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From negative feedback to actionable insights: a computational analysis of service robot adoption challenges in Chinese hotels

Xiaocong Jiang
Tianyang Luo

ABSTRACT

With the rapid rise in labour costs in China's hotel industry, service robots have emerged as a potential solution to enhance service efficiency and reduce operational expenses. However, their adoption rate in Chinese hotels remains low. While prior studies have primarily explored technical performance and costs from a managerial perspective, there is a lack of systematic methodologies examining adoption barriers from the lens of guests' negative emotions. This study employs web-crawling technology to collect 20,900 low-rated reviews from six major Chinese online travel platforms. Using Latent Dirichlet Allocation (LDA) topic modelling combined with computational grounded theory, the authors identified ten key barriers to the adoption of service robots in hotels. Notably, this study introduces "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" as distinct barriers. It also reveals a cascading effect involving service quality, functional utility, and expectation alignment, highlighting that multidimensional interactions drive technology acceptance. These findings provide theoretical and practical insights for optimising service robot deployment, offering new perspectives to improve service efficiency and user acceptance in China's hotel industry.

KEY WORDS

Latent Dirichlet allocation, service robots, hotel industry, adoption barriers

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Tianyang Luo
Hezhou University,
No. 3261, Xiaohe Avenue, Babu District,
Hezhou city, Guangxi province, China, 542899
ORCID 0000-0003-1779-1200

Corresponding author:
e-mail: luotianyang@hzxy.edu.cn

Xiaocong Jiang
School of Business,
Institute of Vocational Technology, SIP
No. 1 Ruoshui Road, Suzhou Industrial Park,
Suzhou city, Jiangsu province, China, 215123
ORCID 0000-0003-4590-1913
e-mail: roy@ivt.edu.cn

Introduction

As labour costs in China continue to rise rapidly (Zuo, 2023), service robots have gained attention in the hotel industry as a potential solution. Research indicates that service robots can replace approx. 30 % of hotel staff labour - equivalent to 1.25 workers - while reducing check-in and checkout times by 30 % and guestroom service response times by 37 % (Zhang et al., 2019; Zhong et al., 2022). Despite their potential to enhance efficiency, adoption rates remain low, with reports highlighting limited uptake in China's hotel sector (Ding et al., 2023). Most studies have

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examined this issue from a managerial perspective, identifying barriers such as slow response speeds (Wang et al., 2023; Chung & Cakmak, 2018) and inefficient human-robot interactions (Tussyadiah & Park, 2018). Additionally, lack of personalisation and emotional engagement (Milohnić & Kapeš, 2024; Tussyadiah & Park, 2018), poor robot design (Milohnić & Kapeš, 2024; Tussyadiah & Park, 2018), inadequate speech recognition (Milohnić & Kapeš, 2024), and unmet guest expectations (Wang et al., 2023) have been noted as critical factors affecting guest acceptance and managerial decisions. These challenges undermine the potential of service robots to improve service quality and replace human labour, making it essential to investigate the barriers hindering their adoption amidst rising labour costs and the need for service optimisation.

However, the literature reveals significant gaps in understanding these adoption barriers, particularly in three areas: data scope, research methodology, and context-specific factors. First, data collection in prior studies often relies on semi-structured interviews with hotel staff (Choi et al., 2019) or surveys (Milohnić & Kapeš, 2024). These methods suffer from small sample sizes and lack generalisability due to variations in robot models (Tuomi et al., 2020), which limits their ability to capture the full spectrum of guest experiences (Ding et al., 2023). Second, methodological limitations include selection bias in thematic analyses due to small samples (Choi et al., 2019), questionable reliability of results (Yörük et al., 2023), and restricted expressiveness in closed-ended surveys (Milohnić & Kapeš, 2024; Rosete et al., 2020). While sentiment analysis has been applied to online reviews (Ceccarelli, 2011), it often fails to uncover the specific reasons for service quality decline (Tuomi et al., 2020). Third, despite China being a key market for service robot applications, its low adoption rate suggests a gap between technical performance and service efficacy (Ding et al., 2023). Scholars note that emerging guest demands for hygiene, safety, and emotional engagement may further impact acceptance (Ceccarelli, 2011); yet, the influence of these factors on guest trust and satisfaction remains underexplored (Tuomi et al., 2020).

Unlike previous studies, this research used web-crawling software to collect 20,900 low-rated reviews of hotel service robots from six major Chinese online travel platforms (Tongcheng, Ctrip, Lvmama, Qunar, Tuniu, and Elong). By applying LDA topic modelling integrated with computational grounded theory, the authors labelled themes and verified their reliability, identifying specific technical and service quality issues. Furthermore, the authors conducted two cross-theme post-hoc analyses - high-frequency word co-occurrence and theme interaction - to explore the complexity of guest feedback in Chinese hotels. The theoretical and practical implications of these findings are discussed in detail below.

This study addresses the following research questions: (1) How can large-scale, cross-platform data collection methods identify key factors affecting guest experiences with service robots across diverse hotel settings? (2) How can improved methodologies reveal the specific impacts of technical and interaction issues on service quality enhancement by service robots? (3) What are the critical technical and service barriers that Chinese hotel guests perceive as limiting service robot adoption?

1. Literature review

1.1. Applications of service robots in the hotel industry

Service robots are intelligent systems designed to perform specific service functions autonomously or semi-autonomously in non-manufacturing environments, aiming to enhance user experience and task efficiency (Kapur & Williams, 2025; Ceglowski & Golub, 2012). Recent studies have quantitatively explored their advantages in the hotel industry, particularly in reducing labour costs and improving operational efficiency. Advances in AI algorithms and declining sensor costs have significantly improved the autonomous navigation capabilities of robots (Lei et al., 2023), driven by developments in Robot Operating Systems (ROS) and Natural Language Processing (NLP) technologies (Rosete et al., 2020). Additionally, service robots can optimise operations by collecting data, such as guest preferences, to enhance service quality (Qi et al., 2024). These technical advantages highlight their potential to address challenges in the hotel sector.

Systematic research has identified various application scenarios for service robots in hotels, including food delivery, luggage handling, front-desk reception, and guest guidance (Choi et al., 2019; Tuomi et al., 2020). Their adaptability varies across hotel types: in luxury hotels, robots enhance guests' perceptions of technological innovation through branding while balancing technology with service experience; in budget hotels, they focus on cost savings (Tuomi et al., 2020; Belanche et al., 2020). These findings underscore the diversity and adaptability of service robot applications across various hotel contexts.

Despite technological advancements, deployment is constrained by market conditions and cultural contexts. In Western markets, service robots are increasingly integrated into luxury hotels and chains, supported by high technology acceptance and robust infrastructure (Yörük et al., 2023). However, even in these regions, adoption rates fall short of expectations, particularly in small and medium-sized hotels, due to cost and maintenance challenges (Stirpe et al., 2020). In contrast, China benefits from strong R&D, manufacturing capabilities, and supply chain advantages, positioning it as a potential leader in robot adoption (Leung et al., 2023). However, low adoption rates suggest that barriers exist related to high expectations of guests for service quality, cultural adaptability, and privacy concerns.

1.2. Evaluation criteria for service robot efficacy in hotels

Evaluating the efficacy of service robots in hotels involves assessing their service levels and guest satisfaction across three dimensions: technical performance, service quality, and user experience.

Technical performance focuses on task execution efficiency, such as whether a delivery robot can complete tasks quickly and accurately. Studies show that efficient task execution significantly enhances guest perceptions of service efficiency (Lestari et al., 2022), while slow response speeds can diminish the overall efficacy. This dimension provides a technical foundation for efficacy evaluation through objective performance metrics.

Service quality is assessed by comparing robot services to human services, emphasising reliability and stability. Research indicates that guests prioritise reliability over emotional engagement (Chiang & Trimi, 2020; Wang et al., 2020). Service robots also demonstrate advantages in improving satisfaction and reducing labour costs (Yang & Chew, 2020). This dimension highlights the practical value of robot services.

User experience evaluates efficacy from a subjective perspective, focusing on guest dissatisfaction due to unmet expectations (Çalişkan & Sevim, 2023). For instance, minor errors in task execution or unnatural interactions can reduce guest recognition of robot functionality (Tung & Au, 2018). Centred on convenience, comfort, and psychological acceptance, this dimension reveals deeper guest needs (Xie & Kim, 2022). By emphasising user perceptions, it offers insights beyond technical metrics, aiding in the identification of areas for improvement and enhancing guest satisfaction (Han et al., 2024).

1.3. Challenges to service robot adoption

Technical performance issues in service robots refer to design or operational failures that hinder their ability to meet expected standards, negatively impacting task execution, service efficacy, and guest experience (Huang et al., 2021). Existing studies categorise these issues into hardware problems (e.g., sensor failures) and software issues (e.g., inadequate algorithm optimisation and limited intelligence) (Hong et al., 2018; Tuomi et al., 2020). Industry data indicate an average failure rate of 15 % in specific scenarios, far exceeding human service levels (Bowen & Morosan, 2018). Slow response speeds (Ceccarelli, 2011; Chung & Cakmak, 2018), high failure rates, and limited intelligence (Choi et al., 2019) directly reduce task accuracy and service quality, affecting efficacy (Chiang & Trimi, 2020). For example, navigation algorithm flaws may cause delivery robots to get lost (García et al., 2023), or speech recognition failures may prevent front-desk robots from processing requests (Milohnić & Kapeš, 2024), leading to service disruptions and guest doubts about reliability.

Additionally, inefficient human-robot interactions and a lack of personalisation are core barriers. Robots often perform poorly in interactions due to limited comprehension or emotional engagement (Garcia et al., 2022), particularly in luxury hotels where empathy is expected, resulting in expectation gaps and resistance (Milohnić & Kapeš, 2024; Wang et al., 2023). Although affective computing technologies (e.g., voice tone analysis) aim to address this (Lajante & Dohm, 2024), their complexity and lack of cross-cultural adaptability limit effectiveness (Rosete et al., 2020). These challenges highlight the need to overcome significant hardware, software, and acceptance barriers to bridge the gap between theoretical benefits and practical outcomes.

Technical improvements should go beyond single-function enhancements, focusing on integrated hardware-software optimisation. For instance, adaptive algorithms can improve robots' responsiveness to dynamic environments (Milohnić & Kapeš, 2024; BenMessaoud et al., 2011). Service improvements should prioritise the precise matching of user needs, such as modular designs for scenario-specific customisation, enhancing service consistency and guest satisfaction (Ye et al., 2022; Tung & Au, 2018). Empirical studies show that optimised systems can significantly improve efficiency and user acceptance in specific tasks (Stirpe et al., 2020; Xie & Kim, 2022).

However, implementing these improvements is constrained by the complexity and applicability of technical development. High costs of integrated optimisation and diverse algorithm adaptation needs may exceed some hotels' capabilities (Goel et al., 2022), while the effectiveness of modular designs in cross-cultural contexts requires further validation (Rasheed et al., 2023). These challenges emphasise the need for a deeper understanding of real-world application contexts. A more systematic approach is necessary to analyse how technical limitations affect service quality (Çalişkan & Sevim, 2023), providing opportunities for future research to explore optimisation pathways, enhance efficacy, and address diverse application needs.

Beyond technical issues, non-technical barriers significantly hinder the adoption of service robots by affecting user acceptance. Resistance often stems from robots' lack of emotional engagement or complex operations, particularly in scenarios requiring personalisation (Rasheed et al., 2023). Studies show that this resistance is often due to unreliable technology, such as speech recognition failures or unintuitive interfaces, eroding trust in convenience and functionality (Tussyadiah & Park, 2018; BenMessaoud et al., 2011). Privacy concerns further exacerbate acceptance challenges, with guests expressing unease about data collection (e.g., camera surveillance) due to inadequate privacy safeguards in design (Leung et al., 2023; Rasmussen et al., 2024). For Chinese guests, cultural dimensions of technology adaptation pose significant barriers. Limitations in understanding local languages and contexts (e.g., difficulties with dialect recognition) reduce interaction efficacy (Leung et al., 2023; Ye et al., 2022), while heightened expectations for hygiene and safety amplify demands for reliability (Lee et al., 2023). Moreover, the appearance and perceived intelligence of robots influence psychological acceptance; designs lacking friendliness or intelligence may diminish perceived service quality (Çalişkan & Sevim, 2023). In guest-facing scenarios (e.g., handling requests or complaints), non-technical issues further impede adoption. Robots often struggle with complex requests or complaints due to limited comprehension and a lack of emotional support, failing to address guest dissatisfaction effectively. Such limitations reduce perceptions of service attitude, impacting satisfaction and acceptance (Yörük et al., 2023; Huang et al., 2021; Zuo, 2023).

Addressing non-technical barriers requires focusing on user experience and cultural adaptability. For example, affective computing can enhance robots' emotional engagement (Lajante & Dohm, 2024), while privacy-preserving designs can build trust (Heuer et al., 2019). For the Chinese market, improving dialect recognition and contextual understanding can meet cultural adaptation needs (Ye et al., 2022). Additionally, refining robot appearance to enhance friendliness and perceived intelligence can improve psychological acceptance (Çalişkan & Sevim, 2023). These strategies improve user experience and trust, thereby significantly enhancing service efficacy and acceptance, and providing practical guidance for the adoption of service robots in hotels.

1.4. Research gaps

Although service robots are applied in various hotel scenarios to complement human services, significant research gaps remain, limiting a comprehensive understanding of the relationship between technical performance issues and service efficacy, which hinders their adoption. These gaps are evident in three areas: data scope limitations, methodological shortcomings, and insufficient exploration of context-specific factors.

First, existing studies often rely on small-scale interviews and surveys, with limited sample sizes and a lack of generalisability due to variations in robot models (Ceccarelli, 2011; Rosete et al., 2020; Tuomi et al., 2020), failing to capture the diversity of guest experiences. Moreover, research from a staff perspective struggles to reflect the true sentiments of guests (Ivanov et al., 2020), thereby limiting insights into the user experience.

Second, methodological limitations include subjective bias in thematic analyses (Choi et al., 2019; Yörük et al., 2023) and failure to uncover specific reasons for service quality decline in sentiment analyses (Ceccarelli, 2011; Tuomi et al., 2020). Closed-ended surveys restrict participants' ability to express personalised sentiments, thereby reducing explanatory power (Milohnić & Kapeš, 2024; Rosete et al., 2020). These methodological shortcomings hinder systematic analysis of how technical and interaction issues impact service quality.

Third, despite China's rapid growth in service robot applications, its low adoption rate remains underexplored (Leung et al., 2023). Most studies focus on managerial perspectives, examining technical performance issues like process optimisation and implementation costs (Ding et al., 2023; Rosete et al., 2020), with limited systematic analysis of guests' subjective perceptions. While some studies mention inefficient interactions, a lack of personalisation, and privacy concerns (Ceccarelli, 2011; Tuomi et al., 2020), they fail to deeply explore how cultural misfit affects guest experience (Choi et al., 2020), how inconvenient operation reduces service quality (Liu et al., 2019), or how slow responses and a lack of emotional engagement impact experience and satisfaction (Chen et al., 2025). Additionally, the specific impact of privacy concerns on the guest experience and acceptance lacks systematic analysis (Chang et al., 2022). These contextual gaps limit a comprehensive understanding of adoption barriers in the Chinese market.

2. Research methods

This study aims to empirically analyse technical and service barriers to service robot adoption from the perspective of a guest. To achieve this, the authors developed a theoretical framework based on the literature, collected user reviews through web-crawling, applied LDA topic modelling to identify key barriers, and validated the findings through qualitative analysis, comparing them with existing studies to confirm technical and service issues. Fig. 1 illustrates the technical framework, covering theoretical foundations, empirical analysis processes, and expected policy implications, from data collection to topic modelling and improvement recommendations, laying the groundwork for a subsequent analysis.

2.1. Data collection

This study used the web-crawling software Gooseeker to collect user reviews related to service robots in Chinese hotels from six major online travel platforms (Tongcheng, Ctrip, Lvmama, Qunar, Tuniu, and Elong) between January 2021 and December 2024. These reviews covered various robot types, including delivery and cleaning robots (Appendix A). These platforms, akin to TripAdvisor, generate substantial daily review data across diverse hotel types - budget, mid-range, and luxury - allowing users to share experiences, post reviews, and rate services.

On a 5-point rating scale, reviews below 3 points typically reflect negative sentiments (Guo et al., 2017), better capturing service deficiencies, and were thus selected as the primary data source (Zheng et al., 2021). The authors initially gathered approximately 837,500 raw reviews from hotels nationwide, spanning budget to luxury categories. To ensure data quality, the authors excluded reviews with fewer than five Chinese characters or lacking specific descriptions (e.g., "good", "bad", "boring"), resulting in a final sample of 20,900 negative reviews with scores below 3 points.

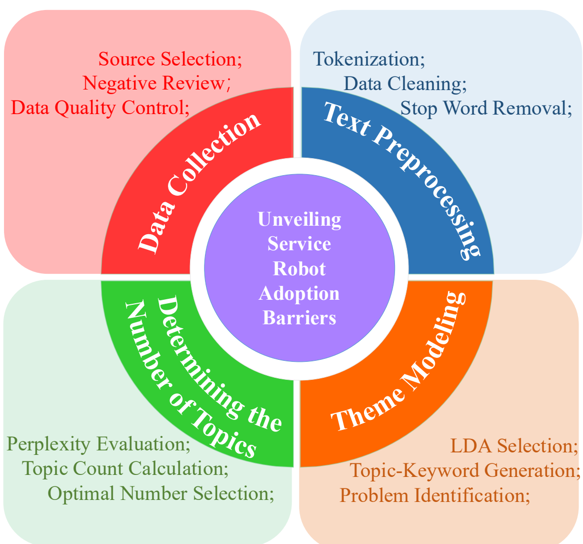


Fig. 1. Integrated framework for unveiling barriers to the adoption of service robots

2.2. Text preprocessing

Text preprocessing followed established methods (Guo et al., 2017; Wang et al., 2019; Taecharungroj & Mathayomchan, 2019) to prepare clean data for topic modelling. First, the authors used the Jieba tool in Python, widely applied for Chinese text processing, to segment the review texts. Second, during data cleaning, the authors removed common but meaningless words (e.g., “can”, “okay”) using a custom dictionary and excluded low-frequency words that were difficult to converge or interpret, refining the extracted features. Third, the authors eliminated irrelevant stop words (e.g., “and”, “is”) using a standard stop-word list from Sichuan University’s AI Lab.

2.3. Topic modelling

The authors employed topic modelling, an unsupervised learning technique, to automatically identify themes in large-scale text data by grouping documents based on themes for further analysis. It assumes that each document contains multiple themes, with each theme represented by a probability distribution of words (Blei, 2012). In this study, topic modelling was used to uncover the primary issues in low-rated reviews, reflecting guests’ core dissatisfactions with service robots. Compared to sentiment analysis, topic modelling better identifies specific reasons for dissatisfaction and overlooked details (Fang & Zhan, 2015; Zhang et al., 2022).

Common topic modelling methods include Latent Semantic Indexing (LSI), Latent Dirichlet Allocation (LDA), Hierarchical Dirichlet Process (HDP), and Probabilistic Latent Semantic Analysis (PLSA). Prior studies show that LDA, with its hierarchical Bayesian probabilistic model, outperforms other methods in large-scale data mining (Wang et al., 2019; Taecharungroj & Mathayomchan, 2019). Thus, the authors selected LDA for our analysis. The LDA model generation process is depicted in Fig. 2, where ϕ denotes the keyword distribution, and its Dirichlet distribution parameter is β; θ denotes the topic distribution, and α is its Dirichlet distribution parameter. z denotes the topic generated by the model, w represents the final keyword generated by the model, S is the word count in the document, and D is the number of documents.

The LDA model generation process mainly involves the following steps:

1) Sampling the “Topic-keyword distribution ϕ “for each topic from the Dirichlet distribution with the parameter β

2) Sampling the “document-topic distribution θ “for each document from the Dirichlet distribution with the parameter α

3) Sampling 1 subject z from θ.

4) Adopt 1 keyword w from ϕ.

2.4. Determining the number of topics

Selecting an appropriate number of topics is critical (Hagen, 2018). Too many topics may lead to uninterpretable results, while too few may reduce dimensional accuracy (Nikolenko et al., 2016). To minimise human intervention and identify the optimal number of topics, we used the perplexity score as an evaluation metric (Blei, 2012). A lower perplexity

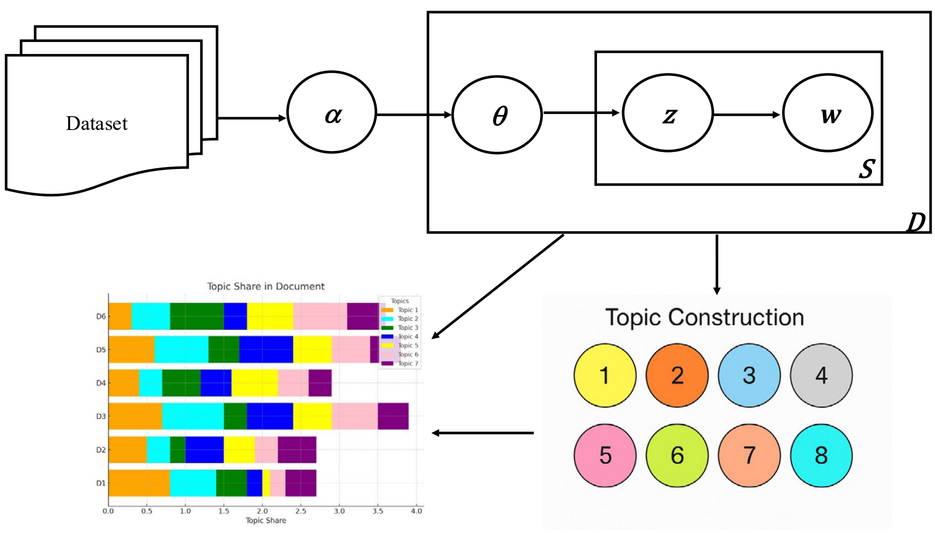


Fig. 2. Structure of the LDA model

score indicates less uncertainty in the model, reflecting better performance and more accurate corpus representation. This method's effectiveness has been validated in prior studies (Zhang et al., 2022). The perplexity score is calculated as follows:

$$P_e = \mathrm{e}\frac{-\Sigma \lg p(w)}{N_l}$$

where is the probability of occurrence of each word w, which equals the sum of the product of the probability values of each topic in the text and the probability value of the vocabulary in the topic; is the total number of words in the text. Through this calculation, we determined 10 as the optimal number of topics, as shown in Fig. 3.

3. Research results

3.1. Qualitative analysis

Using the LDA topic modelling method, the authors identified ten themes and listed the top ten high-frequency words for each. The word weights, word clouds for the ten themes, and negative comment counts are detailed in Table 1. The association between theme distribution and related words is shown in Fig. 4.

