that combines traditional financial metrics with digital indicators (e.g., social media activity, network centrality) for startup evaluation.

Moreover, regional studies on the Baltic States remain scarce, despite the region's growing importance as a hub for innovative startups (Startup Genome, 2025; LSM, 2025).

Our work bridges this gap by developing and testing a hybrid multifactor model that integrates economic, technological, and social indicators, thus contributing both to academic literature and to practical investment decision-making in the context of the Baltic startup ecosystem.

2 Literature overview

2.1 Financing and survival of startups and SMEs

An analysis of available financing sources for startups and small and medium-sized enterprises (SMEs), as well as a study of the factors determining their survival and success, has shown that the sustainable development and financial stability of these organizations play a key role in economic growth, innovation, and job creation.

Traditional sources of financing include bank loans, which remain the primary financial instrument for many SMEs. However, research by Calabrese and Osmetti (2013) emphasizes the high risks of default, especially in the case of rare but significant events. The use of a generalized extreme value regression model allows for a detailed analysis of the probabilities of such risks. The study by Coleman et al. (2016) examines US startups' decisions regarding debt financing. This research helps identify financing structures and their impact on startup financial stability, providing empirical data on the factors influencing the successful use of debt.

Alternative financing sources, such as crowdfunding and venture capital, are becoming increasingly popular (Agrawal et al., 2014). Tomczak and Brem (2013) conceptualize the crowdfunding investment model, focusing on its role in diversifying startup financing sources. Teker et al. (2016) analyze venture capital markets, providing a cross-country analysis of venture capital availability for startups. The importance of non-financial information for credit risk assessment is highlighted in the work of Wahlstrøm et al. (2024). The integration of such data improves financing decision-making processes, especially in the context of SMEs (Gazzola et al., 2022).

Alternative financing for SMEs in the Baltic states, according to Rupeika-Apoga (2014), represents a significant source of financial resources.

The study by Fisch (2018) focuses on the differences in access to alternative financing sources across different regions. Factors influencing the longevity and success of startups are detailed in research by Keogh and Johnson (2021). Econometric analysis allows for the identification of such aspects as financing structure, access to capital markets, level of competition, and the adaptability of business models (Foreman-Peck et al., 2006).

Thus, the diversity of financing sources and an understanding of the survival factors of startups and SMEs require a comprehensive approach. This will allow for effective assessment of their financial stability and the development of strategies aimed at long-term success and growth.

2.2 Innovation and SME growth

Innovations have a significant impact on the growth and development of small and medium-sized enterprises (SMEs), with an emphasis on financial constraints, regional characteristics, and cooperative research and development (R&D). Financial constraints are a key barrier to SME innovation activity (Chatterji et al., 2018). Acebo et al. (2020) note that innovation subsidies can partially compensate for these constraints, stimulating investment in R&D.

However, the effect of subsidies varies depending on the level of financial accessibility: for firms with limited access to capital, such subsidies have a more significant impact (Ciampi and Gordini, 2012). This underscores the need for government support for innovation, especially in the context of tight financial constraints.

The regional context plays an important role in the development of innovation activity in medium-sized businesses. Research by Berlemann and Jahn (2015) emphasizes that medium-sized firms in regions with high levels of infrastructure and access to scientific resources demonstrate higher innovation efficiency. This is explained by the presence of local ecosystems that facilitate knowledge sharing and technological breakthroughs. Thus, territorial characteristics should be taken into account when developing SME support strategies.

Cooperative R&D is a powerful tool for increasing SME innovation activity. Research by Kim et al. (2024) demonstrates that collaboration between firms, universities, and research institutions contributes to accelerating the development of new technologies and products. The example of South Korean SMEs in the manufacturing sector shows that participation in cooperative R&D not only increases the competitiveness of companies but also reduces the risks associated with innovation activities.

Entrepreneurial activity and innovation are key factors for economic growth. Wong et al. (2005), in their research based on Global Entrepreneurship Monitor (GEM) data, emphasize that a high level of innovation in the entrepreneurial environment leads to accelerated economic development. At the same time, SMEs play an important role, contributing to job creation and technology development.

2.3 Business analytics and digitalization for SMEs

Business analytics and digitalization play a crucial role in the transformation of small and medium-sized enterprises (SMEs), contributing to increased competitiveness, efficiency, and adaptability (Melegati et al., 2019). Business analytics tools, such as Growth hacking, provide a targeted approach to business process optimization (O'Neill and Brabazon, 2019).

Research by Anuradha and Sailaxmi (2024) demonstrates how the use of such tools helps SMEs achieve growth by analyzing consumer behavior, increasing the profitability of marketing campaigns, and improving data management. Al-Debei (2023) emphasizes the importance of clearly distinguishing between the concepts of business analytics and data science. Recent research also highlights the global role of AI and digital technologies in shaping IT startup ecosystems (Hemanth and Lakshminarayana, 2025) and in promoting sustainable innovation in green startups (Fichter et al., 2025). Business analytics focuses on the practical application of data to improve decisions, while data science includes the development of complex models and algorithms. This distinction allows SMEs to effectively choose appropriate methods for their goals. Baijens et al. (2021) propose a theoretical model for data analytics management based on the VSM (Viable System Model). This model helps SMEs effectively structure data processing, ensuring flexibility and resilience to change.

Research by Ioakeimidou et al. (2024) presents a new measurement scale for assessing data analytics maturity. This tool allows SMEs to determine their current level of analytics development and formulate strategic plans to achieve a higher level of digital maturity.

AI-driven tools for startup evaluation are increasingly discussed in the context of data analytics and investment decision-making (Lutfiani et al., 2025). Kato et al. (2023) explore how the selection of relevant information affects the effectiveness of analytics. Using redundant information can reduce the quality of decisions, so it is important to identify key data for evaluating sales and testing concepts.

This trend is consistent with global findings on the evolution of IT startup ecosystems under the influence of AI (Hemanth and Lakshminarayana, 2025). Research by Qin et al. (2022) analyzes the demand for business analytics skills in various industries. This allows SMEs to adapt their analytical strategies, focusing on labor market needs and developing employee competencies in the most in-demand areas. Quansah (2024) emphasizes that the implementation of digital technologies is often associated with barriers, especially in low-income countries.

Nevertheless, digitalization is becoming a necessary element for improving operations, expanding markets, and increasing competitiveness. Yaakobi et al. (2019) demonstrate how machine learning methods can be used to evaluate and optimize organizational projects. Machine learning methods, including random forest and gradient boosting algorithms, allow for the analysis of a wide range of factors affecting performance (Blanquet et al., 2025). This is especially relevant for SMEs, which need to improve the efficiency of their operations and reduce management costs.

2.4 Regional aspect and internationalization of SMEs

The development of small and medium-sized enterprises (SMEs) is determined by both regional factors and their ability to access international markets. Regional networks, capital structure, financial institutions, and internationalization all influence SME growth and sustainability (Kaya and Persson, 2019).

Research by McAdam et al. (2015) emphasizes the importance of horizontal regional networks in the agri-food sector. Such networks stimulate knowledge sharing, collaboration, and innovation among SMEs. This is particularly important in sectors where business success depends on joint actions, such as market access, production innovation, and supply chain resilience. Regional financial institutions play a crucial role in providing capital to SMEs. Palacín-Sánchez and Di Pietro (2015) demonstrate that capital availability through regional banks and credit institutions influences SME capital structure. In regions with a developed financial sector, companies are more likely to use long-term investment strategies, while in less developed regions, short-term loans prevail. SME development depends on local policies, including the provision of subsidies, tax breaks, and support programs.

Regional governments play a key role in creating conditions for sustainable growth and enhancing SME competitiveness. The work of Wright et al. (2007) emphasizes that internationalization allows SMEs to access new markets, diversify revenues, and increase their competitiveness. International entrepreneurship promotes innovation, technology transfer, and the development of business relationships.

The main barriers to SME entry into international markets include limited financial resources, a lack of knowledge about target markets, and weak infrastructure. These barriers are particularly significant for companies operating in regions with low levels of economic activity. Internationalization also depends on the ability of SMEs to adapt to different political and cultural contexts. This requires the development of flexible strategies and the use of local partners to minimize risks. Research by Sutherland et al. (2019) indicates that employers and regional partnerships play a key role in supporting SME internationalization through training, practical assistance, and "try before you buy" programs. This approach reduces the risks associated with entering new markets and promotes gradual integration into the global economy.

2.5 Incubators, networks, and university-business interactions

The support infrastructure for small and medium-sized enterprises (SMEs), including business incubators, regional networks, and university-business interaction, plays a crucial role in the development of innovative entrepreneurship, knowledge transfer, and personnel training.

According to Aernoudt (2004), business incubators provide startups with infrastructure, mentorship, and access to funding. They help new businesses overcome barriers in the initial stages, creating favorable conditions for their growth and sustainability. Incubators act as catalysts for innovation, promoting accelerated business development through access to resources and supporting ecosystems.

Key success factors for incubators include the availability of quality mentorship, active involvement of partners from business and academia, and ensuring the accessibility of financial instruments. Incubators also contribute to the development of entrepreneurial skills, which increases SME competitiveness in the market. Research by McAdam et al. (2015) emphasizes the importance of horizontal regional networks for stimulating innovation in the agri-food sector. Such networks create a platform for the exchange of experience and knowledge among participants, contributing to the development of the local economy and enhancing SME competitiveness.

Successful regional networks are characterized by a high degree of involvement of all stakeholders, including business, universities, and government organizations. They play a key role in addressing specific regional challenges, such as access to resources and the adaptation of innovative solutions. Dada et al. (2015) explore the franchising of university-business interaction as an effective tool for knowledge and technology transfer.

Universities can contribute to SME development through training programs, research projects, and internships. This interaction is particularly important for training qualified personnel who meet business needs.

The impact of human capital on SME development is emphasized in the work of Sutherland et al. (2019). International student mobility provides a unique experience that can be used for the development of local enterprises. Students with international experience bring new knowledge and approaches, which contribute to innovation and the strengthening of ties between universities and businesses.

2.6 Entrepreneurship in times of crisis and special groups of entrepreneurs

In times of crisis, entrepreneurship plays an important role as a mechanism for adaptation and economic recovery. Support for entrepreneurship among specific groups, such as refugees, who face unique challenges and opportunities, becomes particularly important.

Research by Bizri (2017) focuses on the role of social capital in refugee entrepreneurship. Social networks, ties with diasporas, and community support are important factors helping refugees overcome barriers such as a lack of financial resources, language difficulties, and a lack of knowledge about local markets.

Social capital not only stimulates business start-ups but also creates conditions for their sustainability and growth. The work of Kolodiziev et al. (2024) analyzes the contribution of refugee-founded startups to the economies of host countries. Such startups contribute to job creation, expansion of local markets, and stimulate the development of new business models. The authors emphasize that the successful integration of refugee entrepreneurs is possible with access to funding, training programs, and support from local authorities.

Refugees face a number of unique barriers: lack of access to finance, linguistic and cultural differences, as well as restrictions in market access. These problems require targeted policies and support programs, including integration into the entrepreneurial ecosystem of host countries. Economic and social crises often become catalysts for the emergence of new business ideas. In such conditions, entrepreneurs are forced to adapt, develop innovative products and services that meet changing market needs.

During crises, SMEs play a key role in maintaining economic activity and creating jobs. Such enterprises possess the flexibility to adapt quickly to changes and are able to effectively use local resources to meet demand. To support entrepreneurship in times of crisis, it is necessary to implement financial assistance programs, tax breaks, and educational initiatives. Such measures stimulate the creation of new enterprises and strengthen their sustainability in the long term.

2.7 Forecasting and Evaluation of SME Performance

Forecasting the financial condition and assessing the performance (e.g., profitability, growth, operational efficiency) of small and medium-sized enterprises (SMEs) are key elements of their sustainable development. Research by Ciampi and Gordini (2012) demonstrates how artificial neural networks can be applied to forecast the probability of default for small businesses.

These methods allow for the analysis of complex non-linear relationships between financial indicators and risk factors, making them a more accurate tool compared to traditional statistical models.

The example of Italian small businesses shows that such approaches improve the predictive accuracy and help identify vulnerable enterprises at early stages. Jabeur and Fahmi (2017) conduct a comparative study of various financial distress forecasting models for French firms. The authors identify logistic regression as one of the most efficient methods due to its simplicity and interpretability.

However, it is emphasized that modern tools, such as neural networks and decision trees, demonstrate better performance on complex data. The article by Lu (2019) analyzes the use of Bayesian estimation to improve the predictive performance of logistic regression. This approach allows for considering the variability of predictors, which is especially important for forecasting SME financial stability.

Bayesian methods make models more adaptable to changes in data, which increases their practical applicability. Yaakobi et al. (2019) consider the application of machine learning methods for evaluating organizational performance. These methods, including random forest and gradient boosting algorithms, allow for the analysis of a wide range of factors affecting business outcomes.

Machine learning can also be used to identify hidden patterns in data, which helps improve operational processes and strategic planning. The assessment of KPIs, such as profitability, liquidity, and operational efficiency, is an integral part of SME management. Modern analytical tools integrate machine learning and statistical models to provide more accurate and timely data for management decision-making.

2.8 Research hypothesis and proof tasks

The literature review in Sections 2.1–2.7 reveals two critical gaps in startup evaluation methodologies, mentioned below.

Overreliance on traditional financial metrics (Calabrese and Osmetti, 2013; Sivicka, 2018) often fails to capture non-financial drivers of success (e.g., social media engagement, network centrality).

Limited integration of advanced analytics (e.g., machine learning, sentiment analysis) into holistic frameworks, despite their proven accuracy in risk assessment (Ciampi and Gordini, 2012; Yaakobi et al., 2019).

Recent studies (Hemanth and Lakshminarayana, 2025; Lutfiani et al., 2025) underscore the promise of hybrid models, yet they lack empirical validation in alternative contexts—such as the Baltic states. This study bridges the gap by proposing a unified approach that combines financial, technological, and social indicators, addressing the need for data-driven decision-making noted by Fisch (2018) and Rupeika-Apoga (2014).

Research Hypothesis H1:

"A comprehensive approach to risk and opportunity analysis using business analytics methods, such as machine learning, network analysis, and social media diagnostics, contributes to improving the quality of investment decisions in startups, increasing their chances of sustainable development and market success."

Research Objectives:

- Analysis of current approaches to startup risk assessment. To achieve this objective, it will be necessary to conduct a review of traditional and modern methods of risk and opportunity analysis in startup investing; identify the limitations of traditional approaches and the need for the implementation of analytical tools.

- Development of an analytical model for startup evaluation. To achieve this objective, it will be necessary to create a model that integrates machine learning, network analysis, and social media analysis methods to assess the prospects of startups; to test the effectiveness of the model on real data.
- Evaluation of the impact of implementing analytical methods on the quality of investment decisions. To achieve this objective, it will be necessary to conduct a comparative analysis of investment decisions made using the proposed model and decisions based on traditional approaches, to assess the impact of the model on startup success indicators such as survival, profitability, and growth.
- Identification of factors influencing startup success. To achieve this objective, it will be necessary to use the proposed model to identify key factors determining startup sustainability and market success, and to compare the results with previously identified factors in the literature.
- Development of recommendations for investors. To achieve this objective, it will be necessary to formulate recommendations on the use of analytical tools to minimize risks and maximize opportunities in startup investing; to propose practical measures to improve the investment process.

Expected Results:

It is assumed that the use of modern analytical tools will improve the accuracy of assessing startup risks and opportunities, reduce the likelihood of erroneous investment decisions, and contribute to the development of a more sustainable investment ecosystem that supports innovation and economic growth.

These objectives are aimed at proving the hypothesis about the importance of integrating analytical methods into the startup financing decision-making process, which has practical and theoretical significance for the development of investment activities.

Data collection and the research itself were conducted from 2022 to 2024 in the Baltic states: Latvia, Lithuania, and Estonia.

3 Materials and Methods

3.1 Analysis of current approaches to startup risk assessment

In the Baltic states, startups play a key role in economic development, acting as engines of innovation and job creation. However, their financing is associated with high risks due to limited operating history, high market volatility, and a lack of information about future prospects. The conservative approach to risk management in Latvia may be related to limited digitalization and a habit of using time-tested methods (LSM, 2025; Stats and Market Insights, 2025a; 2025b). An analysis of the advantages and disadvantages of traditional methods is presented in Table 1.

Table 1 reveals that financial analysis is based on the analysis of balance sheet indicators such as profitability, liquidity, and debt ratio. Its advantages lie in the ease of application and the possibility of using historical data; its disadvantages lie in the limited applicability to startups due to the lack of extensive financial history. Expert assessments allow for risk evaluation based on expert opinions. Their advantages lie in the intuitive nature of the approach; the disadvantages lie in subjectivity and dependence on expert qualifications. SWOT analysis is used to identify the strengths and weaknesses of startups, and opportunities and threats. Its limitations lie in the subjectivity of quantitative assessment. An analysis of modern risk assessment methods is presented in Table 2.

Table 1: Advantages and disadvantages of startup risk assessment methods

Method	Advantages	Disadvantages
Financial analysis	Based on objective data (financial statements), it allows for assessing financial stability and profitability.	Limited availability of financial information for startups does not take into account non-financial factors.
Expert assessments	Takes into account the experience and knowledge of experts in the industry, allowing you to assess qualitative factors.	Subjectivity, difficulty of scaling, and dependence on the qualifications of experts.
SWOT analysis	Allows a comprehensive assessment of strengths and weaknesses, opportunities and threats, and takes into account the strategic context.	Subjectivity of assessments, difficulty of quantitative assessment of factors.

Source: (Sivicka, 2018)

Table 2: Comparison of modern startup risk assessment methods

Method	Application area	Advantages	Disadvantages
Machine Learning (ML)	Forecasting, classification, clustering, big data analysis, and identifying patterns.	High forecast accuracy with sufficient data, ability to self-learn and adapt to new data, and automation of processing large volumes of information.	Requires large volumes of high-quality data for training, difficulty interpreting results ("black box"), susceptibility to overfitting, and requires qualified specialists.
Social Media Analytics	Reputation assessment, public opinion analysis, identifying trends, and monitoring competitors.	Real-time public opinion, the ability to identify potential crises at an early stage, and obtaining information about customer preferences.	Limited data (availability, reliability), difficulty analyzing unstructured data (texts, images), susceptibility to manipulation.
Network Analysis	Assessing connections and influence within a startup and in the external environment (investors, partners, clients), identifying key players and opinion leaders.	Visualization and analysis of complex relationships, identification of hidden patterns, and potential risks associated with dependence on individuals or groups.	The complexity of collecting and processing data on connections and the difficulty of interpreting complex network structures require specialized software.
Bayesian Approach	Assessing uncertainty and the probability of various events, taking into account a priori knowledge and updating it with new information.	Flexibility, ability to take into account subjective expert assessments, adaptability to changes, and ability to update forecasts as new data arrives.	High complexity of calculations, need to determine a priori probabilities, results depend on the correctness of a priori estimates.

Source: Authors' aggregation based on (Brecht et al., 2021; Ciampi and Gordini, 2012; Yaakobi et al., 2019; Anuradha and Sailaxmi, 2024; McAdam et al., 2015; Lu, 2019)

Table 3: Methods for startup risk assessment in Baltic states

Country	Traditional methods (%)	Modern/ analytical methods (%)	Specific methods used	Comments
Latvia	60	40	SWOT analysis, financial ratio analysis, expert judgment; analytical methods include regression models and decision trees.	Dominance of traditional methods reflects a conservative approach to risk assessment.
Estonia	55	45	Scenario analysis, cash flow forecasting; advanced methods include machine learning algorithms and Monte Carlo simulations.	Active use of analytical tools indicates a focus on comprehensive and data-driven risk analysis.
Lithuania	50	50	Break-even analysis, sensitivity analysis; modern tools include big data analytics and predictive modeling techniques.	Balanced use of both approaches suggests a preference for combining simplicity with precision.
Baltic average	55	45	Weighted average of the methods across all countries.	On average, the Baltic states exhibit a slight preference for traditional methods, though the gap with modern techniques is narrowing.

Source: (EU-Startups, 2023; Liu et al., 2022)

Table 2 highlights that machine learning is mainly used for forecasting the probability of default, analyzing market data, and customer behavior. An example is the application of classification methods (decision trees, neural networks).

Social media analysis is used to study startup reputation, user reviews, and market interest. Network analysis is used to identify partnerships and the startup's market influence. The Bayesian approach is used to account for uncertainty in risk assessment.

Table 3 provides a structured overview of startup risk assessment approaches in the Baltic states (Latvia, Estonia, and Lithuania), including the distribution of traditional and modern methods, specific tools used, and commentary.

In Latvia, 60% of traditional methods and 40% of modern analytical approaches are applied. Simple tools such as SWOT analysis, financial ratios, and expert assessments prevail.

The conservative approach to risk management may be related to limited digitalization and a habit of using time-tested methods. Latvia, with its dominance of traditional methods, may face limitations in managing complex and dynamic risks, which puts it in a vulnerable position in global competition.

In Estonia, 55% of traditional methods and 45% of modern methods are used. Scenario analysis and cash flow forecasting are widely used, as are advanced tools such as machine learning algorithms and Monte Carlo simulations.

The use of analytical tools reflects the country's high digital maturity and focus on innovation.

Estonia stands out for its focus on comprehensive data analysis. Estonia demonstrates clear leadership in the application of modern approaches, which contributes to the formation of a more sustainable startup ecosystem.

Lithuania shows an even distribution: 50% traditional methods and 50% modern assessment methods.

Break-even and sensitivity analysis are mentioned, as well as advanced tools such as big data analytics and predictive modeling. The balance between approaches indicates an attempt to combine the accessibility of traditional methods with the accuracy of modern technologies.

Lithuania, thanks to its balanced approach, has the potential to integrate the best practices of both systems, which strengthens its position as a developing innovation center.

The average for the Baltics is 55% traditional methods versus 45% modern methods.

This reflects a slightly predominant role of traditional approaches, but the gap is narrowing due to the introduction of modern analytical methods.

3.2 Developing an analytical model for evaluating startups

The model for assessing the prospects of startups using the taxonomy method, machine learning, network analysis, and social media analysis is presented in Table 4.