The qualitative analysis involved two key steps: coding to assign labels to each theme and reliability testing. For coding, the authors applied the computational grounded theory method (Zhang et al., 2022) and opted for manual coding to address potential issues with machine coding, such as handling slang and internet language. Two trained coders, who are experienced in social media and user reviews, participated in the analysis. They first reviewed the top ten high-frequency words for each theme in Table 1, then examined the top ten high-probability reviews and ten random reviews per theme (Appendix B), independently naming each theme and finalising labels through discussion. For example, Theme 4, with the most negative reviews, focused on robots' lack of flexibility, as seen in comments like "I asked for half a day, and the robot just repeated the same sentence, completely unable to solve my issue" and "During checkout, the robot rigidly told me to find a human, which was too troublesome". Drawing on prior research (Zuo, 2023), the authors categorised this barrier as a service issue due to robots' inability to handle non-standardised demands and labelled it "Lack of Flexibility".

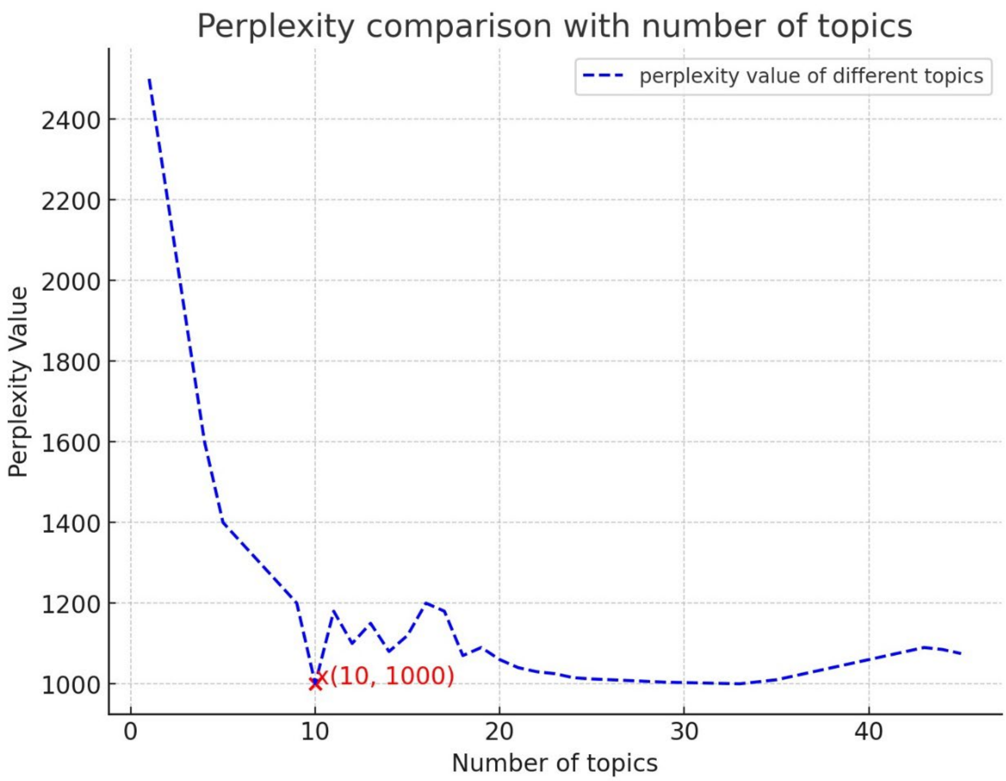


Fig. 3. Perplexity assessment across varying topic numbers

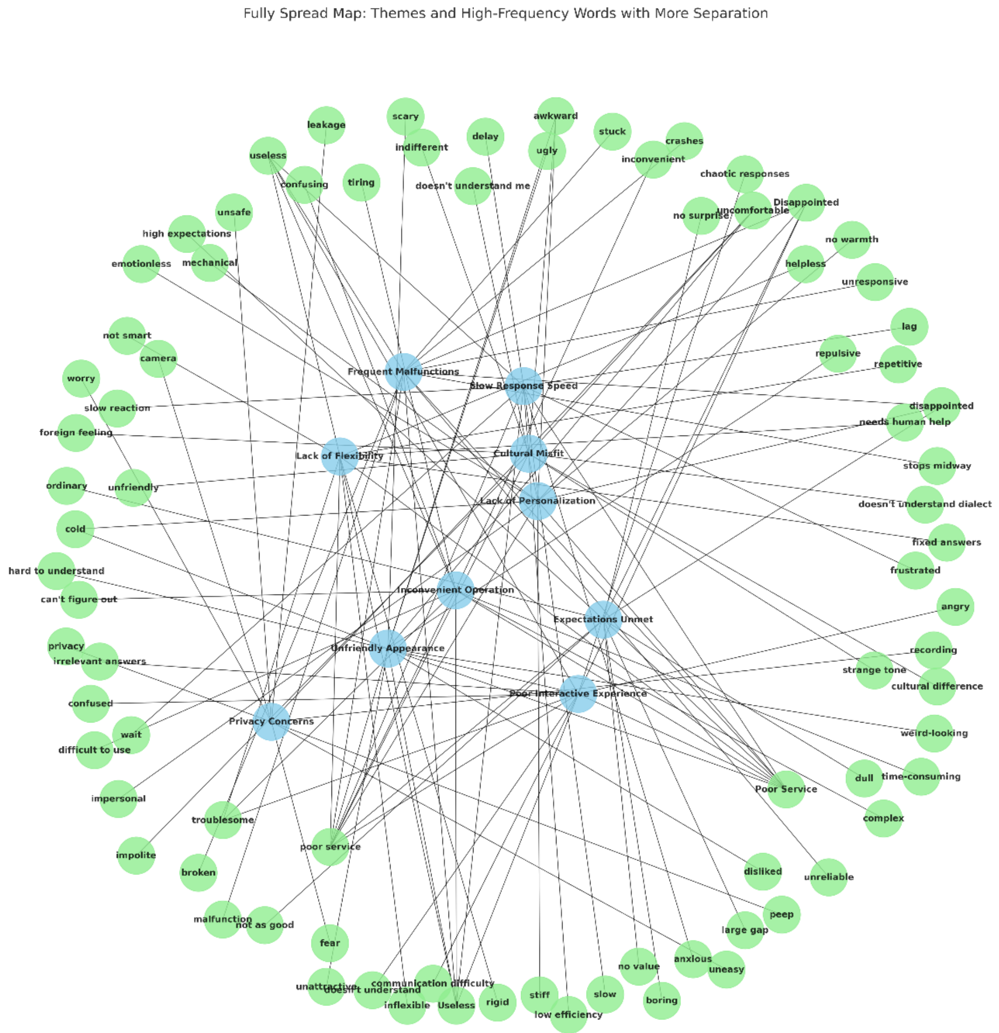
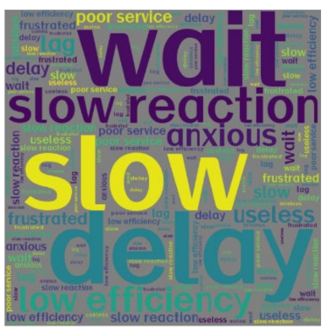
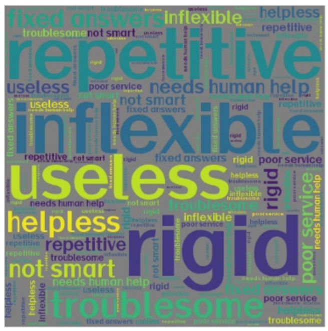
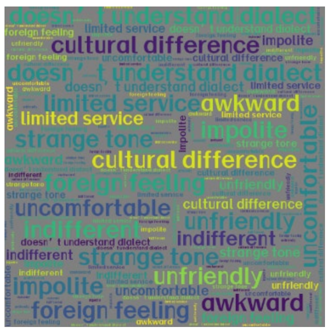
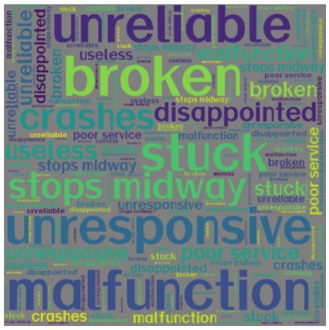
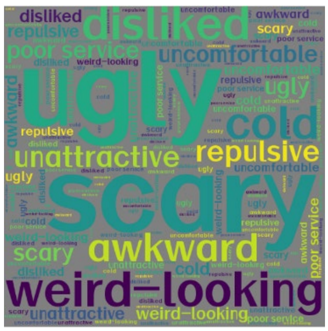
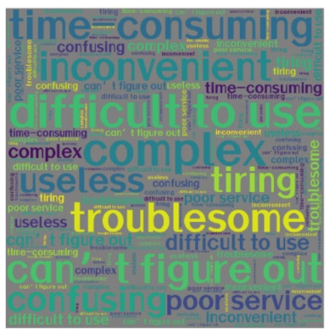


Fig. 4. Theme distribution

Tab. 1. Themes, high-frequency words, and negative comment counts

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
1	Slow Response Speed	slow (0.092), wait (0.070), delay (0.061), slow reaction (0.048), low efficiency (0.034), anxious (0.026), useless (0.021), lag (0.018), poor service (0.015), frustrated (0.012)		2,530

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
2	Lack of Personalisation	cold (0.067), emotionless (0.058), mechanical (0.042), doesn't understand me (0.036), stiff (0.031), disappointed (0.027), no warmth (0.023), awkward (0.019), impersonal (0.016), poor service (0.013)		2,668
3	Privacy Concerns	privacy (0.080), fear (0.062), recording (0.053), camera (0.040), unsafe (0.033), leakage (0.028), peep (0.024), worry (0.020), uncomfortable (0.017), uneasy (0.014)		2,300
4	Lack of Flexibility	rigid (0.071), repetitive (0.050), inflexible (0.041), useless (0.035), troublesome (0.030), helpless (0.025), fixed answers (0.021), not smart (0.018), needs human help (0.015), poor service (0.012)		2,852
5	Cultural Misfit	doesn't understand dialect (0.057), strange tone (0.048), impolite (0.040), foreign feeling (0.034), unfriendly (0.029), cultural difference (0.025), uncomfortable (0.021), awkward (0.018), indifferent (0.015), limited service (0.012)		1,932

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
6	Frequent Malfunctions	malfunction (0.084), broken (0.065), unresponsive (0.052), stuck (0.039), unreliable (0.032), stops midway (0.027), crashes (0.023), disappointed (0.019), useless (0.016), poor service (0.013)		2,254
7	Poor Interactive Experience	doesn't understand (0.051), irrelevant answers (0.044), chaotic responses (0.037), hard to understand (0.032), communication difficulty (0.028), confused (0.024), angry (0.020), useless (0.017), troublesome (0.014), poor service (0.011)		2,047
8	Unfriendly Appearance	ugly (0.060), scary (0.050), weird-looking (0.041), disliked (0.035), cold (0.030), awkward (0.026), unattractive (0.022), repulsive (0.019), uncomfortable (0.016), poor service (0.013)		1,748
9	Inconvenient Operation	difficult to use (0.065), complex (0.055), can't figure out (0.046), time-consuming (0.039), troublesome (0.033), inconvenient (0.028), confusing (0.024), tiring (0.020), useless (0.017), poor service (0.014)		1,863

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
10	Unmet Expectations	no surprise (0.075), high expectations (0.057), disappointed (0.048), not as good (0.041), ordinary (0.035), boring (0.030), no value (0.026), large gap (0.022), dull (0.018), poor service (0.015)		1,624

Tab. 2. Inter-rater consistency test results

Label	LDA-Rater A	LDA-Rater B	Rater A-Rater B
	Kappa (Interpretation)	Kappa (Interpretation)	Kappa (Interpretation)
Slow Response Speed	0.485 (Moderate)	0.451 (Moderate)	0.792 (Substantial)
Lack of Personalisation	0.472 (Moderate)	0.436 (Moderate)	0.803 (Almost Perfect)
Privacy Concerns	0.583 (Moderate)	0.547 (Moderate)	0.874 (Almost Perfect)
Lack of Flexibility	0.449 (Moderate)	0.413 (Moderate)	0.685 (Substantial)
Cultural Misfit	0.395 (Fair)	0.362 (Fair)	0.614 (Substantial)
Frequent Malfunctions	0.504 (Moderate)	0.478 (Moderate)	0.729 (Substantial)
Poor Interactive Experience	0.428 (Moderate)	0.394 (Fair)	0.657 (Substantial)
Unfriendly Appearance	0.367 (Fair)	0.341 (Fair)	0.523 (Moderate)
Inconvenient Operation	0.453 (Moderate)	0.417 (Moderate)	0.691 (Substantial)
Unmet Expectations	0.238 (Fair)	0.219 (Fair)	0.405 (Moderate)

Note: "LDA" refers to the theme with the highest probability match for each comment. Kappa values are Cohen's (1960) Kappa coefficients, interpreted as: < 0.00 (No Agreement), 0.00-0.20 (Slight), 0.21-0.40 (Fair), 0.41-0.60 (Moderate), 0.61-0.80 (Substantial), 0.81-1.00 (Almost Perfect) (Richard & Koch, 1977).

To ensure the reliability of the results, the authors randomly selected 200 reviews for independent labelling by two researchers, following established guidelines (Hagen, 2018; Zhang et al., 2022). The researchers were unaware of the LDA classifications and each other's labels. The authors used Cohen's Kappa coefficient (Cohen, 1960) to assess inter-rater and LDA consistency. As shown in Table 2, consistency between LDA and Raters A and B ranged from fair to moderate (0.219-0.583), while consistency between Raters A and B was higher, ranging from moderate to almost perfect (0.405-0.874). This discrepancy may stem from reviews containing multiple themes, while the authors restricted each review to a single label, leading to disagreements between LDA and human coding on complex reviews. Nevertheless, the Kappa coefficients in Table 2 indicate reasonable reliability of LDA in theme classification (Cohen, 1960), particularly with high inter-rater consistency, validating its effectiveness in handling large-scale reviews. This supports the authors' approach to analysing the impact of technical issues on service quality through improved methods, highlighting the benefits of combining human validation with automated classification.

3.2. Validation of results

Following Hagen (2018), topic modelling results should align with prior literature findings. The authors compared the LDA-identified themes with existing studies, as shown in Table 3. Seven of the ten themes partially overlapped with previous research, though not identically. Specifically, themes like slow response speed, a lack of personalisation, privacy concerns, poor interactive experience, unfriendly appearance, and unmet expectations showed similarities with prior findings.

Topic modelling combines the strengths of quantitative and inductive qualitative analysis (Schmiedel et al., 2018), with LDA excelling in data collection and processing. LDA proved highly effective and comprehensive in analysing negative barriers to service robot adoption in Chinese hotels. As shown in Table 3, beyond validating existing findings, this study identified "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" (Themes 5, 6, and 9) as novel barriers not previously addressed in the literature.

3.3. Cross-theme post-hoc analysis results

This study further explored the complexity of guest feedback on service robots in Chinese hotels through two post-hoc analyses: high-frequency word co-occurrence and theme interaction. The authors identified the cross-theme distribution of high-frequency words, "Poor Service", "Useless", and "Disappointed", and the interaction among "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation". The results of each analysis are presented below.

The high-frequency words "Poor Service", "Useless", and "Disappointed" appeared across multiple themes. Cross-theme analysis revealed that 3.85 % of reviews mentioned these words simultaneously. "Poor Service" spanned eight themes - Slow Response Speed, Lack of Personalisation, Lack of Flexibility, Frequent Malfunctions, Poor Interactive Experience, Unfriendly Appearance, Inconvenient Operation, and Unmet Expectations - appearing in comments like "It took so long to deliver, I waited forever", "It got stuck, so unreliable", "Cold and emotionless, no human touch", and "So hard to use". "Useless" appeared in five themes - Slow Response Speed, Lack of Flexibility, Frequent Malfunctions, Poor Interactive Experience, and Inconvenient Operation - seen in comments like "So inefficient, useless" (Slow Response Speed), "Can't solve problems, useless" (Lack of Flexibility), and "Took forever, useless" (Inconvenient Operation). "Disappointed" was present in three themes - Lack of Personalisation, Frequent Malfunctions, and Unmet Expectations - reflected in comments like "Cold and emotionless, too disappointed" (Lack of Personalisation), "It got stuck, too disappointed" (Frequent Malfunctions), and "Hyped up but so disappointing" (Unmet Expectations).

Cross-theme analysis showed that 4.01 % of reviews (approximately 875) involved multiple themes, such as "It couldn't understand my dialect and got stuck, so hard to use", reflecting interactions among Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation. The co-occurrence rate between Cultural Misfit and Inconvenient Operation was 2.5 %, and between Frequent Malfunctions and Inconvenient Operation, it was 3.0 %, indicating that operational inefficiency is central to these interactions. Specifically, Cultural Misfit, due to dialect recognition failures, led to language adaptation issues,

Tab. 3. Comparison between the themes obtained by the LDA method and those obtained by other methods

TOPIC	(WANG ET AL., 2023)	(MILOHNIĆ & JELENA KAPEŠ, 2024)	(CHUNG & CAKMAK, 2018)	(TUSSYADIAH & PARK, 2018)	(CECCARELLI, 2011)
TOPIC 1. SLOW RESPONSE SPEED	N/A	Slow response speed affects customer satisfaction	Slow response speed impacts user acceptance of service robots	N/A	N/A
TOPIC 2. LACK OF PERSONALISATION	Lack of emotional connection and warmth	N/A	Lack of personalised interaction affects guest acceptance	Lack of human-like interaction and warmth	N/A
TOPIC 3. PRIVACY CONCERNS	Privacy risks associated with service robots (Shizhen (Jasper) Jia et al., 2024)	N/A	N/A	N/A	N/A
TOPIC 4. LACK OF FLEXIBILITY	Poor speech recognition capability	N/A	Lack of flexibility affects usability	N/A	Low efficiency in human-robot interaction
TOPIC 5. CULTURAL MISFIT	N/A	N/A	N/A	N/A	N/A
TOPIC 6. FREQUENT MALFUNCTIONS	N/A	N/A	N/A	N/A	N/A
TOPIC 7. POOR INTERACTIVE EXPERIENCE	N/A	N/A	Poor interactive experience affects customer acceptance	N/A	N/A
TOPIC 8. UNFRIENDLY APPEARANCE	Unattractive robot appearance	N/A	Robot appearance design affects guest acceptance	N/A	N/A
TOPIC 9. INCONVENIENT OPERATION	N/A	N/A	N/A	N/A	N/A
TOPIC 10. UNMET EXPECTATIONS	Importance of expectation management in technology acceptance (Zia and Alotaibi, 2024)	N/A	N/A	N/A	N/A

Note: "N/A" indicates that the topic was not addressed in the corresponding literature.

making operations difficult as users struggled with mismatched interfaces and repeated attempts at different commands. Frequent Malfunctions, such as system freezes, exacerbated this, with operational interruptions (e.g., uncompleted tasks) eroding trust. This interaction was particularly pronounced during peak times, when guest expectations for quick service were frustrated by operational inefficiencies and frequent failures.

4. Discussion of the results

By analysing 20,900 negative reviews, this study identified ten barriers to service robot adoption in the hotel industry from a guest perspective. These findings align with Collins (2020), who argued that users' intrinsic feelings toward technology significantly influence acceptance behaviour. Additionally, Bandura's (1986) social cognitive theory suggests that subjective expectations and experiences shape technology acceptance. This study further indicates that guests' experiential needs extend beyond privacy and technical failures, reflecting broader cultural and service design impacts, differing from Kim et al.'s (2021) findings in Thai hotels. Moreover, we introduce "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" (Themes 5, 6, and 9) as novel challenges, posing new considerations for service robot promotion and development. While Nurul Nabila Said et al. (2023) suggest Chinese users have high tolerance for technical issues, our findings show that cultural adaptability and operational inconvenience significantly reduce acceptance in specific scenarios, profoundly impacting the adoption process in the hotel industry.

4.1. Basic theoretical discussion

Using LDA topic modelling on 20,900 negative reviews from Chinese hotel guests, this study identified ten barriers, seven of which - Slow Response Speed, Lack of Personalisation, Privacy Concerns, Lack of Flexibility, Poor Interactive Experience, Unfriendly Appearance, and Unmet Expectations - align with common issues in prior literature. Below, the authors analysed these themes, integrating theoretical frameworks and representative reviews to highlight their specific manifestations in Chinese hotel contexts.

Slow Response Speed. As one of the most frequent barriers, this theme reflects significant shortcomings in task execution efficiency. For example, a guest noted, "This robot took forever to deliver items; I waited ages at my door", and another stated, "I asked it to fetch something, but it didn't move for ten minutes". While Cao et al. (2023) suggested that technological advancements have improved robot service speed in standardised settings, the analysis by this research authors of 2,530 related reviews found that approx. 75 % (around 1,900) focused on delays in real-time services. This contradicts Cao et al.'s optimistic view, supporting Gupta et al. (2020) on navigation flaws in dynamic settings, indicating the limited applicability of general efficiency improvements in complex hotel environments (e.g., crowded corridors and elevator delays). This delay significantly impacts Chinese guests' expectations for immediacy, as explained by Davis's (1989) Technology Acceptance Model (TAM), which posits that acceptance depends on perceived usefulness. Slow Response Speed directly undermines robots' utility as real-time service tools, with comments like "It's so slow, I'd rather get it myself" reflecting strong dissatisfaction. Further analysis suggests this issue is exacerbated during peak demand periods in hotels.

Lack of Personalisation. This theme highlights a significant lack of emotional interaction, as seen in comments like, "It's so cold, no human touch at all, so disappointed", and "It answers like a machine, no warmth". While Ranieri and Romero (2016) claimed that robots have some human-like features, such as simulating emotions through voice tones, this research analysed 2,668 reviews and found that 68 % (around 1,815) focused on the absence of emotional connection (e.g., "no warmth", "like a machine, not a person"). Such results contradict Cao et al. (2023) and deepen Vallverdú and Trovato's (2016) view that a lack of personalisation is particularly pronounced in high-emotion service settings. This barrier diminishes robots' emotional utility in hotels, reflecting Chinese guests' high expectations for warmth and personalisation, as supported by Ying et al. (2020), who note that Chinese hotel guests prioritise warmth and personalisation over mere technical performance.

Privacy Concerns. This theme reflects guests' distrust in robots' privacy safeguards, with comments like "I feel like it's recording my room information, so uneasy" and "I'm not comfortable, but I was too lazy to get it myself". Prior studies (Jia et al., 2024) have explored privacy risks, and findings of this research align with the privacy paradox (Barnes, 2006). Specifically, while 55 % of 2,300 reviews (around 1,265) expressed concerns about privacy breaches (e.g., "I'm afraid my room info will be leaked"), 20 % (around 460) also indicated continued use driven by convenience, consistent with the privacy paradox's trade-off between concerns and utility. Over 60 % of related comments (around 1,380) focused on psychological resistance (e.g., "I feel my privacy is being invaded", "I always feel unsafe"), rather than technical flaws, suggesting that technical solutions fail to address trust barriers. This psychological resistance can be understood through trust theory (Mayer et al., 1995), which states that trust depends on perceived ability, benevolence, and integrity, while the lack of transparent data handling by robots erodes guest trust.

Lack of Flexibility. This theme indicates robots' inability to handle diverse demands, as seen in comments like "It just repeats the same answer, so useless" and "It's too rigid for last-minute changes". It aligns with TAM's perceived usefulness dimension (Davis, 1989), where guests devalue robots' utility due to their inflexibility, which also affects perceived ease of use. However, it contradicts Buerkle et al. (2023), who suggested that robots have high flexibility, likely because their study focused on industrial multi-tasking and not hotel guests' real-time, personalised needs. Of 2,852 related reviews, 70 % (around 1,998) focused on functional failures in real-time services, supporting Brandstötter et al.'s (2022) findings regarding inadequate scenario adaptability. Tsushima et al. (2025) suggested that this barrier may be improved with the integration of advanced language models, such as ChatGPT, DeepSeek, and Grok.

Poor Interactive Experience. This theme centres on robots' deficiencies in language comprehension and communication, with guests lamenting, "I asked about checkout time, and it gave a chaotic response, totally incomprehensible" or "I explained for ages, but it still didn't understand, so frustrating". This directly ties to TAM's perceived ease of use (Davis, 1989), where inefficient interactions diminish perceived usability. Romero-Gonzalez et al. (2020) emphasised the importance of speech interaction for acceptance, a finding our study corroborates, validating the critical role of language comprehension in hotel services. However, this contradicts Ren et al. (2024), who claim language adaptability has significantly improved. In the dataset of this research, 65 % of the 2,047 related reviews (around 1,330) highlighted failures in real-time communication, indicating that the issue extends beyond mere speech recognition accuracy to a broader lack of adaptation to guests' linguistic habits in hotel settings. This deepens Rasoul Zahedifar et al.'s (2025) research, exposing the limitations of general language adaptability in dynamic hotel environments, such as handling multilingual requests or colloquial expressions. This finding also diverges from Jeong et al. (2024), possibly because their study focused on controlled lab settings or standardised language tests, rather than the diverse, immediate demands of hotel guests.

Unfriendly Appearance. Robot design appearance significantly shapes acceptance, as this theme reveals through comments like "This robot looks so ugly, it feels awkward" and "It looks weird, I don't feel comfortable using it". This supports the aesthetic usability effect (Tractinsky et al., 2000), which posits that attractive designs enhance perceived usability and satisfaction. Of 1,748 related reviews, 60 % (around 1,049) centred on psychological rejection, deepening Saeki and Ueda's (2024) discussion on design psychology and revealing Chinese guests' expectations for aesthetics and comfort beyond functionality. This barrier reduces robots' emotional utility, reflecting Chinese guests' psychological need for familiarity and affinity, possibly tied to a cultural emphasis on harmonious aesthetics and social comfort, as Sadangharn (2022) suggests.

Unmet Expectations. This theme, comprising 1,624 reviews (7.8 % of the total), reflects a significant gap between robot promotion and actual experience, with guests noting, "It was hyped up, but it's no different from regular service" and "It's supposed to be smart, but it can't do anything well". Of these reviews, 70 % (around 1,137) focused on disappointment with intelligent services, supporting Zia and Alotaibi (2024) on the importance of expectation management, and extending Guo et al.'s (2024) expectation theory by showing that Chinese guests' high expectations for efficient, personalised intelligent services were unmet. This contradicts Wu and Huo (2023), who claim robots generally meet user needs.

4.2. Discussion of key findings

This study introduces "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" as significant barriers to service robot adoption in Chinese hotels, previously underexplored or not independently identified. Unlike prior studies focusing on general technology acceptance (e.g., privacy, efficiency), this research, through contextual analysis and large-scale data validation, highlights unique impacts of these barriers in real-time hotel service settings, offering a fresh perspective on adoption complexities.

Cultural Misfit. Identified as a structural barrier rooted in technical limitations, this theme surfaces in comments like “It couldn’t recognise my Sichuan dialect and lacked polite responses”, and “It answered coldly, with no emotional connection, like a foreigner”. While Choi et al. (2020) mentioned cultural differences affecting acceptance, they did not treat it as a distinct barrier. Tuomi et al. (2020) focused on functionality in Western markets, overlooking China’s diverse dialects and politeness norms. Of 1,932 reviews, 62 % (around 1,198) focused on language adaptation and politeness issues, aligning with Ganesh’s (1980) cultural dimension theory, where Chinese collectivist culture expects emotional connection and localisation, unmet by robots, leading to cultural alienation.

Frequent Malfunctions. This theme, identified as a structural barrier, quantifies the impact on Chinese guests’ real-time service expectations, emphasising the need for reliability optimisation tailored to hotel conditions. A typical comment reads, “It got stuck halfway delivering a towel, so unreliable”. While Tuomi et al. (2020) discussed general technical failures, they did not focus on real-time hotel demands. Xu et al. (2023) optimistically suggested that hardware improvements have resolved frequent failures, but 68 % of 2,254 related reviews (around 1,533) highlighted real-time failures - “stuck in the corridor” or “delivery interrupted” - supporting Senthamaraim et al.’s (2024) findings regarding the need for environmental adaptability.

Inconvenient Operation. This theme is another structural barrier that reflects the impact of interface complexity on non-expert users, with comments like “So hard to use, I tried for ten minutes to get water and gave up” and “Too many buttons, I couldn’t figure it out, so frustrating”. Liu et al. (2019) suggested simplifying interaction designs but did not identify it as a distinct barrier. Pepi Stavropoulou et al. (2020) proposed user training, but 64 % of 1,863 reviews (around 1,192) focused on inefficient experiences - “Took forever, useless” or “Too complex, I gave up” - highlighting high expectations for convenience among Chinese guests. Gutsche et al. (2025) predict user-friendliness as key to adoption, resonating with the findings of this research.

4.3. Cross-theme analysis

The high-frequency words “Poor Service”, “Useless”, and “Disappointed”, extracted via LDA, represent service quality, functional utility, and expectation alignment issues, respectively. Their cross-theme overlap reveals a cascading effect of adoption barriers. While prior studies identified these issues independently (Gupta et al., 2020; Buerkle et al., 2023; Wu & Huo, 2023), this study introduces their progressive linkage, where a single flaw triggers a chain reaction amplifying dissatisfaction. A typical review states, “The hotel’s service robot was terrible! I asked for a bottle of water, waited 20 minutes - it was so slow, and it spoke so coldly, no human touch. I’d rather get it myself; it felt useless. The hotel hyped it as a ‘smart assistant,’ but it was so disappointing! I won’t use it again”. This effect erodes trust, significantly reducing acceptance, with some guests stating, “I won’t use robots again”. It highlights Chinese guests’ high standards for immediacy, emotional connection, and promotional consistency, suggesting acceptance is driven by multidimensional factors.

Conversely, the interaction among Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation reveals the complexity of user experience in adoption. Prior studies treated these as separate barriers (Gupta et al., 2020; Buerkle et al., 2023), overlooking their interactions. This study fills the gap, showing that single-dimensional technical improvements (e.g., enhancing hardware reliability) are insufficient. Robot design must simultaneously improve multimodal speech recognition (for cultural adaptation), environment-adaptive hardware (e.g., anti-jamming sensors), and simplified interfaces (e.g., one-button operations) to meet the needs of Chinese user. This supports TAM’s multidimensional drivers (Davis, 1989), where interactions reduce perceived ease of use (due to complexity and failures) and usefulness (due to cultural misfit), further suppressing acceptance through diminished user attitudes and intentions.

Conclusions

Understanding service robot adoption barriers is crucial for hotel practitioners to optimise deployment and enhance guest experience. However, guest-centric methodologies are lacking for a systematic examination of these barriers through negative emotions. This study analyses 20,900 negative reviews from six major Chinese online travel platforms using LDA topic modelling and computational grounded theory. It confirms technical barriers like Slow

Response Speed and Lack of Flexibility, user experience issues like Lack of Personalisation, Poor Interactive Experience, and Unfriendly Appearance, and significant impacts of Privacy Concerns and Unmet Expectations on service efficiency and acceptance. Furthermore, it introduces Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation as key barriers in China. The study also reveals interaction effects among cultural adaptation, reliability, and usability, alongside a cascading effect of service quality, functional utility, and expectation alignment, forming a vicious cycle that significantly reduces acceptance. It emphasises the need for systematic optimisation of multidimensional interactions and cascading effects to meet the high standards of Chinese hotel contexts, providing theoretical support for future research on the multidimensional drivers of technology acceptance.

Theoretical contributions

This study makes several theoretical contributions. First, it overcomes the limitations of traditional research through superior data collection methods. Unlike prior studies relying on small-scale interviews and surveys with limited sample sizes and generalisability (Ceccarelli, 2011; Rosete et al., 2020; Tuomi et al., 2020), this study used web-crawling to collect 20,900 negative reviews from six major Chinese online travel platforms, providing a robust guest-centric approach to understanding adoption barriers. Second, traditional thematic analyses are prone to subjective bias (Yörük et al., 2023) and fail to uncover specific reasons for service quality decline (Nurul Nabila Said et al., 2023). This study used LDA integrated with computational grounded theory to identify ten barriers to service robot adoption from negative reviews. Third, by focusing on the unique expectations of Chinese hotel guests, this study addresses a gap in prior research, which often examines technical performance and costs from a managerial perspective (Rosete et al., 2020; Leung et al., 2023), neglecting a systematic analysis of guests' subjective perceptions. We introduce "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" as distinct barriers and reveal their practical-expectation cascading effect with service quality, functional utility, and expectation alignment through cross-theme interactions. Specifically, while prior studies (Tuomi et al., 2020; Xu et al., 2023) focused on independent impacts of technical failures, ignoring interactions with cultural or operational factors, and Leung et al. (2023) overlooked cultural dimensions in Chinese contexts, this study quantifies these interactions. It reveals a cascading cycle of trust-efficiency-culture in dynamic hotel settings, where expectations for quick, personalised services are disrupted by Cultural Misfit, worsened by Inconvenient Operation, and collapse due to Frequent Malfunctions. This suggests that adoption barriers stem from complex couplings, emphasising the need for an ecological approach to optimise reliability and adaptability to meet Chinese hotel standards. Additionally, the cross-theme overlap of "Poor Service", "Useless", and "Disappointed" forms a linked cycle, where technical limitations trigger functional constraints, exacerbating dissatisfaction due to unmet expectations, providing a theoretical basis for contextual optimisation.

Practical implications

Based on these findings, the authors propose the following recommendations to optimise service robot deployment, enhancing service quality and guest satisfaction. For technical issues, such as response delays and Frequent Malfunctions, hotels should enhance navigation algorithms with real-time path optimisation and deploy anti-jamming sensors in complex environments to improve efficiency and reliability, addressing delivery delays and task interruptions. The newly identified Inconvenient Operation barrier requires simplifying interaction interfaces to reduce usage difficulty and frustration. Human-robot interaction challenges, including Lack of Personalisation, Poor Interactive Experience, and Lack of Flexibility, necessitate integrated improvements. Incorporating affective interaction features and large language models can mitigate coldness and chaotic responses while enhancing adaptability to diverse demands. The newly identified Cultural Misfit barrier demands tailored adaptations, such as multi-dialect recognition and local etiquette protocols, to bridge language and cultural gaps. Additionally, unfriendly appearances can be addressed by designing culturally aesthetic forms to enhance emotional acceptance. To tackle Unmet Expectations and Privacy Concerns, hotels should establish continuous feedback mechanisms to align marketing with performance and implement transparent data policies to alleviate psychological resistance. Moreover, the cross-theme interaction of Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation requires simultaneous improvements in language adaptation and interface simplicity to mitigate cultural barriers exacerbating operational inefficiencies, alongside enhanced hardware reliability to reduce trust erosion from failures. Similarly, the cascading effect of "Poor Service", "Useless", and "Disappointed" necessitates holistic improvements in response efficiency, emotional interaction, and expectation alignment to break the cycle from efficiency deficits to trust crises. Furthermore, addressing cross-theme effects requires comprehensive optimisation. Simultaneously enhancing reliability, usability, and cultural adaptability can disrupt the cycle of widespread dissatisfaction from single failures. Additionally, establishing an integrated ecosystem of staff and robots, with staff trained to support during peak times or failures, ensures service continuity, meeting guests' high expectations for immediacy, warmth, and consistency.

Limitations and future research

Despite providing comprehensive insights into service robot adoption barriers through large-scale web-crawling and LDA topic modelling, this study has limitations. First, its focus on negative reviews from Chinese hotel guests may not fully capture positive experiences or perspectives from non-Chinese markets, limiting generalisability. Additionally, data from six major online travel platforms exclude offline feedback or niche platforms, potentially missing some user voices. Second, while LDA effectively identifies key barriers, it relies on explicit textual expressions, failing to capture implicit emotions or non-verbal factors, possibly underestimating their impact on service quality. Future research can address these limitations by expanding the data scope to multilingual markets or offline interviews to compare acceptance across cultural contexts. Additionally, integrating visual analysis or emotion detection technologies (e.g., facial expression recognition) can complement text analysis, revealing non-verbal impacts on guest experience. Finally, longitudinal experiments can validate the dynamic effects of technical improvements (e.g., dialect recognition) on trust and satisfaction, providing precise practical guidance for service robot optimisation.

Declaration of conflicting interests

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Data availability statement

The data used to support the findings of this study are included within the article.

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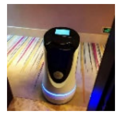
Appendices

Appendix A. Types of hotel service robots

TYPE	FUNCTION DESCRIPTION	IMAGE
Hotel Concierge Robot	Guides guests to rooms, suitable for large hotels. Features map navigation, elevator calling, and smooth operation to enhance the check-in experience.	
Delivery Robot	Equipped with drawers or compartments to deliver items like toothbrushes, towels, slippers, and meals, ensuring privacy.	
Carpet Cleaning Robot	Automatically cleans hotel carpets, reducing manual cleaning workload and improving hygiene efficiency with path planning and vacuuming functions.	
Assistive Robot	Supports guests with mobility issues (e.g., elderly or disabled), providing mobility assistance or item transport to enhance convenience.	

Appendix B. Top 10 high-probability and random reviews for each topic

LABEL	EXAMPLE OF COMMENTS
Topic 1. Slow Response Speed	
Top 10 High-Probability Reviews	This robot was so slow in delivering items; I waited half a day at my door. Its response to my question was painfully slow, driving me crazy. Waiting for the robot during checkout was a complete waste of time. The service efficiency is so low, nowhere near as fast as human staff. The delay was ridiculous; I waited 20 minutes for breakfast. It's so frustrating to use this robot when I'm in a hurry. It lagged several times and didn't even deliver the towel. It's slower than a turtle; I'd rather go to the front desk myself. The service was so poor, I wanted to complain about the wait. Useless, it took twice as long as a human to deliver something.
Random 10 Related Reviews:	I saw the robot stuck in the corridor; I waited 10 minutes for it to move. I asked for directions, and it kept repeating "please wait", which annoyed me. It took longer to deliver water than for me to buy it downstairs — unbelievable. The efficiency is absurdly low; my breakfast was cold by the time it arrived. I found the answer myself while waiting for its response. It got stuck when I was rushing to check out, ruining my mood. Slower than a snail — how can the hotel even use this? The slow service drove me nuts; I won't use it again. I ordered a cup of coffee and fell asleep waiting for it. It took half an hour to crawl to my room — ridiculous.

Topic 2. Lack of Personalisation	
Top 10 High-Probability Reviews	The robot is so cold, with no human touch at all. Asking it a question feels like talking to a machine — completely emotionless. Its mechanical responses left me so disappointed. It doesn’t understand me; the service feels so stiff. There’s no warmth at all, not as good as human service. It was so awkward, like talking to myself. The lack of human touch made me very uncomfortable. Its cold tone gave no sense of interaction. The service was terrible, far too mechanical. So disappointing; the robot isn’t friendly at all.
Random 10 Related Reviews	I asked if it could hurry, and it just repeated “please wait” — so cold. Its emotionless responses made me feel so isolated. I complained about the room, but it felt like talking to a wall. The stiff tone made me not want to use it again. Asking a simple question was so awkward. There’s no warm interaction; it felt like staying in a factory. Human staff would at least smile; this robot had nothing. Its cold attitude made me a bit angry. The lack of human touch doesn’t suit a hotel setting. The mechanical service made me miss human front desks.
Topic 3. Privacy Concerns	
Top 10 High-Probability Reviews	This robot has a camera; I’m afraid of being secretly recorded. There’s no privacy protection at all — who knows what it’s recording? I’m worried it might be recording audio; it feels so unsafe. Seeing it staring at me made me very uncomfortable. I don’t dare use it; I’m afraid my personal information might get leaked. It gives such a strong sense of being watched; I turned it off immediately. Safety concerns make me hesitant to use it. The camera is always on — it’s so creepy. I don’t feel secure; I always think I’m being monitored. No matter how good the service is, I won’t use it — too little privacy.
Random 10 Related Reviews	It took a photo while delivering something; I quickly moved away. The recording feature made me afraid to speak freely. The hotel said it’s fine, but I’m still worried about data leaks. The unsafe feeling kept me locking my door the whole time. I saw it had a camera, so I pushed it into a corner. The possibility of being watched made me unable to sleep at night. I felt uncomfortable — who knows where those videos go? I’m scared it might transmit my voice somewhere. I don’t dare use it; who can guarantee it’s not recording? Privacy issues made me prefer going to the front desk myself.
Topic 4. Lack of Flexibility	
Top 10 High-Probability Reviews	The robot is so rigid; it only says fixed phrases. It just keeps repeating the same response — useless for any question. It can’t adapt at all; it couldn’t solve my problem. So troublesome; I ended up having to find a human. I felt helpless; it only said, “Please contact the front desk”.

	Its fixed answers made me feel so foolish. It's not smart; it freezes on slightly complex requests. The service is terrible — way too inflexible. Useless; it got confused the moment I changed my request. Getting human help was faster than using it.
Random 10 Related Reviews	I wanted to change the water delivery time, but it just said no. I asked how to turn off the lights, and it repeated itself three times — useless. It can't adapt; I asked about breakfast options, and it froze. So troublesome; I ended up getting the item myself. I felt so helpless; the robot was utterly clueless. Its fixed responses made me think it's just a decoration. It's not smart; it even got directions wrong. The service is too rigid, not user-friendly at all. Useless; anything slightly complex, and it tells me to find a human. I wanted to adjust the checkout time, and it just told me to go to the front desk.
Topic 5. Cultural Misfit	
Top 10 High-Probability Reviews	The robot doesn't understand dialects; it couldn't comprehend what I said. Its tone is so strange, not polite at all. It doesn't feel friendly, so different from how locals speak. It has such a foreign vibe; I'm not used to it. The cultural gap made me feel so awkward. It doesn't understand local customs — too cold. The service is poor; its tone isn't friendly at all. Its impolite responses made me very angry. The cold attitude doesn't feel like local service. So awkward; talking to it felt so strange.
Random 10 Related Reviews	I spoke in my Sichuan dialect, and the robot couldn't understand — so disappointing. Its tone was odd, like a foreigner; the service was terrible. Not friendly at all; it felt like talking to an alien. I'm not used to its way of responding — too stiff. The cultural gap was huge; it didn't understand my local question. It lacks politeness; it responded so coldly to everything. The service is terrible, with no local flavour at all. Its foreign vibe made me not want to use it again. The cold responses made me uncomfortable. It was awkward; I gave up after chatting with it for two sentences.
Topic 6. Frequent Malfunctions	
Top 10 High-Probability Reviews	The robot kept malfunctioning; it stopped halfway while delivering something. It broke down twice — too unreliable. It didn't move at all when I asked it to deliver water. It got stuck several times; the service had to rely on humans to fix it. It stopped midway, and I got so annoyed waiting. It crashed twice; the experience was terrible. So disappointing; it always has issues. Useless; it broke down on the way while delivering something. The service is poor; the malfunction rate is outrageously high. So unreliable; it breaks every time I use it.

Random 10 Related Reviews	It got stuck in the hallway while delivering a towel; no one fixed it for ages. After it broke down, I had to go to the front desk myself to get the item. It didn’t move several times; the hotel even said it was normal. It got stuck, and I had to push it to get it moving — so ridiculous. It stopped in the elevator midway; the service was completely disrupted. After crashing, its screen went black — really scary. So disappointing; it broke down halfway through delivering water. Useless; it has so many issues, I don’t dare call it anymore. The service was terrible; it broke down, and no one cared. So unreliable; it stopped working right after I used it.
Topic 7. Poor Interactive Experience	
Top 10 High-Probability Reviews	It didn’t understand anything I asked; its responses were chaotic. It answered irrelevantly; I asked one thing, and it replied with something else. Its responses were so chaotic; even asking for directions, it got it wrong. It couldn’t understand my words; communication was too difficult. It was so confusing; talking to it felt like solving a riddle. I got angry; it kept answering my questions incorrectly. Useless; it couldn’t explain anything clearly. So exhausting; I talked to it for ages with no result. The service is poor; the interactive experience was awful. Communication was so difficult, I wanted to smash it.
Random 10 Related Reviews	I asked where breakfast was, and it told me to ask the front desk — so frustrating. It answered irrelevantly; I asked about turning off the lights, and it said the weather was nice. Its chaotic responses left me completely lost; it’s so dumb. It couldn’t understand Mandarin; I had to repeat myself three times with no result. Its confusing responses made me give up entirely. I got angry; it messed up even a simple question. Useless; talking to it was like talking to a brick wall. So exhausting; I explained for ages, and it still asked me to repeat. The service is terrible; the interaction was a complete mess. Communication was tough; I couldn’t even get the WiFi password from it.
topic8： Unfriendly Appearance	
Top 10 High-Probability Reviews	The robot looks so ugly; I didn’t feel good seeing it. It’s scary; seeing it at night felt like encountering a monster. Its weird appearance made me not want to approach it. I didn’t like its look — too cold. It felt awkward; its appearance isn’t likeable at all. It’s not attractive; I had no interest in using it. I felt a strong sense of rejection; I got annoyed just looking at it. It’s uncomfortable; its appearance is too strange. The service is poor, and it looks so ugly, too. Its cold design made me not want to use it.
Random 10 Related Reviews	It’s so ugly; I didn’t even want to look at it while it was delivering something. It’s scary; I almost got frightened by its shadow at night. Its weird appearance made me feel the hotel was low-class. I didn’t like it; it looked like a big metal block. It felt so awkward; I just pushed it away. It’s not attractive at all; it doesn’t look cute in the slightest. I rejected its appearance; it’s too unfriendly. It’s uncomfortable; I wanted to stay away from it when I saw it.

	No matter how good the service is, its ugly look can't be saved. Its cold appearance gave me no good impression.
Topic 9. Inconvenient Operation	
Top 10 High-Probability Reviews	The robot is too hard to use; I couldn't figure it out. It's ridiculously complicated; I couldn't understand how to operate it. It wastes time; ordering something took forever to figure out. So troublesome; I'd rather go get it myself. It's inconvenient and really exhausting to use. I couldn't figure out its buttons; it's too complicated. Useless; operating it was so difficult. The service is poor; it's too hard to get started with. It's exhausting; I don't want to touch it again after using it once. I couldn't figure it out, so I had to ask for help in the end.
Random 10 Related Reviews	It's ridiculously hard to use; I tried ordering water and struggled for ten minutes. It's so complicated, I just gave up. It wastes time; ordering breakfast took longer than making it myself. So troublesome; the screen was even hard to press. It's inconvenient; elderly people wouldn't be able to use it at all. I couldn't figure out how to turn it on — so dumb. Useless; I operated it for ages with no response. The service is terrible; it's exhausting to use. It's exhausting; I pressed buttons for ages, and it barely moved. I couldn't figure it out; asking it anything was pointless.
Topic 10. Unmet Expectations	
Top 10 High-Probability Reviews	There's no surprise; using it felt no different from regular service. I had high expectations, but I was so disappointed. It's not as good as human service; it doesn't feel advanced at all. It's very ordinary, nothing special. It's boring; I got tired of it after using it twice. It has no value; my expectations were all for nothing. There's a huge gap; the promotion was better than the reality. It's dull; it's not as cool as I imagined. The service is poor; I thought it would be very smart. So disappointing; it's too average.
Random 10 Related Reviews	No surprise; I thought it would be a high-tech experience. I had high expectations, but it's just a decoration. It's not as good as humans; human service is more thoughtful. It's so ordinary; I got excited for nothing. It's boring; using it isn't fun at all. It has no value; it's flashy but not practical. There's a huge gap; the advertisement was too exaggerated. It's dull; I'd rather they didn't have a robot. The service is average; my expectations fell flat. So disappointing; I thought it would be convenient.