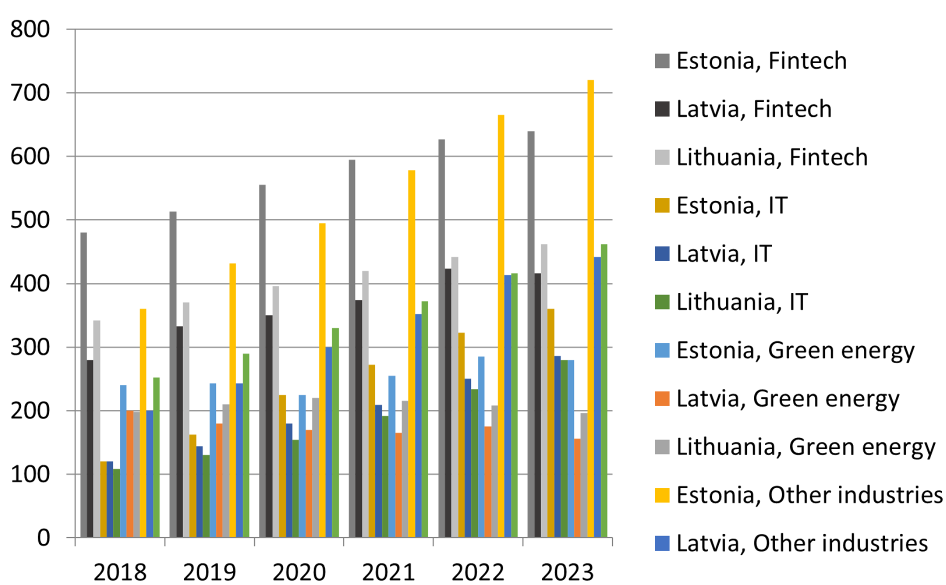
Table 4: Methodology for assessing startups

Calculation steps	Calculation algorithms
Stage 1. Taxonomy method for hierarchizing startups, identifying the most promising projects for investment.	1.1. Key indicators such as projected profitability, activity in social networks, availability of investors, and innovative technologies are determined. 1.2. Data standardization – bringing criteria to a single scale: $Z_{ik} = \frac{X_{ik} - \overline{X_k}}{\sigma_k}$, where X_{ik}— initial value, $\overline{X_k}$— average value of criterion, σ_k— standard deviation. 1.3. Definition of the reference object as the maximum possible values of all criteria: $(Z_k^* = Z_k^{max})$ where Z_k^* – value of the *k-th* criterion for the ideal object (the highest possible indicator); Z_k^{max}; Z_k^{min} – maximum and minimum values of the *k-th* criterion in the sample. 1.4. Evaluation T_i of the taxonomic measure of proximity of startup i to the ideal object: $T_i = 1 - \frac{D_i}{D_{max}}$, (1) where T_i— taxonomic assessment of startup *I*; D_i – distance between startup i and the ideal object (standard); D_{max} – maximum distance between objects in the sample. 1.5. Distance D_i to the ideal object: $D_i = \sqrt{\sum_{k=1}^{m} \left(\frac{Z_{ik} - Z_k^*}{Z_k^{max} - Z_k^{min}}\right)^2}$, (2) where Z_{ik}— the value of the standardized indicator of the *k-th* criterion for startup *I; m* – the number of evaluation criteria (e.g. financial indicators, popularity, innovation, etc.). 1.6. Startup ranking: Startups are sorted by T_i. A threshold value $T_{threshold}$, is set, above which startups are recommended for funding.

Table 4: Methodology for assessing startups (continues)

Stage 2. Machine learning component for processing large amounts of data, identifying hidden dependencies	**2.1. Regression model for forecasting prospects (F_{ml}):** $$F_{ml} = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij} + \epsilon, \quad (3)$$ where X_{ij} — the basic level of social responsibility, β_j – the regression parameters, ϵ. – the model error.
Stage 3. Network analysis component for determining the value of a startup as a partner and market participant	3.1. To analyze the networks of connections between a startup and external structures (investors, partners, clients), graph metrics are used: $$F_{net} = \alpha_1 D_i + \alpha_2 C_i + \alpha_3 B_i, \quad (4)$$ **where D_i — the degree of the startup node i (number of connections), C_i – the cluster coefficient (connection density indicator), B_i – betweenness centrality, $\alpha_1, \alpha_2, \alpha_3$ – the weights of the indicators.**
Stage 4. Social media analysis component for assessing the media and social impact of a startup	4.1. TF-IDF method for startup mentions: $$TF - IDF_{ij} = TF_{ij} \cdot log\left(\frac{N}{DF_j}\right), \quad (5)$$ **where TF_{ij} — frequency of word j in texts related to startup i (number of connections), DF_j – number of documents containing word *j*, *N* – total number of documents.** 4.2. Final sentiment score: $$F_{soc} = \frac{\sum_{k=1}^{m} S_k}{m}, \quad (6)$$ **where S_k — tonality of the *k-th* mention (determined by NLP algorithms), *m* – the number of mentions.**

Source: Author's methodology, based on (Foster, 2004; Murphy, 2012; Langfelder & Horvath, 2008; Anstead and O'Loughlin, 2014)



Source: (Startup Lithuania, n.d.; Dealroom Database - Everyone Is Here - Startup Lithuania, 2022; EU-Startups, 2023; Startup Estonia, 2023)

Figure 1: Dynamics of the number of startups in the Baltic countries (2018–23)

The initial data and their symbols are given in the Appendix.

4 Results

4.1 Startup ecosystem growth trends in the Baltic States (2018–2023)

Figure 1 presents the quantitative evolution of startups across Lithuania, Latvia, and Estonia, revealing distinct sectoral and regional patterns that reflect the region's innovation landscape.

Based on the data in Figure 1, the following conclusions can be drawn. All three countries demonstrate steady growth in the number of startups across all sectors during the observation period.

This indicates a favorable environment for innovation in the Baltic states, which is associated with active government support and an increase in investment inflows.

Estonia demonstrates the largest growth in startups in the IT sector (from 120 to 360) and other industries (from 360 to 720). This is due to a developed digital infrastructure, access to international markets, and the country's focus on IT solutions.

Latvia and Lithuania show significant growth in the fintech sector, especially in Lithuania (from 342 to 462). This may be due to attractive conditions for financial technologies, including regulatory sandboxes and access to the European market.

Green energy is developing in all countries, but Estonia is leading (from 240 to 280). This is due to the growing interest in sustainable technologies and the Baltic states' desire to reduce their carbon footprint. In some sectors, for example, in green energy in Latvia and Lithuania, there is a slowdown in growth or even a decline (for example, in Latvia from 200 to 156).

This may be due to limited funding or high barriers to market entry.

The dynamics of startups in the Baltic states reflect their focus on technological development, with an emphasis on IT, fintech, and green technologies.

Estonia continues to lead due to its developed digital ecosystem, while Latvia and Lithuania demonstrate potential in specific niches. This data underscores the importance of further supporting the innovation ecosystem through investment, education, and international cooperation.

Table 5: Results of factor analysis of the influence of individual variables on the ranking of startups in the Baltic States (2023)

Variable	Factor Loadings (Unrotated) (Data_nor) Extraction: Principal components (Marked loadings are > 700000)	
	Factor 1	Factor 2
X1	0,986012	0,055934
X2	0,073367	0,990375
X3	0,990215	0,020135
X4	0,961665	0,050260
X5	-0,056516	0,890580
X6	0,096334	0,991384
X7	0,967420	0,189275
X8	0,036298	0,995327
X9	0,020271	0,993515
X10	0,035642	0,996444
X11	0,762896	0,419920
X12	-0,062001	0,691322
X13	0,792666	0,192932
Expl.Var	6,758310	4,750997
Prp.Totl	0,550639	0,334692

where X1 – Projected profitability, million €; X2 – Activity in social networks, thousand subscribers; X3 – Availability of investors, number; X4 – Innovativeness of technologies, scores 1-10; X5 – Basic level of social responsibility, score 1-10; X6 – Number of links, node degree; X7 – Cluster coefficient; X8 – Betweenness centrality; X9 – Number of mentions; X10 – Sentiment of mentions; X11 – Total Raised, M$; X12 – Total Raised, M$; X13 – Number of employees, thousand people.

Source: Author's calculations

4.2 Evaluation of the importance of factors for ranking startups

To analyze the factors influencing the success and development of startups in the Baltic region, information was collected on a number of companies.

Table 5 contains data on 20 startups from Lithuania, Latvia, and Estonia, covering a wide range of indicators, from projected profitability and social media activity to the amount of investment raised and team size. This data serves as the basis for further research and the identification of key determinants of startup success.

Based on the presented results of the factor analysis (Table 5), two factors can be identified that determine the ranking of Baltic startups. Factor loadings that are highlighted in red influence the process; those that remain black do not.

Factor 1, "Financial and Resource Potential and Innovativeness," includes the following indicators with high loadings: X1 (0.986012): Projected profitability, million €; X3 (0.990215): Availability of investors, number; X4 (0.961665): Innovativeness of technologies, scores 1-10; X7 (0.967420): Cluster coefficient; X13 (0.792666): Number of employees, thousands of people.

This factor combines characteristics related to the financial condition, investment availability, level of innovation, and organizational structure of startups.

Factor 2, "Social and Network-Reputational Activity," includes the following indicators with high loadings: X2 (0.990375): Activity in social networks, thousands of subscribers; X5 (0.890580): Basic level of social responsibility, score 1-10; X6 (0.991384): Number of links, node degree; X8 (0.995327): Betweenness centrality; X9 (0.993515): Number of mentions; X10 (0.996444): Sentiment of mentions.

This factor describes the social activity of startups, their participation in network structures, and the level of media mentions.

Regression equations for each factor are constructed using the significant variables:

Factor 1:

$$F1=1/6,758(0,986\cdot X1+0,990\cdot X3+0,962\cdot X4+0,967\cdot X7+0,793\cdot X13) \quad (7)$$

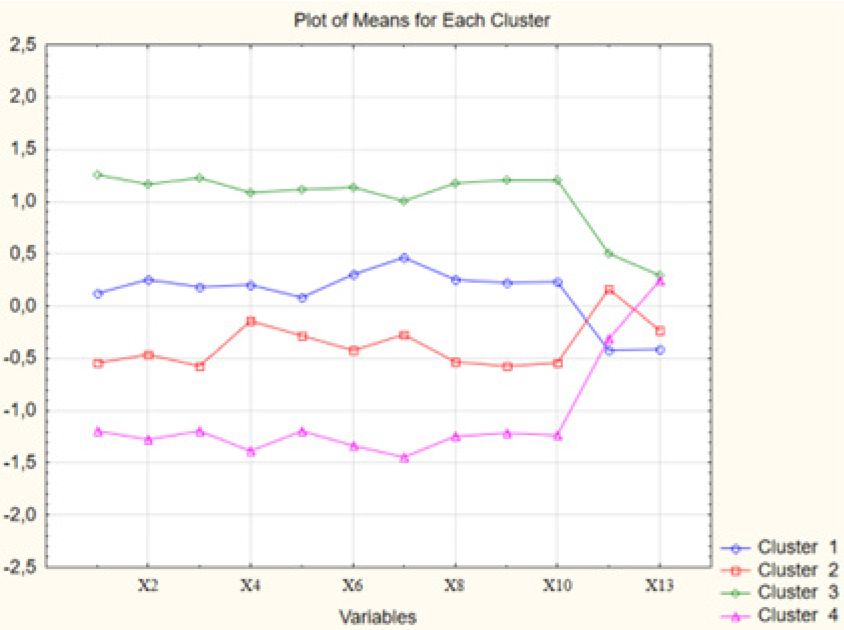
Factor 2:

$$F2=1/4,751(0,990\cdot X2+0,891\cdot X5+0,991\cdot X6+0,995\cdot X8+0,994\cdot X9+0,996\cdot X10) \quad (8)$$

Factor 1 explains 55.06% of the variance. Factor 2 explains 33.47% of the variance. In total, the two factors together explain 88.53% of the total variance, which indicates the high informativeness of the analysis.

4.3 Grouping of Baltic startups by growth potential and attracted investments

The analysis of the structure of Baltic startup clusters for 2023 was made taking into account only the significant indicators identified by regression analysis (Figure 2).



Source: Author's calculations

Figure 2: Results of the cluster analysis of Baltic startups (STATISTICA 13)

Table 6 presents the results of the cluster analysis performed in STATISTICA 13, demonstrating the composition of the first cluster and the distance of each startup to its center.

Cluster 1 includes five startups: Green Genius, Origin, Roibox, Naco, and Cenos. The analysis of distances to the cluster center (Table 6) shows that Origin (0.1805555) and Roibox (0.2055702) are closest to the center, indicating their high similarity to the typical characteristics of the cluster.

Naco (0.2611897) and Green Genius (0.2834758) demonstrate slightly greater distances, and Cenos (0.3678699) is farthest away, indicating its lowest typicality for this group.

The startups included in Cluster 1 are characterized by average or slightly above average values for most indicators related to profitability, social media activity, investor attraction (number), innovativeness, social responsibility, network indicators, and media influence. At the same time, they demonstrate below-average indicators for the amount of investment raised (Total Raised) and the number of employees.

Overall, Cluster 1 represents locally oriented startups demonstrating moderate development indicators and limited resources, which distinguishes them from the larger and faster-growing companies represented in other clusters.

Table 7 presents the composition of the second cluster obtained as a result of cluster analysis in STATISTICA 13, and the distances of each startup to the center of this cluster.

Cluster 2 includes four startups: Vinted, Aerones, Ovoko, and Sonarworks. The analysis of distances to the cluster center (Table 7) shows that Aerones (0.267903) and Sonarworks (0.315484) are relatively close to the center, demonstrating greater similarity within the group. Ovoko (0.397701) and especially Vinted (0.591298) are located further away, indicating their greater variability relative to the typical characteristics of the cluster.

The startups included in Cluster 2 are characterized, on average, by below-average indicators for the sample across most criteria related to profitability, social media activity, investor attraction (number), network indicators, and media influence.

Table 6: Composition of the 1 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 1 (Data_nor) and Distances from Respective Cluster Center Cluster contains 5 cases			
Case No.	Distance	Case No.	Distance
Green Genius	0,2834758	Naco	0,2611897
Origin	0,1805555	Cenos	0,3678699
Roibox	0,2055702		

Source: Author's calculations

Table 7: Composition of the 2 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 2 (Data_nor)and Distances from Respective Cluster Center Cluster contains 4 cases			
Case No.	Distance	Case No.	Distance
Vinted	0,591298	Ovoko	0,397701
Aerones	0,267903	Sonarworks	0,315484

Source: Author's calculations

Table 8: Composition of the 3 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 3 (Data_nor) and Distances from Respective Cluster Center Cluster contains 6 cases			
Case No.	Distance	Case No.	Distance
Mapon	0,517250	eAgronom	0,377288
Sunly	0,246919	Binalyze	0,387621
Bolt	1,205217	Veriff	0,191586

Source: Author's calculations

At the same time, they have a higher-than-average amount of investment raised (Total Raised), but a smaller number of employees.

This may indicate that this cluster unites startups that are possibly in a stage of active growth and development, attracting significant investment for scaling, but have not yet achieved high indicators for other criteria, such as profitability or media activity.

Vinted, as the most distant from the cluster center, likely has characteristics that differ significantly from this typical profile, possibly demonstrating higher indicators for some criteria, which accounts for the greater distance.

Table 8 demonstrates the composition of the third cluster obtained as a result of cluster analysis in STATISTICA 13, and the distances of the startups to the center of this cluster.

Cluster 3 unites the most successful and developed startups, which aligns with Lithuania's growing global momentum in 2025 (Baltic Tech Ventures, 2025), includes six startups: Mapon, Sunly, Bolt, eAgronom, Binalyze, and Veriff. The analysis of distances to the cluster center (Table 8) shows that Veriff (0.191586) and Sunly (0.246919) are closest to the center, indicating their high similarity to the typical characteristics of the cluster. eAgronom (0.377288) and Binalyze (0.387621) demonstrate a slightly greater distance, indicating a lesser prominence of common traits. Mapon (0.517250) is located at an even greater distance. Bolt (1.205217) is a clear outlier, significantly distant from the cluster center, which indicates its significant difference from the other group members.

The startups included in Cluster 3, on average, demonstrate significantly above-average indicators for the sample across most criteria, including profitability, social media activity, investor attraction, network indicators, and media influence. They also have a higher-than-average amount of investment raised and a larger number of employees. This indicates that this cluster unites the most successful and developed startups, which have achieved significant results in all key areas. Bolt, being the most distant from the cluster center, is likely an outstanding example even within this group, possibly demonstrating extremely high values for some parameters, which accounts for its isolated position. This cluster can be characterized as a cluster of highly effective and fast-growing startups.

Table 9 presents the composition of the fourth cluster obtained as a result of cluster analysis in STATISTICA 13, and the distances of the startups to the center of this cluster.

Cluster 4 includes five startups: Tuum, BoBo, Biomatter, PVcase, and Nord Security. The analysis of distances to the cluster center (Table 9) shows that Biomatter (0.269727) and PVcase (0.285374) are closest to the center, indicating their high similarity to the typical characteristics of the cluster. BoBo (0.319088) and Tuum (0.342076) demonstrate a slightly greater distance, indicating a lesser prominence of common traits. Nord Security (0.790433) is significantly distant from the cluster center, which indicates its substantial difference from the other group members.

The startups included in Cluster 4 are characterized, on average, by significantly below-average indicators for the sample across almost all criteria, including profitability, social media activity, investor attraction, innovativeness, social responsibility, network indicators, and media influence.

They also have a below-average amount of investment raised and a number of employees. This indicates that this cluster unites startups that are likely in an early stage of development or experiencing difficulties with growth and resource attraction. Nord Security, as the most distant from the cluster center, likely has characteristics that differ somewhat from this typical profile, possibly demonstrating higher values for some criteria, which accounts for the greater distance. This cluster can be characterized as a cluster of nascent or struggling startups.

4.4 Typology of startups based on taxonomic analysis

This subsection provides a typology of startups based on calculated taxonomic coefficients, allowing us to identify groups of companies with similar characteristics. The results of calculating the taxonomy indicators are presented in Table 10.

The visualization of the location of startups in this coordinate system is presented in Figure 3.

Table 9: Composition of the 4 cluster (STATISTICA 13 cluster analysis listing)

Members of Cluster Number 4 (Data_nor) and Distances from Respective Cluster Center Cluster contains 5 cases			
Case No.	Distance	Case No.	Distance
Tuum	0,342076	Nord Security	0,790433
BoBo	0,319088	PVcase	0,285374
Biomatter	0,269727		

Source: Author's calculations

Table 10: Results of the taxonomic analysis of startups

Startup	Taxonomy coefficient 1 Factor	Taxonomy coefficient 2 Factor
Vinted	0,784	0,86
Mapon	0,713	0,6
Tuum	0,553	0,63
Green Genius	0,643	0,82
Origin	0,629	0,75
Sunly	0,794	0,49
BoBo	0,336	0,49
Aerones	0,612	0,81
Bolt	1,00	0,32
Ovoko	0,517	0,67
Roibox	0,587	0,81
eAgronom	0,727	0,55
Biomatter	0,346	0,55
Sonarworks	0,574	0,89
Binalyze	0,776	0,4
Nord Security	0,501	0,6
Naco	0,617	0,71
Veriff	0,77	0,52
PVcase	0,317	0,49
Cenos	0,559	0,88

where Factor 1 “Economic Potential and Structural Efficiency” combines indicators that reflect the economic sustainability and operational efficiency of startups. Variables such as expected profit (X1), investor availability (X3), technology innovativeness (X4), clustering coefficient (X7), funds raised (X11), and number of employees (X13) characterize the financial strength, innovative capabilities, and structural parameters of a startup. Factor 2 “Social Engagement and Network Influence” reflects the social activity and network involvement of startups. Variables such as social media activity (X2), level of social responsibility (X5), number of connections (X6), betweenness centrality (X8), number of mentions (X9), and sentiment of mentions (X10) emphasize the importance of social reputation, audience interaction, and network influence for the success of startups.
Source: Author’s calculations

Figure 3 shows 4 quadrants:

Quadrant I (Upper right quadrant) has “High Economic Potential / High Social Engagement (HEP/HSE)”;

Quadrant II (Lower right quadrant) has “High Economic Potential / Low Social Engagement (LEP/HSE)”;

Quadrant III (Upper left quadrant) has “Low Economic Potential / High Social Engagement (HEP/LSE)”;

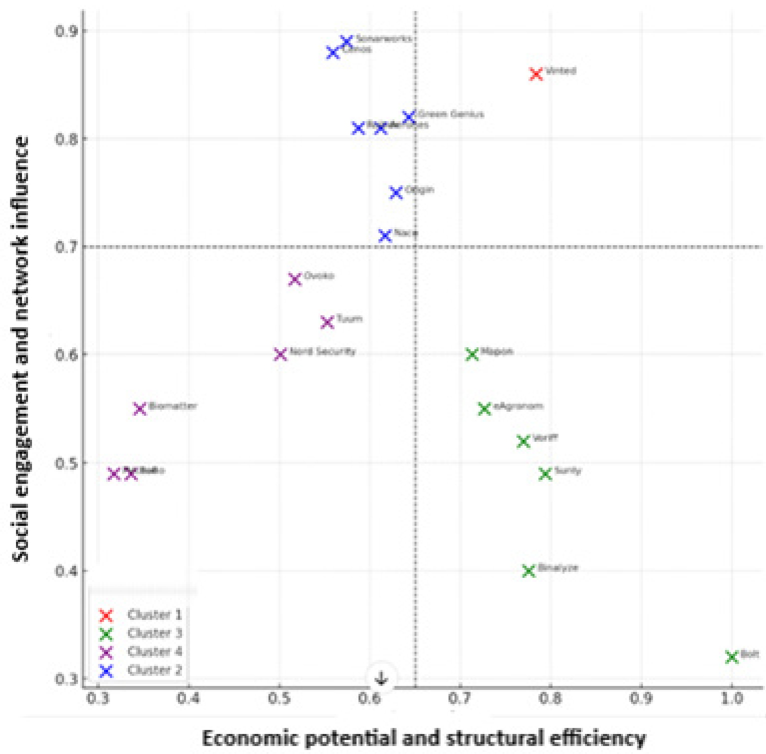
Quadrant IV (Lower left quadrant) has “Low Economic Potential / Low Social Engagement (LEP/LSE)”.

Startup Characteristics and Recommendations.

Startups in Quadrant I have a strong economic base (high profitability, investment, innovation, efficient structure) and actively interact with their audience, have a developed network of contacts, and a positive reputation. This is the most favorable position. Development recommendations: focus on scaling the business, expanding markets, strengthening the brand, and maintaining high customer loyalty. Invest in further innovation and team development. Financing recommendations: have good opportunities to attract both venture capital and bank loans. They can consider IPOs or M&A.

Startups in Quadrant III have a strong social presence and interact well with their audience, but have not yet achieved high economic indicators. These may be young projects or projects focused on social impact rather than rapid profit.