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Generative artificial intelligence-driven medical digital twin technologies in blockchain Internet of Things wearable sensor and computer vision-based extended reality healthcare metaverse

George Lăzăroiu
Tom Gedeon
Katarzyna Halicka
Danuta Szpilko

A B S T R A C T
The research problem of this paper was whether medical image, behavioral pattern, and physiological data analysis further artificial intelligence-based disease progression prediction, big medical data analysis and processing, and treatment planning optimization, digital twin- and generative artificial intelligence-based disease progression prediction and medical process simulation, patient outcome and pathological condition improvement, and medical service efficiency and resource allocation. We show that physiological measurement indicator modeling and simulation and patient diagnosis and clinical workflow optimization necessitate generative artificial intelligence- and machine learning-based metaverse wearable and implantable medical devices. Our analyses debate on medical metaverse digital twin generative artificial intelligence and machine learning-based big clinical and medical imaging data interoperability and analysis harnessed in remote medical treatment and healthcare practices, healthcare delivery and patient outcome enhancement, real-time medical anomaly detection, timely medical treatment and response prediction, and immersive medical procedure and healthcare delivery simulation in blockchain Internet of Things wearable sensor and computer vision-based extended reality healthcare metaverse. Our results and contributions clarify that clinical decision support systems and generative artificial intelligence-based patient medical disease and health data processing and analysis configure clinical patient care and outcome prediction, health risk forecasting, medical abnormality detection, and remote patient vital sign and health issue monitoring.

K E Y W O R D S
generative artificial intelligence, medical digital twin technologies, blockchain, Internet of Things, computer vision, extended reality healthcare metaverse

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George Lăzăroiu
Curtin University, Kent Street, Bentley Western 6102, Australia
Toronto Metropolitan University, 350 Victoria Street, Toronto, Ontario, M5B 2K3, Canada
Cardiff Metropolitan University, Western Avenue, Cardiff, CF5 2YB, United Kingdom
ORCID 0000-0002-3422-6310
Corresponding author:
e-mail: phd_lazaroiu@yahoo.com

Tom Gedeon
Curtin University, Kent Street, Bentley Western 6102, Australia
ORCID 0000-0001-8356-4909
e-mail: tom.gedeon@curtin.edu.au

Katarzyna Halicka
Bialystok University of Technology, Wiejska 45A, 15-351 Białystok, Poland
ORCID 0000-0001-6370-8995
e-mail: k.halicka@pb.edu.pl

Danuta Szpilko
Bialystok University of Technology, Wiejska 45A, 15-351 Białystok, Poland
ORCID 0000-0002-2866-8059
e-mail: d.szpilko@pb.edu.pl

Introduction

The background of the study

Generative artificial intelligence-enabled medical and physiological data acquisition and analysis articulate personalized health monitoring and diagnostic assistance by convolutional neural and generative adversarial network-based personalized healthcare monitoring, diagnosis, and rehabilitation, Internet of Things-enabled vital sign and personalized healthcare monitoring, infection and injury patient immune response prediction, and clinical documentation,

Lăzăroiu, G., Gedeon, T., Halicka, K. & Szpilko, D. (2025). Generative artificial intelligence-driven medical digital twin technologies in blockchain Internet of Things wearable sensor and computer vision-based extended reality healthcare metaverse. *Engineering Management in Production and Services, 17*(3), 27-50. doi: 10.2478/emj-2025-0018

data reconstruction, diagnosis, and decision support. Virtual healthcare monitoring and practical treatment simulation and modeling, deep learning-based medical imaging techniques, and generative artificial intelligence-driven medical digital twin technologies (Andronie et al., 2023a, b) in Internet of Healthcare Things assist in medical imaging and wearable device-based motion sensor data acquisition, real-time rehabilitation condition monitoring and analysis, and deep and machine learning-based patient care and treatment outcome optimization across virtual healthcare environments. Synthetic medical imaging and physiological data and personalized health monitoring and rehabilitation training systems enable health condition early anomaly detection and disease progression simulation and treatment planning customization.

3D virtual patient medical imaging and cognitive computing-based multimodal big healthcare data fusion, Internet of Things medical devices and sensors, and blockchain and distributed ledger technologies shape digital twin-based personalized medicine and healthcare services, deep convolutional generative adversarial network-based personalized medical intervention, therapeutic strategy, and clinical care process simulation and modeling, and artificial intelligence-based disease diagnosis, early intervention, progression, prognosis, and treatment prediction. Deep and machine learning algorithms (Lăzăroiu et al., 2024) optimize multi-scale and multi-modal big healthcare, molecular profiling, and clinical data modeling, interconnected health trajectory monitoring and prediction, and real-time digital twin-based patient care, precision treatment, and healthcare delivery coordination. Wearable medical devices are instrumental in computational synthetic image-based virtual patient simulation and modeling, artificial intelligence-based clinical intervention outcome predictions, and disease prevention and patient care optimization. Mobile edge networks, human digital twin technologies, and big medical imaging data analytics improve immersive personalized healthcare, medication, treatment planning, and rehabilitation services. Blockchain- and Internet of Things sensor-based wearable and implantable devices can be harnessed in deep reinforcement learning-based customized healthcare and personalized medication services and human digital twin modeling and simulation.

Edge computing and digital twin technologies (Lăzăroiu et al., 2022a, b) can be leveraged in virtual healthcare systems and patient services, patient flow diagnosis and monitoring, random forest- and generative adversarial network-based treatment progress assessment and disease extent, and patient care and healthcare delivery optimization. Personalized treatment planning and decision support, real-time digital twin patient vital sign tracking and monitoring, timely virtual medical interventions for complication risk reduction, and realistic synthetic clinical data develop on Internet of Things medical devices and digital twin healthcare networks. Remote patient monitoring and healthcare services, real-time vital sign tracking for timely intervention, and predictive analytics-based tailored treatment planning integrate machine and deep learning-based clinical big data analytics and cyber-physical healthcare systems. Physiological measurement indicator modeling and simulation and patient diagnosis and clinical workflow optimization necessitate generative artificial intelligence- and machine learning-based metaverse wearable and implantable medical devices. Extended reality and wearable sensor technologies (Andronie et al., 2021) are pivotal in deep and machine learning-based patient health issue early detection and risk reduction and immersive medical wearable-based patient data analysis.

The research gap of the study

The research problem of this paper was whether digital twin- and Internet of Things-based real-time multimodal proactive health intervention data fusion articulate generative artificial intelligence digital twin-based clinical practice, multidimensional big healthcare and clinical data modeling, sensor and actuator-based personalized disease diagnosis and treatment, personalized therapy planning, and heterogeneous multi-source real-time medical data analysis for personalized diagnostic and treatment outcome enhancement. Wearable and motion sensor technologies assist in pathological condition diagnosis and treatment, proactive medical intervention outcome assessment, medical process and patient outcome optimization, early intervention and disease progression prevention, and digital twin-based diagnostic accuracy optimization and failure risk prediction, supporting clinical decision-making. Real-time patient health status and data monitoring and analysis enable Internet of Things interconnected device healthcare and vital sign monitoring, personalized clinical disease diagnosis and treatment planning, patient risk minimization, tailored therapeutic interventions, healthcare service and patient care enhancement, and deteriorating condition earlier detection modeling and simulation.

We show how medical image, behavioral pattern, and physiological data analysis further artificial intelligence-based disease progression prediction, big medical data analysis and processing, and treatment planning optimization, digital twin- and generative artificial intelligence-based disease progression prediction and medical process simulation, patient outcome and pathological condition improvement, and medical service efficiency and resource allocation. Medical digital twin technologies shape hospital operation and clinical communication simulation, targeted treatment plan evaluation, medical process simulation and resource management, and disease course, surgical procedure, and intervention risk prediction. Multi-source heterogeneous medical image data and physiological indicator analysis optimize medical history data-based disease diagnosis and treatment prediction and simulation and personalized health management. Machine and deep learning artificial neural network-based multidimensional clinical data analysis improve quality medical care and patient condition forecasting, disease treatment prediction and planning, risk factor identification, and big healthcare and multimodal patient data processing accuracy and efficiency.

We clarify that healthcare predictive modeling can be deployed in effective patient treatment simulation and prediction, personalized disease and condition progression forecasting, and patient outcome optimization, supporting clinical decision-making simulation. Virtual remote clinical patient care and engagement, vital sign monitoring, and treatment choice effectiveness develop on patient-specific and medical data analytics. Deep convolutional neural generative adversarial network-based disease prognosis prediction, Internet of Things patient health monitoring, machine learning and artificial neural network-based clinical patient digital twin trajectory and treatment response prediction, and decision tree and logistic regression-based disease outcome forecasting and patient digital twin clinical trial augmentation require multimodal medical imaging data. Extended reality artificial intelligence and machine learning-based big medical and healthcare data mining are pivotal in preventive care and medical treatment planning, patient diagnosis, treatment, and engagement optimization, healthcare service delivery, virtual medical and therapeutic procedures, and patient care and health outcome enhancement. Blockchain Internet of Medical Things wearable sensor-based big patient medical diagnosis data mining and analysis are instrumental in illness prevention, identification, and diagnosis, remote patient care and health issue monitoring, patient diagnosis and clinical treatment, illness risk factor detection, and treatment procedure and patient involvement improvement.

The objectives of the study

Clinical decision support systems and generative artificial intelligence-based patient medical disease and health data processing and analysis configure clinical patient care and outcome prediction, health risk forecasting, medical abnormality detection, and remote patient vital sign and health issue monitoring. Medical image computing and analysis and clinical predictive analytics and decision support systems articulate patient engagement and healthcare delivery process enhancement, remote medical consultation and surgical procedures, remote healthcare services, and disease prediction and prevention. Predictive healthcare analytics assists patient care delivery and engagement monitoring, virtual healthcare and preventive treatment services, clinical medical diagnosis and treatment planning and decisions, and remote patient care and healthcare delivery improvement. Medical image and diagnosis analysis and multimodal patient physiological signal and condition data further medical and healthcare digital twin generative artificial intelligence-based treatment planning and clinical decision simulation, optimal diagnostic outcome prediction, and medical response and recovery enhancement.

This is the first paper covering how Internet of healthcare Things wearable sensor-based real-time virtual patient health status tracking optimizes effective therapeutic intervention and response development, patient treatment response and disease state simulation and modeling, and disease trajectory prediction, prevention, progression, and treatment. Personalized big medical data-driven clinical decision modeling and forecasting improve patient and medical digital twin artificial intelligence-based therapeutic scenario and response assessment, generative adversarial network-based diagnosis and therapy prediction, and clinical decision support and patient prognosis assessment personalization. Medical metaverse digital twin generative artificial intelligence and machine learning-based big clinical and medical imaging data interoperability and analysis can be harnessed in remote medical treatment and healthcare practices, healthcare delivery and patient outcome enhancement, real-time medical anomaly detection, timely medical treatment and response prediction, and immersive medical procedure and healthcare delivery simulation in blockchain Internet of Things wearable sensor and computer vision-based extended reality healthcare metaverse.

Predictive digital twin explainable artificial intelligence deep learning-based medical and surgical scenario simulation can be leveraged in health outcome and medical therapy improvement, remote patient vital physiological parameter and medical condition monitoring, diagnostic and therapeutic planning, and clinical diagnosis and treatment. Remote patient health parameter and status monitoring, precise disease prediction, diagnosis, and progression, clinical treatment outcome and surgical procedure optimization, and patient diagnostic accuracy and recovery progress assessment develop on edge and cloud computing-based surgical outcome prediction modeling. Cloud and edge computing-based disease development and treatment adjustment monitoring requires cyber-physical medical systems and predictive healthcare digital twin generative artificial intelligence and machine learning-based medication adherence simulation and modeling in computer vision- and medical imaging-based healthcare digital twin metaverse. Clinical patient synthetic physiological and condition data monitoring and analysis are pivotal in medical imaging and generative adversarial network-based therapeutic intervention and development, clinical treatment response and decision support accuracy, therapeutic outcome simulation, and disease prevention and prognosis.

The manuscript comprises introduction, literature review (section 1), methodology (section 2), results: analysis of operations carried out by selected companies (section 3), discussion (section 4), and conclusions.

1. Literature review

Digital twin Internet of Things medical connected devices, generative adversarial network-based medical image segmentation and augmentation, and synthetic patient human digital twin data (Chen et al., 2024a) configure generative artificial intelligence-driven human digital twins in Internet of Things healthcare services for precise and customized diagnosis, rehabilitation, and treatment, haptic feedback simulation and tactile sensation replication, immersive personalized treatment plan simulation, and synthetic physiological and medical data-based disease prediction and diagnosis. Extended reality-based medical imaging and computer-simulated virtual patient imaging technologies (Katsoulakis et al., 2024) further predictive healthcare interventions, generative artificial intelligence cognitive digital twin-based personalized disease treatment and prevention, personalized synthetic patient early intervention, prevention, diagnosis, treatment planning, care, and therapy in digital twin healthcare environments. Deep learning-based medical imaging diagnosis data (Li et al., 2024) configure artificial intelligence digital twin-based healthcare services for clinical diagnosis and treatment, disease progression simulation, quality patient care provision, wearable device-based medical image diagnostic and patient outcome accuracy, and medical digital twin-based patient-specific treatment response prediction.

Clinical virtual patient trajectory simulation and modeling (Bordukova et al., 2024) integrate healthcare digital twin generative artificial intelligence deep learning-based multimodal big clinical and biomedical synthetic data. Extended reality artificial intelligence deep learning-based clinical patient synthetic imaging data mining (Demuth et al., 2025) enhances early medical intervention and surgery procedure planning simulation, multimodal virtual patient synthetic health status data interoperability, and predictive healthcare digital twin generative artificial intelligence and machine learning-based clinical patient diagnosis and medical procedure assessment. Generative artificial and convolutional neural network-based real-time patient pathophysiological state, condition, and response monitoring data analysis (Takahashi et al., 2025) is instrumental in predictive digital twin deep reinforcement learning-based personalized treatment planning modeling and virtual medical treatment and therapeutic intervention simulation.

Sensor and actuator-based remote patient care, health indicator, and physiological data monitoring, treatment option and disease progression assessment, and healthcare and hospitalization service optimization (Rahim et al., 2024) integrate interconnected digital twin-based artificial intelligence medical cyber-physical systems, streamlining personalized patient diagnosis. Extended reality-based healthcare delivery systems (Vallée, 2024) assist in virtual healthcare services for remote consultations, Internet of Things sensor- and physiological parameter-based patient-centric healthcare delivery, and timely personalized interventions, artificial intelligence and machine learning-based treatment response prediction, targeted preventive measures, patient health status assessment, and disease progression simulation, digital twin- and predictive modeling-based patient outcome and healthcare delivery optimization, and artificial intelligence digital twin- and machine learning-based specific disease and health condition risk factors for targeted preventive measures. Sensor artificial intelligence-based healthcare digital twin systems and medical wearable and robotic devices (Pellegrino et al., 2025) enhance historical health and clinical data-based personalized therapeutic and patient care intervention monitoring, patient condition simulation and outcome optimization, and virtual medical practice.

Internet of Things-based medical digital twin and wearable sensor technologies (Qoseem et al., 2024) configure deep convolutional generative adversarial network-based personalized healthcare delivery and interventions, health outcome and anomaly detection enhancement, and clinical patient and knowledge management. Healthcare decision support systems (Jameil & Al-Raweshidy, 2024) further healthcare service delivery and patient outcome optimization, mobile edge computing-based personalized medical and therapeutic treatments, artificial intelligence and machine learning-based personalized health intervention modeling and simulation, and emergency response operational efficiency augmentation. Support vector machine and random forest-based big healthcare and clinical data processing and analysis (Yu et al., 2024) improve machine and deep learning-based health condition and physiological indicator monitoring, real-time wearable device-based patient physiological indicator assessment, and artificial intelligence- and convolutional neural network-based health status evaluation.

Medical digital twin-based multi-scale clinical patient data analysis and modeling (Niarakis et al., 2024) can be leveraged in cloud computing- and predictive artificial intelligence-based patient health state and prognosis forecasting, virtual patient health and pathological condition, early potential abnormality diagnosis, and medical and pathological knowledge. Personalized patient treatment and clinical decision-making processes and clinical and therapeutic outcome prediction (Mollica et al., 2024) require predictive artificial intelligence digital twin- and Internet of Medical Things-based virtual clinical practice decision-making simulation. Personalized healthcare process and treatment planning modeling and simulation (Raman et al., 2024) are pivotal in patient outcome, diagnosis, and treatment improvement, remote virtual healthcare delivery and surgical operations, and patient care and outcome optimization across immersive extended reality and blockchain digital twin-based healthcare metaverse.

Big data-driven medical service and clinical recommendation accuracy improvement (Shamshiri et al., 2025) necessitates medical and healthcare image-guided digital twin artificial intelligence-based virtual patient disease diagnosis simulation and modeling. Internet of Medical Things wearable sensor-based patient health status and treatment protocol analysis (Ullah et al., 2025) is instrumental in patient well-being and treatment planning improvement, anomalous health condition simulation and forecasting, patient status and medical complication prediction, health abnormality and disease detection, and virtual healthcare procedures. Digital twin artificial intelligence and machine learning-based medical decision support and clinical practice modeling (Ortega-Martorell et al., 2025a) enables disease progression and treatment response, personalized pathophysiology, prevention, and treatment planning, patient recovery and outcome improvement, accurate health condition diagnosis, and clinical care and rehabilitation treatment enhancement. Predictive clinical digital twin artificial intelligence and machine learning-based tailored therapeutic intervention and clinical decision-making simulation and modeling (Baumgartner & Brislinger, 2025) can be deployed in personalized disease diagnosis and treatment planning monitoring and prediction accuracy, clinical outcome enhancement, and pathology and disease progression.

Digital twin Internet of Healthcare Things wearable sensor-based patient healthcare and medical condition monitoring (Bozkaya-Aras et al., 2025) develops on healthcare artificial intelligence digital twin and deep learning-based patient vital physiological parameter and data fusion processing. XGBoost, random forest, and multilayer perceptron neural network-based remote patient condition, vital sign, and response time monitoring (Jameil & Al-Raweshidy, 2025) requires predictive healthcare digital twin artificial intelligence and machine learning-based predictive medical analysis. Blockchain Internet of Things wearable sensor and actuator-based healthcare delivery and medical procedure simulation (Roopa & Venugopal, 2025) is instrumental in patient physiological attribute and health condition monitoring, real-time treatment plan and medication adherence development, personalized patient treatment and outcome optimization, patient health condition targeting and outcome improvement, and health complication prediction.

Internet of Medical Things wearable sensor-based patient health state and physiological parameter monitoring simulation and healthcare digital twin artificial intelligence and machine learning-based clinical decision and data modeling (Somers et al., 2025) further cyber-physical medical system-based treatment response prediction and personalized disease diagnosis, medical condition treatment, and physical rehabilitation. Digital twin artificial intelligence deep reinforcement and machine learning-based real-time patient disease data interoperability, analysis, and modeling (Okegbile et al., 2025) shape edge and cloud computing-based tailored personalized healthcare service optimization. Healthcare and medical digital twin artificial intelligence deep and machine learning-based remote big multimodal clinical patient physiological, health, and condition monitoring data processing, analysis, and interoperability (Zhang et al., 2025) optimize remote therapeutic and medication adherence monitoring, tailored healthcare therapeutic interventions, patient outcome and treatment adherence improvement, and patient surgical therapy and diagnostic interpretation prediction.

2. Research methods

We inspected 446 digital twin healthcare start-ups, selected 82 companies based on their public impact, and identified three main topics for analysis covering predictive healthcare generative artificial intelligence and machine learning-based personalized therapy and treatment adherence modeling, generative artificial intelligence digital twin-based patient treatment and medical intervention optimization, and medical and healthcare predictive digital twin generative artificial intelligence and machine learning-based multi-scale multimodal real-time synthetic clinical healthcare and medical data analysis (table 1). Evidence map visualization, study screening, and data extraction and reporting tools leveraged for qualitative and quantitative data, collection, management, and analysis in research synthesis include AMSTAR (for literature search usability), CADIMA (for critical appraisal management), Catchii (for article relevance assessment), Colandr (for smart citation sorting), Eppi-Reviewer (for machine learning-based data clustering), Litstream (for keyword-based streamlined literature characterization), MMAT (for content validity evaluation), PICO Portal (for artificial intelligence-based evidence mapping), ROBIS (for methodological quality deficiency inspection), SRDR+ (for research question data management), and Systematic Review Accelerator (for search string duplicate exclusion).

Topic 1. Predictive healthcare generative artificial intelligence and machine learning-based personalized therapy and treatment adherence modeling

Cloud computing and multi-modal generative artificial intelligence technologies and multi-modal big synthetic personalized healthcare data (Chen et al., 2024b) enhance generative adversarial network-based personalized treatment planning and tailored healthcare services for medical record and image analysis and medical condition monitoring and prediction. Multi-modal physiological and healthcare data (Thangaraj et al., 2024) enhance digital twin- and deep learning-based personalized patient care, generative artificial intelligence- and digital twin-based clinical decision-making and trial augmentation, personalized clinical scenario and diagnostic workflow simulation, and machine learning- and generative artificial intelligence-based real-time patient disease risk prediction. Patient healthcare trajectory forecasting, patient health, medical condition, and vital sign monitoring, illness and disease prevention and treatment prognosis, and medical event detection, diagnosis, and prediction (Javaid et al., 2024) necessitate cloud computing- and predictive digital twin deep learning-based big clinical biomedical and healthcare data mining.

Decision tree and random forest regression-based virtual patient care condition modeling (Chaddad & Jiang, 2025) can be deployed in virtual surgical and medical procedures, cloud-based healthcare diagnosis and treatment, tailored medical care, real-time patient physiological indicator and health status monitoring, and immersive therapeutic and surgical interventions. Predictive healthcare generative artificial intelligence and machine learning-based personalized therapy and treatment adherence modeling (Mazhar et al., 2025) configures patient care and healthcare delivery optimization, clinical healthcare decision-making process and medical condition forecasting, and timely preventive medical intervention. Deep and machine learning-based wearable sensor fusion and motion capture systems and 6G digital twin and edge computing artificial intelligence-based immersive healthcare augmentation technologies (Brahmi et al., 2024) can be harnessed in preventive sensor-based real-time remote patient physiological parameter monitoring.

Multimodal Internet of Things medical devices (Nguyen & Voznak, 2024) further patient outcome and healthcare service optimization, remote patient vital sign and health status monitoring, tailored virtual healthcare services and medical procedures, and wearable sensor-based early health and medical condition detection in immersive medical artificial intelligence digital twin-based healthcare metaverse. Patient healthcare outcome monitoring and timely intervention improvement, early health issue and stage disease detection, patient vital sign tracking and recovery time reduction, and real-time personalized health and remote patient monitoring (Sinha, 2024) necessitate digital twin artificial intelligence Internet of Medical Things and wearable sensor-based disease progression simulation. Individualized big data-driven treatments and tailored therapeutic interventions, clinical patient outcome improvement, disease prediction, prevention, detection, progression, and treatment, patient care, response, engagement, and outcome optimization, and healthcare diagnostic services (Tamura et al., 2024) develop on digital twin artificial intelligence-based personalized patient care and stratification data modeling.

Healthcare digital twin artificial intelligence of things-based patient data interoperability (Iranshahi et al., 2025) shapes blockchain Internet of Things wearable sensor and actuator-based disease diagnosis and treatment forecasting, simulation, and monitoring. Predictive biomedical and healthcare digital twin artificial intelligence and machine learning-based patient clinical treatment scenario simulation and modeling (Strigari et al., 2025) improve personalized therapy outcome and treatment planning optimization. Healthcare artificial intelligence digital twin and medical imaging-based personalised patient diagnosis, treatment, prognosis, and care analysis and forecasting (Guerrero Quiñones & Puzio, 2025) can be leveraged in virtual healthcare delivery, practices, and services, real-time health-related event and medical condition prediction, patient physiological characteristic and vital function monitoring, and virtual surgery procedures.

Topic 2. Generative artificial intelligence digital twin-based patient treatment and medical intervention optimization

Healthcare and patient digital twin technologies and multidimensional big healthcare and clinical workflow data scalability and interoperability (Noeikham et al., 2024) can be deployed in precision treatment advice, predictive maintenance-based diagnosis and treatment planning services, health app and wearable device-based health deterioration early sign detection, localized disease manifestation simulation, and specific patient digital prognosis tailoring and condition prediction. Medical imaging-based diagnosis, treatment, and therapeutic tailoring (Vidovszky et al., 2024) can be harnessed in generative artificial intelligence digital twin-based patient treatment and medical intervention optimization, health outcome and clinical trial design improvement, virtual clinical practice, and clinical trial outcome prediction. Cloud and edge computing-based virtual patient health and medical imaging data processing and analysis (Lin et al., 2025) enable medical decision support simulation and modeling, diagnosis and treatment accuracy optimization, and robotic surgical assistance.

Personalized healthcare decision making (Gaffinet et al., 2025) integrates blockchain Internet of Things wearable sensor and actuator-based multi-modal real-time patient synthetic physiological state, health parameter, and medical condition data analysis, processing, fusion, monitoring, and prediction. Digital twin modeling and extended reality-based data visualization technologies (Xames & Topcu, 2024) enable patient vital sensor data collection, artificial neural network- and deep learning-based disease diagnosis, prognosis, and treatment, early disease detection, and medical procedure and disease diagnosis accuracy optimization in virtual operating rooms. Recurrent neural network- and imaging-based disease diagnosis and progression, real-time physiological condition data monitoring, virtual healthcare practices, and personalized medical treatments and healthcare interventions (Tang et al., 2024) develop on wearable sensor- and digital twin artificial intelligence-based disease diagnosis and clinical analysis in virtual clinical settings.

Predictive digital twin artificial intelligence-based medical diagnosis and condition simulation (Jones et al., 2024) can be harnessed in diagnostic accuracy and patient outcome enhancement, big patient-specific disease diagnosis and treatment data augmentation, real-time virtual patient engagement and condition monitoring, and remote immersive specialized patient-centric care across digital twin healthcare metaverse. Healthcare digital twin artificial intelligence convolutional neural network-based real-time abnormal condition analysis (Bhatia, 2024) shapes elevated patient life expectancy, remote patient health condition assessment and monitoring, early health risk detection, and abnormal bodily experience forecasting. Machine and deep reinforcement learning-based virtual healthcare services, medical practices, and surgical procedures and edge and cloud computing-based Remote patient health and disease monitoring (Wu et al., 2024) necessitate artificial intelligence blockchain Internet of Things wearable sensor and medical metaverse digital twin-based-based clinical decision support systems.

Topic 3. Medical and healthcare predictive digital twin generative artificial intelligence and machine learning-based multi-scale multimodal real-time synthetic clinical healthcare and medical data analysis

Internet of Medical Things-based remote patient condition, physiological parameter, and vital sign monitoring (Rowan, 2024) require digital twin extended reality-based medical devices and digital health and blockchain medical technologies. Wearable healthcare devices (Thomason, 2024) can be leveraged in predictive artificial intelligence and machine learning-based patient diagnostic outcomes, Internet of Medical Things wearable sensor- and immersive healthcare metaverse-based disease detection and prevention, and generative artificial intelligence digital twin- and machine learning-based clinical decision-making support. Medical and healthcare predictive digital twin generative artificial intelligence and machine learning-based multi-scale multimodal real-time synthetic clinical healthcare and medical data analysis (Ren et al., 2025) shapes preventive measure and clinical decision-making optimization, clinical disease pathology, and disease progression prediction and monitoring.

Big data-driven patient health and disease monitoring, diagnostic and prognostic value, timely specific treatment-based patient and intervention response prediction, and disease and treatment progression (De Domenico et al., 2025) necessitate disease state and pathological progression analysis and predictive digital twin generative artificial intelligence and machine learning-based tailored clinical therapeutic decision-making simulation and modeling. Self-tracking Internet of Things wearable tools (Venkatesh et al., 2024) improve artificial intelligence and deep learning-based organ health digital twins for big data-driven precision therapy, remote public health monitoring, healthcare delivery, and clinical decision making. Decision tree- and support vector machine-based healthcare digital twin systems (Khan et al., 2024) are pivotal in Internet of Healthcare Things and cyber-physical medical system-based personalized diagnosis and treatment, timely intervention simulation, remote patient physiological and vital sign data monitoring, and early abnormality detection.

Healthcare predictive digital twin artificial intelligence-based real-time patient physiological data mining (Checcucci et al., 2025) integrates virtual clinical practices and surgical procedures and treatment resistance prediction and response monitoring in extended reality environments. Predictive digital twin artificial intelligence and machine learning-based pathophysiological disorder simulation (Ortega-Martorell et al., 2025b) enhances virtual clinical practice, individualized recovery and preventive measure planning, adverse event reduction, and medical image analysis and treatment guidance. Extended reality Internet of Things wearable and implantable biomedical sensor and actuator-based real-time multimodal patient physiological state parameter and health status data processing and analysis (Subramaniam et al., 2024) articulate patient medical condition, disease trajectory and progression, and treatment decision, artificial neural network-based virtual surgical procedures, and diagnostic and therapeutic disease interventions.

Healthcare digital twin artificial intelligence-based disease progression modeling and healthcare outcome and patient management simulation (Oulefki et al., 2025) can be leveraged in big data-driven personalized medical intervention and patient care optimization. Deep convolutional neural network- and cloud computing-based early disease detection (Riahi et al., 2025) develops on predictive healthcare digital twin artificial intelligence and machine learning-based clinical decision-making modeling and simulation. Internet of Medical Things wearable sensor-based early disease diagnosis and treatment, deep learning convolutional neural network-based personalized treatment planning, health risk detection, real-time remote patient care and condition enhancement, and patient outcome improvement (Sharma et al., 2025) require healthcare and patient digital twin and artificial intelligence and machine learning-based big clinical patient physiological and health data mining in virtual healthcare delivery.

Tab. 1 Healthcare generative artificial intelligence startups

No.	Companies
1	Abridge employs generative and ambient artificial intelligence technologies to instantly turn chats between patients and clinicians into structured contextually-aware clinical notes, creating verifiable clinical documentation, summarizing medical conversations, and transcribing medical discussions. Abridge works on 50+ specialties, saves clinicians over 70+ hours a month of documentation, and recognizes, understands, and takes accurate notes across 14+ languages, tackling clinician burnout and patient adherence and automatically generating clear and concise personalized care post-visit summaries.
2	Ada Health uses generative artificial intelligence to accurately analyze patient-reported symptoms and provide timely personalized medical assessments and triage recommendations, interpreting user symptoms and medical history for potential health issue guidance.
3	Aidoc's artificial intelligence operating system analyzes images across specialties to flag acute abnormalities across the body, and thus radiologists prioritize life-threatening cases, reducing emergency room visits by 59 minutes and shortening average hospital stays by 18 hours. Aidoc supports coordinated timely interventions and real-time clinical decision-making, identify critical conditions, reduce silos in care delivery, and automate triage and flag urgent findings, enabling fast and informed decisions across specialties.
4	Ambience Healthcare automates clinical paperwork and provides real-time transcription and summarization of patient contacts, with its AutoScribe generating patient notes instantly during doctor-patient meetings and automatically adds them to EHR, its AutoCDI focusing on improving the clinical documentation process, analyzing notes and health records to apply accurate codes to bills during discharge, and its AutoRefer dealing with writing referral letters for both sending and receiving medical specialists.
5	Amazon Web Services offers generative artificial intelligence-assisted healthcare data analytics capabilities in clinical note writing, and together with Philips advance PACS image processing and enhance radiology workflows for diagnosis and treatment, connected care, and personal health optimization.
6	Amina AI assistant, clinically tested and powered by Infermedica's engine, provides intelligent symptom triage, guiding patients through initial healthcare interactions, automating answers to common medical questions and concerns, speeding up the diagnostic process by 65%, and resulting in faster and more accurate patient assessments. By early hypertension and diabetes screening, the risk of late-stage health complications is reduced.
7	Arcadia uses artificial intelligence and machine learning to analyze patient records and provides tools for patient engagement using artificial intelligence for audience segmentation, separating patients into smaller groups to which healthcare providers can tailor messaging.
8	Arterys Inc. is developing advanced generative artificial intelligence-driven imaging solutions for diagnostic precision, focusing on enhancing imaging accuracy and workflow efficiency. Its Arterys Cardiac MRI platform uses artificial intelligence to automate and improve cardiac imaging analysis, providing cloud-based artificial intelligence imaging solutions.
9	Athelas develops artificial intelligence-powered platforms and connected devices to support chronic disease management and streamline healthcare operations. Its remote patient monitoring tools allow clinicians to track vital signs through internet-connected devices, enabling timely interventions without requiring in-person visits. Athelas' ambient artificial intelligence transcription service automates clinical documentation, helping providers capture and organize patient data more efficiently.
10	With data drawn from millions of clinical interactions, Augmedix develops artificial intelligence-powered ambient documentation tools to reduce administrative workload in healthcare settings. Its platform captures natural clinician–patient conversations and converts them into structured medical notes, data entries, and point-of-care notifications, streamlining clinical workflows and supporting decision-making without disrupting the interaction between provider and patient.
11	August AI is implementing generative artificial intelligence into its healthcare and well-being workflow with an accuracy score of 94.8% on the USMLE, while providing 24/7 mental health support by offering guidance and emotional assistance.
12	Combining automation, computational design, and wet-lab testing, BigHat Biosciences and its Milliner™ platform integrate a high-speed synthetic biology lab with machine learning to design, build, and test antibody candidates in iterative cycles for affinity, stability, specificity, and immunogenicity optimization, supporting the development of next-generation therapeutics for cancer, inflammation, and infectious disease.
13	Biofourmis Care, a virtual care platform, transforms chronic condition management, its artificial intelligence-enabled system combining FDA-cleared algorithms with clinical-grade wearables to deliver comprehensive remote patient monitoring while managing heart failure, hypertension, diabetes, lipid management, and atrial fibrillation, with 24/7 clinical support teams providing personalized care.
14	care.ai has developed an artificial intelligence-assisted smart care facility platform with always-aware ambient intelligent sensors, monitoring the care environment for 24/7 hours to automatically detect problems that may emerge beforehand. The platform has been implemented in over 1,500 care facilities, using artificial intelligence to streamline operations and minimize human error. care.ai and Google Cloud's generative artificial intelligence have automated administrative tasks and improved healthcare facility management.
15	Integrating real-time data monitoring and machine learning to support clinical decision-making and care coordination and detect changes in patient health earlier, Cera is a digital-first home healthcare company delivering technology-enabled services (e.g., nursing, telehealth, and medication management), providing over 60,000 in-home patient appointments daily for more than 30 million people through a network of carers and nurses. Cera develops and deploys artificial intelligence tools to modernize care delivery and support aging populations with personalized services at home, predicting over 80% of hospitalization risks and 83% of falls in advance.

16	Focusing on using artificial intelligence to assess heart disease through non-invasive imaging, Cleerly provides artificial intelligence-powered analysis of coronary computed tomography angiography scans to assess heart health and plan treatments. Its platform analyzes 3D coronary computed tomography angiography (CCTA) scans to identify and measure atherosclerosis and other markers of coronary artery disease, providing clinicians with detailed, quantifiable insights into heart health, aiming to support earlier, more informed decision-making without the need for invasive procedures. Cleerly combines artificial intelligence with expert-validated methodologies to enable more precise evaluations of plaque, ischemia, and stenosis, aiming improve diagnostic accuracy and facilitate clearer communication between providers and patients in the management of cardiac care.
17	CodaMetrix is specialized in artificial intelligence-powered autonomous medical coding, its natural language processing-based platform translating clinical documentation from electronic health records into billing codes across multiple specialties. Its hybrid model integrates human oversight for outlier cases while scaling automation for routine workflows.
18	By analyzing and synthesizing large amounts of diverse real-time healthcare data, Corti uses advanced artificial intelligence to guide healthcare professionals in making the best care decisions. Corti simplifies the documentation process after patient interactions by automatically generating accurate procedure and diagnosis codes, reducing healthcare costs, saving provider time, and minimizing human error for accurate and reliable patient records.
19	Databricks offers generative artificial intelligence-powered features to support use cases such as customized patient engagement and documentation summarization.
20	Deep Genomics show how artificial intelligence can provide unprecedented personalization and precision in patient therapeutics and interventions, changing genetic disease treatments and using generative artificial intelligence to decode complex biological data and design personalized therapeutics. Its advanced generative algorithms can analyze genetic information down to the molecular level, predict how genomic variations translate into biological outcomes for individual patients, and rapidly generate targeted therapies customized at the DNA level, enabling targeted interventions tailored to individual genetic profiles and minimizing side effects of more general therapies.
21	Doximity GPT is a generative artificial intelligence tool providing HIPAA-compliant documentation.
22	eClinicalWorks enables healthcare providers to manage patient information and clinical data, and leverages generative artificial intelligence to streamline several common workflows, such as summarizing patient records, identifying high-risk patients using predictive analytics and automatically matching documents to patients to eliminate the need for administrative staff to sort them manually.
23	Edison Health Services is an artificial intelligence-driven platform enhancing clinical workflows and patient care.
24	Enlitic deploys artificial intelligence to standardize medical imaging data for speeding up interpretation and improving accuracy, while tackling the analysis of medical images.
25	Ephion Health checks the biomechanical parameters of gait and assess a patient's functional capacity. This multi-sensor-wearable healthcare artificial intelligence platform leverages machine learning for exact patient analysis, neuromuscular disease monitoring, and elderly patient fall risk assessment.
26	EvolutionaryScale's flagship model family, ESM3, trained on billions of natural proteins and built using large-scale computing power, is built to interpret, generate, and reason over protein sequence, structure, and function, simulating evolutionary processes. ESM Cambrian is a parallel model family optimized for protein representation learning.
27	Ezra has developed several artificial intelligence-based properties for early cancer detection/screening. Ezra Flash AI enhances MRI images, Ezra Prostate AI enhances MRI images acquired at faster speeds, Ezra Reporter AI converts Radiology Reports into lay-term translations, and MyEzra is a booking system patient portal, all in one.
28	Flatiron Health connects cancer centers and uses artificial intelligence to analyze patient data, improving cancer treatment and accelerating research, thus providing integrated patient population data and business intelligence analytics to enhance patient care and treatment outcomes, and incorporating real-world data from EHRs with genomic data and employing machine learning to curate and analyze this data.
29	Formation Bio leverages artificial intelligence and its proprietary technology to improve the efficiency of clinical-stage drug development, integrating software tools to streamline clinical trial design, execution, and data quality, helping bring treatments to patients faster and at a lower cost. By combining technical infrastructure with operational expertise, Formation Bio supports faster, more adaptive trials across a range of therapeutic areas. Formation Bio and OpenAI develop artificial intelligence-powered tools for drug development and patient recruitment.
30	Freenome focuses on early cancer detection using artificial intelligence, multiomics, and blood sample analysis.
31	General Electric Company (GE Healthcare) innovates in diagnostic imaging, monitoring, biomanufacturing, and cell therapy technologies, developing advanced imaging systems like MRI and CT scanners, ultrasound devices, and healthcare IT solutions. GE Healthcare integrates generative artificial intelligence for personalized medicine and diagnostics and treatment planning,
32	Generate:Biomedicines uses machine learning and generative biology to design novel protein therapeutics. Its platform learns from millions of proteins to model the relationship between structure and function, enabling the generation of entirely new molecules with therapeutic intent across immunology, oncology, and infectious diseases. Generate:Biomedicines integrates computational methods with biological engineering to increase the speed and success rate of drug development.

33	Google offers artificial intelligence tools tailored for healthcare, its large language model, Med-PaLM 2, trained on medical data, being available for use case trials. Hospitals can use Med-PaLM generative artificial intelligence technology to analyze data to help diagnose complex diseases, fill out records, or as a concierge for patient portals. Google is working with Bayer to automate drafting of clinical trial communications in multiple languages and is partnering with iCad to integrate artificial intelligence tools in the company's devices to detect breast cancer.
34	Gramener and its proprietary generative artificial intelligence tool AInonymize address clinical operations, fastening clinical data redaction and quickly navigating regulatory hurdles. AInonymize assigns risk scores to documents, helping medical teams identify and mitigate vulnerabilities, ensuring the anonymization of patient data according to regulations, freeing up clinicians' time, and reducing risks of compliance issues.
35	Gridspace automates patient communication through phone calls, scheduling inquiries, reminders and real-time responses, and thus patient engagement is scalable 24/7 without burdening clinical staff.
36	HCA Healthcare and Google Cloud use generative artificial intelligence technology to improve clinical documentation workflows, and thus clinicians and nurses can focus more on patient care, document critical medical information from conversations during patient visits quickly and more efficiently, reducing administrative burdens, enhancing clinical workflows, improving patient outcomes, and reducing healthcare costs.
37	Healome's LongevityGPT app focuses on addressing questions related to aging, longevity, and general health. Delivering real-time medical guidance and tracking health metrics by use of advanced natural language processing, LongevityGPT offers personalized, evidence-based insights and recommendations to help users make informed decisions about their health and wellness.
38	Health Catalyst's Healthcare.AI supports descriptive and predictive analytics in readmission risk and healthcare program outcome assessment.
39	Healx focuses on rare and orphan diseases by using generative artificial intelligence algorithms and machine learning models to rapidly discover and evaluate new treatment candidates from massive biomedical datasets, shortening the path from research to clinical trial.
40	Hippocratic AI develops LLM-powered chatbots for the healthcare industry and focuses on keeping healthcare data safe while providing scalable support and prioritizing patient safety, equitable access, and clinical utility. Hippocratic AI's generative artificial intelligence tools as virtual nurses can augment healthcare delivery, expanding access to care and improving patient outcomes by patient triage and care navigation optimization, with artificial intelligence healthcare agents addressing patient needs related to chronic care, nutrition, monitoring, screening, testing, and assisted living.
41	Hoppr AI uses generative artificial intelligence to analyze medical imaging data (e.g., CT scans, EKGs, and echocardiograms), its algorithms being designed to provide real-time insights and automated assessments, accelerating diagnosis and treatment processes with greater accuracy.
42	Humana's artificial intelligence-powered virtual assistants automate patient data access for healthcare business administrative staff by using predictive and descriptive analytics models.
43	IBM's generative artificial intelligence services have their primary use cases center around creating healthcare chatbots and running analytics on healthcare data by use of cloud and quantum computing, enhancing diagnostics, drug discovery, and personalized medicine. IBM's generative artificial intelligence services improve patient outcomes, streamline operations, and innovate treatments, analyzing complex medical records.
44	Imagene covers artificial intelligence-powered precision oncology, aiming to make cancer research and diagnostics more accessible, scalable, and effective by capturing complex, generalizable, and versatile features and patterns within biopsy images and omics data modalities. Its CanvOI tool delivers robust performance even in small-data scenarios, from diagnostics to biomarker discovery and drug development, providing rapid, reliable insights into disease mechanisms and tumor microenvironments, while accelerating biomarker-driven therapeutic strategies and advancing precision medicine.
45	Insilico Medicine use generative artificial intelligence algorithms to create promising drug candidates for rare diseases or complex medical conditions, shortening the research-to-patient timeline and changing care for millions suffering from underserved medical conditions. Its proprietary artificial intelligence software models and tests molecular structures, speeding up pharmaceutical R&D, especially in rare or orphan diseases that are too expensive or complex to develop, leading to faster timelines, lower costs, and quicker patient access to life-saving treatments.
46	Insitro combines statistical models with stem cell models and utilizes machine learning to accelerate the identification and validation of targets for drugs. Insitro uses machine learning and large, high-quality, multimodal datasets to decode human biology and develop transformative medicines, and data-driven predictions to provide insights and purposefully design treatments. Insitro harnesses genetics, human cohort data, and cellular data to accelerate the drug discovery and development pipeline, while creating predictive disease models. Insitro deploys generative AI, combining in vitro cellular data with human clinical data.
47	With its Gaudi and Habana Labs' artificial intelligence chips, Intel has enhanced performance in healthcare applications such as diagnostics and personalized medicine.
48	K Health utilizes clinical-grade medical chat and predictive artificial intelligence models trained on large datasets, supporting physicians by analyzing symptoms and patient history to inform diagnosis and treatment decisions. K Health provides artificial intelligence-driven virtual primary care, urgent care and chronic condition management, and mental health support. K Health combines machine learning with human oversight to improve care delivery and help clinicians focus on patient outcomes, making diagnostic suggestions personalized to the patient. K Health's artificial intelligence technology combines patient assessments with relevant EMRs to generate comprehensive medical charts with personalized insights.
49	Komodo Health's MapAI platform combines artificial intelligence with the industry's most comprehensive healthcare map to deliver real-time insights into disease trends, treatment pathways, and patient populations. Its MapLab platform features an artificial intelligence-powered analytics assistant that enables users to generate insights through natural language processing.