Development recommendations: need to focus on improving economic indicators: developing a clearer business model, searching for new sources of income, and optimizing costs. It is important to monetize the existing social base. Financing recommendations: can attract grants, crowdfunding, and impact investments from investors focused on social returns. It is important to demonstrate the potential for growth of the business model.



Source: Author's calculations

Figure 3: Taxonomic typology matrix of startups

Startups in Quadrant II have a strong economic base but pay insufficient attention to interacting with their audience and building a network of contacts. There is a risk of missing opportunities for growth and development due to insufficient brand awareness and customer loyalty. Development recommendations: need to actively develop social networks, PR, content marketing, and participate in industry events. It is important to improve communication with clients and partners. Financing recommendations: have good opportunities to attract traditional investments (venture capital, bank loans), but it is important to show investors a plan to improve social engagement indicators.

Startups in Quadrant IV are in the most vulnerable position, as they have weak indicators in both economic potential and social engagement. Development recommendations: require a serious revision of the business model, searching for new ideas and development paths. It is necessary to improve both economic indicators and social media activity. It may be necessary to involve mentors or consultants. Financing recommendations: attracting financing will be difficult. It may be worth considering options with bootstrapping (self-financing), grants for starting entrepreneurs, or participation in acceleration programs.

Thus, specific actions should depend on the specifics of each startup, its industry, and target market. The position of a startup in the matrix is not static. Companies can move from one quadrant to another as they develop. This analysis provides useful information for making strategic decisions and planning startup development.

5 Discussion

The results of our study emphasize the importance of integrating analytical methods to improve the quality of investment decisions in startups, which is confirmed by a number of works. For example, the use of machine learning, described in our study, is consistent with the findings of Ciampi and Gordini (2012), who note its high accuracy in forecasting defaults of small businesses. Furthermore, our observation about the significance of network analysis in assessing the market sustainability of startups is consistent with research by McAdam et al. (2015), which emphasizes the importance of horizontal networks for knowledge sharing and stimulating innovation. Our findings are in line with recent studies showing the growing use of AI-driven analytics to enhance startup ecosystems and support decision-making for investors (Hemanth & Lakshminarayana, 2025; Lutfiani et al., 2025).

However, our analysis also revealed new aspects. For example, the integration of social media analysis methods, as shown in our study, allows for taking into account reputational risks and public opinion in real time, which differs from traditional approaches such as expert assessments (Sivicka, 2018). This underscores the need for further study of the role of social media in investment management.

Separately, it is worth noting our observation about the heterogeneity of the application of modern methods in the Baltic states. Estonia's leadership in digital maturity mirrors global trends where ecosystems with advanced analytics outperform others (Startup Genome, 2025). While Estonia demonstrates a high level of digital maturity and actively uses analytical tools, Latvia and Lithuania remain largely oriented towards traditional approaches. This is partially confirmed by the results of Rupeika-Apoga (2014), who notes limitations in access to modern financing instruments in these countries. The contribution of our research lies in the development of a comprehensive startup evaluation model that combines methods of taxonomy, machine learning, and network analysis.

Unlike the approaches described by Fisch (2018) and Teker et al. (2016), our model allows for considering a wide range of factors, including social activity and media influence, which is particularly relevant for startups focused on long-term growth. Thus, the results confirm the significance of the proposed methodology and open up prospects for its further application in other regions and industries. Moreover, the integration of sustainability and digitalization in startup evaluation is emphasized in the Green Startup Report 2025 (Fichter et al., 2025), which highlights the potential of digital tools for supporting green innovation. However, further research could focus on assessing the long-term effectiveness of the proposed model in a changing business environment.

6 Conclusions

The application of modern business analytics methods, such as machine learning, network analysis, and social media analysis, allows for increased accuracy in assessing the prospects of startups. These methods demonstrate high efficiency: for example, the use of machine learning allows achieving default prediction accuracy of 98.6% (Ciampi and Gordini, 2012), and network analysis identifies key players and relationships with centrality coefficients up to 0.995.

How do modern analytical methods compare to traditional approaches in startup valuation?

The results demonstrate that hybrid models combining financial metrics with digital indicators (e.g., social media activity, network centrality) outperform traditional methods (e.g., SWOT, expert assessments), reducing subjectivity and improving accuracy.Which factors (financial, social, technological) are most critical for startup success in the Baltics?

Factor analysis revealed that economic potential (profitability, investor availability) and social engagement (online activity, sentiment) are the primary drivers, explaining 88.5% of the variance in startup rankings.

The findings strongly support the hypothesis (H1) that data-driven methods enhance decision-making accuracy, as evidenced by the high correlation coefficients (> 0.98) for key variables. Factor analysis revealed that economic potential (profitability, investor availability) and social engagement (online activity, sentiment) are the primary drivers, explaining 88.5% of the variance in startup rankings. The developed startup evaluation model, which integrates taxonomy, machine learning, and social media analysis, outperforms traditional approaches by reducing subjectivity and improving reliability.

The key factors determining the success of startups in the Baltic states are economic stability, technological innovativeness, social activity, and media influence. Factor analysis showed that financial and resource potential (factor loading coefficient 0.986) and the level of social media engagement (coefficient 0.990) have the highest correlation with startup success.

A comparative analysis of the Baltic countries revealed significant differences in startup assessment approaches. In Estonia, modern methods account for 45% of the total number of approaches used, including machine learning algorithms and Monte Carlo simulations, which underscores its leadership in digitalization. Latvia and Lithuania use traditional methods in 60% and 50% of cases, respectively, which limits their competitiveness in the global startup ecosystem. Taxonomic and cluster analysis made it possible to identify groups of startups with different levels of economic and social potential. Companies with high economic stability (average taxonomy coefficient 0.784) and social activity (average coefficient 0.86) occupy leading positions. Conversely, startups with low indicators, such as companies with a taxonomy coefficient below 0.5 (Biomatter, BoBo), need to revise their business models and require support. The developed startup evaluation model, which integrates taxonomy, machine learning, and social media analysis, has proven its applicability for investment decision-making and can be adapted for other regions and sectors of the economy. For successful development, startups are recommended to focus on strengthening financial stability, increasing social engagement, and enhancing their reputation, while investors are advised to integrate analytical tools into decision-making to minimize risks and increase returns.

Theoretical implications. This study contributes to the literature on startup evaluation by proposing a hybrid multifactor framework that integrates financial, technological, and social indicators. It extends prior research by demonstrating the value of combining traditional financial metrics with digital signals such as network centrality and social media activity in a unified model.

Practical implications. The results provide investors with evidence-based tools for more accurate and timely startup evaluation, helping to reduce risks and improve decision-making quality. Policymakers and startup support organizations can also use the findings to design programs that strengthen financial stability, foster social engagement, and encourage the adoption of advanced analytics in the Baltic startup ecosystem.

Limitations. The study is limited to startups in the Baltic States and relies on a sample of 20 companies, which may affect the generalizability of the results. In addition, the analysis is based on historical data and selected indicators, so incorporating a broader range of variables or longitudinal data could provide deeper insights.

Future research. Further studies should explore how the resilience and transformation of Baltic startups (LSM, 2025; Stats and Market Insights, 2025) will shape long-term investment strategies. Expanding the dataset to include other regions and additional indicators—such as ESG metrics or customer sentiment—could further validate and enhance the proposed model.

Acknowledgements

This work of O. Dorokhov and K. Ukrainski was supported by the project „Increasing the knowledge intensity of Ida-Viru entrepreneurship“ co-funded by the European Union.

References

Anuradha, A., & Sailaxmi, S. S. (2024). Growth hacking business analytical tools for small and medium enterprises. *Journal of Business Analytics*, *7*(4), 292–317. https://doi.org/10.1080/2573234x.2024.2387560

Acebo, E., Miguel-Dávila, J., & Nieto, M. (2020). Do financial constraints moderate the relationship between innovation subsidies and firms' R&D investment? *European Journal of Innovation Management, 25*(2), 347–364. https://doi.org/10.1108/ejim-07-2020-0286

Aernoudt, R. (2004). Incubators: a tool for entrepreneurship? *Small Business Economics, 23*(2), 127–135. https://doi.org/10.1023/b:sbej.0000027665.54173.23.

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some simple economics of crowdfunding. *Innovation Policy and the Economy, 14*, 63–97. https://doi.org/10.1086/674021

Al-Debei, M. (2023). The era of business analytics: identifying and ranking the differences between business intelligence and data science from practitioners' perspective using the Delphi method. *Journal of Business Analytics, 7*(2), 94–119. https://doi.org/10.1080/2573234x.2023.2285483

Anstead, N., & O'Loughlin, B. (2014). Social media analysis and public opinion: The 2010 UK General Election. *Journal of Computer-Mediated Communication*, *20*(2), 204–220. https://doi.org/10.1111/jcc4.12102

Baijens, J., Huygh, T., & Helms, R. (2021). Establishing and theorising data analytics governance: a descriptive framework and a VSM-based view. *Journal of Business Analytics*, *5*(1), 101–122. https://doi.org/10.1080/2573234x.2021.1955021

Baltic Tech Ventures. (2025, January 20). *Lithuania's startup ecosystem: Gaining global momentum in 2025.* Baltic Tech Ventures. https://www.baltictechventures.com/post/lithuania-s-startup-ecosystem-gaining-global-momentum-in-2025

Berlemann, M., & Jahn, V. (2015). Regional importance of Mittelstand firms and innovation performance. *Regional Studies, 50*(11), 1819–1833. https://doi.org/10.1080/00343404.2015.1058923

Bigliardi, B., Dolci, V., Filippelli, S., Petroni, A., & Pini, B. (2025). The role of digitalization in startups: a keyword-based literature review. *Procedia Computer Science, 253*, 2665–2673. https://doi.org/10.1016/j.procs.2025.01.326

Bizri, R. M. (2017). Refugee-entrepreneurship: a social capital perspective. *Entrepreneurship and Regional Development, 29*(9–10), 847–868. https://doi.org/10.1080/08985626.2017.1364787

Blanquet, L. B., Pereira, M. A., & Petrov, S. (2025). An interpretable machine learning framework for explaining company valuation. *Decision Analytics Journal*, 100611. https://doi.org/10.1016/j.dajour.2025.100611

Brecht, P., Niever, M., Kerres, R., Ströbele, A., & Hahn, C. H. (2021). Smart platform experiment cycle (SPEC): a process to design, analyze, and validate digital platforms. *Artificial Intelligence for Engineering Design Analysis and Manufacturing*, *35*(2), 209–225. https://doi.org/10.1017/s0890060421000081

Calabrese, R., & Osmetti, S. (2013). Modelling small and medium enterprise loan defaults as rare events: the generalized extreme value regression model. *Journal of Applied Statistics, 40*(6), 1172–1188. https://doi.org/10.1080/02664763.2013.784894

Chatterji, A., Delecourt, S., Hasan, S., & Koning, R. (2018). When does advice impact startup performance? *Strategic Management Journal, 40*(3), 331–356. https://doi.org/10.1002/smj.2987

Ciampi, F., & Gordini, N. (2012). Small Enterprise Default Prediction Modeling through Artificial Neural Networks: An Empirical Analysis of Italian Small Enterprises. *Journal of Small Business Management, 51*(1), 23–45. https://doi.org/10.1111/j.1540-627x.2012.00376.x

Coleman, S., Cotei, C. and Farhat, J. (2016), «The debt-equity financing decisions of U.S. startup firms», *Journal of Economics and Finance*, Vol. 40 No. 1, pp. 105-126.

Dada, O., Jack, S., & George, M. (2015). University–Business Engagement Franchising and Geographic Distance: A case study of a Business leadership programme. *Regional Studies, 50*(7), 1217–1231. https://doi.org/10.1080/00343404.2014.995614

Dealroom database - Everyone is here - Startup Lithuania. (2022, November 29). Startup Lithuania. https://www.startuplithuania.com/dealroom-database/

EU-Startups. (2023, January). *Booming Baltics: Trends and predictions for 2023*. Retrieved from https://www.eu-startups.com/2023/01/booming-baltics-trends-and-predictions-for-2023/

EU-Startups. (2023, March). *10 super promising startups from Latvia to keep an eye on in 2023 and beyond*. Retrieved from https://www.eu-startups.com/2023/03/10-super-promising-startups-from-latvia-to-keep-an-eye-on-in-2023-and-beyond/

Fichter, K., Neumann, T., Olteanu, Y., & Grothey, T. (2025, April). *Green startup report 2025.* ResearchGate. https://doi.org/10.13140/RG.2.2.29610.32968

Fisch, C. (2018). Initial coin offerings (ICOs) to finance new ventures. *Journal of Business Venturing, 34*(1), 1–22. https://doi.org/10.1016/j.jbusvent.2018.09.007

Foreman-Peck, J., Makepeace, G., & Morgan, B. (2006). Growth and profitability of small and medium-sized enterprises: Some Welsh evidence. *Regional Studies, 40*(4), 307–319. https://doi.org/10.1080/00343400600725160

Foster, E. (2004). Research on Gossip: Taxonomy, methods, and future directions. *Review of General Psychology*, *8*(2), 78–99. https://doi.org/10.1037/1089-2680.8.2.78

Gazzola, P., Paterson, A., Amelio, S., & Ferioli, M. (2022). Certified B Corporations and Innovation: Crowdfunding as a tool for Sustainability. *Sustainability, 14*(24), 16639. https://doi.org/10.3390/su142416639

Hemanth, J. B., & Lakshminarayana, K. (2025, April). *AI and the evolution of IT startup ecosystems: A global perspective.* International Journal of Scientific Research in Engineering and Management, 8(1). https://doi.org/10.55041/IJSREM44391

Ioakeimidou, D., Chatzoudes, D., & Chatzoglou, P. (2024). Assessing data analytics maturity: proposing a new measurement scale. *Journal of Business Analytics*, 1–15. https://doi.org/10.1080/2573234x.2024.2439990

Jabeur, S., & Fahmi, Y. (2017). Forecasting financial distress for French firms: a comparative study. *Empirical Economics, 54*(3), 1173–1186. https://doi.org/10.1007/s00181-017-1246-1

Kato, T., Kamei, S., Ootsubo, T., & Ichiki, Y. (2023). More information is not better: examining appropriate information for estimating sales performance in concept testing. *Journal of Business Analytics*, *6*(3), 188–202. https://doi.org/10.1080/2573234x.2023.2167670

Kaya, M. C., & Persson, L. (2019). A Theory of Gazelle Growth: Competition, Venture capital finance and policy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3680711

Keogh, D., & Johnson, D. (2021). Survival of the funded: Econometric analysis of startup longevity and success. *Journal of Entrepreneurship Management and Innovation, 17*(4), 29–49. https://doi.org/10.7341/20211742.

Kim, M., Han, Y. S., & Cho, R. (2024). The role of cooperative R&D in innovation performance of SMEs: evidence from South Korean materials, parts, and equipment firms. *Asian Journal of Technology Innovation*, 1–26. https://doi.org/10.1080/19761597.2024.2349210

Kolodiziev, O., Gukaliuk, A., Shcherbak, V., Riabovolyk, T., Androshchuk, I., & Pas, Y. (2024). The impact of refugee startups on host country economies: business models and economic adaptation. *Economic Studies journal, Bulgarian Academy of Sciences - Economic Research Institute, 2,* 175-201. https://ideas.repec.org/a/bas/econst/y2024i2p175-201.html

Langfelder, P., & Horvath, S. (2008). WGCNA: an R package for weighted correlation network analysis. *BMC Bioinformatics, 9*(1). https://doi.org/10.1186/1471-2105-9-559

Liu, Y., Zeng, Q., Li, B., Ma, L., & Ordieres-Meré, J. (2022). Anticipating financial distress of high-tech startups in the European Union: A machine learning approach for imbalanced samples. *Journal of Forecasting*, *41*(6), 1131–1155. https://doi.org/10.1002/for.2852

LSM. (2025, February 1). *2025 predictions for the Latvian startup scene.* LSM.lv. https://eng.lsm.lv/article/economy/business/01.02.2025-2025-predictions-for-the-latvian-startup-scene.a586010/

Lu, Y. (2019). Bayesian assessment of predictors' contributions to variation in the predictive performance of a logistic regression model. *Journal of Business Analytics*, *2*(2), 134–146. https://doi.org/10.1080/2573234x.2019.1678400

Lutfiani, N., Wijono, S., Rahardja, U., & Purnomo, H. D. (2025). Advancing startup ecosystems through AI-Driven Matchmaking: A comprehensive bibliometric analysis. International Journal of Engineering Science and Information Technology, 5(1), 446–454. https://doi.org/10.52088/ijesty.v5i1.1095

McAdam, M., McAdam, R., Dunn, A., & McCall, C. (2015). Regional Horizontal Networks within the SME Agri-Food Sector: An Innovation and Social Network Perspective. *Regional Studies, 50*(8), 1316–1329. https://doi.org/10.1080/00343404.2015.1007935

Melegati, J., Goldman, A., Kon, F., & Wang, X. (2019). A model of requirements engineering in software startups. *Information and Software Technology, 109*, 92–107. https://doi.org/10.1016/j.infsof.2019.02.001

Murphy, K. (2012). *Machine Learning : A Probabilistic Perspective*. http://cds.cern.ch/record/1981503

O'Neill, M., & Brabazon, A. (2019). Business analytics capability, organisational value and competitive advantage. *Journal of Business Analytics*, *2*(2), 160–173. https://doi.org/10.1080/2573234x.2019.1649991

Palacín-Sánchez, M., & Di Pietro, F. (2015). The role of the regional financial sector in the capital structure of Small and Medium-Sized Enterprises (SMEs). *Regional Studies, 50*(7), 1232–1247. https://doi.org/10.1080/00343404.2014.1000290

Qin, H., Koong, K., Wen, H., & Liu, L. (2022). Mapping business analytics skillsets with industries: empirical evidence from online job advertisements. *Journal of Business Analytics*, *6*(3), 167–179. https://doi.org/10.1080/2573234x.2022.2136541

Quansah, E. (2024). Digitalization the necessary evil: integrating digital technologies in businesses of BOP countries. *Information Technology for Development*, 1–29. https://doi.org/10.1080/02681102.2024.2432890

Rupeika-Apoga, R. (2014). Alternative financing of SMEs in the Baltic States: myth or reality? *Procedia - Social and Behavioral Sciences, 156*, 513–517. https://doi.org/10.1016/j.sbspro.2014.11.231

Sivicka, J. (2018). Features of valuation of startup companies. *Economic Scope*, *0*(132), 163–174. https://doi.org/10.30838/p.es.2224.240418.163.60

Startup Estonia. (2023). Annual Report: Estonia's Startup Ecosystem. Retrieved from https://www.startupestonia.ee/annual-report

Startup Genome. (2025). *The Global Startup Ecosystem Report 2025*. https://startupgenome.com/report/gser2025/introduction

Startup Lithuania. (n.d.). Startup Lithuania. https://www.startuplithuania.com/

Stats and Market Insights. (2025b, January 15). *Lithuania startup ecosystem in 2025: A year of resilience and transformation.* Stats and Market Insights. https://www.statsandmarketinsights.com/blog/85/lithuania-startup-ecosystem-in-2025-a-year-of-resilience-and-transformation

Stats and Market Insights. (2025a, January 15). *Latvia startup ecosystem in 2025: A year of resilience and transformation.* Stats and Market Insights. https://www.statsandmarketinsights.com/blog/36/latvia-startup-ecosystem-in-2025-a-year-of-resilience-and-transformation

Sutherland, M., Thompson, D., & Edirisingha, P. (2019). Try before you buy: a small business employer (SME) perspective of international student mobility in England. *Studies in Higher Education, 46*(7), 1256–1271. https://doi.org/10.1080/03075079.2019.1680965

Teker, D., Teker, S., & Teraman, Ö. (2016). Venture Capital Markets: A Cross Country analysis. *Procedia Economics and Finance, 38*, 213–218. https://doi.org/10.1016/s2212-5671(16)30192-7

Tomczak, A., & Brem, A. (2013). A conceptualized investment model of crowdfunding. *Venture Capital, 15*(4), 335–359. https://doi.org/10.1080/13691066.2013.847614

Wahlstrøm, R., Becker, L., & Fornes, T. (2024). Enhancing credit risk assessments of SMEs with non-financial information. *Cogent Economics & Finance, 12*(1). https://doi.org/10.1080/23322039.2024.2418910

Wong, P., Ho, Y., & Autio, E. (2005). Entrepreneurship, Innovation and Economic Growth: Evidence from GEM data. *Small Business Economics, 24*(3), 335–350. https://doi.org/10.1007/s11187-005-2000-1

Wright, M., Westhead, P., & Ucbasaran, D. (2007). Internationalization of Small and Medium-sized Enterprises (SMEs) and International entrepreneurship: a critique and policy implications. *Regional Studies, 41*(7), 1013–1030. https://doi.org/10.1080/00343400601120288

Yaakobi, A., Goresh, M., Reychav, I., McHaney, R., Zhu, L., Sapoznikov, H., & Lib, Y. (2019). Organisational project evaluation via machine learning techniques: an exploration. *Journal of Business Analytics, 2*(2), 147–159. https://doi.org/10.1080/2573234x.2019.1675478

Valeriia Shcherbak is a Professor at the Department of Economic and Entrepreneurship, Sumy National Agrarian University, Ukraine, and also works at the Poltava University of Economics and Trade, Ukraine. She earned her Doctor of Economic Sciences degree in 2009 and received the academic title of Professor at V. N. Karazin Kharkiv National University, Ukraine. Her research focuses on sustainable rural development, digital transformation, inclusive economy, geoinformation platforms for tourism, and refugee integration during crises. She is the author of the textbook Marketing Distribution Policy and has published more than 300 scientific articles.

Oleksandr Dorokhov is a Visiting Professor at the Department of Public Economics and Policy, University of Tartu, Estonia. He earned his PhD in Technical Science from the Kharkiv National Automobile and Highway University, Ukraine. Until February 2022, he worked as a Professor of the Department of Information Systems at the Simon Kuznets Kharkiv National University of Economics, Ukraine. His research focuses on multicriteria decision support systems, computer modeling in economics, fuzzy logic, and modeling the functioning of startups and entrepreneurial ecosystems.

Kadri Ukrainski is a Professor in Research and Innovation Policy and Head of the Department of Public Economics and Policy, University of Tartu, Estonia. She earned her PhD from the Faculty of Economics and Business Administration at the University of Tartu, Estonia. Her research focuses on science and innovation policy, startups, high/deep-tech technologies, and the possibilities that public sector agents, such as universities, ministries, SOEs, and agencies, have to facilitate such processes in societies.

Deniss Djakons is a Professor and Rector at ISMA University of Applied Sciences, Latvia. He earned his Dr.oec (Doctor of Economics) degree and currently leads the institution while maintaining an active research profile. His scholarly work focuses on higher education financing, strategic management of territorial development, and the social responsibility of businesses in global supply chains. His publications particularly examine innovation policy, university development strategies, and comparative studies of education systems in transition economies.

Olha Kovalyova is an Associate Professor at the Department of Economics and Entrepreneurship, Sumy National Agrarian University, Ukraine. She earned her Ph.D. in Economics and specializes in agricultural economics and sustainable land management. Her research focuses on optimizing economic potential in agro-industrial sectors, sustainable fertilizer management, and innovative approaches to agricultural enterprise development. She has contributed significantly to studies on farmland evaluation, food security, and ecological-economic systems in agriculture.

Liudmyla Dorokhova is a Visiting Professor at the Department of Marketing, University of Tartu, Estonia. She earned her PhD in Pharmacy from the National University of Pharmacy, Ukraine. Until February 2022, he worked as a Professor at the Department of Marketing, National University of Pharmacy, Ukraine. Her research focuses on medical and healthcare startups, consumer behavior and choice, and decision-making models.

Poslovna analitika in digitalizacija kot gonili ocenjevanja startupov: izkušnje baltskih držav

Namen: Raziskava izhaja iz prepoznanega pomena startupov kot ključnih dejavnikov gospodarske rasti ter iz potrebe po razvoju učinkovitih metod za ocenjevanje njihove uspešnosti v razmerah tveganja in negotovosti. Glavni cilj je bil preučiti dejavnike, ki vplivajo na delovanje in uspešnost startupov, z uporabo faktorske in klastrske analize. Preizkušena je bila hipoteza, da uporaba napredne poslovne analitike pri ocenjevanju startupov prispeva k višji kakovosti investicijskega odločanja.
Metode: Raziskava temelji na kombinaciji kvantitativnih in kvalitativnih pristopov. Podatki o 20 startupih iz Latvije, Litve in Estonije v petletnem obdobju so bili obdelani z uporabo faktorske in klastrske analize. Za oceno nefinančnih kazalnikov sta bili uporabljeni strojno učenje in analiza sentimenta na družbenih omrežjih.
Rezultati: Ugotovitve kažejo, da so kazalniki, kot so predvidena dobičkonosnost, aktivnost na družbenih medijih in stopnja inovativnosti, ključni pri razvrščanju startupov. Delež uporabe tradicionalnih metod v baltskih državah znaša 55 %, medtem ko sodobna orodja predstavljajo 45 %, kar poudarja vlogo digitalizacije pri ocenjevanju tveganj. Startupi z visokimi koeficienti klastriranja in pozitivnim razpoloženjem omemb so izkazali nadpovprečne rezultate.
Sklepne ugotovitve: Ugotovitve raziskave potrjujejo, da integracija poslovne analitike in digitalizacije bistveno izboljšuje zanesljivost ocenjevanja startupov. Razvit model, ki združuje finančne kazalnike z mrežno in sentimentno analizo, predstavlja celovit okvir za investitorje in omogoča zmanjševanje investicijskih tveganj ter učinkovitejše strateško odločanje. Potrjeno je bilo, da podatkovno podprti pristopi izboljšujejo kakovost odločanja in zmanjšujejo investicijska tveganja.

Ključne besede: *Start-up podjetja, Poslovna analitika, Digitalna transformacija, Ocenjevanje uspešnosti, Baltske države, Investicijska tveganja*

Appendix: Data about startups

Startup	Country	Projected profitability, M$	Activity in social net-works, ths. subscribers	Avail-ability of investors, number	Innovativeness of technologies, scores 1-10	Basic level of social respon-sibility, score 1-10	Number of links, node degree	Cluster coefficient	Betweenness centrality	Number of mentions	Senti-ment of mentions	Total Raised, M$	Total Raised, M$	Number of em-ployees, ths. of people
		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
Vinted	Lithuania	2	5	2	8	7	10	0,60	50	100	60	677,54	12	1
Mapon	Latvia	5	10	5	9	9	15	0,80	100	200	150	3	2996	0,1
Tuum	Estonia	1	2	1	6	6	5	0,40	20	50	20	49,82	202	0,1
Green Genius	Lithuania	3	7	3	7	8	12	0,70	70	150	100	109,8	193	0,2
Origin	Latvia	4	9	4	8	7	14	0,75	90	180	120	4,35	3478	0,2
Sunly	Estonia	6	12	6	9	8	18	0,85	120	250	180	364,84	206	0,2
BoBo	Lithuania	0,5	1	0	5	5	3	0,20	5	20	-10	7,01	803	0,01
Aerones	Latvia	2,5	6	2	7	6	9	0,55	40	90	50	12,01	4617	0,25
Bolt	Estonia	7	15	7	10	9	20	0,90	150	300	220	1015,71	45	5
Ovoko	Lithuania	1,5	3	1	6	7	7	0,45	30	70	30	22,2	917	0,2
Roibox	Latvia	3,5	8	3	8	8	13	0,72	80	160	110	3,29	56,01	0,05
eAgronom	Estonia	5,5	11	5	9	9	17	0,82	110	230	160	13,19	704	0,5
Biomatter	Lithuania	0,8	1,5	0	4	6	4	0,30	10	30	-5	7,2	1144	0,05
Sonar-works	Latvia	2,8	6,5	2	7	7	11	0,65	60	110	70	5,6	6886	0,01
Binalyze	Estonia	6,5	13	6	9	8	19	0,88	130	270	190	30,81	553	0,1
Nord Security	Lithuania	1,2	2,5	1	5	6	6	0,35	25	60	15	100	1144	5
Naco	Latvia	4,2	9,5	4	8	7	15	0,78	95	190	130	1,65	6886	0,01
Veriff	Estonia	5,8	11,5	5	9	8	18	0,84	115	240	170	184,62	639	1
PVcase	Lithuania	0,7	1,2	0	4	5	3	0,25	8	25	-8	100,35	1452	0,25
Cenos	Latvia	3,2	7,5	3	7	6	12	0,68	65	130	80	1,47	7742	0,05

Source: https://www.seedtable.com/best-startups-in-lithuania; https://www.seedtable.com/best-startups-in-latvia; https://www.seedtable.com/best-startups-in-estonia

DOI: 10.2478/orga-2025-0023

Navigating Success: How Decision–Making Transforms Software Performance into Business Performance in the Logistics Industry from an Emerging Country

Bükra DOĞANER DUMAN[1], Gültekin ALTUNTAŞ[2]

[1] Istanbul University, Institute of Social Sciences, Transportation and Logistics Management Program, Central (Beyazit) Campus, Fatih, Istanbul, Türkiye, bukra.doganer@ogr.iu.edu.tr

[2] Istanbul University, Faculty of Transportation and Logistics, Department of Logistics, Central (Beyazit) Campus, Fatih, Istanbul, Türkiye, altuntas@istanbul.edu.tr

Background/Purpose: This study investigates the mediating role of decision–making performance in the link between software performance and overall business performance in the logistics sector of an emerging economy. As logistics companies increasingly rely on digital infrastructures, understanding how advanced systems contribute to strategic outcomes is critical for sustaining competitiveness.
Methods: A conceptual framework was developed integrating ERP systems, big data analytics, and IoT applications. In this model, software performance is positioned as the independent variable, decision–making performance as the mediator, and business performance as the dependent variable. Data were collected from medium- and large–scale logistics firms and analyzed using regression and bootstrapping methods through SPSS and the PROCESS Macro.
Results: The findings reveal that software performance significantly improves decision–making performance (β = 0.552, $p < 0.01$), which in turn has a strong positive effect on business performance (β = 0.817, $p < 0.01$). The mediation analysis confirms that decision–making performance mediates the effect of software performance on business outcomes.
Conclusion: The results highlight the strategic importance of aligning digital capabilities with organizational decision processes. By demonstrating the mediating role of decision–making, the study highlights that the effective use of advanced analytical tools is crucial for optimizing performance and achieving a sustainable competitive advantage in logistics.

Keywords: *Software performance, Decision–making performance, Business performance, TMS systems, Logistics industry, Emerging economy*

1 Introduction

In today’s highly competitive business environment, it is recognized that sustainable growth and competitive advantage depend not only on financial resources but also on effective, timely decision–making at both strategic and operational levels to respond to environmental uncertainties, competitive pressure, and technological changes. Un-

Received: 4th April 2025; Accepted: 3rd October 2025

der uncertain and volatile market conditions, the capacity to make accurate, fast, and flexible decisions is considered a decisive factor for both daily operations and long–term strategic positioning (James & Mark, 1996; Chatterjee et al., 2023). Decision–making performance is closely linked to a business's ability to respond to environmental uncertainties, competitive pressures, and technological disruptions, thereby driving organizational agility, sustainable competitive advantage, and overall business performance (Grover et al., 2018; Wang et al., 2016; Baum & Wally, 2003).

The decision–making process is operationalized as involving problem identification, data collection, evaluation of alternatives, decision execution, and feedback mechanisms (Sauter, 2014). Its effectiveness is dependent upon decision–makers' analytical capabilities, real–time access to quality data, and the supporting technological infrastructure. Business systems – including ERP, Decision Support Systems (DSS), and Business Intelligence (BI) – are employed to integrate vast amounts of structured and unstructured data, thereby enhancing analytical capacity and decision accuracy (Hopkins & Hawking, 2018; HassabElnaby et al., 2011).

A shift is observed from intuition–based decision models to data–driven, predictive analytics–driven approaches, which substantially improve both decision quality and business performance (Chatterjee et al., 2023; McAfee & Brynjolfsson, 2017). Central to this transformation are ERP systems that integrate data across departments, providing decision–makers with real–time insights, predictive analytics, and scenario–based forecasting tools (Carton & Adam, 2010; Ouiddad et al., 2020).

Within the logistics industry, ERP and Transportation Management Systems (TMS) are utilized to optimize decision–making for supply chain coordination, fleet management, and order fulfillment (Wang et al., 2016; Mishra et al., 2023). Given the complex and dynamic nature of logistics operations, fast and accurate decision–making is deemed essential for ensuring on–time deliveries, reducing costs, and maintaining customer satisfaction (Dubey et al., 2021a). TMS is further enhanced by the integration of AI, IoT, and geospatial analytics, which facilitate real–time tracking, demand forecasting, automated routing, personalized service offerings, and predictive maintenance (Hopkins & Hawking, 2018; Goswami et al., 2025).

It is argued by Carton and Adam (2010) that while real–time data processing via ERP and TMS improves decision speed, the overall effectiveness depends on the quality of data integration and system responsiveness. Similarly, Ouiddad et al. (2020) and HassabElnaby et al. (2011) report that ERP systems significantly enhance decision-making accuracy. However, they may yield mixed effects on decision speed, particularly when manual data processing or offline data warehouses are involved.

The integration of DSS with ERP and TMS is implemented as a strategic response to these limitations, enabling the generation of customized reports, AI–driven recommendations, and scenario analysis to optimize both the speed and accuracy of strategic decision–making (Alake et al., 2025; Chatterjee et al., 2023). Moreover, the emergence of Big Data analytics and Machine Learning is employed to enhance decision–making performance through predictive modeling and prescriptive analytics, thereby allowing businesses to anticipate disruptions and make proactive adjustments (Wang et al., 2016).

While prior studies have confirmed the operational and financial benefits of ERP and TMS (Akkermans et al., 2003; Gattiker & Goodhue, 2005; Hendricks et al., 2007), the underlying mechanisms through which these systems create business value remain ambiguous. Scholars have increasingly emphasized that enterprise systems do not automatically lead to superior business performance; instead, their value is realized through organizational capabilities that mediate this relationship (Wade & Hulland, 2004; Mithas et al., 2011). Within such mediators, decision-making performance is recognized as a critical channel that translates technological capabilities into strategic and operational success by improving decision speed, accuracy, and flexibility. However, empirical evidence on this mediating effect remains limited, particularly in the logistics industry, where digital adoption is uneven and businesses often struggle with operational inefficiencies (Gunasekaran et al., 2017; Dubey et al., 2021b). This gap is significant because logistics operations are highly dynamic and vulnerable to fluctuations in demand, cost pressures, and disruptions, making effective decision-making a crucial element in competitiveness. By examining the mediating role of decision-making performance, this study aims to enhance our understanding of how TMS impacts business performance. In doing so, it not only provides theoretical contributions to the literature on enterprise systems and performance alignment but also offers practical insights for managers in emerging economies who must maximize returns from digital investments under conditions of uncertainty (Tallon, 2008; Liang et al., 2010).

Despite these advancements, it is acknowledged that the effectiveness of decision–making performance in driving improved operational efficiency, enhanced decision-making capabilities as well as business success is contingent upon several contextual factors, including organizational alignment, user training, system customization (Nicolaou, 2004), rigid system structures, resistance to change, managerial support, process reengineering, cultural adaptation (Bahrami & Jordan, 2009), business data literacy, system interoperability, and leadership adaptability (Grover et al., 2018). The enhanced decision accuracy and real–time analytics provided by ERP and TMS are realized only when decision–makers are equipped to leverage these insights effectively.

This study examines the multifaceted effects of TMS software on decision–making performance in logistics, investigating how decision speed, accuracy, and flexibility influence overall business performance. It is anticipated that the findings will contribute to an improved understanding of how digital decision–making frameworks translate into competitive advantage, particularly in emerging economies where logistics inefficiencies persist.

2 Literature Review

Enterprise Resource Planning (ERP) systems have been integral to organizational decision–making processes for the past two decades. Existing literature highlights their significant role in improving decision accuracy and enhancing decision–making speed, as presented in Table 1. However, empirical findings on these performance dimensions are inconsistent and sometimes contradictory. While some studies suggest that ERP systems facilitate faster and more accurate decision–making by integrating real–time data and streamlining information flow, others indicate that complex system architecture, data integration challenges, and issues related to user adaptability may hinder decision efficiency. This divergence in findings highlights the need for a more nuanced examination of how ERP systems impact decision–making performance across various business contexts. Consequently, the subsequent subsections delve deeper into the various components of decision–making.

Table 1: The Effects of ERP Systems on Decision–Making Performance

Theme	Findings	Impact Area	Supporting Studies
Information Quality	ERP systems enhance information accuracy and completeness, improving decision–making accuracy.	Decision Accuracy	HassabElnaby et al. (2011); Ouiddad et al. (2020)
System Quality	ERP system design and user-friendliness improve decision–making quality.	Decision Accuracy	Ouiddad et al. (2020)
Integration Challenges	Poor integration of ERP with other systems may negatively affect both decision accuracy and speed.	Decision Accuracy and Speed	Carton & Adam (2010)
Reality Distortion	ERP may sometimes distort organizational reality, leading to inaccurate decisions.	Decision Accuracy	Carton & Adam (2010)
Real–Time Data Access	ERP aims to increase decision speed through real–time data access, though this is not always achieved.	Decision Speed	Carton & Adam (2010)
Manual Data Integration	The need for manual data gathering from non–ERP systems may slow down decision–making.	Decision Speed	Carton & Adam (2010)
Strategic Fit	ERP contributes positively to decision–making and financial performance when aligned with prospector strategies.	Strategic Decision Performance	HassabElnaby et al. (2011)
Organizational Capabilities	ERP enhances organizational capabilities, improving the quality of decision-making and flexibility.	Strategic Decision Performance	HassabElnaby et al. (2011)
Financial Performance	ERP indirectly enhances financial performance through improved decision quality and organizational capabilities.	Outcome (Indirect Effect)	Wier et al. (2007)
BI (Business Intelligence) Integration	Integrating ERP with BI systems further enhances decision–making accuracy and speed.	Decision Accuracy and Speed	Hou & Papamichail (2010); Ouiddad et al. (2018)
ERP's Role in Logistics Decision–Making	ERP systems support logistics decision–making by integrating real–time data; however, system complexity may slow response times.	Decision Speed and Accuracy	Alake et al. (2025); Carton & Adam (2010)
Advanced Analytics & Big Data	The integration of ERP with big data analytics enhances decision–making performance by improving predictive capabilities.	Decision Accuracy and Strategic Impact	Chatterjee et al. (2023); Wang et al. (2016)
Process Optimization & Digitalization	ERP enables process transparency, facilitating better data–driven decision-making in logistics.	Decision Quality and Speed	Hopkins & Hawking (2018)

Source: Authors' work

3 Impact on Decision Accuracy

Several studies emphasize that ERP systems significantly enhance decision–making accuracy. It is demonstrated that information systems play a critical role in improving both analytical capacity and decision quality (Pilepić & Šimunić, 2009) and the integrated, high–quality information infrastructure provided by ERP systems enables decision–makers to access more complete, accurate, and up–to–date information, thereby improving both strategic and tactical decision accuracy (HassabElnaby et al., 2011; Ouiddad et al., 2020). HassabElnaby et al. (2011) show that ERP systems enhance organizational capabilities, indirectly improving business performance, while Ouiddad et al. (2020) find that information and system quality directly contribute -by providing decision-makers with real-time, reliable, and comprehensive data, establishing a strong link between internal processes and strategic objectives (Kumar & Van Hillegersberg, 2000)- to decision quality. Bernroider and Koch (1999) reveal that ERP systems broaden the scope and consistency of decision evaluations.

Recent advancements in Big Data analytics are also shown to enhance decision accuracy within ERP systems. Big Data analytics enables decision–makers to process vast amounts of data from multiple sources, thereby improving forecasting and strategic decision–making (Chatterjee et al., 2023). Moreover, the integration of ERP with Decision Support Systems (DSS) further improves decision quality by providing real–time insights and predictive analytics (Alake et al., 2025). In addition, IoT–enabled logistics are found to further enhance decision accuracy by offering real–time visibility into supply chain and operational performance, thereby enabling timely and precise decisions (Goswami et al., 2025; Mishra et al., 2023).

4 Impact on Decision–Making Speed

The impact of ERP systems on decision–making speed remains a debated topic. Some studies argue that ERP systems accelerate decision–making through real–time data access (Carton & Adam, 2010), whereas others report that this effect is context–dependent and sometimes limited by integration challenges. Carton and Adam (2010) find that despite the promise of faster decisions, delays may occur due to offline data warehouses, manual data integration, and system complexity. Furthermore, excessive data availability may increase the cognitive load on decision–makers, potentially leading to decision paralysis (Carton & Adam, 2010). In the logistics industry, where dynamic, fast–paced environments demand instant yet accurate decisions, the integration of AI–driven analytics and IoT–enabled data streams with ERP is proposed to mitigate delays by automating routine decisions and prioritizing high–impact areas (Hopkins & Hawking, 2018). Grover et al. (2018) further indicate that Big Data analytics enables proactive strategy adjustments based on real–time insights, while AI–driven decision support minimizes human biases and accelerates decision–making (Wang et al., 2016).

5 ERP and Organizational Capabilities

It is suggested that the impact of ERP systems on decision–making performance is not solely technical but is significantly influenced by organizational capabilities. HassabElnaby et al. (2011) emphasize that ERP systems indirectly improve decision quality by enhancing organizational capabilities, especially in businesses pursuing innovative and agile strategies. Conversely, businesses that do not adapt their business processes to ERP functionalities may experience suboptimal decision performance. Wier et al. (2007) report that ERP systems indirectly affect financial performance through improved decision–making efficiency and strategic agility, highlighting the need for complementary managerial competencies, a data–driven culture, and continuous system optimization.

6 ERP and Decision Support Systems (DSS)

Decision Support Systems (DSS) are shown to play an integral role in enhancing the decision–making capabilities of ERP systems. Alake et al. (2025) note that when DSS are integrated with ERP systems, decision accuracy and speed are substantially improved through the provision of customized, real–time reports that facilitate rapid, informed decisions. In logistics, DSS helps managers prioritize tasks, allocate resources efficiently, and optimize delivery routes for maximum efficiency. Moreover, the combination of Big Data analytics and DSS within ERP frameworks has considerable potential for enabling data–driven decision-making in supply chain management, allowing for more informed and timely decisions in volatile market environments (Dubey et al., 2021a).

7 ERP–Business Intelligence (BI) Integration and Supporting Systems

Another critical element in enhancing decision–making is the integration of ERP with Business Intelligence (BI) systems. ERP systems alone may not suffice; when integrated with BI tools, decision–making performance is further enhanced by enabling advanced data analysis and visualization (Hou & Papamichail, 2010). Ouiddad et al. (2018) emphasize that ERP–BI integration has become increasingly important for improving decision quality by leveraging historical data, identifying patterns, and generating actionable insights. BI–driven ERP systems are also found to improve decision speed by automating routine analyses, reducing reliance on manual data processing, and providing real–time dashboards for executives. In logistics, ERP–BI integration is demonstrated to optimize fleet management, route planning, and supply chain coordination, ultimately enhancing decision efficiency and operational resilience (Chatterjee et al., 2023; Wang et al., 2016). As businesses in emerging economies navigate infrastructural and logistical complexities, leveraging ERP–BI analytics is considered a strategic differentiator for decision–making effectiveness.

8 Research Model and Hypotheses

The primary objective of this study is to investigate whether the impact of software performance on business performance is mediated by decision–making performance. In this research, software performance is conceptualized as the independent variable (X), decision–making performance as the mediating variable (M), and business performance as the dependent variable (Y). The research model is grounded in a conceptual framework widely adopted in the literature, emphasizing the relationship between decision–making capabilities and business performance (Lee et al., 2011; Rosemann & de Bruin, 2004; Tallon, 2008). Furthermore, the model posits that, in addition to the direct effect of software performance on business performance, there exists an indirect effect mediated by decision–making performance.

The research model of this study is presented in Figure 1. Within this framework, the following hypotheses are tested:

H1: Software performance has a positive and significant effect on decision–making performance.

H2: Decision-making performance has a positive and significant effect on business performance.

H3: Software performance has a direct positive and significant effect on business performance.

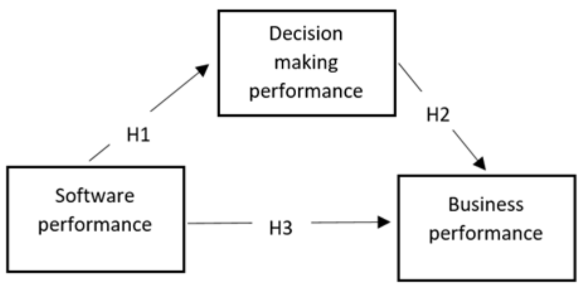
H4: The effect of software performance on business performance is significant through decision-making performance indirectly.

9 Research Population and Sample

The population of this study comprises medium- and large–scale logistics companies operating in Turkey. Data are collected using a convenience sampling method from businesses that actively utilize the Transportation Management System (TMS) software. To identify the sampling frame, a survey is conducted among middle and senior managers working in the logistics, operations management, and information systems departments. Out of 182 distributed surveys, 124 valid responses are obtained, yielding a response rate of 68,1%.