50	LeewayHertz's ZBrain, an enterprise-grade generative artificial intelligence platform, helps healthcare organizations enhance patient care, optimize operations, and foster innovation through tailored generative artificial intelligence solutions. ZBrain apps are built on GPT-4, Llama 3, Gemini, and Mistral to transform healthcare processes in terms of efficiency, accuracy, and overall effectiveness.
51	Markovate creates custom artificial intelligence frameworks that yield more precise diagnostics, streamline administrative functions, and personalize patient care. Its custom artificial intelligence applications integrate seamlessly with any hospital or medical center's record-keeping infrastructures, facilitating quick, data-driven decisions leading to a revolutionized healthcare experience that amplifies patient satisfaction while optimizing operational efficiency.
52	MDI Health harnesses artificial intelligence to enhance clinical outcomes, reduce costs, and improve quality measures, optimizing medication treatment, offering an unprecedented, comprehensive analysis of each patient, and autonomously generating personalized clinical recommendations to improve quality metrics. MDI Health's technology runs in-depth personalized analyses across the entire patient population, analyzing medications, health conditions, lab values, demographics, etc. MDI Health instantly generates personalized recommendations for medication regimen changes, meticulously designed to prevent medical complications, enabling significant improvement to patients' health outcomes.
53	MEDITECH has integrated Google's generative artificial intelligence into its EHR systems, improving the efficiency and accuracy of EHRs to enhance patient care.
54	Medtronic integrated generative artificial intelligence into healthcare, enhancing patient outcomes through artificial intelligence-driven diagnostics, personalized treatment plans, and robotic-assisted surgeries.
55	Microsoft's Azure Health Bot helps developers create chatbots to discuss healthcare information with patients and care providers, while its AI Health Insights assesses healthcare data. Epic's collaboration with Microsoft Azure uses generative artificial intelligence models to secure patient messaging and automate clinical documentation, writing physician notes, freeing clinicians from administrative tasks, allowing for more comprehensive and personalized patient consultations, and providing real-time artificial intelligence-driven recommendations for clinical follow-ups and preventive care, thus reduce the time clinicians spend documenting or replying to patient messages. GPT is integrated into EHR workflows to automatically draft replies to patient messages. Azure Health Bot streamlines medical note-taking, integrating GPT-4 into its clinical note-taking software. Microsoft Cloud for Healthcare integrates data analytics and machine learning to improve patient outcomes, deploying artificial intelligence for personalized medicine and predictive analytics. Microsoft's Azure Health Bot uses artificial intelligence-powered solutions to boost productivity and precision across all healthcare settings: its speech recognition technology designed specifically for clinical documentation lets healthcare professionals dictate into their EHR systems, reducing the documentation burden while ensuring more accurate and consistent patient records.
56	MySense AI transforms patient monitoring through an advanced well-being analytics platform, deploying seven discrete sensors, a wearable device, and a home gateway that collectively gather thousands of daily data points to create personalized digital portraits of patient wellness, showing a 46% reduction in unplanned hospital admissions and average cost savings of £16,458 per patient annually.
57	Nabla offers artificial intelligence-powered assistance to medical professionals in areas including patient communication, medical record keeping, and data analysis, transcribing doctor-patient interactions in real-time and creating organized clinical notes in a matter of seconds. Nabla Copilot helps clinicians and patients reduce the labor needed for paperwork and form filling. Its generative artificial intelligence technology helps clinicians instantly take notes, perform medical coding, and ensure smooth integrations with EHR, independently capturing all physician-patient in-person or virtual meetings across any medical specialty. Nabla CoPilot features multiple clinical templates, making it adaptable for large health system customers, instantly generating clinical notes from doctor-patient interactions and seamlessly updating patients' medical records.
58	NeuroCreate's generative artificial intelligence-based FlowCreate combines principles of neuroscience and artificial intelligence to guide users towards an enhanced state of flow and overall well-being, providing personalized recommendations, real-time guidance, and neuroscience-based techniques.
59	Noah Labs Ark's healthcare artificial intelligence platform integrates data from smartwatches, ECGs, and blood pressure monitors to provide real-time patient monitoring, working with the Mayo Clinic and Charité Berlin in voice-based artificial intelligence diagnosis of heart failure by analyzing voice samples for early detection of cardiac conditions.
60	Notable automates healthcare operations across more than 10,000 sites of care, handling over a million workflows daily, including scheduling, intake, referrals, chart review, and care gap closure, and helping providers reduce manual administrative tasks and improve patient care. Notable integrates directly into clinical and operational systems, supporting health systems in streamlining processes, reducing overhead, and enabling more personalized care experiences.
61	In healthcare, NVIDIA's GPUs and artificial intelligence platforms like NVIDIA Clara power generative artificial intelligence applications, enhancing medical imaging, drug discovery, and personalized medicine, integrating AI into clinical workflows.
62	Oracle Cerner's advanced natural language processing and artificial intelligence algorithms automate clinical note-taking and patient summaries during medical encounters, translating doctor-patient conversations into structured, ready-to-use EHR content and resulting in reduced administrative workload and more physician time for direct patient care.
63	Owkin's healthcare artificial intelligence platform integrates cutting-edge machine learning and biological insights into drug discovery and development. Its K1.0 Turbigo operating system supports drug discovery and diagnostic development using proprietary artificial intelligence methodologies, transforming patient care delivery while improving operational efficiency and clinical outcomes.
64	PareIT's artificial intelligence-powered summarization reduced turnaround time by 40x, offered greater accuracy in document analysis, and minimized clinical errors, achieving 85% accuracy and improving efficiency and reliability.

65	PathAI's artificial intelligence-powered software for digital pathology improves disease diagnosis accuracy and support drug development. PathAI develops diagnostic assistance tools using generative imaging algorithms trained on millions of pathology data points, quickly and accurately identifying cancer and other critical diseases, resulting in faster and reliable patient diagnosis and targeted care delivery. Its models are trained on large-scale, expertly annotated datasets to support the analysis of tissue samples, enabling pathologists to detect disease markers more precisely. PathAI's artificial intelligence-powered pathology improves patient outcomes in both clinical and research settings, particularly in oncology, to aid in diagnostics, biomarker discovery, and clinical trial support. PathAI partners with pharmaceutical companies and pathology labs to improve laboratory workflows and accelerate therapeutic development, combining computational expertise with medical insight to support more efficient and confident clinical decision-making, streamlining analysis, and helping bring effective treatments to patients more quickly. The AISight is an end-to-end image management system that helps the integration of artificial intelligence algorithms in pathology analysis without any obstacles. PathAI and Cleveland Clinic have digitized hundreds of thousands of pathology specimens and created millions of whole slide images across multiple disease areas.
66	Philips Healthcare improves patient outcomes and advances medical innovations, offering a comprehensive range of products and services including diagnostic imaging, patient monitoring systems, and healthcare informatics, and developing integrated solutions for personalized healthcare. Philips Healthcare integrates artificial intelligence and data analytics to enhance clinical decision-making and patient care.
67	Qure.ai develops Generative artificial intelligence tools to automate the interpretation of medical imaging, including X-rays, CT scans, and ultrasounds. Its artificial intelligence models assist clinicians in detecting and prioritizing conditions such as tuberculosis, lung cancer, and stroke, speeding up diagnosis, improving workflow efficiency, and expanding access to care in resource-constrained settings. Qure.ai makes diagnostic services more equitable, its solutions supporting both clinical decision-making and population health initiatives and helping medical teams deliver timely interventions while managing high patient volumes, with a focus on neurological systems and musculoskeletal structures.
68	RapidAI uses artificial intelligence-powered imaging solutions for vascular and neurovascular conditions, assisting physicians in identifying strokes, aneurysms, pulmonary embolisms, and other critical conditions. Its software analyzes CT and MRI scans in real time to support faster diagnosis and treatment decisions across emergency and inpatient settings. RapidAI's platform is integrated into care workflows at over 2,000 hospitals, improving care coordination and patient outcomes in time-sensitive, high-acuity scenarios, and spanning a growing range of use cases, including triage, perfusion imaging, and treatment planning.
69	Sanofi and BioMap's artificial intelligence platform co-develops advanced artificial intelligence modules for biotherapeutic drug discovery to create protein LLMs enabling biologics design and multiparametric optimization, accelerating drug discovery, and helping find new disease treatments.
70	Siemens Healthineers integrates generative artificial intelligence into diagnostic and therapeutic solutions, enhancing precision, and operational efficiency, with developments in MRI and CT imaging.
71	SigTuple enable AI-assisted remote reviews, leveraging advanced artificial intelligence and robotics to reduce eye strain.
72	Subtle Medical applies generative artificial intelligence to medical imaging. Its proprietary artificial intelligence-powered software processes MRI and CT scan data, using advanced generative algorithms to improve image clarity, enhance diagnostic accuracy, and reduce radiation dose by up to 60%.
73	By combining speech recognition, large language models, and contextual medical data, voice-enabled clinical assistant, Suki Assistant transforms clinical note-taking by capturing clinician-patient conversations in real-time, intelligently converting spoken dialogue into structured, accurate medical documentation, reducing administrative overhead, supporting clinical decision-making across healthcare settings, and turning physician-patient conversations into concise, accurate clinical notes. Clinicians can dictate notes directly or rely on ambient generation, with innovative suggestions for diagnosis codes and documentation accuracy. Suki Assistant significantly reduces documentation workloads, with its generative artificial intelligence technologies boosting clinical efficiency and enhancing healthcare professionals' satisfaction. Suki AI leverages natural language processing and machine learning to significantly reduce the administrative burden on physicians, helping doctors create clinical notes, retrieve patient information from EHRs, and streamline ICD-10 coding, and leading to a 76% reduction in documentation time, thus allowing doctors to focus more on patient care. Suki and Google's generative artificial intelligence-powered Gen 2 can generate a clinical note by listening into a conversation and filling in a note automatically. Designed to reduce the time spent on paperwork, the platform supports more efficient workflows across a variety of specialties and care settings.
74	Sword Health combines artificial intelligence and clinical expertise to deliver virtual care for musculoskeletal conditions, pelvic health, and injury prevention, connecting patients with licensed physical therapists and artificial intelligence-powered tools to support personalized treatment and recovery, and improving access to high-quality care while reducing the need for in-person visits, surgeries, and high-cost interventions. Sword Health's AI Care pairs human clinicians with artificial intelligence-driven guidance to scale care delivery and enhance patient outcomes, treating a wide range of conditions, from chronic pain to postpartum recovery, and including support for movement therapy, clinical coordination, and long-term prevention.
75	Synthego leverages CRISPR-based technologies for life science research and therapeutic development, offering a range of solutions from research-grade tools to IND-enabling and GMP-grade materials and supporting scientists through each stage of the drug development process. By integrating automation, bioinformatics, and molecular biology, Synthego provides high-quality reagents and data-driven workflows to streamline genome editing at scale. Its vertically integrated platform is designed to reduce bottlenecks in early discovery, preclinical validation, and clinical manufacturing.

76	Tempus sorts through large volumes of clinical and biological data to provide doctors with individualized therapy recommendations, thus improving diagnosis precision and treatment efficacy. Tempus personalizes treatment regimens by using artificial intelligence models to analyse multimodal genetic, clinical, and imaging data, to find actionable biomarkers and match patients to clinical trials and tailored medicines. By processing vast amounts of clinical and molecular data, Tempus supports physicians in making real-time, data-driven decisions for personalized patient care. Its platform combines analytics, machine learning, and diagnostic assays to provide insights that help identify targeted therapies, predict treatment responses, and connect patients to relevant clinical trials across a range of diseases, accelerating therapeutic discovery and development. Tempus's solutions include data integration tools, algorithmic models, and artificial intelligence-enabled assistants that help close gaps in care and inform clinical research, continuously improving patient outcomes by learning from each case and working to make individualized medicine more accessible and actionable. Tempus uses artificial intelligence to process huge amounts of clinical and molecular data across major disease types to provide personalized insights for patient care.
77	Unlearn.AI uses generative artificial intelligence to build virtual representations of patients, simulating how their health might respond to different treatments, enabling healthcare providers to tailor treatment strategies, predict patient responses more accurately, and streamline clinical trials.
78	Verantos generates high-validity data for clinical, regulatory, and reimbursement use, integrating and enriching data from electronic health records, claims, and registries, and applying artificial intelligence and data curation techniques to produce clinically robust, research-grade evidence. By focusing on data completeness, traceability, and accuracy, Verantos supports applications across therapeutic areas and stages of the product lifecycle, enabling large-scale studies that incorporate unstructured clinical information.
79	Verily has developed a sophisticated platform designed to enable more personal, precise, artificial intelligence-driven care experiences while reducing healthcare costs, bridging the gaps between clinical research and care. Its platform includes an opinionated FHIR model, analytics engines, and modeling tools to integrate disparate datasets, using data from various clinical and non-clinical sources to develop solutions.
80	VideaHealth integrates generative artificial intelligence in dental healthcare, creating tools to detect, predict, and manage oral disease. The generative artificial intelligence-driven software analyzes vast amounts of dental imaging data, using predictive analytics to detect issues like cavities, periodontal disease, and oral cancer earlier and more accurately than traditional methods. By empowering dentists and oral surgeons with accurate assessments of patients' oral health conditions at the earliest stages, VideaHealth improves clinical outcomes, reduces treatment costs, and patient engagement in dental healthcare.
81	Viz.ai uses artificial intelligence for accelerated care coordination for life-threatening diseases like stroke and hypertrophic cardiomyopathy, analyzing medical images and clinical data.
82	Emphasizing responsible AI use in healthcare operations, XpertDox provides artificial intelligence-powered autonomous coding solutions for urgent care chains, pediatric clinics, primary care organizations, women's care organizations, federally qualified health centers or community health centers, and billing and RCM companies. XpertCoding uses artificial intelligence, natural language processing, and big data analytics to automatically code over 94% of claims without human intervention, with over 99% coding accuracy. The platform is EHR-agnostic and comes with a business intelligence suite with data analytics, audit trail, performance dashboard, and CDI modules that provide healthcare organizations with critical operational insights.

Sources: Authors' elaboration on the basis of (https://aimmediahouse.com, https://www.alpha-sense.com, https://www.bain.com/, https://cellstrat.medium.com, https://www.emergenresearch.com, https://gramener.com, https://thehealthcaretechnologyreport.com, https://riseapps.co, https://www.solutelabs.com, https://spsoft.com/, https://www.techtarget.com).

3. Research results

Blockchain Internet of Medical Things wearable sensor- and medical imaging-based medical diagnosis, care, and treatment adherence simulation articulate medical abnormality detection, patient health and response monitoring, and real-time clinical patient involvement and medical data processing, analysis, and interoperability. Tailored health issue and medical treatment planning prediction modeling assists virtual healthcare services in therapeutic efficacy and patient outcome enhancement, clinical early disease detection and diagnosis, and customized medical care. Internet of Things devices and wearable sensors can be harnessed in multifactorial healthcare data analysis for patient treatment and outcome optimization in personalized and precision medicine, health digital twin-informed therapies, and artificial intelligence-enabled medical devices for clinical workflow decision-making. Health-connected sensor and multimodal patient physiological data can be deployed in health digital twin-based clinical and patient care customization for increased therapeutic efficacy, pathological condition parameter customization modeling, and synthetic patient data for disease progression simulation. Medical device digital twins can be leveraged in health outcome predictions, virtual clinical services, and treatment planning prediction, increasing patient engagement. Organ system biological process granular modeling, virtual healthcare delivery, and real-time remote digital twin patient monitoring develop on cloud computing-based digital health technologies and machine learning algorithms.

Connected smart medical devices and clinical and physiological data further immersive medical procedure virtual representations, convolutional neural network-based health condition prediction, and personalized early diagnosis, prevention, treatment, and prognosis in Internet of Things-based smart healthcare and medical twin virtual environments. Digital twin healthcare systems and deep learning and extended reality technology-based medical digital twin technologies shape blockchain-based digital twin haptic assistance and healthcare services in remote digital twin-based patient health status and condition monitoring, patient treatment and care optimization, and real-time medical sensor data collection across virtual intensive care units and operating rooms. Real-time clinical patient data optimize clinical decision support and diagnostic decision-making processes, patient diagnostic and treatment plan data based on physiological parameters and medical records, remote patient-tailored disease treatment and monitoring, and digital twin-based personalized treatments, healthcare services, and medical procedures. Blockchain- and cloud computing-based personalized healthcare digital twin technologies and disease prediction modeling algorithms enhance artificial intelligence and machine learning-based personalized care planning, monitoring, and treatment, real-time patient flow simulation, and healthcare delivery and interventions.

Machine learning-based personalized healthcare and medical services for health risk prediction, digital twin-based potential health deterioration simulation and modeling, patient health status evaluation and forecasting, virtual healthcare delivery and patient care services, and personalized patient vital sign monitoring and condition screening require multimodal Internet of Things medical devices. Patient-centric digital twin- and Internet of Things-based diagnosis and treatment, critical vital sign monitoring, patient vital data gathering and assignment enhancement, and past medical history-based specific disorder and disease severity prediction necessitate context-aware Internet of Things-based medical and patient-centric cyber-physical systems. Patient body implanted sensors are pivotal in real-time patient data and health record-based personalized artificial intelligence medical services and cloud- and digital twin-based healthcare management. Patient health state and vital sign sensor data and big healthcare data analytics are instrumental in critical patient sign and condition identification and medical image-based disease detection and progression. Internet of Things sensor- and digital twin-based patient data collection and processing and interconnected sensor data-based wearable medical devices configure health status-based patient state prediction and personalized patient monitoring and healthcare services. Healthcare digital twin-based interconnected embedded Internet of Things medical sensors and actuators articulate patient health monitoring, diagnosis, and prediction, machine learning-based critical sign detection, patient state and disease progression forecasting, and patient vital sign and condition monitoring.

Artificial intelligence cyber-physical medical systems enable remote patient-specific medical condition monitoring and tailored timely interventions and treatments, big healthcare data-driven personalized treatment planning and risk assessment, remote Internet of Things wearable sensor-based patient health parameter monitoring, Internet of Things wearable device-based treatment planning and intervention personalization for patient outcome optimization, and personalized health risk factor identification. Healthcare digital twin technologies further immediate patient health status assessment for early detection and personalized intervention, recurrent neural network- and k-nearest neighbor-based disease progression assessment, deep convolutional neural network- and random forest-based treatment outcome evaluation, digital twin real-time patient data and health parameter-based disease progression simulation and prediction, and patient health data-based potential medical complication identification and personalized treatment planning. Virtual healthcare service modeling shapes predictive modeling- and machine learning-based patient care optimization, individual patient risk and health condition assessment, preventive measure implementation for adverse health event timely interventions, treatment effectiveness evaluation, and remote patient health parameter and vital sign monitoring. Appropriate treatment decision simulation optimizes remote disease progression tracking, Internet of Things wearable sensor-based patient-specific disease progression and tailored treatment planning evaluation, and digital twin-based medical intervention tailoring, deterioration and complication early sign detection, and treatment plan adjustment

Immersive extended reality technologies and machine and deep learning-based Internet of Things multi-sensor data fusion improve multi-scale and multi-factorial big healthcare data modeling, specific patient disease stage visualization, and digital twin-based clinical decision support. Computer vision- and cloud-based 6G digital twin-based remote monitoring systems can be deployed in artificial intelligence digital twin and edge computing-based context-aware Internet of Things 6G healthcare sensing networks. Artificial intelligence deep learning-based big healthcare data clustering and forecasting can be leveraged in Internet of Things cloud computing and extended reality-based early disease and irregular body event detection simulation and modeling. Digital twin- and wearable actuator-based disease diagnosis and healthcare interventions, physiological and pathological state monitoring for disease risk prediction and detection, pathological feature discerning, and computer vision and Internet of Things sensor-based clinical analysis and treatment planning integrate Internet of Things-based wearable device and medical multimodal sensor data. Multimodal artificial intelligence- and medical imaging-based diagnostic support, real-time early prevention and physiological state prediction, health outcome simulation and modeling, and personalized medical condition diagnosis and treatment require big healthcare and clinical data in virtual clinical settings. Machine and deep learning-based proactive healthcare measures and interventions, wearable and implantable sensor-based vital sign and medical condition monitoring, and artificial intelligence- and medical imaging-based health condition, diagnosis, and treatment forecasting necessitate multidimensional medical and patient sensor data analysis.

Digital twin artificial intelligence-based big healthcare and clinical data analytics and convolutional neural network-based synthetic medical data augmentation are instrumental in machine and deep learning-based personalized treatment planning and healthcare services for disease diagnosis and patient care optimization, medical decision support, and patient vital sign monitoring. Artificial intelligence-based Internet of Things and digital twin sensor technologies and big wearable medical device data articulate virtual predictive analytics-based patient-specific anatomical and healthcare service delivery simulations. Artificial intelligence and machine learning-based big medical sensor data analysis and critical care resource and patient management systems assist in blockchain and digital twin-based real-time remote patient and health data monitoring, Internet of Things-based patient care and clinical operation enhancement, and early disease identification and prevention. Artificial intelligence cyber-physical medical and cloud-based healthcare systems enable cloud and cognitive computing-based virtual healthcare services, deep and machine learning-based digital health interventions, digital twin-based surgical operation precision forecasting, and treatment planning simulation.

Digital twin healthcare systems shape healthcare delivery and monitoring networks, multi-agent reinforcement learning-based patient care and healthcare intervention optimization, preemptive health intervention simulation and forecasting, personalized patient treatment and monitoring, and patient care enhancement. Artificial intelligence Internet of Things-based healthcare devices optimize mobile edge computing- and Internet of Things motion sensor-based patient health indicator monitoring, health trajectory projection, and predictive analytics-based personalized treatment planning. Cloud computing- and digital twin-based healthcare monitoring and biometric sensor systems enhance real-time Internet of Things motion sensor and physiological parameter data monitoring. Digital healthcare delivery systems Can be harnessed in real-time mobile healthcare data processing, digital twin-based healthcare delivery and patient outcome enhancement, disease prevention and treatment optimization, medical device operations, and biometric motion sensor-based therapeutic and patient outcome improvement. Wearable device and patient health data can be deployed in healthcare delivery and data analysis enhancement, real-time patient health and care monitoring, predictive analytics-based patient healthcare outcome optimization, and predictive healthcare interventions and services.

Disease pathophysiological and medical decision processes, personalized therapy interventions, patient vital sign assessment and monitoring, treatment response and prognostic prediction, virtual clinical practice modeling, and personalized patient care and therapy response improvement develop on explainable artificial intelligence deep learning- and physics-informed neural network-based virtual patient-tailored treatment simulation. Automated medical decision-making processes, personalized therapeutic intervention prediction, and disease state and progression integrate multi-modal big synthetic healthcare and patient data scalability and interoperability and wearable non-invasive sensor-based clinical and therapeutic decision support modeling and simulation. Machine and deep learning-based patient-reported outcome optimization, medical image interpretation, and patient-specific treatment response and resistance prediction necessitate clinical decision support and invasive procedure simulation in digital twin healthcare metaverse. Healthcare treatment planning and intervention forecasting, virtual patient engagement, treatment response prognostication, tailored surgical planning, and timely treatment decisions and predictions require Internet of Medical Things sensor-based multiscale big clinical and medical imaging data modeling and deep and machine learning-based disease progression trajectory simulation.

Metaverse-based health and therapeutic intervention modeling and simulation are instrumental in diagnostic precision and therapeutic response enhancement, personalized treatment efficacy and therapeutic intervention improvement, tailored patient treatment planning, and health risk and patient care management. Patient state and healthcare delivery modeling configures digital twin and artificial intelligence and machine learning-based healthcare services, surgical intervention and patient outcome optimization, and diagnosis and treatment process enhancement. Machine learning and artificial intelligence-based medical procedure and healthcare service simulation articulates artificial Internet of Things-based disease prevention and diagnostic accuracy improvement, treatment planning and recovery outcome enhancement, and interactive health interventions in remote healthcare settings. Predictive healthcare analytics assists in surgical accuracy and medical procedure optimization, healthcare delivery and patient recovery time improvement, customized patient care and health outcome enhancement, surgical and treatment outcome predictability, and remote patient engagement and medical condition monitoring across immersive therapeutic environments. Artificial intelligence digital twin metaverse-based predictive healthcare analytics enables immersive patient-centered care, therapeutic intervention and patient recovery optimization, real-time patient data monitoring and analysis, and patient outcome and therapeutic intervention enhancement.