As part of the research, questionnaire forms are distributed to employees working in logistics companies. A total of 126 completed questionnaires are included in the analysis, after adjusting for both positive and negative statements, ensuring no data deficiencies. Only two responses do not provide answers to the questions concerning the business for which they work.

The descriptive statistics presented in Table 2 reveal that many participants (49.2%) are employed in medium–sized businesses, with nearly half (54.8%) working in businesses with an annual financial balance exceeding 100 million TL. The participants are predominantly in the 26–35 (35,7%) and 36–45 (30,2%) age brackets. Most participants hold at least a bachelor's degree (62,7%), while 18,3% have completed postgraduate education. In terms of professional background, a substantial proportion of participants have significant experience, with 42,1% possessing over 12 years of industry–specific experience and 40.5% having more than 12 years of professional experience. Overall, the sample is characterized by a predominance of experienced professionals working in medium to large–scale businesses.



Source: Authors' work

Figure 1: Proposed Research Model

Table 2: Demographic and Organizational Profile of the Respondents

Variable	Categories	Frequency	Percentage (%)
Business Size	Micro	11	8,7
	Small	15	11,9
	Medium	62	49,2
	Large	17	13,5
	Very Large	21	16,7
Annual Financial Balance	< 10 million TL	15	11,9
	10–100 million TL	27	21,4
	100–500 million TL	36	28,6
	> 500 million TL	33	26,2
Age	18–25	22	17,5
	26–35	45	35,7
	36–45	38	30,2
	46–55	20	15,9
	56+	1	0,8
Education Level	Associate	24	19,0
	Bachelor	79	62,7
	Master	21	16,7
	Doctorate	2	1,6
Industrial Experience	< 3 years	24	19,0
	3–6 years	23	18,3
	6–9 years	14	11,1
	9–12 years	12	9,5
	>12 years	53	42,1
Professional Experience	< 3 years	22	17,5
	3–6 years	25	19,8
	6–9 years	15	11,9
	9–12 years	13	10,3
	>12 years	51	40,5

Source: Authors' work

10 Measurement Instruments and Variables

The measurement scales used in this study are developed based on established literature and adapted into Turkish. Each construct is operationalized as a multidimensional conceptual structure and measured using a five–point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree in accordance with the following explanations:

a) Software Performance: Measured through 5 factors comprising 16 items, covering service, technological competence, functionality, software vendor performance, and cost (Doğaner Duman & Altuntaş, 2024).

b) Decision–Making Performance: Measured through several dimensions, including coherence of case analysis, strategic planning, decision effectiveness, analysis capability, rapid decision making, access to information, rapid identification of problems and opportunities, and coordination between units (Gable, Sedera, & Chan, 2008; Huber, 1990; McLaren et al., 2011; Mithas et al., 2011; Tippins & Sohi, 2003; Aydıner, 2016).

c) Business Performance: Measured through indicators such as return on investment, employee productivity, customer complaint response time, market share, sales volume, customer satisfaction, growth rate, profitability, service/product cost, and number of customers (Vickery, 1993; King & Zeithaml, 2001; Rosenzweig, 2003).

11 Validity and Reliability

The test of normality is conducted using skewness and kurtosis values as benchmarks. The fact that the skewness and kurtosis values for the scales remain within ±1,5 (Tabachnick & Fidell, 2013) or ±2,0 (George & Mallery, 2010) indicates that the data are normally distributed. Given that the skewness coefficients for the model's dimensions ranged from -1.439 to -0.941, and the kurtosis values ranged from 0.907 to 1.375, both falling within the acceptable thresholds, parametric tests can be appropriately applied in the subsequent analyses of these dimensions.

The dataset's suitability for factor analysis is assessed using the Kaiser–Meyer–Olkin (KMO) Test and Bartlett's Test of Sphericity. KMO values above 0,50 and statistically significant Bartlett's Test results ($p < 0{,}01$) are required for adequacy (Altuntaş et al., 2020). As presented in Table 3, all scales demonstrate superb sampling adequacy (KMO > 0,90), and Bartlett's Test confirms significant intercorrelations ($p < 0{,}01$), validating the dataset's suitability for factor analysis.

The exploratory factor analysis reveals a three–factor structure of the latent construct, as presented in Table 4. The first factor predominantly includes indicators related to software performance, the second factor aggregates metrics reflecting process performance, and the third factor encompasses variables related to business performance. A significant proportion of standardized factor loadings ($\lambda \geq 0{,}50$) exceeds conventional psychometric thresholds, indicating strong item–construct alignment. This empirical configuration supports the triadic measurement model proposed by existing theoretical frameworks. In addition, inter–factor correlations remain within acceptable psychometric limits ($\Delta\lambda < 0{,}30$), confirming discriminant validity across the latent constructs. Convergent validity is verified through average variance extracted (AVE) values greater than 0,50, and discriminant validity is further validated using the Fornell–Larcker criterion (Hair et al., 2019). The Confirmatory Factor Analysis (CFA) confirms that the model has a three–factor structure, with fit indices under acceptable thresholds ($\chi 2$ / df = 2.36, CFI = 0.94, TLI = 0.92, RMSEA = 0.062, and SRMR = 0.048).

Reliability is crucial for ensuring the validity of measurements. The internal consistency of the scales used to measure software, process, and business performance is assessed using both Composite Reliability (CR) and Cronbach's alpha coefficients, as shown in Table 4. All dimensions demonstrate exceptional reliability, with CR and Cronbach's alpha values exceeding 0.90 and 0.95, respectively, for all sub-dimensions. These values exceed the threshold for internal consistency as outlined by Nunnally and Bernstein (1994) and surpass the acceptable limits set by George and Mallery (2003), where values below 0.50 are considered inadequate. Therefore, the scales are deemed reliable and retained for further analysis.

Table 3: KMO and Bartlett's Test Results

Variable	KMO Value	Chi–Square	Bartlett's Test (p)
Software Performance	0,903	1138,49	Significant (p < 0.01)
Decision–Making Performance	0,924	1218,94	Significant (p < 0.01)
Business Performance	0,934	1285,57	Significant (p < 0.01)

Source: Authors' work

Table 4: Standardized Factor Loadings and Cronbach's Alpha, AVE, and CR Values of Factors

No.	Construct	Item	Standardized Factor Loadings	Cronbach's Alpha	Average Variance Explained (AVE)	Composite Reliability (CR)
1	**Software Performance**			0,964	0,659	0,892
		SoftPerf3	0,860			
		SoftPerf5	0,790			
		SoftPerf2	0,780			
		SoftPerf1	0,770			
		SoftPerf4	0,749			
2	**Decision–Making Performance**			0,967	0,568	0,913
		DMPerf6	0,801			
		DMPerf7	0,800			
		DMPerf8	0,787			
		DMPerf3	0,754			
		DMPerf2	0,746			
		DMPerf1	0,740			
		DMPerf5	0,731			
		DMPerf4	0,660			
3	**Business Performance**			0,952	0,656	0,927
		BusPerf5	0,842			
		BusPerf2	0,826			
		BusPerf4	0,765			
		BusPerf12	0,762			
		BusPerf6	0,734			
		BusPerf8	0,693			
		BusPerf7	0,689			
		BusPerf3	0,683			
		BusPerf2	0,672			
		BusPerf9	0,603			
		BusPerf10	0,598			
		BusPerf11	0,497			

Source: Authors' work

12 Data Analysis Method

Hypothesis testing and mediation analysis are performed using SPSS 28 and the PROCESS Macro v4.0 (Hayes, 2022), a robust statistical tool designed for path analysis and mediation modeling. Model 4 of the PROCESS Macro is applied to simultaneously test the direct effect of software performance on business performance, as well as the indirect effect mediated by decision–making performance. This methodology aligns with current best practices for examining complex interrelationships in business research (Zhao et al., 2023).

13 Findings

Before mediation modeling, a Pearson correlation analysis is done, as presented in Table 5. The results reveal statistically significant and positive relationships ($p < 0.01$) between all variables. A strong positive correlation is observed between software performance and decision–making performance ($r = 0.800$, $p < 0.01$), as well as between decision–making performance and business performance ($r = 0.654$, $p < 0.01$). These findings suggest that decision–making performance is significantly related to overall business success. In addition, the correlation coefficient between software performance and business performance ($r = 0.722$, $p < 0,01$) is relatively stronger, indicating that the impact of software performance on business performance may be mediated indirectly through decision–making performance.

Following Pearson correlation, to assess the mediation effect, the bias-corrected bootstrap method is employed using 5,000 resamples and 95% confidence intervals (CIs), incorporating the lower limit confidence interval (LLCI) and upper limit confidence interval (ULCI). This non-parametric approach is favored over conventional techniques, such as the causal steps method proposed by Baron and Kenny (1986) and the Sobel test, as it relaxes the assumption of normality and enhances statistical power, particularly in studies with small to moderate sample sizes (Gürbüz, 2019a; Gürbüz, 2019b; Hayes, 2022). The bootstrap method is especially beneficial in the context of emerging economies – such as Türkiye's logistics industry – where diverse business practices and infrastructural limitations may lead to deviations from normal data distributions.

A regression analysis is conducted to test the hypotheses of the mediation model based on Model 4 – Simple Mediation Model, as outlined by Hayes (2022). This model incorporates a mediator variable, examining both direct and indirect effects. To examine the mediation relationships in this study, a regression analysis using the bootstrap method is employed (Gürbüz, 2019a; Gürbüz, 2019b). All analyses are performed using Hayes' (2022) PROCESS Macro, with the bootstrap technique applied using 5.000 resamples. For statistical significance, the obtained 95% confidence intervals should not include zero (0) (Gürbüz, 2019a; Gürbüz, 2019b).

For the analysis model presented in Table 6, the effect of software performance on decision–making performance (path a) is found to be statistically significant and positive ($\beta = 0.0552$, 95% CI = [0.7095, 0.9281], $p < 0.00$). Software performance accounts for approximately 63% of the variance in decision–making performance. Similarly, the results indicate that decision–making performance has a statistically significant and positive effect on overall business performance (path b) ($ß = 0,817$, 95% CI = [0,2811, 0.6047], $p < 0,00$).

Table 5: Pearson Correlation Analysis Results

No.	Variable	Arithmetic Mean	Standard Deviation	1	2	3
1	**Software Performance**	3,771	1,080	1,00		
2	**Decision–Making Performance**	3,859	1,508	0,800*	1,00	
3	**Business Performance**	3,514	0,886	0,654*	0,722*	1,00

Source: Authors' work

Table 6: Results of the Mediation Model between Variables

Variable				
	Decision-Making Performance (Mediator)		**Business Performance**	
		%95 CI		**%95 CI**
Model	**ß / SE**	**LLCI/ULCI**	**ß / SE**	**LLCI/ULCI**
Software Performance	0,0552	0,7095 / 0,9281	0,0837	0,0078 / 0,3392
Decision-Making Performance (Mediator)	–	–	0,817	0,2811 / 0,6047
Constant	0,2166	0,3415 / 1,1988	0,2069	0,7471 / 1,5609
Model Summary	*$R^2 = 0,6394$*		*$R^2 = 0,5378$*	
	F = 219,8737	*p = 0,000*	*F = 71,5659*	*p=0,000*

Source: Authors' work

Table 7: Mediation Effect Results of Decision–Making Performance

Direct Effect								
			Effect	***S. H.***	***LLCI***	***ULCI***	***t***	***p***
Software Performance	**Business Performance**		0,1735	0,0837	0,0078	0,3392	2,0727	0,00
Indirect Effect								
Software Performance	**Process Performance**	**Business Performance**	0,3626	0,0841	0,1591	0,4970		
Total Effect			0,5361	0,557	0,4259	0,6464	9,6229	0,00

The analysis results reveal that the effect of TMS software performance on overall business performance is mediated by decision–making performance. The bootstrap analysis, conducted to assess whether decision–making performance mediates the relationship between software performance and overall business performance, indicated a significant mediation effect. Since the 95% confidence interval obtained through the bootstrap method does not include zero (0), it is concluded that decision–making performance plays a significant mediating role in the relationship between software performance and overall business performance.

The mediation analysis results, as presented in Table 7, indicate that the direct effect of software performance on overall business performance ($\beta = 0.1735$, 95% CI [0.0078, 0.3392]) is positive and statistically significant ($p < 0.01$). Furthermore, the indirect effect of software performance on overall business performance, mediated through decision–making performance ($\beta = 0.3626$, 95% CI [0.1591, 0.4970]), is also positive and statistically significant ($p < 0.01$). The total effect of software performance on overall business performance, combining both direct and indirect effects ($\beta = 0.536$, 95% CI [0.4259, 0.6464]), is likewise positive and statistically significant ($p < 0.01$). These findings suggest that enhancing the effectiveness of TMS systems software results in a more substantial impact on overall business performance by improving decision–making processes.

14 Conclusion, Limitations, Future Research Directions, and Recommendations

This study examines the impact of software performance on decision–making performance and overall business performance in logistics companies, with a particular focus on the mediating role of decision–making performance. The findings demonstrate that software performance has a significant influence on business performance through both direct and indirect pathways. A robust positive relationship is observed between software performance and decision–making performance ($\beta = 0.0552$, 95% CI = [0.7095, 0.9281], $p < 0.01$), with software performance enhancing the quality, accuracy, and speed of the decision–making process. This supports the view that systems such as ERP and TMS facilitate faster and more accurate decisions by providing integrated information, real–time data access, and advanced analytical capabilities (Hou & Papamichail, 2010; HassabElnaby et al., 2011). Furthermore, the integration of big data analytics strengthens these outcomes by improving forecasting and decision accuracy (Chatterjee et al., 2023; Wang et al., 2016).

A key finding is that decision–making performance significantly mediates the effect of software performance on overall business performance. This aligns with the findings of Carton and Adam (2010) and Ouiddad et al. (2020), who emphasize that software systems, such as ERP, primarily contribute to business performance through their impact on decision–making processes. The identified indirect effect suggests that the influence of software performance on overall business performance is more pronounced when mediated by decision–making performance. Given the dynamic and complex structure of the logistics industry, these findings underscore the crucial role of effective decision–making processes in achieving business success. IoT–enabled analytics in logistics (Hopkins & Hawking, 2018) further reinforce the capacity for real–time decision–making and operational agility.

Further analysis reveals that decision–making performance has a substantial and statistically significant impact on business performance ($\beta = 0.817$, 95% CI = [0.2811, 0.6047], $p < 0.00$). This indicates that, particularly in decision–intensive areas such as order management, transportation planning, fleet optimization, and customer service, the effectiveness of decision–making processes directly affects performance indicators, including cost efficiency, customer satisfaction, and operational effectiveness (Alake et al., 2025).

Overall, the study supports existing literature by confirming that software performance enhances business performance through decision–making processes, particularly within the logistics industry. It validates the frequently discussed notion that ERP and similar systems function not only as technical tools but also as integral components of organizational decision–making frameworks (Tallon, 2008; Hou & Papamichail, 2010). Moreover, by integrating big data analytics, businesses can better forecast trends and mitigate risks, ultimately strengthening their competitive position (Chatterjee et al., 2023; Wang et al., 2016).

The findings suggest that logistics companies should not focus solely on improving software performance but also ensure that software systems are effectively integrated with decision–making processes. Managers should structure systems, such as ERP and TMS, to support and enhance decision–making capabilities. Furthermore, integrating complementary tools – such as Decision Support Systems (DSS) and Business Intelligence (BI) – with ERP can further enhance both the quality and speed of decision-making.

The results indicate that the contribution of enterprise software to business performance should be understood primarily through the lens of decision-making performance rather than as a direct and unconditional outcome of system use. This finding is consistent with the broader enterprise systems literature, which has long emphasized that information systems yield business value through organizational capabilities and contextual mechanisms rather than in isolation (Wade & Hulland, 2004; Mithas et al., 2011). By empirically demonstrating the mediating role of decision-making performance, the study advances this stream of research. It provides robust evidence that decision quality, accuracy, and speed are the primary channels through which software investments in the logistics industry translate into measurable improvements in business performance. These insights reinforce the relevance of theoretical perspectives such as the resource-based view and the dynamic capabilities framework, which argue that organizational performance stems not from technology itself but from the business's ability to reconfigure and integrate technology into core processes (Tallon, 2008; Liang et al., 2010).

From a practical standpoint, the findings highlight that logistics businesses should not evaluate ERP and TMS projects merely as operational tools but as strategic enablers of organizational agility and competitiveness. Investments in software performance must be complemented by initiatives that enhance decision-making capabilities, such as training programs, data governance structures, and the integration of advanced analytics tools. Furthermore, the results underline that businesses in dynamic and uncertain environments—such as logistics providers—are more likely to achieve sustainable performance gains if they can leverage these systems to shorten decision cycles, increase accuracy, and align operational decisions with strategic objectives. In this sense, software systems should be regarded as integral elements of decision-making frameworks rather than as stand-alone technological artifacts.

The study also contributes to the literature by offering empirical evidence from an emerging economy context, where digital adoption is often uneven and logistics inefficiencies are prevalent. This contextual contribution is important because much of the existing research on ERP and TMS has been conducted in developed economies, and the transferability of those findings to other contexts has been questioned. By confirming that decision-making performance is a key mechanism in this setting as well, the study provides valuable insights for both scholars and practitioners seeking to understand how digital systems can foster competitiveness under resource constraints and institutional challenges.

Improving the software usage skills of decision–makers also emerges as a critical factor. Logistics companies should provide continuous training for employees and develop guided materials to facilitate the effective and efficient use of these systems. Additionally, continuous monitoring and evaluation of software–supported decision-making processes, coupled with regular reporting to management, will help maximize the benefits derived from these systems. Managers should not only focus on the technical performance of software but also strive to simplify and optimize decision–making processes, thereby making the impact of software on decision–making performance more tangible.

For researchers, exploring the relationship between software performance, decision–making performance, and business performance across different industries and various types of software presents an important avenue for future study. Analyses that consider the sub-dimensions of decision–making performance—such as decision speed, decision accuracy, and decision quality—could elucidate which aspects are most influenced by software systems. Moreover, developing comprehensive structural models that examine the impact of ERP and similar systems on decision–making, in conjunction with variables such as organizational learning, agility, and innovation, would significantly advance the literature. Finally, employing qualitative or mixed–method approaches could provide deeper insights into the impact of software use on decision–making processes by capturing decision–makers' perceptions and experiences regarding system usage.

References

Akkermans, H., Bogerd, P., Yücesan, E., & Van Wassenhove, L. N. (2003). The impact of ERP on supply chain management: Exploratory findings from a European Delphi study. *European Journal of Operational Research, 146*(2), 284–301. https://doi.org/10.1016/S0377-2217(02)00550-7

Alake, A. A., Awodiran, M. A., Ayomide, A. N., & Foluke,

A. (2025). The effect of decision support systems on strategic business decisions: Evidence from manufacturing companies in Nigeria. *Asian Journal of Economics, Business and Accounting, 25*(1), 232–244.

Altuntaş, G., Akca, M., & Polat, D. D. (2020). Yöneticiye duyulan güven ile işten ayrılma niyeti arasındaki ilişkide lider–üye etkileşiminin rolü [The role of leader–member exchange (LMX) on the relationship between trust in managers and intention to leave]. *Toros Üniversitesi İİSBF Sosyal Bilimler Dergisi, 7*(12), 86–114.

Aydıner, A. S. (2016). *Bilişim sistemleri kapasitesinin firma performansına etkisinin ölçümü* [Measuring the impact of information system capabilities on firm performance] [Unpublished doctoral dissertation]. Bahçeşehir Üniversitesi.

Bahrami, B., & Jordan, E. (2009). Impacts of enterprise resource planning implementation on decision–making processes in Australian organisations. *Pacific Asia Conference on Information Systems.*

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Baum, J. R., & Wally, S. (2003). Strategic decision speed and firm performance. *Strategic Management Journal, 24*(11), 1107–1129. https://doi.org/10.1002/smj.343

Bernroider, E. W. N., & Koch, S. (1999). ERP selection process in midsize and large organizations. In *Proceedings of the 5th Americas Conference on Information Systems* (pp. 1022–1024). Association for Information Systems.

Carton, F., & Adam, F. (2010). Understanding the impact of technology on managerial decision–making: The case of the ERP system. *Decision Support Systems, 49*(3), 463–473. https://doi.org/10.1016/j.dss.2010.06.002

Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U., & Bag, S. (2023). Assessing the impact of big data analytics on decision–making processes, forecasting, and performance of a firm. *Technological Forecasting and Social Change, 196,* 122824. https://doi.org/10.1016/j.techfore.2023.122824

Doğaner Duman, B., & Altuntaş, G. (2024). Taşımacılık yönetim sistemleri (TYS) yazılımlarının seçiminde kullanılan kriterlerin belirlenmesi ve sınıflandırılmasına yönelik bir model önerisi [A proposal for a model to determine and classify criteria used in selecting transportation management system (TMS) software]. *VIII. Ulaştırma ve Lojistik Ulusal Kongresi,* Zonguldak.

Dubey, R., Bryde, D. J., Blome, C., Roubaud, D., & Foropon, C. (2021a). Supply chain agility, adaptability, and alignment: Empirical evidence from the Indian automotive industry. *International Journal of Operations & Production Management, 41*(3), 258–278. https://doi.org/10.1108/IJOPM-03-2020-0175

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Roubaud, D., & Giannakis, M. (2021b). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics, 231,* 107861. https://doi.org/10.1016/j.ijpe.2020.107861

Gable, G., Sedera, D., & Chan, T. (2008). Re–conceptualizing information system success: The IS–impact measurement model. *Journal of the Association for Information Systems, 9*(7), 377–408. https://doi.org/10.17705/1jais.00164

Gattiker, T. F., & Goodhue, D. L. (2005). What happens after ERP implementation: Understanding the impact of interdependence and differentiation on plant-level outcomes. *MIS Quarterly, 29*(3), 559–585. https://doi.org/10.2307/25148695

George, D., & Mallery, P. (2003). *SPSS for Windows step by step: A simple guide and reference* (4th ed.). Allyn & Bacon.

George, D., & Mallery, M. (2010). *SPSS for Windows step by step: A simple guide and reference* (10th ed.). Pearson.

Goswami, S. S., Mondal, S., Sarkar, S., Gupta, K. K., Sahoo, S. K., & Halder, R. (2025). Artificial intelligence-enabled supply chain management: Unlocking new opportunities and challenges. *Artificial Intelligence and Applications, 3*(1), 110–121.

Grover, V., Chiang, R. H., Liang, T. P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems, 35*(2), 388–423.

Gunasekaran, A., Subramanian, N., & Papadopoulos, T. (2017). Information technology for competitive advantage within logistics and supply chains: A review. *Transportation Research Part E: Logistics and Transportation Review, 99,* 14–33. https://doi.org/10.1016/j.tre.2016.12.008

Gürbüz, S. (2019a). *AMOS ile yapısal eşitlik modellemesi* [Structural equation modeling with AMOS]. Ankara: Seçkin Yayıncılık.

Gürbüz, S. (2019b). *Sosyal bilimlerde aracı, düzenleyici ve durumsal etki analizleri* [Mediation, moderation, and moderated mediation analyses in social sciences]. Ankara: Seçkin Yayıncılık.

HassabElnaby, H. R., Hwang, W., & Vonderembse, M. (2011). The impact of ERP implementation on organizational capabilities and firm performance. *International Journal of Accounting Information Systems, 12*(2), 107–129. https://doi.org/10.1016/j.accinf.2010.11.001

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). Guilford Press.

Hendricks, K. B., Singhal, V. R., & Stratman, J. K. (2007). The impact of enterprise systems on corporate performance: A study of ERP, SCM, and CRM system implementations. *Journal of Operations Management, 25*(1), 65–82. https://doi.org/10.1016/j.jom.2006.02.002

Hopkins, J., & Hawking, P. (2018). Big data analytics and IoT in logistics: A case study. *The International Journal of Logistics Management, 29*(2), 575–591. https://doi.org/10.1108/IJLM-05-2017-0109

Hou, C. K., & Papamichail, K. N. (2010). The impact of integrating enterprise resource planning systems with business intelligence systems on decision–making performance: An empirical study of the semiconductor industry. *International Journal of Technology, Policy and Management, 10*(3), 277–293. https://doi.org/10.1504/IJTPM.2010.034633

Huber, G. P. (1990). A theory of the effects of advanced information technologies on organizational design, intelligence, and decision making. *Academy of Management Review, 15*(1), 47–71. https://doi.org/10.5465/amr.1990.4308227

James, W., & Mark, H. (1996). Decision–making in organizations: A contextual approach. *Organizational Studies, 17*(5), 805–825. https://doi.org/10.1177/017084069601700504

King, A. W., & Zeithaml, C. P. (2001). Competencies and firm performance: Examining the causal ambiguity paradox. *Strategic Management Journal, 22*(1), 75–99. https://doi.org/10.1002/1097-0266(200101)22:1<75::AID-SMJ145>3.0.CO;2-I

Kumar, K., & Van Hillegersberg, J. (2000). ERP experiences and evolution. *Communications of the ACM, 43*(4), 23–26. https://doi.org/10.1145/332051.332063

Lee, J.-N., Chu, P.-Y., & Tseng, C.-H. (2011). Corporate performance of ICT-enabled business process re-engineering. *Industrial Management & Data Systems, 111*(5), 735–754. https://doi.org/10.1108/02635571111137288

Liang, T. P., You, J. J., & Liu, C. C. (2010). A resource-based perspective on information technology and firm performance: A meta analysis. *Industrial Management & Data Systems, 110*(8), 1138–1158. https://doi.org/10.1108/02635571011077807

McAfee, A., & Brynjolfsson, E. (2017). *Machine, platform, crowd: Harnessing our digital future.* WW Norton & Company.

McLaren, T., Head, M., & Yuan, Y. (2011). Supply chain collaboration and firm performance: The impact of information sharing and partner relationship capabilities. *Journal of Supply Chain Management, 47*(2), 19–37. https://doi.org/10.1111/j.1745-493X.2011.03229.x

Mishra, D., Gunasekaran, A., Childe, S. J., Papadopoulos, T., & Dubey, R. (2023). Big data and predictive analytics in supply chain sustainability: A review. *Journal of Business Research, 158,* 113662. https://doi.org/10.1016/j.jbusres.2022.113662

Mithas, S., Ramasubbu, N., & Sambamurthy, V. (2011). How information management capability influences firm performance. *MIS Quarterly, 35*(1), 237–256. https://doi.org/10.2307/23043496

Nicolaou, A. I. (2004). Firm performance effects in relation to the implementation and use of enterprise resource planning systems. *Journal of Information Systems, 18*(3), 79–94. https://doi.org/10.2308/jis.2004.18.3.79

Nunnally, J. C., & Bernstein, I. H. (1994). *The assessment of reliability.* Psychometric Theory, 3, 248–292.

Ouiddad, A., Chafik, O. K. A. R., Chroqui, R., & Hassani, I. B. (2018, November). Does the adoption of ERP systems help improving decision-making? A systematic literature review. In *2018 IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD)* (pp. 61–66). IEEE.

Ouiddad, A., Okar, C., Chroqui, R., & Hassani, I. (2020). Assessing the impact of enterprise resource planning on decision–making quality: An empirical study. *Kybernetes, 49*(8), 2107–2127. https://doi.org/10.1108/K-04-2019-0273

Pilepić, L., & Šimunić, M. (2009). Information systems and decision making. *Economic Research–Ekonomska Istraživanja, 22*(4), 111–124. https://doi.org/10.1080/1331677X.2009.11517318

Rosemann, M., & de Bruin, T. (2004). Towards a business process management maturity model. In *Proceedings of the 13th European Conference on Information Systems.*

Rosenzweig, E. D., Roth, A. V., & Dean, J. W., Jr. (2003). The influence of an integration strategy on competitive capabilities and business performance: An exploratory study of consumer products manufacturers. *Journal of Operations Management, 21*(4), 437–456. https://doi.org/10.1016/S0272-6963(03)00037-8

Sauter, V. L. (2014). *Decision support systems for business intelligence.* John Wiley & Sons.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Pearson.

Tallon, P. P. (2008). Inside the adaptive enterprise: An information technology capabilities perspective on business process agility. *Information Technology and Management, 9*(1), 21–36. https://doi.org/10.1007/s10799-007-0021-y

Tippins, M. J., & Sohi, R. S. (2003). IT competency and firm performance: Is organizational learning a missing link? *Strategic Management Journal, 24*(8), 745–761. https://doi.org/10.1002/smj.337

Vickery, S. K., Droge, C., & Markland, R. E. (1993). Production competence and business strategy: Do they affect business performance? *Decision Sciences, 24*(2), 435–456. https://doi.org/10.1111/j.1540-5915.1993.tb00482.x

Wade, M., & Hulland, J. (2004). Review: The resource-based view and information systems research:

Review, extension, and suggestions for future research. *MIS Quarterly, 28*(1), 107–142. https://doi.org/10.2307/25148626

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics, 176,* 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014

Wier, B., Hunton, J., & HassabElnaby, H. R. (2007). Enterprise resource planning systems and non–financial performance incentives: The joint impact on corporate performance. *Journal of Information Systems, 21*(2), 63–78. https://doi.org/10.2308/jis.2007.21.2.63

Zhao, Z., Luo, Y., Wang, J., & Zhou, H. (2023). Mediation analysis for high-dimensional mediators. *Statistica Sinica, 33*(4), 1881–1902. https://doi.org/10.5705/ss.202022.0363

Dr. Bükra Doğaner Duman is an Assistant Professor at Istanbul Arel University's Vocational School of Logistics. She earned her Ph.D. in Transportation and Logistics from Istanbul University with a dissertation on the impact of Transportation Management Systems (TMS) software on business performance through decision-making and process mechanisms. She also holds an M.A. in Logistics Management from Istanbul Ticaret University, where she completed her thesis on halal logistics as a strategic link in halal and healthy food supply chains. Dr. Duman's teaching covers undergraduate courses such as Sustainable Logistics, Customs Regulations, Transportation Systems, Logistics Applications, and Environmental Protection & Occupational Safety. Her research interests focus on logistics software performance, sustainable logistics practices, transportation systems, supply chain performance measurement, and digital transformation in logistics enterprises.

Dr. Gültekin Altuntaş serves as an Associate Professor in the Department of Logistics at Istanbul University's Faculty of Transportation and Logistics. His scholarly expertise encompasses entrepreneurship, management, strategic management, organizational behavior, and human resources. His academic qualifications include a Ph.D. in Strategic Entrepreneurship (2010), complemented by dual master's degrees in Entrepreneurship (Ball State University, USA, 2004) and Business Management & Organization (Istanbul University, 2021), as well as two bachelor's degrees in Business Administration (Istanbul University, 2002) and Management Information Systems (Anadolu University, 2019). Since 2011, Dr. Altuntas has been teaching a range of courses, including Management, Strategic Management, Entrepreneurship, and Innovation Management, to both university students and industry professionals. Extending his impact beyond the classroom, he provides advisory services for public and private industrial projects, performs peer reviews for academic journals, and contributes his expertise to the evaluation boards of technoparks and development agencies.

Usmerjanje k uspehu: kako odločanje preoblikuje programsko uspešnost v poslovno uspešnost v logistični industriji države v vzponu

Ozadje in namen: Raziskava proučuje posredovalno vlogo uspešnosti odločanja v odnosu med programsko uspešnostjo in celotno poslovno uspešnostjo v logističnem sektorju države v vzponu. Ker se logistična podjetja vse bolj zanašajo na digitalno infrastrukturo, je razumevanje, kako napredni informacijski sistemi prispevajo k strateškim rezultatom, ključno za ohranjanje konkurenčnosti.
Metode: Razvit je bil konceptualni model, ki povezuje sisteme ERP, analitiko velikih podatkov in aplikacije interneta stvari (IoT). V modelu je programska uspešnost opredeljena kot neodvisna spremenljivka, uspešnost odločanja kot posredovalna spremenljivka, poslovna uspešnost pa kot odvisna spremenljivka. Podatki so bili zbrani med srednje velikimi in velikimi logističnimi podjetji ter analizirani z regresijsko in bootstrap analizo z uporabo programov SPSS in PROCESS Macro.
Rezultati: Ugotovitve kažejo, da programska uspešnost pomembno izboljšuje uspešnost odločanja ($\beta = 0{,}552$, $p < 0{,}01$), ta pa ima močan pozitiven vpliv na poslovno uspešnost ($\beta = 0{,}817$, $p < 0{,}01$). Analiza posredovanja potrjuje, da uspešnost odločanja posreduje vpliv programske uspešnosti na poslovne rezultate.
Sklep: Rezultati poudarjajo strateški pomen usklajevanja digitalnih zmogljivosti z organizacijskimi procesi odločanja. Z dokazovanjem posredovalne vloge odločanja raziskava izpostavlja, da je učinkovita uporaba naprednih analitičnih orodij ključna za optimizacijo uspešnosti in doseganje trajne konkurenčne prednosti v logistični industriji.

Ključne besede: *Programska uspešnost, Uspešnost odločanja, Poslovna uspešnost, Sistemi TMS, Logistična industrija, Gospodarstva v vzponu*

DOI: 10.2478/orga-2025-0024

Use of Chatbots in Human Resource Management for More Efficient Knowledge Sharing – Systematic Literature Review

Nejc BERNIK, Polona ŠPRAJC

University of Maribor, Faculty of Organizational Sciences, Kranj, Slovenia, nejc.bernik1@um.si, polona.sprajc@um.si

Purpose: This study examines how chatbots, as part of generative artificial intelligence (GenAI), can assist human resource (HR) professionals in supporting more effective knowledge management (KM), especially knowledge sharing (KS). The research aims to understand the strategic roles of chatbots in Human Resource Management (HRM). It offers propositions for their effective deployment to support KS and enhance their utilisation within organisations.
Methodology: A systematic literature review (SLR) was carried out using the databases Web of Science (WoS) and Scopus. After applying inclusion and exclusion criteria, 16 relevant articles were selected for detailed analysis.
Results: The findings show that chatbots can significantly enhance KS by automating HRM processes. They enable personalised training, offer continuous support, and promote employee performance, engagement, and innovation. Furthermore, chatbots assist HR professionals in focusing on strategic tasks by lowering administrative workload. Several challenges are also identified, including ethical concerns, privacy issues, data quality problems, reduced social interaction, and risks to creativity and critical thinking.
Conclusion: Chatbots offer a transformative opportunity for HRM to enhance KS, organisational memory, and digital learning, thereby supporting competitive advantage in knowledge-intensive settings.

Keywords: *Chatbots, Generative artificial intelligence (GenAI), Human resource management (HRM), Knowledge management (KM), Knowledge sharing (KS)*

1 Introduction

In recent years, chatbots have become integral to both professional and personal life, with tools such as ChatGPT, Siri, and Google Gemini. Powered by generative artificial intelligence (GenAI), they enable natural language interaction, simulate human communication, and provide relevant and desired information to users (Venusamy et al., 2020). Their organisational adoption in recent years demonstrates their adaptability and value by offering intuitive communication and automating routine tasks to help employees resolve queries and problems efficiently.

Chatbots also have potential in knowledge management (KM), particularly in knowledge sharing (KS), which remains a persistent challenge in many organisations. This occurs when older employees retire without distributing expertise to younger employees, mainly due to the absence of systematic KM practices such as mentoring protocols, succession planning, and structured KS. These gaps risk the loss of critical organisational know-how, experience,

Received: 20th August 2025; Accepted: 20th October 2025

and best practices. With the integration of chatbots into human resource management (HRM) processes, they can enhance KS systems and help preserve and share organisational knowledge. HRM plays a central role in this process, and combining chatbot capabilities with HRM aligns with the strategic needs of knowledge-intensive organisations (Mogea, 2023), where intellectual capital—employee expertise, organisational know-how, and innovation capacity—is a vital competitive asset.

A keyword-based literature search showed that relatively little research has examined the intersection of chatbots, KS, and HRM. Combining KM and HRM theories with socio-technical perspectives provides a solid conceptual base for studying the role of chatbots in organisational settings. It is therefore important to investigate how chatbots can be effectively integrated into HRM practices to support KS, while also addressing ethical, organisational, and security-related challenges. This perspective guided the design of our systematic literature review (SLR), which is presented in the following section.

2 Theoretical background

The rapid emergence of GenAI technologies has reshaped both the theoretical and practical approaches to KM and HRM. Chatbots, as conversational GenAI systems, bring together these two perspectives by functioning as intelligent intermediaries between knowledge repositories and employees, thereby enhancing accessibility, reducing communication barriers, and supporting a culture of continuous learning (Chowdhury et al., 2023). At the same time, their introduction raises new theoretical questions concerning trust, employee acceptance, and the socio-technical integration of AI into organisational processes (Meyer et al., 2023). To address these dynamics, it is useful to frame the discussion of chatbots within existing KM and HRM theories, while also recognising the transformative impact of GenAI on organisational practices and the broader transition toward Society 5.0 (Roblek et al., 2021). Following Trist & Bamforth (1951) these developments align with socio-technical systems theory, which emphasises the joint optimisation of social and technical structures when new technologies are introduced into work environments.

2.1 Knowledge sharing

KM is a strategic and systematic process for creating, sharing, storing, and applying knowledge within organisations (Teece, 1998; Vrontis et al., 2019). According to Summerscales (2024) the goal of KM is to strengthen organisational effectiveness, foster innovation, and improve competitiveness by making sure that relevant knowledge is accessible to the appropriate individuals when needed. Organisational knowledge is commonly divided into explicit and implicit forms—explicit being formalised and documented, and implicit (tacit) being personal and experience-based (Brauner & Becker, 2006; Krišelj et al., 2025).

A central component of KM is KS, defined as the exchange of explicit and implicit knowledge, skills and expertise among employees or teams. While often used interchangeably with “knowledge transfer,” KS has been described as more specific to the KM context and particularly linked to the use of information systems (Chou & Tang, 2014; Paulin & Suneson, 2012). Following (Argote, 2024), knowledge transfer is broader in scope and may occur across different domains and settings. For this reason, the present study adopts the KS perspective, recognising its importance in fostering collaboration, problem-solving, and continuous learning in organisations.

The encouragement of KS depends largely on HR managers, who implement policies, procedures, and systems to facilitate knowledge exchange across teams and departments.(Matošková & Směšná, 2018; Sammarra et al., 2017). Strategic HRM practices—such as mentoring, digital repositories, and peer collaboration—are typical of knowledge-intensive organisations, enabling informed decision-making, higher efficiency, and more substantial commitment (Battistelli et al., 2019; Swart & Kinnie, 2003). With the rise of GenAI, (Chowdhury et al., 2023) wrote that KS has become even more important, as GenAI tools can organise, contextualise, and update knowledge assets, making them more accessible.

2.2 Chatbots in HRM

As part of GenAI tools, chatbots are increasingly used in organisations to support effective KM (Al-Sharafi et al., 2023). Powered by large language models (LLMs), they can understand and generate human-like text (Meyer et al., 2023). This enables them to answer employee questions, contextualise information, summarise documents, recommend solutions, and adapt to specific communication styles and knowledge needs (Ashfaq et al., 2020; Majumder & Mondal, 2021). Acting as intelligent interfaces, chatbots capture, distribute, and reuse organisational knowledge across departments (Abdelwhab Ali et al., 2019) and contribute to organisational memory by preserving procedural and experiential knowledge in structured digital form (Madanchian, 2024).

They improve HRM processes, such as selection, onboarding, training, employee education, etc (Frischen & Fiebig, 2025; Sharma, 2021). Chatbots can also provide employees with real-time, consistent responses to their queries, functioning as digital coaches (Alhusban et al., 2025) and contributing to talent development. By analysing employee interactions, chatbots support skills mapping and competency-based workforce planning, acting as strategic enablers within knowledge-intensive environments where intellectual capital drives innovation and adaptability (Mogea, 2023)

With the strategic integration of chatbots in HRM, as Sharma (2021) wrote, chatbots can deliver a rapid return on investment and contribute to preserving organisational knowledge that might otherwise be lost (Deepa et al., 2024). By safeguarding knowledge and enabling continuous development, chatbots can also support the transition toward a digitalised Society 5.0 (Roblek et al., 2021).

3 Methodology

Our motivation for conducting this study stems from recognising the significant potential of integrating chatbots into HRM processes. Our experience working in large mid-European organisations showed that chatbots were rarely used in HRM, particularly in KM and KS. A preliminary review of the relevant literature confirmed this observation, as relatively few studies have examined the intersection of chatbots, KS, and HRM. This gap motivated us to conduct an extensive SLR.

The research problem we address is the limited adoption of chatbots in HRM to support KS. To explore this issue, we formulated three research questions (RQ):

RQ1: How do chatbots improve KS in organisations?

RQ2: How can chatbots enable HRM to support more effective KS?

RQ3: What should organisations be aware of when implementing chatbots for KS?

We used two of the largest scientific databases for SLR: Web of Science (WoS) and Scopus (Zhu & Liu, 2020). To identify the most relevant studies on using chatbots in HRM for KS, we focused on four core terms: chatbots, HRM, KS, and AI. These were further expanded with synonyms to capture a broader range of publications.

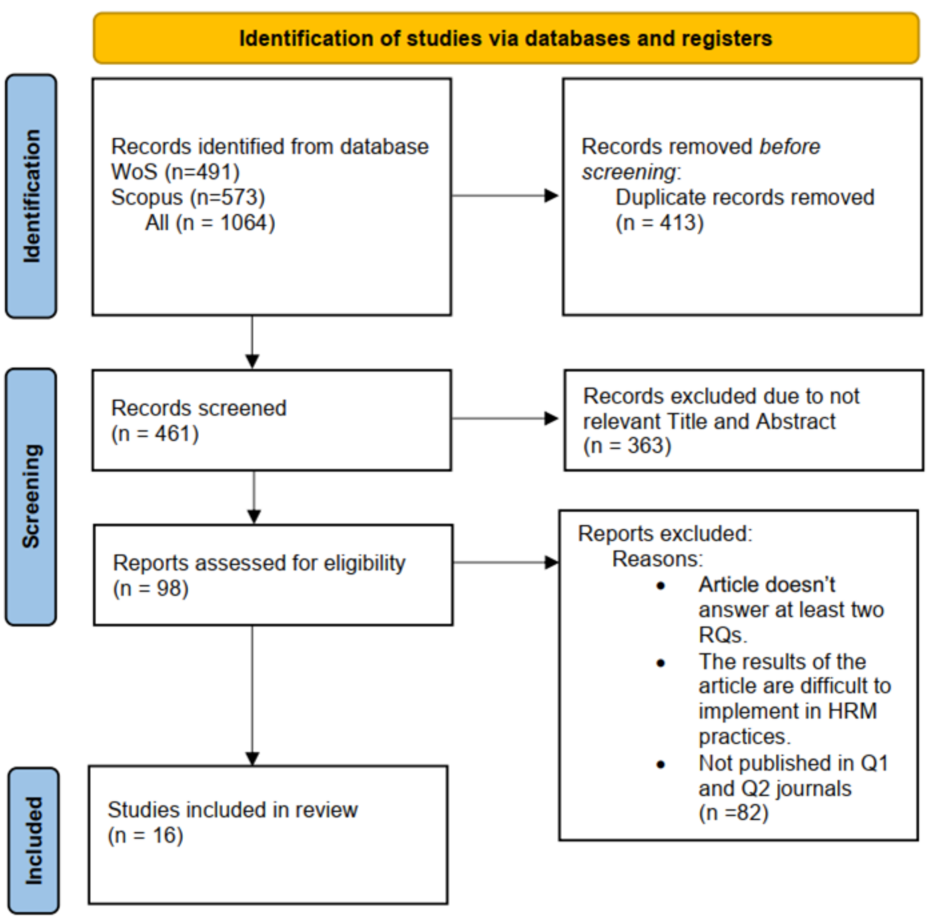


Figure 1: PRISMA flow diagram

The terms were combined using Boolean operators (AND, OR). The whole search string was as follows:

("chatbot" OR "LLM" OR "virtual assistant") AND ("AI" OR "artificial intelligence") AND ("knowledge transfer" OR "knowledge sharing" OR "knowledge distribution") AND ("" OR "human resource"). We applied the following inclusion criteria: only peer-reviewed journal articles published between 2020 and 2025 and written in English. Using this procedure, we identified a total of 16 relevant articles. Figure 1 presents the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) flow diagram with the complete search strategy and screening process.

The research was conducted on 12 August 2025, and based on the initial search across both databases, we identified 1,064 articles. After removing duplicates, 461 articles were screened by reviewing their titles and abstracts. From this step, 363 articles were excluded due to non-compliant or irrelevant titles and abstracts.

This left 98 articles, which were thoroughly reviewed, including their results, findings, and discussions. At this stage, we excluded papers that did not address at least two of our research questions, presented findings that would be difficult to implement in HR practices (as not all studies were HR-oriented), and were not published in Q1 or Q2 ranking journals.

In the final step, 16 articles were selected, fully obtained, and analysed in detail. These studies formed the primary evidence base for our research and provide the foundation for addressing the three research questions.