Multimodal big patient health and medical data shape Internet of Things blockchain digital twin and immersive extended reality-based healthcare operations, treatment delivery improvement, virtual healthcare services and surgical procedures, personalized medical and mobile health interventions, and illness prevention and patient satisfaction optimization. Blockchain Internet of Medical Things cloud computing- and immersive healthcare artificial intelligence deep learning-based big clinical data mining optimizes health status monitoring and tracking, clinical decision and patient recovery support, and patient medical condition and diagnosis. Big healthcare data fusion and interoperability simulation and healthcare operation and service modeling enhance computer vision artificial intelligence and immersive extended reality-based patient treatment plan development and Internet of Medical Things- and edge computing-based disease forecasting. Personalized patient healthcare experiences can be attained by use of medical image processing, healthcare operation enhancement, and patient health issue sharing. Personalized healthcare delivery and experiences can be achieved through treatment decisions and surgical procedures, edge computing-based remote healthcare delivery, and immersive clinical care. Internet of Healthcare Things- and remote sensing-based early diagnosis intervention and metaverse healthcare service simulation improves patient health tracking and monitoring, patient diagnosis and treatment prediction, and health status tracking.

Support vector machine and gradient boosting-based immersive medical diagnosis accuracy simulation can be deployed in timely medical intervention and treatment decisions, disease progression diagnosis, and machine and deep learning-based personalized treatment planning development and adjustment. Logistic regression and random forest-based medication effect modeling can be leveraged in condition diagnosis and treatment optimization, disease progression, and virtual surgical procedures. Treatment plan tailoring, virtual medical practice, health issue prediction, and patient health and outcome monitoring develop on computer vision- and deep convolutional neural network-based medical image analysis.

4. Discussion of the results

We have developed our research on synthetic patient and clinical data for immersive disease progression simulation and prediction (Chen et al., 2024a), generative artificial intelligence and machine learning-based clinical practice, medical care, and treatment decisions (Earp et al., 2024), machine learning and augmented intelligence-based personalized patient health diagnosis, treatment, and monitoring (Cecconi et al., 2024), multi-sensory virtual human-computer interaction in the healthcare generative artificial intelligence metaverse (Wang et al., 2024), interactive and engaging extended reality-based patient physiological state and condition monitoring (Yu et al., 2024), virtual healthcare delivery, diagnosis, and treatment simulation for healthcare quality and medication adherence improvement, disease diagnosis and patient result optimization, and remote patient outcome and treatment procedure monitoring (Nguyen & Voznak, 2024), health anomaly detection, simulation, and modeling for patient health monitoring, analysis, and prediction (Iranshahi et al., 2025), and patient trajectory simulation for personalized treatment planning and prediction accuracy (Riahi et al., 2025).

Related previous research focused mainly on customized medical services for patient treatment planning and disease diagnosis and anomaly detection (Chen et al., 2024b), medical artificial intelligence digital twin-based patient treatment predictions and medical decisions (Earp et al., 2024), healthcare generative artificial intelligence deep and machine learning-based diagnostic precision and clinical decision enhancement (Cecconi et al., 2024), sensor-based wearable medical devices and medical imaging, prognosis, and diagnostics tools for patient health, care, and condition monitoring (Xames & Topcu, 2024), personalized therapy and treatment (Niarakis et al., 2024), real-time patient data monitoring (Nguyen & Voznak, 2024), medical treatment and healthcare delivery data (Strigari et al., 2025), and clinical and medical intervention prediction (Somers et al., 2025).

Our findings complement recent research on generative artificial intelligence digital twin healthcare technologies for healthcare operation disruption prevention and real-time remote patient inflow, symptom, and progress monitoring (Noeikham et al., 2024), machine learning-based treatment decisions and healthcare practices (Earp et al., 2024), big data-driven predictive digital twin-based healthcare delivery and timely intervention improvement (Cecconi et al., 2024), cloud computing and medical blockchain-based big healthcare sensor data (Brahmi et al., 2024), virtual clinical case and therapeutic scenario simulation (Mollica et al., 2024), artificial intelligence digital twin cyber-physical medical and intuitive rehabilitation system-based patient engagement and outcome optimization (Tao et al., 2024), and big data-driven disease diagnosis and prognosis for patient health risk and anomaly detection and prediction (Jameil & Al-Raweshidy, 2025).

We identified similar results on diagnostic medical imaging technologies for virtual reality rehabilitation therapies (Rowan, 2024), machine learning-based medical treatment decision-making optimization (Earp et al., 2024), Internet of Medical Things wearable sensor- and clinical decision support system-based clinical patient condition and outcome optimization (Cecconi et al., 2024), medical multi-sensor fusion-based wearable health monitoring (Yu et al., 2024), patient care and treatment planning simulation (Mollica et al., 2024), patient-centric practice and personalized remedy planning simulation (Tao et al., 2024), and wireless body area networks for patient diagnosis, classification, treatment, and prognosis (Jameil & Al-Raweshidy, 2025).

Our findings support previous research on medical data accuracy simulation and prediction (Li et al., 2024), healthcare digital twin-based real-time clinical trajectory and decision prediction, remote patient monitoring, and adverse effect reduction (Cecconi et al., 2024), healthcare generative Artificial Intelligence of Things-based personalized preventive care and patient data accuracy (Al-Hawawreh & Hossain, 2025), digital twin artificial intelligence- and Internet of Things sensor network-based patient physiological indicator assessment (Yu et al., 2024), diagnostic accuracy and recovery outcome optimization (Raman et al., 2024), disease diagnosis, treatment, and progression (Wu et al., 2024), and Internet of Things cyber-physical medical system-based timely medical interventions and health prediction accuracy (Jameil & Al-Raweshidy, 2025).

Conclusions

Healthcare Artificial Intelligence of Things- and cyber-physical medical system-based predictive diagnostic imaging and physiological process modeling is pivotal in diagnostic accuracy and treatment efectiveness optimization, virtual healthcare service and clinical practice, patient care and outcome improvement, and precise preventive and medical interventions. Healthcare blockchain Internet of Things sensor and actuator-based real-time clinical and healthcare data processing and analysis are instrumental in edge and fog computing-based personalized treatment planning, early diagnosis enhancement, patient data-based customized treatments and therapies, and timely healthcare delivery. Blockchain and edge computing-based patient treatment and diagnosis data management and interoperability configure remote patient status and physiological parameter monitoring, patient data management and interoperability, surgical error chance and patient recovery time reduction, and customized treatment planning adherence. Deep and machine learning-based medical image analysis, big predictive clinical data analytics and mining, and treatment outcome modeling articulate medication adherence tracking and early disease sign detection accuracy. Deep convolutional neural network-based predictive healthcare analytics assists in patient health status and deterioration prediction, therapy development, medical image fusion, immediate personalized treatment planning adjustment, and early diagnosis accuracy and healthcare delivery improvement.

Predictive big healthcare data analytics enables personalized treatment planning and disease prediction, medical procedure reliability, patient outcome enhancement, ineffective treatment decrease, and real-time patient health progress monitoring. Tailored treatment scenario and patient condition simulation and real-time clinical patient data interoperability further preventive care and health outcome prediction, patient healthcare trajectory and condition data management, and virtual healthcare practices. Blockchain Internet of Things sensor- and deep learning healthcare digital twin-based virtual healthcare service and medical treatment simulation and big patient healthcare data tracking and interoperability optimize personalized care delivery, physical abnormality forecasting, and timely proactive healthcare intervention. Predictive healthcare digital twin artificial intelligence-based cyber-physical medical systems optimize deep reinforcement learning and cloud computing-based mobile health interventions. Digital twin artificial Intelligence and machine learning-based predictive healthcare analytics and disease and treatment progression modeling enhance disease progression forecasting.

Healthcare digital twin artificial intelligence and medical wearable sensor-based disease progression modeling and simulation improve patient treatment and intervention responses, disease progression and rehabilitation treatment forecasting, and diagnostic and therapeutic service delivery. Patient clinical parameter data can be harnessed in personalized risk assessment and prediction enhancement, treatment personalization and clinical investigation optimization, rehabilitation and prognosis outcome improvement, clinical neuroimaging data evaluation, condition risk prediction, and health status history. Predictive digital twin artificial intelligence and machine learning-based pathophysiological disorder simulation can be deployed in severity disease progression prevention and variability, therapeutic efficacy and patient outcome optimization, patient prognosis prediction, accurate personalised diagnosis and treatment planning, clinical decision support, and disease stage patient clinical care trajectory enhancement. Healthcare digital twin artificial intelligence and medical wearable sensor-based disease progression modeling and simulation can be leveraged in disease progression and prognosis, patient outcome and clinical decision-making improvement, targeted therapeutics and interventions, patient health condition monitoring, targeted screening and treatment, and medical rehabilitation interventions.

Theoretical Contributions to the Literature

Medication adherence and therapeutic interventions, disease prevention and early diagnosis enhancement, patient physiological parameter and health status monitoring, virtual diagnostic and treatment procedures, and medical treatment, therapeutic, and intervention planning integrate Internet of Things implantable and wearable sensor-based multimodal patient health and medical imaging data interoperability. Early anomaly and issue detection, virtual personalized medical and surgical interventions, targeted patient disease treatment or therapy planning, patient outcome and therapeutic enhancement, and virtual healthcare delivery require patient healthcare and treatment data mining. Health prediction accuracy, virtual healthcare service simulation, patient outcome and disease treatment improvement, targeted treatment and surgical planning development, and patient treatment response prediction integrate artificial neural network and machine learning-based big healthcare data analytics.

Digital twin and extended reality healthcare metaverse-based clinical patient treatment and care data analysis and personalized patient care and healthcare service simulation are pivotal in immersive mobile medical services for diagnosis, treatment, and therapy planning. Healthcare and medical artificial intelligence digital twin-based multimodal medical diagnostic image data mining is instrumental in medical Internet of Things wearable sensor and computer vision-based immersive personalized treatment prediction, planning, and intervention. Metaverse medical artificial intelligence and machine learning-based clinical patient health condition and disease data interoperability configures healthcare delivery practices and services for personalized patient diagnosis, treatment planning, and engagement. Artificial intelligence blockchain Internet of Things wearable sensor-based real-time patient physiological parameter data processing, analysis, tracking, and monitoring necessitate extended reality and healthcare Internet of Things-based patient health abnormality and service simulation. Cloud and edge computing-based healthcare intervention and decision modeling are pivotal in health condition diagnosis and prognostication, health risk and anomaly detection, patient outcome and healthcare delivery enhancement, clinical and medical therapeutic treatment forecasting, and healthcare scenario and preventive therapy optimization.

Healthcare artificial intelligence digital twin-based disease diagnosis and treatment modeling assists in patient-specific response prediction, personalized early diagnosis, and pathology treatment planning and intervention. Deep and machine learning-based pathology treatment and analysis simulation enables implantable and prosthetic device-based patient pathophysiology, health, treatment, and disease prognosis monitoring. Physiological process modeling furthers patient disease diagnosis, prognosis, and treatment, health prognostication and disease risk prediction, and medical diagnostic practices and therapeutic interventions. Generative adversarial network-based pathophysiology patient data processing and interoperability can be harnessed in real-time therapy prognosis and monitoring, treatment outcome and decision prediction, and virtual clinical practice. Synthetic medical imaging and diagnostic accuracy data analysis can be deployed in therapeutic treatment response and decision forecasting, personalized patient healthcare and treatment outcome improvement, and patient health condition, engagement, and outcome prediction.

Practical Contributions to the Literature

Healthcare predictive digital twin artificial intelligence and machine learning-based big healthcare data fusion and analytics configure medical disorder deterioration and abnormality detection, patient vital sign monitoring and care optimization, and adverse event risk reduction. Cloud and edge computing-based medical condition and disorder progression analysis and patient-specific healthcare predictive digital twin-based medical scenario and disease progression simulation articulate remote patient disease diagnosis, treatment response, progression, and prognosis. Cyber-physical medical and healthcare system-based patient condition monitoring and analysis assist in machine and deep learning-based clinical decision and medication adherence optimization, disease progression prediction, and patient treatment outcome evaluation. Deep reinforcement learning and computer vision-based early disease prevention, detection, diagnosis, and treatment simulation enables personalized healthcare procedure, intervention, diagnosis, treatment, and rehabilitation, real-time patient-specific healthcare data monitoring, and treatment outcome and health improvement prediction. Support vector machine and convolutional neural network-based big clinical synthetic patient healthcare and pathological condition data fusion and interoperability further patient-specific surgical procedure and treatment response improvement, edge computing and predictive healthcare analytics-based health problem and anomaly detection, and tailored treatment planning and clinical practice.

Internet of Things-based cyber physical medical system-based timely medical intervention modeling and simulation shape patient health status and disease progression forecasting and monitoring, treatment response accuracy enhancement, and condition medication and treatment. Patient and healthcare digital twin-based health scenario analysis and simulation can be harnessed in disease prediction and patient care enhancement, virtual surgical procedures and therapeutic interventions, and personalized patient condition treatment and care improvement. Virtual patient trajectory and healthcare service analysis and multimodal healthcare data interoperability can be deployed in clinical decision-making and practice enhancement, individualized treatment planning, healthcare procedure and intervention optimization, and delivery and long-term healthcare outcome prediction. Real-time patient physiological process and health status monitoring, early disease diagnosis, prognosis, and prevention, virtual healthcare delivery and clinical condition, and patient-specific therapy response integrate blockchain Internet of Things wearable sensor and medical image-based big spatial 3D patient health data interoperability and analysis.

Limitations and Further Directions of Research

Cloud computing- and Internet of Medical Things-based real-time patient health monitoring data analysis is pivotal in artificial neural network-based healthcare services for medical image-guided deep neural network machine learning-based early disease diagnosis, patient care and treatment outcome optimization, personalized treatment and medical decision planning, patient condition monitoring and tracking, and health state prediction. Real-time multimodal clinical patient condition data analysis and disease progression and treatment prognosis simulation can be harnessed in personalized medical decision-making and patient outcome improvement and patient-specific therapeutic response and treatment planning. Blockchain Internet of Medical Things wearable sensor-based disease prevention, diagnosis, and development simulation enhances realtime personalized remote clinical decision support, cloud computing-based healthcare delivery and therapeutic decision design forecasting, surgical outcome and medical treatment prediction, remote big patient syntactic vital sign, medical condition, and health data tracking, and patient disease and therapeutic intervention monitoring.

Healthcare digital twin and artificial intelligence deep learning-based real-time remote patient vital sign and health monitoring data mining configures patient health status and data anomaly prediction, medical diagnosis and treatment, patient care procedure and preventive measure optimization, patient healthcare and condition data interpretation, and anomaly early sign identification. Decision tree and random forest-based clinical patient health condition and treatment modeling articulates real-time patient vital sign, physiological characteristic, and health status monitoring, disease status forecasting accuracy, diagnosis and therapeutic procedure optimization, and patient health status and abnormality prediction. Extended reality and cloud computing-based disease prediction and prognostic intervention simulation assist in logistic regression and support vector machine-based real-time patient vital sign and health status monitoring, patient care and healthcare service improvement, health status and condition prediction, and artificial neural network and k-nearest neighbor-based clinical practice and timely medical intervention enhancement.

Compliance with ethical standards

This article does not contain any studies with human participants or animals performed by the authors. Extracting and inspecting publicly accessible files (scholarly sources) as evidence, before the research began no institutional ethics approval was required.

Data availability statement

All data generated or analyzed are included in the published article.

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Conflict of interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Key elements of digital competence in professional sales & service work: Development and evaluation of a self-assessment scale for frontline employees

Thomas Süße
Maria Kobert
Julia Siderska

ABSTRACT
Modern work in sales & service is increasingly enhanced and supported by digital technologies. As a result, frontline employees' digital competencies are becoming a key success factor for sales & service work. Nevertheless, especially with regards to professional work, there is still a lack of knowledge about how to measure digital competencies. So far, specific empirical contribution focussing on professional digital work environments being increasingly knowledge-intense, collaborative, and virtualized are still very rare. In this article we seek to make a substantial contribution in that area of research. Based on the state-of-the art literature about digital competence among employees in professional work this article is one of the very few that introduces an empirically evaluated scale of digital competence based on a sample size of N=1,283. We suggest a context-related set of five dimensions of digital competence named (1) effective usage of technologies and tools, (2) farsighted & critical information handling, (3) sustained cooperation & communication, (4) integrative knowledge generation, and (5) co-creative problem solving. Evaluation of these five dimensions is conducted with the help of technostress, virtualization of work, space-time flexibility at work and availability for work-related issues. Finally, we present a critical reflection about the scale's five dimensions.

KEY WORDS
digital competence, digitalization of work, digital cooperation, sales & service, frontline employees, human-computer interaction

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Thomas Süße
Hochschule Bielefeld -
University of Applied Sciences and Arts,
Interaktion 1, 33619 Bielefeld, Germany
ORCID 0000-0001-6832-7753

Corresponding author:
e-mail: thomas.suesse@hsbi.de

Maria Kobert
Hochschule Bielefeld -
University of Applied Sciences and Arts,
Interaktion 1, 33619 Bielefeld, Germany
ORCID 0000-0002-1423-9499

Julia Siderska
Bialystok University of Technology,
Wiejska 45A, 15-351 Białystok, Poland
ORCID 0000-0001-5717-8043
e-mail: j.siderska@pb.edu.pl

Introduction

Digital transformation, defined by the convergence of advanced technologies and the integration of physical and digital systems, has significantly influenced both individual and organizational activities. Prior research highlights that information technology has reshaped how people communicate and work, while also shaping essential competencies such as knowledge, skills, and attitudes (Piwowar-Sulej et al., 2024). In the emergence of the digital era, the rapid integration of transformational and constantly enhancing digital technologies demands new skills and competencies of employees (Atalay et al.,

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2018; Gudanowska et al., 2020; Rollnik-Sadowska et al. 2024). Rapid technological advancements are reshaping service frontlines, creating more complex touchpoints. These evolving interactions place higher expectations on frontline employees to provide a positive customer experience (Xie et. al., 2025). The discussion about digital competence of the work force has gained increasing awareness and is developing towards a novel and important research stream in human-computer interaction (Murawski & Bick, 2017). A main reason for that development can be seen in the fact that digital competence of employees has increasingly been considered as a critical success factor for the digital transformation in and of organizations. Boyaci & Atalay (Atalay et al., 2018), for example, state that employees need to be able to find, process and structure information, solve complex problems, be creative and innovative and communicate and cooperate effectively through digital technologies. These job demands express the shift from a rather technical orientation of so-called digital skills or IT skills towards a much wider perspective of content- and context-related higher-order competencies (Claro et al., 2012). However, when discussing about human actors' competencies, the terms competence and skill are often used interchangeably. In this study we refer to Bassellier et al. (Bassellier et al., 2001) who define competence as an individual's "potential which leads to an effective behavior". Thus, contrary to digital skills that are defined as "the ability to use the computer or other devices such as a smartphone" (Oggero et al., 2020), digital competencies do not only include abilities such as using software or operating a digital device, but integrate a complex set of effective behavioral patterns that are based on "a large variety of complex cognitive, motor, sociological, and emotional abilities, which users need in order to function effectively in digital environments" (Eshet-Alkalai, 2004).

Although, a growing number of instruments to measure digital competencies or skills already exist, most of them remain fragmented or limited to specific domains (Bouwmans et al., 2024), are rather focused on skills than competencies or do not consider the broad range of competencies needed to cope with the range of digitalization demands in human-computer interaction in professional work environments. Furthermore, as Oberländer et al. (Oberländer et al., 2020) state in their literature review about digital competence, empirical based research so far is mainly focused on the educational sector. Thus, frameworks explicitly focusing on professional work beyond education and learning are still very rare.

This article seeks to address this gap in research. Empirical-based development of a digital competence scale is conducted for frontline employees in sales & service work, a work environment that has gained increasing importance during the last decades and is crucial for the shift towards a service-based and co-creative economy. Typical responsibilities of frontline employees are detecting customer needs, obtaining information about competitors, identifying potential resources and capabilities that the organisation can develop, and processing knowledge to innovate (González-González & García-Almeida, 2021). Frontline employees are instrumental in adapting their service to suit the individual customer needs. In high contact services, like financial, healthcare and airlines, they need to deal with every customer differently as the interactions are highly personal and variable in nature. Detailed information about customers and their path to service facilitate frontline employees to adapt the service in an optimal fashion (Motamarri et al., 2017). Thus the job of frontline employees includes a lot of information processing.

So far, digitalization has had significant impact on the work of frontline employees in sales and service work fields (Evans et al., 1999; Temerak et al., 2024). New digital technologies enhanced by latest AI advancements make it, for example, possible to collect, analyze, systematize and structure huge amounts of customer and market data to support customer relationship management, enable selling via digital sales channels as well as facilitate more specific and agile communication with customers and colleagues (Alavi & Habel, 2021). Thus, due to the increasing adaption of information and communication technology the tasks and activities for frontline employees are constantly changing. Capturing and processing data makes it, for example, possible to organize, store and use sales-related knowledge. This demands for appropriate digital competences of frontline workers (Singh et al., 2019). Sales digitalization expands the role of technology by including Internet of Things (IoT), AI agents and digital products and services. Processes, such as customer relationship management, repetitive or straight-by sales and other tasks are increasingly automated. AI-based chatbots, for example, can answer customer questions immediately and with accuracy (Pemer, 2021). Overall, research highlights the potential for digitalization to enhance the capabilities of sales and service and especially frontline employees (González-González & García-Almeida, 2021; Lages & Piercy, 2012; Motamarri et al., 2017; Paluch et al., 2022). A frontline employee's attitude and orientation toward their organizational role is a key factor in determining the quality of service delivered to customers (Jung et al., 2023). In this regard the increasing demand for different skills and competencies for frontline employees is highlighted by recent research

(Guenzi & Nijssen, 2021; Motamarri et al., 2017; Paluch et al., 2022; Pemer, 2021). The skills and competencies outlined, include, among others, proficiency in general computing software and data analytics, the ability to use new technologies to analyze consumer behavior and anticipate purchasing needs, the capability to use advanced digital and social strategies to produce more leads and commercial transactions. Furthermore, frontline workers are expected to accompany the customer during the complete buying process and with the opportunities offered by big data they will also have to learn to organize the information at hand and convert it to real sales while customers are developing more towards co-creators of the final solution (Elhajjar et al., 2024). To effectively perform their roles in a digitalized environment, frontline employees will also have to be able to design, develop and implement digital information systems (Mahlamäki et al., 2020) or to monitor, control or optimize operations to deliver value to customers through Digital-Product Service Systems (Aufreiter et al., 2021). With regards to these development in human-computer interaction in professional sales work the main research question of this article is: What are key dimensions of a not all-encompassing but context-specific scale of digital competence for frontline employees in sales & service work and how can these dimensions be measured?