4 Results

With the program VOSviewer, we conducted literature visualisation of selected 16 articles (Figure 2). We got four different colours representing keyword clusters that frequently co-occur in the analysed literature. The blue cluster highlights KS linked to HRM, which relates to information flow and impact. The green cluster centres on AI connected with ChatGPT, KM and opportunities. The red cluster relates to management and performance, emphasising the role of AI-based virtual assistants in supporting knowledge exchange in organisations. The yellow cluster reflects technology and challenges, pointing to barriers in adopting AI tools. The map illustrates that research connects chatbots, HRM and KS through opportunities, performance, and technological challenges.

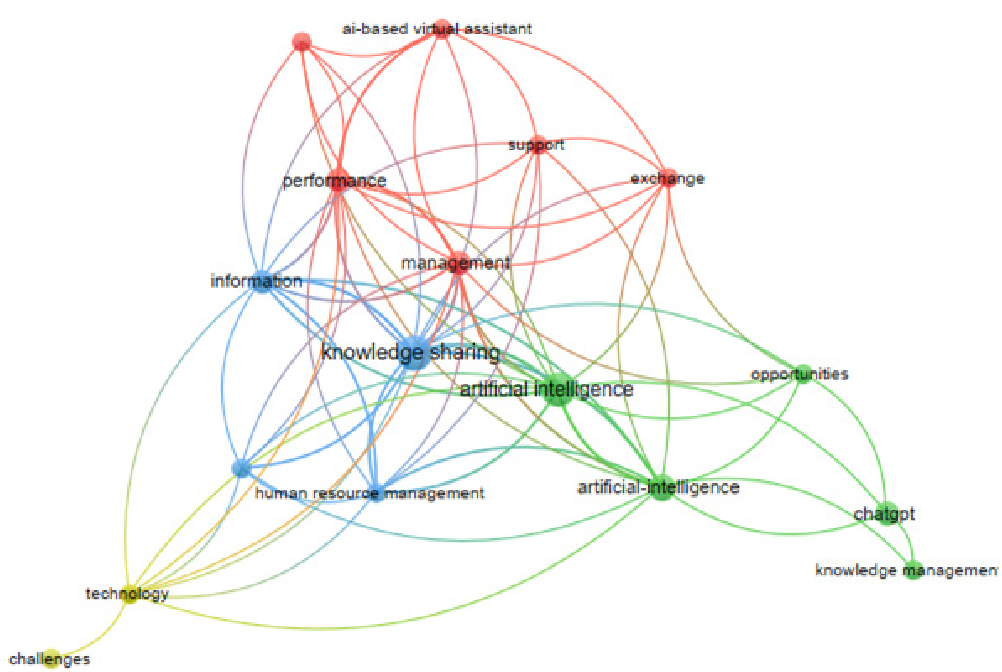


Figure 2: VOSviewer keywords visualisation

These clusters illustrate how the field is still in an emerging stage, where research streams are fragmented but interconnected. The concentration of studies around KS and HRM (blue) suggests that scholars recognise the importance of knowledge flows but have not yet fully examined chatbot-specific contributions. The presence of AI and ChatGPT in the green cluster reflects the dominance of technological discussions, whereas the red and yellow clusters highlight the managerial and ethical concerns that are increasingly shaping debates on AI adoption. Together, these clusters indicate that chatbot research in HRM is developing along both technological and human-centred dimensions, underscoring the relevance of a socio-technical perspective.

All 16 selected articles were published from 2021 to 2025. Most of them were published in 2025. The most cited article was from Duong et al. (2023), which received 84 citations by the time of review, followed by (Soleimani et al., 2021) with 48 citations and Alavi et al. (2024) with 43 citations.

Selected articles were chosen because they were related to at least two of our research questions. Specifically, they explored combinations such as HRM and KS, chatbots and KS, HRM and chatbots, or all three domains—chatbots, KS, and HRM. The criteria for selecting these articles are presented in the middle column of Table 1, explaining how each article addresses our research questions. The last column indicates the journal ranking (Q1 or Q2) in which each article was published.

Table 1: Selected articles and their connection to our RQs

Authors	Related to our RQ	Q
(Alavi et al., 2024)	**RQ1**: GenAI can significantly transform KM by automating and enhancing KS, as it can convert implicit knowledge into explicit knowledge. **RQ3**: The transformation of KM and KS raises ethical concerns and requires building trust in GenAI-generated knowledge among employees.	Q1
(Arbulú Ballesteros et al., 2024)	**RQ1**: Effort expectancy and performance expectancy significantly influence students' behavioural intention to use ChatGPT, which strongly predicts its actual use. KS correlates with actual use and the behavioural intention to use ChatGPT. **RQ3**: The use of ChatGPT poses a threat to students' critical and creative skills and thinking.	Q1
(Murugan et al., 2024)	**RQ2**: GenAI is highly effective for facilitating KS when onboarding new employees. It can tailor content to be relevant and engaging through interactive tutorials and simulations, easing integration into the organisation, particularly for roles requiring hands-on learning and experience. Employees may also feel less inhibited when asking GenAI questions than when approaching supervisors or co-workers. **RQ3**: The organisation may lose control over what knowledge is transferred to employees. Moreover, excessive reliance on GenAI and chatbots can reduce employee creativity.	Q1
(Nguyen & Fry, 2022)	**RQ1**: Online AI knowledge sharing capabilities can foster trust, build employee self-confidence using digital platforms, and cultivate a KS culture among younger employees. This can enhance their knowledge self-efficacy and lead to improved job performance. **RQ3**: A lack of technical support for employees who encounter problems or have questions can hinder effective implementation.	Q1
(Rezaei et al., 2024)	**RQ2**: AI within KS can help decision-makers identify best work practices and improve strategies. **RQ3**: Organisations should adopt strong privacy measures, address AI-related ethical issues, and use fairness-aware algorithms supported by legal safeguards to protect rights, ensure transparency, and safeguard data ownership (including intellectual property). Failure to do so may provoke employees' mistrust, uncertainty, and anticipatory anxiety.	Q1
(Malik et al., 2024)	**RQ1**: AI can automatically collect, organise, and update HRM knowledge from diverse sources (e.g., performance data, recruitment records, training outcomes). **RQ2**: AI in HRM improves decision-making, personalises KS for each employee, and motivates them to participate in AI-mediated KS (AI-MKS).	Q1
(He et al., 2025)	**RQ1**: Intelligent agents enable more informed, data-driven decisions, fostering stronger managerial innovation and KS. **RQ2**: AI enhances managerial creativity by leveraging organisational knowledge, improving information distribution, and applying advanced analytics. **RQ3**: High costs of AI technology, expertise, and infrastructure, integration difficulties, and competition for skilled professionals often hinder implementation and cause delays.	Q1

Table 1: Selected articles and their connection to our RQs (continues)

(Terblanche & Tau, 2025)	**RQ1**: Chatbots as coaches offer guidance, motivation, and personalised feedback to boost students' clarity, commitment, and progress, enhancing self-regulation, accountability, and time management for improved goal achievement. **RQ3**: Due to high costs and the inability to predict final expenses, organisations are often unwilling to adopt chatbots.	Q2
(Dutta & Mishra, 2024)	**RQ1**: Virtual assistants (VAs) can enhance employee engagement. **RQ2**: VAs are emerging as a value-adding HRM practice that raises expectations while fostering a greater sense of meaningfulness and psychological safety. They promote interactive communication with employees, positively influence engagement, and encourage employees to share their feelings and concerns openly.	Q1
(Alhusban et al., 2025)	**RQ1**: Chatbots offer 24/7 support. **RQ2**: ChatGPT can mentor new employees by providing them with training, guidance, and resources to help them integrate effectively into the organisation. **RQ3**: Adopting ChatGPT may lead to job losses, particularly in positions involving repetitive or easily automatable tasks.	Q1
(Duong et al., 2023)	**RQ1**: ChatGPT is easy to use and helps students complete learning tasks quickly and accurately—such as providing feedback or correcting grammar—thereby enhancing learning outcomes while reducing teachers' workload. **RQ3**: Concerns regarding data privacy.	Q1
(Hui et al., 2024)	**RQ1**: AI virtual assistants serve as catalysts for team innovation by bridging explicit and tacit knowledge through decision-support capabilities and facilitating social network connections. **RQ2**: AI virtual assistants enhance HRM by automating repetitive tasks, providing data-driven insights, improving recruitment and performance decisions, and delivering personalised training through adaptive learning.	Q2
(Lambiase et al., 2025)	**RQ1**: Chatbots with speech recognition can become more desirable among employees. **RQ3**: Privacy violations and a lack of trust in chatbots.	Q1
(Soleimani et al., 2021)	**RQ2**: AI in recruitment holds significant potential to improve recruitment and selection processes while reducing unconscious bias in hiring decisions. **RQ3**: Organisations should be careful not to rely entirely on AI, as excluding human judgment can result in biased, unethical, or contextually inappropriate decisions.	Q2
(Sumbal et al., 2024)	**RQ1**: The utilisation of ChatGPT by employees enhances work efficiency and saves time, which can be redirected toward creative and value-adding activities. **RQ2**: ChatGPT can be adapted to retrieve relevant information required by employees for informed decision-making while supporting tacit KM through collaborative KS. **RQ3**: It may reduce employees' critical thinking skills and weaken collaboration among team members.	Q1
(Olan et al., 2024)	**RQ1**: Proper training and involvement in AI adoption can boost acceptance, enhance skills, and maintain motivation. AI-supported KS environments improve innovation and task execution. **RQ2**: Candidate screening and administrative tasks free HRM professionals for strategic work and employee engagement, while AI-driven analytics provide data-based insights to improve decisions in talent acquisition, retention, and performance management.	Q1

Most observed articles showed strong alignment between research aims, data collection, and analysis, indicating satisfactory methodological rigour. However, few reported bias diagnostics or ethical approval, and generalisability was often limited to sector-specific samples.

By establishing a clear methodological framework, our study ensures transparency and replicability, which are crucial for strengthening the reliability of systematic literature reviews (Zhu & Liu, 2020). The rigorous screening process and reliance on peer-reviewed Q1 and Q2 journals provide a solid empirical foundation for addressing the proposed research questions. At the same time, the applied procedure reflects broader methodological standards in management and information systems research, where structured reviews are increasingly used to map emerging fields such as AI-driven HRM (Deepa et al., 2024). Building on these methodological choices, the following section presents the results of the review, highlighting the main thematic clusters and research trends at the intersection of chatbots, HRM, and KS.

5 Discussion

To present the research findings as effectively as possible to HR managers and organisations, and to encourage them to consider the introduction of chatbots into HRM processes as a potential source of competitive advantage, we summarised the insights from all 16 selected articles in the form of answers to the three research questions.

Our findings complement existing research on the role of chatbots in HRM and place them within a broader theoretical, organisational, and societal framework.

5.1 RQ1: How do chatbots improve KS in organisations?

Chatbots, powered by GenAI, can significantly enhance KS by fostering employee innovation and creativity (He et al., 2025). Their ease of use enables employees to complete learning tasks efficiently—such as receiving instant feedback—thus improving job performance (Duong et al., 2023). Hui et al. (2024) conducted a survey where they discovered that chatbots used in connection with organisational leadership, KS, absorptive capacity and team innovation play a significant role in strengthening employees' decision-making. With that in mind, they can serve as coaches for effective KS (Terblanche & Tau, 2025).

Within KS, chatbots also facilitate the organisation, retrieval, and utilisation of diverse knowledge resources, helping organisations leverage knowledge for competitive advantage (Nguyen & Fry, 2022). This advantage is achieved by influencing employees' behavioural intentions, motivating them to perform better, and encouraging greater effort in task execution (Arbulú Ballesteros et al., 2024). Alavi et al. (2024) described GenAI as the core technology behind chatbots, further supporting KS by providing employees with immediate answers, reducing hesitation in asking questions, and increasing the overall flow of shared knowledge.

Trust in chatbots is also critical because when employees perceive them as reliable, AI-mediated KS acts as a social exchange mechanism that enhances job performance, increases satisfaction, and reduces turnover intentions (Malik et al., 2024; Olan et al., 2024). Personalised chatbot-driven training programmes can strengthen KS by identifying employee needs and delivering tailored, up-to-date content (Alhusban et al., 2025). Sumbal et al. (2024) conducted a case study where they found out that chatbot programmes boost efficiency, save time for creative and value-adding activities and ultimately drive innovation within organisations.

Authors' findings confirm that chatbots can significantly improve and affect KS practices in HRM, which opens the way for connecting them with established models of technology adoption. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) emphasise that perceived usefulness, ease of use, social influence, and facilitating conditions are key factors influencing employees' readiness to adopt digital tools (Hashim et al., 2022; Leesakul et al., 2022). In the context of chatbot adoption, trust emerges as a particularly critical dimension, as KS relies heavily on employees' confidence in the quality, reliability, and fairness of GenAI-generated content (Malik et al., 2024; Nguyen & Fry, 2022). Without such trust, employees may resist adoption or limit their engagement with chatbot-supported KS processes.

In conclusion, the findings clearly address RQ1 by demonstrating that chatbots, as GenAI-driven tools, improve KS through enhanced accessibility, automation, trust, and behavioural motivation, leading to higher innovation, engagement, and organisational performance.

5.2 RQ2: How can chatbots enable HRM to support more effective KS?

Chatbots can enable HRM to support more effective KS by helping HR professionals identify best practices and refine strategies (Rezaei et al., 2024). They improve efficiency, accuracy, and accessibility by taking over routine and administrative tasks, allowing employees to concentrate on more complex, value-adding activities (Malik et al., 2024; Nguyen & Fry, 2022). In this regard, He et al. (2025) argued that chatbots can relieve HR professionals from administrative routine tasks, enabling them to address strategic challenges, foster creativity, and enhance information distribution.

Beyond administrative support, chatbots strengthen HRM through automation, data-driven insights, improved recruitment and performance decisions, and personalised training via adaptive digital learning (Hui et al., 2024). They can act as digital coaches across HRM processes. For instance, in recruitment, the GenAI recruitment systems demonstrate how chatbots can support data labelling, job function analysis, and machine learning improvements, leading to faster recruitment, reduced bias, fairer decision-making, and timely candidate communication (Soleimani et al., 2021). Similarly, as digital coaches, chatbots can provide employees with relevant information for informed decision-making (Sumbal et al., 2024).

Their constant availability makes them also valuable for onboarding and coaching, offering rapid answers, personalised guidance, and interactive communication that enhance employee engagement (Duong et al., 2023). This coaching role encourages employees to express ideas and concerns openly, reducing HRM workload and increasing job satisfaction (Alhusban et al., 2025; Dutta & Mishra, 2024; Olan et al., 2024). Organisations implementing advanced chatbots for automating recruitment, screening, and training tasks will lower operational costs and improve long-term HRM efficiency (Pejić Bach et al., 2025; Tursunbayeva & Renkema, 2023).

Thus, the evidence directly answers RQ2 by confirming that chatbots enable HRM to support more effective KS through automation, data-driven personalisation, and digital coaching, allowing HR professionals to focus on strategic and developmental tasks that strengthen their satisfaction and commitment.

5.3 RQ3: What should organisations be aware of when implementing chatbots for KS?

Chatbots collect knowledge from various sources, which requires organisations to carefully assess the legitimacy of the information to avoid losing control over what is shared with employees. They must carefully manage the type and scope of knowledge that GenAI distributes to protect privileged data and prevent undermining employee curiosity and creativity (Alavi et al., 2024; Duong et al., 2023). Furthermore, the use of chatbots may reduce participation among employees and limit social interaction within the workplace.

As noted by (Alhusban et al., 2025) the adoption of chatbots carries potential risks of workforce reduction, particularly in roles dominated by repetitive and automatable activities. Since not all employees are familiar with the latest digital and GenAI technologies, organisations should implement targeted technical support and tailored educational programmes (Nguyen & Fry, 2022). According to Rezaei et al. (2024), such programmes should help develop basic skills for each employee privacy protections, address GenAI-related ethical issues, and promote the use of fairness-aware algorithms supported by legal safeguards that protect individual rights, ensure transparency, and secure data ownership, including intellectual property. In addition, organisations should incorporate cybersecurity measures to safeguard sensitive organisational data, protect against unauthorised access, and ensure the secure integration of chatbots and connected GenAI technology within existing infrastructure (Bernik et al., 2022; Podbregar & Šprajc, 2018). Employees should also be prepared for the psychological and organisational impacts of GenAI adoption using continuous awareness-building, structured training, and open communication, which can help reduce mistrust, uncertainty, and anticipatory anxiety (Lambiase et al., 2025).

At the same time, overreliance on chatbots can negatively affect employees' critical thinking, weaken collaboration, and create risks related to intellectual property rights and information accuracy (Sumbal et al., 2024). Many organisations also lack awareness of the potential benefits of chatbots or how to effectively integrate them into operations, which may lead to hesitation in adoption (He et al., 2025). In some cases, costs may escalate unexpectedly, as organisations underestimate the financial implications of chatbot implementation (Terblanche & Tau, 2025). Finally, organisations must avoid relying exclusively on GenAI technologies in decision-making, since excluding human judgment can result in biased, unethical, or contextually inappropriate outcomes (Soleimani et al., 2021).

Overall, these insights address RQ3 by highlighting that successful chatbot implementation for KS depends on ethical governance, employee trust, data security, and responsible integration that balances technological efficiency with human judgment and creativity.

5.4 Practical guidelines for organisations

Based on our analysis, several guidelines can be proposed for the effective integration of chatbots in HRM:

- Gradual implementation – Start with routine tasks (e.g., answering FAQs, administrative support) and progressively expand toward more complex processes such as onboarding, competency development, and decision support.
- Human–AI complementarity – Ensure chatbots complement rather than replace human interaction, particularly in processes that require empathy, complex judgment, and ethical decision-making.
- Training and digital literacy – Provide targeted training programmes that address both technical use and broader awareness of ethics, data protection, and cybersecurity.
- Security and ethics – Establish robust policies for data protection, intellectual property, and transparent decision-making to prevent bias, misuse, and loss of trust.
- Monitoring outcomes – Continuously assess the effects of chatbot adoption on employee satisfaction, engagement, and the quality of KS to enable timely adjustments.

By following these guidelines, organisations can approach chatbot implementation in a structured and responsible way that balances efficiency gains with ethical and human-centred considerations. The emphasis on gradual integration, complementarity with human interaction, and continuous monitoring highlights that the successful use of chatbots in HRM is not only a technological challenge but also a cultural and strategic one. This perspective underscores the need for leadership commitment, transparent communication, and employee involvement throughout the adoption process, ensuring that chatbots become genuine enablers of KS and organisational learning rather than isolated digital tools.

By demonstrating that chatbots are not merely optional digital tools, this study advances understanding of HRM and KM by integrating socio-technical and knowledge-based perspectives to explain how chatbots can reshape organisational knowledge dynamics. It conceptualises chatbots as mediators that enhance human capabilities and transform KS into a continuous, technology-augmented process. Building on this integration, the study contributes to the scholarly discourse on the integration of chatbots within HRM by examining their transformative potential for KS. The conclusions are derived from a PRISMA-based systematic literature review (SLR) of 16 Q1–Q2 articles indexed in Web of Science and Scopus. As a synthesis of secondary data, these findings should be interpreted with caution and substantiated through future multi-site empirical investigations.

In practical terms, the study provides actionable guidance for HR professionals. Chatbots should be implemented gradually, designed to complement rather than replace human interaction, and governed by robust data and ethical frameworks. Continuous monitoring through employee experience and KS quality indicators is essential to ensure sustainable performance outcomes.

6 Conclusion

Study contributes to the growing body of research on the integration of chatbots into HRM processes by emphasising their potential to transform KS and organisational learning. The findings demonstrate that chatbots, as part of GenAI technologies, can automate routine HRM tasks, preserve organisational memory, and enhance employee engagement, thereby supporting long-term competitiveness in knowledge-intensive environments. At the same time, their successful use requires careful attention to trust, ethical concerns, and the socio-technical interplay between employees and technology. This study also demonstrates that despite the increasing visibility of GenAI, empirical evidence on chatbot adoption in HRM remains limited, leaving considerable room for future cross-national and cross-sectoral research.

Beyond organisational outcomes, the integration of chatbots also resonates with the broader vision of Society 5.0, which highlights the importance of human-centred digital transformation (Roblek et al., 2021). By reducing digital divides, supporting intergenerational KS and enabling adaptive learning, chatbots can help organisations respond to the demands of a rapidly changing socio-economic landscape. However, this transformation will only succeed if leadership provides clear guidance, transparent communication, and continuous training to ensure that AI complements rather than replaces human judgement.

For HR professionals, the study underscores the importance of adopting a structured approach to chatbot implementation that combines gradual integration, robust security and privacy safeguards, and continuous monitoring of employee experiences. In this way, chatbots can evolve from being isolated digital tools into strategic enablers of KS and HRM.

Funding

The University of Maribor, Faculty of Organisational Sciences, and the authors gratefully acknowledge the financial support of the Slovenian Research and Innovation Agency (project No. P5-0018).

References

Abdelwhab Ali, A., Panneer Selvam, D. D. D., Paris, L., & Gunasekaran, A. (2019). Key factors influencing knowledge sharing practices and its relationship with organizational performance within the oil and gas industry. *Journal of Knowledge Management*, *23*(9), 1806–1837. https://doi.org/10.1108/JKM-06-2018-0394

Alavi, M., Leidner, D., & Mousavi, R. (2024). *Knowledge Management Perspective of Generative Artificial Intelligence (GenAI)* (SSRN Scholarly Paper No. 4782875). Social Science Research Network. https://doi.org/10.2139/ssrn.4782875

Alhusban, M. I., Khatatbeh, I. N., & Alshurafat, H. (2025). Exploring the influence, implications and challenges of integrating generative artificial intelligence into organizational learning and development. *Competitiveness Review: An International Business Journal*. https://doi.org/10.1108/CR-06-2024-0121

Al-Sharafi, M. A., Al-Emran, M., Arpaci, I., Iahad, N. A., AlQudah, A. A., Iranmanesh, M., & Al-Qaysi, N. (2023). Generation Z use of artificial intelligence products and its impact on environmental sustainability: A cross-cultural comparison. *Computers in Human Behavior*, *143*, 107708. https://doi.org/10.1016/j.chb.2023.107708

Arbulú Ballesteros, M. A., Acosta Enríquez, B. G., Ramos Farroñán, E. V., García Juárez, H. D., Cruz Salinas, L. E., Blas Sánchez, J. E., Arbulú Castillo, J. C., Licapa-Redolfo, G. S., & Farfán Chilicaus, G. C. (2024). The Sustainable Integration of AI in Higher Education: Analyzing ChatGPT Acceptance Factors Through an Extended UTAUT2 Framework in Peruvian Universities. *Sustainability*, *16*(23), 10707. https://doi.org/10.3390/su162310707

Argote, L. (2024). Knowledge Transfer Within Organizations: Mechanisms, Motivation, and Consideration. *Annual Review of Psychology*, *75*(Volume 75, 2024), 405–431. https://doi.org/10.1146/annurev-psych-022123-105424

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020).

I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 101473. https://doi.org/10.1016/j.tele.2020.101473

Battistelli, A., Odoardi, C., Vandenberghe, C., Di Napoli, G., & Piccione, L. (2019). Information sharing and innovative work behavior: The role of work-based learning, challenging tasks, and organizational commitment. *Human Resource Development Quarterly*, *30*(3), 361–381. https://doi.org/10.1002/hrdq.21344

Bernik, I., Prislan, K., & Mihelič, A. (2022). Country Life in the Digital Era: Comparison of Technology Use and Cybercrime Victimization between Residents of Rural and Urban Environments in Slovenia. *Sustainability*, *14*(21), 14487. https://doi.org/10.3390/su142114487

Brauner, E., & Becker, A. (2006). Beyond knowledge sharing: The management of transactive knowledge systems. *Knowledge and Process Management*, *13*(1), 62–71. https://doi.org/10.1002/kpm.240

Chou, C.-H., & Tang, T.-I. (2014). Exploring the Distinction between Knowledge Transfer and Knowledge Sharing by Bibliometric Method. *Journal of Industrial and Intelligent Information*, *2*(3), 179–183. https://doi.org/10.12720/jiii.2.3.179-183

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Deepa, R., Sekar, S., Malik, A., Kumar, J., & Attri, R. (2024). Impact of AI-focussed technologies on social and technical competencies for HR managers – A systematic review and research agenda. *Technological Forecasting and Social Change*, *202*, 123301. https://doi.org/10.1016/j.techfore.2024.123301

Duong, C. D., Vu, T. N., & Ngo, T. V. N. (2023). Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator. *The International Journal of Management Education*, *21*(3), 100883. https://doi.org/10.1016/j.ijme.2023.100883

Dutta, D., & Mishra, S. K. (2024). Artificial intelligence-based virtual assistant and employee engagement: An empirical investigation. *Personnel Review*, *54*(3), 913–934. https://doi.org/10.1108/PR-03-2023-0263

Frischen, L., & Fiebig, M. (2025). A Perfect Start with Retrieval-Augmented Generation: Building a Chatbot to Support the Onboarding Process in SMEs. *Studies in Health Technology and Informatics*, *327*, 876–877. https://doi.org/10.3233/SHTI250487

Hashim, M. Z., Che Razak, R., Muhammad, N., Mansor, F. A., & Wan Azib, W. N. H. (2022). The Determinants of Digital Workplace Adoption: A Conceptual Framework. *International Journal of Academic Research in Business and Social Sciences*, *12*(10), Pages 477-492. https://doi.org/10.6007/IJARBSS/v12-i10/14822

He, L., Yousaf, Z., & Palazzo, M. (2025). Synergetic legacy of organizational innovativeness, knowledge sharing, artificial intelligence adoption and big data analytic capability in human resource management. *The International Journal of Human Resource Management*, *36*(8), 1407–1430. https://doi.org/10.1080/09585192.2025.2510546

Hui, Z., Khan, N. A., & Akhtar, M. (2024). AI-based virtual assistant and transformational leadership in social cognitive theory perspective: A study of team innovation in construction industry. *International Journal of Managing Projects in Business*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/IJMPB-10-2023-0241

Krišelj, T., Markič, M., Zoran, A. G., & Kolnik, T. Š. (2025). Knowledge Management Factors as Building Blocks of Quality of Care in Healthcare Systems. *Organizacija*, *58*(1), 20–30. https://doi.org/10.2478/orga-2025-0002

Lambiase, S., Catolino, G., Palomba, F., & Ferrucci, F. (2025). Motivations, Challenges, Best Practices, and Benefits for Bots and Conversational Agents in Software Engineering: A Multivocal Literature Review. *ACM Computing Surveys*, *57*(4), 1–37. https://doi.org/10.1145/3704806

Leesakul, N., Oostveen, A.-M., Eimontaite, I., Wilson, M. L., & Hyde, R. (2022). Workplace 4.0: Exploring the Implications of Technology Adoption in Digital Manufacturing on a Sustainable Workforce. *Sustainability*, *14*(6), 3311. https://doi.org/10.3390/su14063311

Madanchian, M. (2024). From Recruitment to Retention: AI Tools for Human Resource Decision-Making. *Applied Sciences*, *14*(24), 11750. https://doi.org/10.3390/app142411750

Majumder, S., & Mondal, A. (2021). Are chatbots really useful for human resource management? *International Journal of Speech Technology*, *24*(4), 969–977. https://doi.org/10.1007/s10772-021-09834-y

Malik, A., Tuyet-Mai, N., & Budhwar, P. (2024). Towards a Conceptual Model of AI-Mediated Knowledge Sharing Exchange of HRM Practices: Antecedents and Consequences. *IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT*, *71*, 13083–13095. https://doi.org/10.1109/TEM.2022.3163117

Matošková, J., & Směšná, P. (2018). Human resource management practices stimulating knowledge sharing. *Management & Marketing*, *12*(4), 614–632. https://doi.org/10.1515/mmcks-2017-0036

Meyer, J. G., Urbanowicz, R. J., Martin, P. C. N., O'Connor, K., Li, R., Peng, P.-C., Bright, T. J., Tatonetti, N., Won, K. J., Gonzalez-Hernandez, G., & Moore, J. H.

(2023). ChatGPT and large language models in academia: Opportunities and challenges. *BioData Mining*, *16*(1), 20. https://doi.org/10.1186/s13040-023-00339-9

Mogea, T. (2023). Improving Knowledge Sharing in Organizations. *Populer: Jurnal Penelitian Mahasiswa*, *2*(1), Article 1. https://doi.org/10.58192/populer.v2i1.647

Murugan, M., Yuan, B., Venner, E., Ballantyne, C. M., Robinson, K. M., Coons, J. C., Wang, L., Empey, P. E., & Gibbs, R. A. (2024). Empowering personalized pharmacogenomics with generative AI solutions. *Journal of the American Medical Informatics Association: JAMIA*, *31*(6), 1356–1366. https://doi.org/10.1093/jamia/ocae039

Nguyen, T.-M., & Fry, M.-L. (2022). Online knowledge sharing capability of young employees: An empirical study. *Journal of Global Scholars of Marketing Science*, *32*(3), 415–433. https://doi.org/10.1080/21639159.2020.1808849

Olan, F., Nyuur, R. B., & Arakpogun, E. O. (2024). AI: A knowledge sharing tool for improving employees' performance. *Journal of Decision Systems*, *33*(4), 700–720. https://doi.org/10.1080/12460125.2023.2263687

Paulin, D., & Suneson, K. (2012). Knowledge transfer, knowledge sharing and knowledge barriers—Three blurry terms in KM. *Electronic Journal of Knowledge Management*, *10*(1), 81–91.

Pejić Bach, M., Palić, M., & Šimičević, V. (2025). The Impact of Usability and Reliability on ChatGPT Satisfaction among Gen Z and Gen Y. *Organizacija*, *58*(3), 211–226. https://doi.org/10.2478/orga-2025-0013

Podbregar, I., & Šprajc, P. (2018). Adaptability of state to a new CI challenges – with focus on cyber warfare domain. *National Security and the Future*, *19*(1–2), 187–199.

Rezaei, M., Pironti, M., & Quaglia, R. (2024). AI in knowledge sharing, which ethical challenges are raised in decision-making processes for organisations? *MANAGEMENT DECISION*. https://doi.org/10.1108/MD-10-2023-2023

Roblek, V., Meško, M., & Podbregar, I. (2021). Mapping of the Emergence of Society 5.0: A Bibliometric Analysis. *Organizacija*, *54*(4), 293–305. https://doi.org/10.2478/orga-2021-0020

Sammarra, A., Profili, S., Maimone, F., & Gabrielli, G. (2017). Enhancing Knowledge Sharing in Age-Diverse Organizations: The Role of HRM Practices. In *Age Diversity in the Workplace: An Organizational Perspective* (Vol. 17, p. 0). Emerald Publishing Limited. https://doi.org/10.1108/S1877-636120170000017009

Sharma, G. (2021). A literature review on application of Artificial Intelligence in Human Resource Management and its practices in current organizational scenario. *2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, 594–600. https://doi.org/10.1109/I-SMAC52330.2021.9640954

Soleimani, M., Intezari, A., & Pauleen, D. J. (2021). Mitigating Cognitive Biases in Developing AI-Assisted Recruitment Systems: A Knowledge-Sharing Approach. *International Journal of Knowledge Management*, *18*(1), 1–18. https://doi.org/10.4018/ijkm.290022

Sumbal, M. S., Amber, Q., Tariq, A., Raziq, M. M., & Tsui, E. (2024). Wind of change: How ChatGPT and big data can reshape the knowledge management paradigm? *Industrial Management & Data Systems*, *124*(9), 2736–2757. https://doi.org/10.1108/imds-06-2023-0360

Summerscales, J. (2024). Harvesting tacit knowledge for composites workforce development. *Composites Part A: Applied Science and Manufacturing*, *185*, 108357. https://doi.org/10.1016/j.compositesa.2024.108357

Swart, J., & Kinnie, N. (2003). Sharing knowledge in knowledge-intensive firms. *Human Resource Management Journal*, *13*(2), 60–75. https://doi.org/10.1111/j.1748-8583.2003.tb00091.x

Teece, D. J. (1998). Research Directions for Knowledge Management. *California Management Review*, *40*(3), 289–292. https://doi.org/10.2307/41165957

Terblanche, N., & Tau, T. (2025). Exploring the use of a goal-attainment, artificial intelligence (AI) chatbot coach to support first-time graduate employees. *Industry and Higher Education*, *39*(3), 279–290. https://doi.org/10.1177/09504222241287090

Trist, E. L., & Bamforth, K. W. (1951). Some Social and Psychological Consequences of the Longwall Method of Coal-Getting: An Examination of the Psychological Situation and Defences of a Work Group in Relation to the Social Structure and Technological Content of the Work System. *Human Relations*, *4*(1), 3–38. https://doi.org/10.1177/001872675100400101

Tursunbayeva, A., & Renkema, M. (2023). Artificial intelligence in health-care: Implications for the job design of healthcare professionals. *Asia Pacific Journal of Human Resources*, *61*(4), 845–887. https://doi.org/10.1111/1744-7941.12325

Venusamy, K., Krishnan Rajagopal, N., & Yousoof, M. (2020). A study of Human Resources Development through Chatbots using Artificial Intelligence. *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, 94–99. https://doi.org/10.1109/ICISS49785.2020.9315881

Vrontis, D., Christofi, M., & Thrassou, A. (2019). Knowledge Management: A Critical Review of Existing Research. In *Cross-Functional Knowledge Management*. Routledge.

Zhu, J., & Liu, W. (2020). *A tale of two databases: The use of Web of Science and Scopus in academic papers* (No. arXiv:2002.02608). arXiv. https://doi.org/10.48550/arXiv.2002.02608

Nejc Bernik is a doctoral student and young researcher at the Faculty of Organizational Sciences, University of Maribor. His primary research interests focus on knowledge management, digital literacy, teamwork and human resource training.

Polona Šprajc is a Full Professor at the Faculty of Organizational Sciences, University of Maribor. Her research interests encompass organisation and management, crisis management, critical infrastructure, and human resource management.

Uporaba klepetalnih robotov v kadrovskem managementu za učinkovitejši prenos znanja – sistematični pregled literature

Namen: Študija preučuje, kako lahko klepetalni roboti kot del generativne umetne inteligence pomagajo kadrovskim strokovnjakom pri učinkovitejšem upravljanju znanja , zlasti pri prenosu znanja. Namen raziskave je razumeti strateško vlogo klepetalnih robotov v kadrovskem managementu ter oblikovati predloge za njihovo učinkovito implementacijo pri podpori prenosa znanja, s čimer bi se povečala njihova uporaba v organizacijah.
Metodologija: Izveden je bil sistematični pregled literature z uporabo baz podatkov Web of Science (WoS) in Scopus. Po uporabi vključitvenih in izključitvenih meril je bilo za poglobljeno analizo izbranih 16 relevantnih znanstvenih člankov.
Rezultati: Ugotovitve kažejo, da lahko klepetalni roboti bistveno izboljšajo prenos znanja z avtomatizacijo kadrovskih procesov. Omogočajo namreč usposabljanja, nudijo stalno podporo ter spodbujajo uspešnost, zavzetost in inovativnost zaposlenih. Poleg tega omogočajo, da se kadrovski strokovnjaki bolj osredotočijo na strateške naloge, saj klepetalni roboti zmanjšajo administrativne naloge , s tem obremenitve. Klepetalni roboti lahko prinesejo tudi izzive, kot so etična vprašanja, težave z zasebnostjo in kakovostjo podatkov, zmanjšano socialno interakcijo ter tveganja za ustvarjalnost in kritično mišljenje.
Zaključek: Klepetalni roboti predstavljajo priložnost nadgradnje za kadrovski management, saj krepijo prenos znanja, znanje organizacij, digitalno učenje ter prispevajo h konkurenčni prednosti v vedno intenzivnejših okoljih.

Ključne besede: *Klepetalni roboti, Generativna umetna inteligenca, Kadrovski management, Upravljanje znanja, Prenos znanja*

Appendix

On the day 12.08.2025	WoS	Scopus
Search criteria	English Article 2020-2025	English Article 2020-2025
	TOPIC: (“chatbot” OR “llm” OR “virtual assistant”) AND (“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) AND (“hr” OR “human resource”) = 0	(“chatbot” OR “llm” OR “virtual assistant”) AND (“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) AND (“hr” OR “human resource”) = 0
	TOPIC: (“chatbot” OR “llm” OR “virtual assistant”) AND (“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) = 12	(“chatbot” OR “llm” OR “virtual assistant”) AND (“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) = 13
	TOPIC: (“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) AND (“hr” OR “human resource”) = 11	(“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) AND (“hr” OR “human resource”) = 13
	TOPIC: (“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”)= 469	(“ai” OR “artificial intelligence”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”)= 537
	TOPIC: (“chatbot” OR “llm” OR “virtual assistant”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) AND (“hr” OR “human resource”) = 0	(“chatbot” OR “llm” OR “virtual assistant”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) AND (“hr” OR “human resource”) = 0
	TOPIC: (“chatbot” OR “llm” OR “virtual assistant”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) = 39	(“chatbot” OR “llm” OR “virtual assistant”) AND (“knowledge transfer” OR “knowledge sharing” OR “knowledge distribution”) = 52
All together	491	573

AUTHOR GUIDELINES / NAVODILA AVTORJEM

Manuscripts considered for publication in Organizacija (organizacija.fov@um.si) are those which:

- *Contain original work* – which is not published elsewhere in any medium by the authors or anyone else and is not under consideration for publication in any other medium. The author(s) is/are also responsible for any violations of the copyright regulations.
- *Are focused on the core aims and scope of the journal*: Organizacija is an interdisciplinary peer reviewed journal that seeks both theoretically and practically oriented research papers from the area of organizational science, business information systems and human resources management.
- *Are clearly and correctly written* – should contain all essential features of a complete scientific paper, should be written in a clear, easy to understand manner and be readable for a wide audience.
- *Are written in English* – should be clearly and grammatically written, in an easily readable style. Attention to detail of the language will avoid severe misunderstandings which might lead to rejection of the paper. Correct language is the responsibility of the authors. Unless the author is an English native speaker, the paper must be proofread by a language editor, English native speaker

All parts of the manuscript should be type-written (font size 12), with margins of 2.5 cm. Pages should be numbered consecutively throughout the manuscript. The text should be subdivided into numbered chapters. Figures and tables, consecutively numbered (Figure 1, Figure 2, ...; Table 1, Table 2, …) can be included in electronic form in the text. All lettering and figure elements must be large enough to be readable when figure or table has been reduced to fit journal page or column. All figures and tables must be specifically referred in the text. Colour pictures cannot be published in the printed version of the journal; colours appear only in the internet version. The paper should start with a cover page with names and mailing and electronic addresses of the authors. To assure the anonymity of the refereeing procedure the names of the authors should not appear in the text.

Detailed Guidelines for Authors are available at https://sciendo.com/journal/orga - for Authors.

All the papers will be reviewed by at least two referees. Based on the opinions and suggestions of the reviewers, the editors accept the paper, demand minor or major enhancements, or reject the paper. If major enhancements are required the upgraded paper is reviewed again.

Manuscripts can be submitted via journal web site (https://organizacija.fov.um.si). For further information and clarifications contact Organizacija's editorial office (organizacija.fov@um.si or maja.mesko@um.si).

Address of the Editorial office:
University of Maribor,
Faculty of Organizational Sciences
Kidričeva cesta 55a
4000 Kranj, Slovenia
Phone: +386-4-2374-297

V reviji Organizacija objavljamo znanstvene članke, rezultate raziskovalnega dela avtorjev. Predloženi prispevki naj bodo napisani v angleškem jeziku. Imeti morajo strukturo IMRAD, ki je običajna za znanstvena in strokovna besedila. Objavljamo dela s predmetnega področja revije, ki še niso bila objavljena in niso bila poslana v objavo v kakšni drugi reviji ali zborniku. Avtorji so odgovorni za vse morebitne kršitve avtorskih pravic.

Besedilo naj bo oblikovano za tiskanje na papirju in levo poravnano. Na začetku prispevka, takoj za naslovom, naj bo povzetek (izvleček) dolžine največ 250 besed, ključne besede, v končni – sprejeti verziji članka pa na koncu prispevka tudi kratek strokovni življenjepis vsakega od avtorjev (do 10 vrstic) in letnica rojstva (zaradi vnosa podatkov v knjižnični informacijski sistem COBISS, v reviji letnica ne bo objavljena). Na prvi strani besedila naj bodo napisani le naslov prispevka, imena in (poštni in elektronski) naslovi avtorjev članka, po možnosti tudi telefonska številka enega od avtorjev. Da bi zagotovili anonimnost recenziranja, naj se imena avtorjev ne pojavljajo v besedilu prispevka. Na koncu članka, za življenjepisi, naj bo slovenski prevod naslova, povzetka in ključnih besed.

Članek naj bo razčlenjen v oštevilčena poglavja. Naslovi članka, poglavij in podpoglavij naj bodo napisani z malimi črkami, da so razvidne kratice. Slike in tabele v elektronski obliki vključite kar v besedilo. Besedilu so lahko priložene slike in/ali tabele na papirju v obliki pripravljeni za preslikavo. V tem primeru naj bo vsaka slika na posebnem listu, oštevilčene naj bodo z arabskimi številkami, v besedilu naj bo označeno, kam približno je treba uvrstiti sliko: na tem mestu naj bo številka slike/tabele in njen podnapis. Slike bomo praviloma pomanjšali in jih vstavili v članek. Upoštevajte, da morajo biti oznake in besedila na vseh slikah dovolj velika, da bodo čitljiva tudi pri velikosti slike, kot bo objavljena v reviji. Vse slike naj bodo črno-bele z belim ozadjem; barvnih slik v tiskani verziji revije ne moremo objaviti, barve so vidne le v spletni verziji.

Članki morajo biti pred objavo v Organizaciji lektorirani. Končno verzijo mora lektorirati naravni govorec oz. lektor s primerljivim znanjem angleščine.

Podrobna navodila avtorjem za pisanje in oblikovanje člankov so na https://sciendo.com/journal/orga - for Authors.

Predložene prispevke pregledata in ocenita najmanj dva recenzenta. Na osnovi mnenj in predlogov recenzentov uredniški odbor ali urednik sprejmejo prispevek, zahtevajo manjše ali večje popravke in dopolnitve ali ga zavrnejo. Če urednik oziroma recenzenti predlagajo večje popravke, se dopolnjeni prispevek praviloma pošlje v ponovno recenzijo.

Članke za objavo lahko predložite preko spletnega mesta https://organizacija.fov.um.si/submissions/. Za nadaljnje informacije in pojasnila se lahko obrnete na uredništvo Organizacije (organizacija.fov@um.si ali maja.mesko@um.si).

Naslov uredništva:
Univerza v Mariboru,
Fakulteta za organizacijske vede
Kidričeva cesta 55a
4000 Kranj
Tel.: 04-2374-297

Prva slovenska revija za organizacijska in kadrovska raziskovanja in prakso. Revijo sofinancira Javna agencija za raziskovalno dejavnost Republike Slovenije.
Ponatis in razmnoževanje deloma ali v celoti brez pisnega dovoljenja nista dovoljena. Izdajatelj: Univerza v Mariboru, Fakulteta za organizacijske vede Kranj,
Založba MODERNA ORGANIZACIJA, Kidričeva cesta 55a, KRANJ, telefon: 04 23 74 200,
E-pošta: organizaija.fov@um.si. Uredništvo revije: Kidričeva cesta 55a, 4000 Kranj.
Letna naročnina: 47 EUR + ddv.
Na leto izidejo 4 številke. Tisk: CICERO, Begunje, d. o. o.
Naklada 130 izvodov.

Organizacija is covered by the following services: Cabell's Directory, CEJSH (The Central European Journal of Social Sciences and Humanities), Celdes, Clarivate Analytics - Emerging Sources Citation Index (ESCI), CNPIEC, Die Elektronische Zeitschriftenbibliothek, DOAJ, EBSCO - TOC Premier, EBSCO Discovery Service, ECONIS, Ergonomics Abstracts, ERIH PLUS, Google Scholar, Inspec, International Abstracts in Operations Research, J-Gate, Microsoft Academic Search, Naviga (Softweco), Primo Central (ExLibris), ProQuest - Advanced Polymers Abstracts, ProQuest - Aluminium Industry Abstracts, ProQuest - Ceramic Abstracts/World Ceramics Abstracts, ProQuest - Composites Industry Abstracts, ProQuest - Computer and Information Systems Abstracts, ProQuest - Corrosion Abstracts, ProQuest - Electronics and Communications Abstracts, ProQuest - Engineered Materials Abstracts, ProQuest - Mechanical & Transportation Engineering Abstracts, ProQuest - METADEX (Metals Abstracts), ProQuest - Sociological Abstracts, ProQuest - Solid State and Superconductivity Abstracts, Research Papers in Economics (RePEc), SCOPUS, Summon (Serials Solutions/ProQuest), TDOne (TDNet), TEMA Technik und Management, WorldCat (OCLC)

CONTENTS - 4/2025

Založba Moderna organizacija