To answer this research question, the article follows a three-step process. In the first step a set of competencies that are regarded as important for frontline employees is derived conceptually and complemented by context-related empirical research. In the second step empirical data gathered over a period of several years from different domains in the fields of interest is analyzed with the help of exploratory as well as a confirmatory factor analysis. In the third step the resulting digital competence scale derived from confirmatory factor analysis validated by taking into account the other variables measured which are technostress, virtualization of work, space-time flexibility at work and availability for work-related issues.

1. Literature review

1.1. Conceptualizations of digital competence

There are several different conceptualizations of the construct of digital competence. Aznar and Gonzales (Aznar & González, 2010) for example, define digital competence as an individual actor's set of competencies needed for the effective usage of latest information and communication technology to solve problems in non-work and work-related contexts. According to Eshet-Alkalai (Eshet-Alkalai, 2004) digital competence should consist of "reading instructions from graphical displays in user interfaces; using digital reproduction to create new, meaningful materials from existing ones; constructing knowledge from a nonlinear, hypertextual navigation; evaluating the quality and validity of information; and have a mature and realistic understanding of the rules that prevail in the cyberspace". Ferrari et al. (Ferrari, Anusca, 2012) state that the five facets information management, communication in digital environments, content-creation, safety and problem solving build up the digital competence dimensions whereas Calvani et al. (Calvani et al., 2008) refer to technological, cognitive, ethical and integrated capabilities that are needed to cope with digitalization demands. Ilomaki et al (Ilomäki et al., 2016) suggest that digital competence consists of the four dimensions: technical competence; the ability to use digital technologies in a meaningful way, e.g. for working; the ability to evaluate digital technologies critically; and the motivation to participate and commit in the digital culture. The Digital Competence Framework (DigComp) introduced by the EU has gained high attention by research and practice (Carretero Gomez et al., 2017; Vuorikari et al., 2022) as well. This framework contains the five dimensions information and data literacy, communication and collaboration, digital content creation, safety as well as problem solving and focusses on European citizens in general. Recent scales that have first been tested and developed in the education sector already refer to the DigComp framework (Krempkow, 2022). Other works take into consideration similar competencies such as understanding computer use, evaluating, managing, transforming, creating and sharing as well as using information safely and securely (Fraillon et al., 2014; Hatlevik & Hatlevik, 2018). From the above considerations, it can be followed that a digital competence scale can be considered as a complex and multidimensional construct consisting of several sub-dimensions.

However, the majority of recent literature on digital competence is focused on the field of education and mostly consist of self-assessment questionnaires that aim at assessing students' or teachers' digital information searching, content creation, communication, problem solving as well as technical skills (Budai et al., 2023; Miltuze & Litiņa, 2021; Parra-Camacho et al., 2023; Pettersson, 2018; Reisoğlu, 2022; Zhao et al., 2021). One scale that goes beyond the education sector stems from Van Laar et al. (van Laar et al., 2018, 2020). It is an

Tab. 1. Conceptualizations of digital competence from literature

Author(s)	Conceptualization
(Eshet-Alkalai, 2004)	reading instructions from graphical displays in user interfaces; using digital reproduction to create new, meaningful materials from existing ones; constructing knowledge from a nonlinear, hyper-textual navigation; evaluating the quality and validity of information; have a mature and realistic understanding of the rules that prevail in the cyberspace
(Ferrari, Anusca, 2012)	information management, communication in digital environments, content-creation, safety and problem solving
(Fraillon et al., 2014)	technical competence; the ability to use digital technologies in a meaningful way, e.g. for working; the ability to evaluate digital technologies critically; and the motivation to participate and commit in the digital culture
(Fraillon et al., 2014)	understanding computer use, evaluating, managing, transforming, creating and sharing as well as using information safely and securely
(van Laar et al., 2018, 2020)	information management, communication, collaboration, critical thinking, creativity and problem solving
(Oberländer et al., 2020)	25 distinct dimensions of digital competences, starting with the ability of handling the functionalities of hard- and software, over programming and information processing skills, communication and collaboration competencies up to security, law and ethics as well as skills to train and educate others

extensive 21st century digital skill framework validated for creative industries and consisting of the dimensions information management, communication, collaboration, critical thinking, creativity and problem solving. Another scale that is based on the DigComp framework is a self-concept scale consisting of 25 items and the five factors communicate, process and store, generate content, safe application and solve problems that was constructed and validated on a large sample including employees from different branches (Schauffel et al., 2021). Overall, an extensive literature review from Oberländer et al. (Oberländer et al., 2020) on digital competence, which also takes into consideration the EU's DigComp framework as well as the framework developed by Van Laar et al. comes up with a set of 25 distinct dimensions of digital competence, starting with the ability of handling the functionalities of hard- and software, over programming and information processing skills, communication and collaboration competencies up to security, law and ethics as well as skills to train and educate others. Another conclusion made by the literature review conducdet by Oberländer et al. (Oberländer et al., 2020) is that there is still a lack of scientific research on this topic, especially when it comes to adults in professional work contexts. Table 1 provides a summary of influential conceptualization of the concept of digital competence.

1.2. Digital competence for frontline employees in professional sales & service work

By taking into consideration the conceptualizations provided by the literature summarized above and specific facets of competence relevant for sales & service-oriented working environments, Author et al.

Tab. 2. Digital competence dimensions for frontline employees in sales & service

Dimension	Description
(1) Effective usage of technologies & tools	Ability of accessing the functionalities of technologies and tools effectively; basic understanding about the interrelationships or interfaces between various tools; recognizing or deal with upcoming problems
(2) Farsighted data & information handling	Awareness of potential security and privacy risks while working with sensitive data and information from people as well as organizations.
(3) Critical information evaluation & handling	Reflecting about the quality of information; evaluating various sources of information, e. g. based on their reliability; identifying appropriate information.
(4) Sustained cooperation & communication	providing mutual support; communicating constructively and effectively; sharing expertise and innovative knowledge; acting cooperatively
(5) integrative knowledge generation	Integrating knowledge from various sources during a collective and discursive process in order to contribute to knowledge innovation.
(6) co-creative problem-solving	development of solutions in work-related settings with the help of applying digital tools, digitalized knowledge and other digital resources in an effective manner in closed interaction with other actors

(Author et al., 2018) introduced an initial digital competence framework for stakeholders in Product-Service Systems consisting of ten self-assessment items. This specific set of items is grouped into three sub-dimensions: confident handling of digital resources to collect relevant information, problem-oriented usage of digital resources for own and collective problem-solving processes as well as critical evaluation of information from digital sources. In a later contribution Authors built on the above findings and extended the initial three dimensional model towards a six-dimensional digital competence framework. Based on a qualitative analysis on expert interviews among frontline employees during the digital transformation of an organization's sales unit a six-dimensional framework has been developed represented in Table 2. These dimensions comprise of (1) effective usage of technologies & tools, (2) farsighted data & information handling, (3) critical information evaluation & handling, (4) sustained cooperation & communication (4), (5) integrative knowledge generation and (6) co-creative problem-solving (Authors). Due to the explicit focus of this study and the six dimensions of digital competence revealed we take up this systematization as the basis for the further development of a self-assessment scale of digital competence that relates to frontline employees in sales & service work.

1.3. Measurements

The items to measure the construct presented in Table 2 were developed or created taking into consideration existing literature on digital competence and specific competence demands in professional sales & service work. The digital competence construct for jobs in the field of sales & service differs from other constructs in that the dimensions specifically focus on co-creative, knowledge-intense and highly context-related tasks. Thus, the items mainly include the confident and critical searching, sensing, recombining and creating information and knowledge as well as the communication of this information through digital tools. It is a self-assessment scale, consisting of thirty items that are measured at the individual level with a seven-point Likert-type scale (Strongly Disagree; Disagree; Slightly Disagree; Neutral; Slightly Agree; Agree; Strongly Agree). Furthermore, multi-item measurement was used as the combination of multiple items prevents random error in the items and therefore increases the reliability (Sarstedt & Wilczynski, 2009). Moreover, multiple items cover a larger number of distinct construct facets and therefore increase construct validity (Wanous et al., 1997).

2. Research methods

In this section, we refine our conceptually derived digital competence scale illustrated in Table 2 and Table 3 by applying statistical methods. We collect quantitative data by applying the questionnaire as it is shown by Table 3.

2.1. Sample

Data was collected by five online surveys between 2017 and 2023 and resulted in five samples summarized by Table 4.

By aggregating all data from the five samples we reach a total sample of N=1283. In the following table (Table 5) descriptive statistics are illustrated for the aggregated sample.

From the total sample we drew a random subsample of 30% with N=385 as a construction sample for performing an exploratory factor analysis (EFA). On the remaining sample (N = 898), we perform a confirmatory factor analysis (CFA) as we explain below. We perform EFA with SPSS 28 and CFA with AMOS.

2.2. Exploratory Factor Analysis (EFA)

The EFA is a multivariate statistical method that was first applied by Spearman (1904). Today, this method is commonly used for the development and validation of measurements in social sciences (Fabrigar & Wegener, 2011). We perform the EFA on the construction sample (N=385).

First, we test whether our data is appropriate for performing an EFA via the Bartlett's test for sphericity and the Kaiser-Meyer-Olkin (KMO) measure (Fabrigar & Wegener, 2011). The Bartlett's test tests the null hypothesis that the correlation matrix of items is an identity matrix to ensure that there are some relationships between items or group of items. Thus, the Bartlett's test should be significant. The Kaiser-Meyer-Olkin measure is a measure of the proportion of variance among items that might be common in variance. KMO values between 0,8 and 1 indicate that the sample is adequate for EFA. In our case, the Bartlett's test is significant with $Chi^2(300)=3462{,}748$ and $p < 0.001$ and the KMO value amounts to .894. Since both tests indicate that the sample is adequate for EFA, we proceed with the analysis.

We perform a Varimax rotation and use a Weighted Leasts Squares (WLS) Estimator. To determine, whether the five-dimensional structure from sec-

Tab. 3. Measures of digital competence for frontline employees in sales & service

Dimensions	Items	No
(1) Effective usage of technologies and tools	I can confidently handle the functions and opportunities of digital platforms, websites or other digital tools.	1
	I easily find the relevant information I need by exploring the internet	2
	I'm well able to search effectively for relevant information online.	3
	The internet helps me to keep up with changes within the organization and beyond.	4
	In order to question dominant perspectives or the status quo I also use online tools to express my opinion.	5
(2) Farsighted data & information handling	I constantly evaluate the information provided by the internet or by digital media.	6
	I obey rules and regulations in online environments even when no one is watching.	7
	I use online tools to share my expertise or my knowledge with others. (-)	8
(3) Critical information evaluation & processing	I critically reflect about digital information provided online.	9
	I critically compare digital information from various providers or sources.	10
	I critically evaluate the authenticity of sources of digital information.	11
(4) Sustained cooperation & communication	I am careful about how I say things online so they don't come across the wrong way.	12
	If I disagree with people online, I watch my language so it doesn't come across as mean.	13
	I think about making sure that things I say and post online will not be something I regret later.	14
	I take steps to try to prevent problems with other workers during online collaboration.	15
	I try to avoid creating problems for online coworkers or colleagues.	16
	I help others who have been absent to participate in online cooperation.	17
	I help orient new people in online environments even though it is not required.	18
	I attend online meetings that are not mandatory, but are considered important.	19
(5) Integrative knowledge generation	I create my own classifications of digital information in order to combine information in a problem-specific manner.	20
	I structure complex tasks and problems with the help of digital tools and methods.	21
	I can develop new problem solutions with the help of information provided by the internet	22
	I recombine information from various digital sources to solve complex problems.	23
	I use online information and digital tools particularly for my own development and improvement.	24
	In order to keep up with latest trends I read online newsfeeds.	25
(6) Co-creative problem-solving	In order to solve novel problems I often use the information provided by online resources and digital media.	26
	I'm well able to use digital information to solve individual problems.	27
	I'm well able to use digital information to solve problems in teams.	28
	I'm well able to use digital information from online platforms in combination with other sources of information (e.g. books).	29
	I use online tools to improve the work context or professional environment in some way.	30

Tab. 4. Samples used for EFA and CFA

Sample 1 N=128	Data was collected in 2017 and 2018. Respondents were Bachelor and Master students from Management and Engineering studies in Germany taking part in a learning laboratory designed as a digital sales & service business ecosystem simulating an actual work environment of frontline employees.
Sample 2 N=174	Data was collected in 2018. Respondents were students in Finland and France taking part in a learning laboratory designed as a digital sales & service business ecosystem simulating an actual work environment of frontline employees.
Sample 3 N=145	Data was collected in 2019. Respondents were professionals from various sectors and industries working as frontline employees and studying part-time in Germany.
Sample 4 N=633	Data was collected by an open online survey in Germany, which took place in the period from June 16th 2020 to August 31st 2020, during the COVD-19 pandemic. Respondents were professionals from various sectors of industry working as frontline employees in the broader area of sales & services and studying part-time.
Sample 5 N=203	Data was collected in the end of 2022 and the beginning of 2023. Respondents were frontline employees from various knowledge related industry sectors.

Tab. 5. Descriptive statistics

Gender	Male	Female	Diverse	Not specified
Sample 1	65 / 50.8 %	63 / 49.2 %	-	-
Sample 2	80 / 46 %	92 / 52.9 %	-	2 / 1.1 %
Sample 3	88 / 60.7%	57 / 39.3 %	-	-
Sample 4	174 /27.5%	459 /72.5%	-	-
Sample 5	158 / 77.8%	39 /19.2%	2 / 1%	4 /2%
Aggregated	565 /44%	710 / 55.4%	2 /0.1%	6 /0.5%

Age (years)	18 - 27	28 - 37	38 - 47	48 - 57	>57	Not specified
Sample 1	118 /92.2 %	10 /7.8 %	-	-	-	-
Sample 2	157 /90.2 %	11 / 6.4 %	6 / 3.4 %	-	-	-
Sample 3	129 / 89%	15 / 10.3 %	1 / 0.7 %	-	-	-
Sample 4	436 /68.9 %	134 /21.2 %	34 / 5.4 %	21 / 3.3 %	-	8 / 1.3 %
Sample 5	92 /45.3%	41 /20.2%	27 /13.3%	24 /11.8%	19 /9.4%	-
Aggregated	932 / 72.6%	211 / 16.4%	68 /5.3 %	45 /3.5%	19 /1.5%	8 / 6.2%

Education	High school diploma	Apprentice-ship	Master craftsman	Bachelor	Master	Other
Sample 1	94 / 73.4 %	34 / 26.6 %	-	-	-	-
Sample 2	137 /78.7 %	37 / 21.3 %	-	-	-	-

Sample 3	104 / 71.7%	41 / 28.3%	-	-	-	-
Sample 4	96 / 15.2 %	382 /60.3 %	27 / 4.3 %	32 / 5.1%	12 / 1.9%	84 / 13.3 %
Sample 5	75 / 36.9%	56 /27.6%	8 / 3.9%	28 / 13.8%	28 /13.8%	8 / 3.9%
Aggregated	506 / 39.4%	550 / 42.9%	35 / 2.7%	60 / 4.7%	40 /3.1%	92 / 7.2 %

Work experience (years)	0	< 2	2 - 5	> 5
Sample 1	53 / 41.4 %	34 / 26.6 %	12 / 9.4 %	29 / 22.6 %
Sample 2	83 / 47.7 %	60 / 34.5 %	10 / 5.7 %	21 / 12.1 %
Sample 3	18 / 12.4%	93 / 64.1%	21 / 14.5 %	13 / 9%
Sample 4	56 /8.8%	39 / 6.2%	231 / 36.5%	307 /48.5%
Sample 5	6 / 3%	12 /5.9%	57 /28.1%	128 /63.1%
Aggregated	216 / 16.8%	238 / 18.6%	331 / 25.8%	498 /38.8 %

Industry sector	Construction, Architecture	Services	Engineering, Technology	Health	IT, Computer	Arts, Culture, Design	Agriculture, Nature	Media	Sciences	Manufacturing	Pedagogics	Transport, Logistics	Business, Administration	Not specified
Samp. 1	-	-	-	-	-	-	-	-	-	-	-	-	-	128/ 100%
Samp. 2	-	-	-	-	-	-	-	-	-	-	-	-	-	174/ 100%
Samp. 3	-	-	-	-	-	-	-	-	-	-	-	-	-	145 /

tion in Table 3 is supported numerically, we perform a parallel analysis, which reveals a structure consisting of five factors to be suitable. This supports our conceptual considerations. Only items significantly correlated with at least two other items and with factor loadings above 0,33 are included into the analysis. Thus, for the first round we drop the items 5, 16, 17, 18 and 19. We next exclude the items 4, 20 and 30 since they show loadings of above 0.33 on more than one factor. We run another EFA with the remaining 22 items. The result consists of five factors with factor 1 consisting of items 1, 2 and 3; factor 2 included items 6, 9, 10, 11 and 25; factor 3 the items 12, 13, 14, 7 and 15; factor 4 the items 21, 22, 23, 24; and factor 5 included the items 26, 27, 28 and 29. The total variance explained amounts to 48,17 %. The results of the EFA are illustrated in Table 6.

2.3. Reliability

As a next step, we analyze the reliability of the five factors on the validation sample (N=898). Cronbach's Alpha (α) (Cronbach, 1951) is a widely used measure for construct's reliability. Usually, a value of $\alpha > .7$ is seen as an indicator for a good reliability of a scale (Taber, 2018). In our sample, $\alpha > 0.7$ for all five factors (see Table 6). However, for factor 2 and factor 5, the reliability can be increased by dropping item 25 and item 26 respectively. The final α values are illustrated in Table 8.

2.4. Confirmatory Factor Analysis (CFA)

In order to confirm the five factor structure obtained through EFA, we performed a confirmatory factor analysis (CFA) on the validation sample (N=898), after dropping item 25 for factor 2 and item 26 for factor 5. Though our data are not normally distributed, maximum likelihood (ML) estimator seems to be appropriate since the data set is reasonably large (Hoyle, 2000). To determine goodness of fit, there are a lot of fit indices, mentioned in the literature.

First of all, there are absolute fit indexes such as the Goodness of Fit Index (GFI), the Adjusted Goodness of Fit Index (AGFI), which takes into account the degrees of freedom as well as the root mean square error of approximation (RMSEA) (Hoyle, 2000). GFI and AGFI range from zero to 1.0, whereas values greater than .90 are viewed as indicative of good fit (Hair et al., 2006). The minimum value of RMSEA is zero, a value it will take when a model exactly reproduces a set of observed data. A value of .05 indicates a close fit, .08 indicates a marginal fit, and .10 indicates a poor fit (Browne, 1993; Fabrigar et al., 1999). Another well-known value is Chi^2/df, where df represents the degrees of freedom. However, there is no consensus about a good value for Chi^2/df. The recommendations vary from 3, 2 or less to 5 (Arbuckle, 2005). Another well-known parameter is the (Standardized) Root Mean Squared Residual (S)RMR, which is a measure of the average unexplained covariances in a model. A model is considered to have a good fit, if the value for (S)RMR is less than 0.05 (Hair et al., 2006).

Furthermore, there are also comparative fit indexes, which are used to compare the fit of a proposed model with the fit of a strategically chosen baseline model (Bentler & Bonett, 1980). The standard baseline model is referred to as the null model or independence model. The commonly used comparative fit index is the CFI, which like GFI and AGFI varies between 0 and 1 and indexes the relative reduction in lack of fit of a proposed model over the null model. Values of .90 or higher indicate an acceptable fit (Hu & Bentler, 1995). Often, it is also recommended to use the Tucker-Lewis Index (TLI), which also has to be greater than 0,9 to show an acceptable fit (Jahn, 2007). The index values for the present model are illustrated in Table 7.

All values apart from RMR and SRMR indicate a good fit. Since RMR is very close to .05 and SRMR is equal to 0.05, we can conclude that our model has an acceptable or even good fit (Browne, 1993; Fabrigar et al., 1999).

3. Research Results

3.1. Digital Competence framework for frontline employees in sales & service work

In Table 8 the resulting construct consisting of the five factors confident (1) effective usage of technologies and tools, (2) farsighted & critical information handling, (3) sustained cooperation & communication, (4) integrative knowledge generation, (5) co-creative problem solving is presented.

The facet Effective usage of technologies and tools reflects, on the one hand, the ability of handling the functionalities of digital tools confidently on the other hand it focuses on fast and effective information detection and handling, which is formerly important as the work of frontline employees gets increasingly knowledge intense. Compared to the construct in table 3 that was derived conceptually and through qualitative methods, in the construct that is derived numerically the facet does not include item 4 and item 5. Farsighted & critical information handling is concerned with the capability of being reflective and critical with information provided by digital media or other digital sources. It also includes the ability to compare different sources and to evaluate those due to their credibility. This competence is often seen to be important for people in the digital age and especially for those who are concerned with information gathering and processing tasks. The factor combines the two factors Farsighted data & information handling and

Tab. 6. Results of EFA

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Including items (no)	1, 2, 3	6, 9, 10, 11, 25	12, 13, 14, 7, 15	21, 22, 23, 24	26, 27, 28, 29
Variance explained (%)	8,62	10,51	10,21	8,87	9,96
Reliability (α)	.800	.796	.771	.810	.779

Tab. 7. Fit indices for CFA

GFI	AGFI	RMSEA	RMR	SRMR	Chi^2/df	CFI	TLI
.932	.910	.059	.057	.050	3.21	.925	.910

Tab. 8. Digital competence framework: final result

Item		Factor loadings				
(1) Effective usage of technologies and tools		1	2	3	4	5
1	I can confidently handle the functions and opportunities of digital platforms, websites or other digital tools.	.676				
2	I easily find the relevant information I need by exploring the internet	.862				
3	I'm well able to search effectively for relevant information online.	.531				
(2) Farsighted & critical information handling						
6	I constantly evaluate the information provided by the internet or by digital media.		.549			
9	I critically reflect about digital information provided online.		.755			
10	I critically compare digital information from various providers or sources.		.650			
11	I critically evaluate the authenticity of sources of digital information.		.732			
(3) Sustained cooperation & communication						
12	I am careful about how I say things online so they don't come across the wrong way.			.483		
13	If I disagree with people online, I watch my language so it doesn't come across as mean.			.723		
14	I think about making sure that things I say and post online will not be something I regret later.			.670		
7	I obey rules and regulations in online environments even when no one is watching.			.601		
15	I take steps to try to prevent problems with other workers during online collabora-tion.			.508		
(4) Integrative knowledge generation						
21	I structure complex information and problems with the help of digital tools and me-thods.				.473	
22	I can develop new problem solutions with the help of information provided by the internet				.691	
23	I recombine information from various digital sources to solve complex problems.				.613	
24	I use online information and digital tools particularly for my own development and improvement.				.562	
(5) Co-creative problem solving						
27	I'm well able to use digital information to solve individual problems.					.749
28	I'm well able to use digital information to solve problems in teams.					.797
29	I'm well able to use digital information in combination with other sources of informa-tion (e.g. books).					.458
Percentage of Variance explained (sum: 50.1 %)		8.5	11.0	11.6	10.5	8.5
Mean value		6.05	5.25	5.66	5.31	5.37
Standard deviation		.897	1.06	0.92	0.96	0.97
Cronbach's alpha		.800	.816	.771	.810	.794

Critical information evaluation & processing from table 3 whereas items 7 and 8 are missing in the final result. The next factor, Sustained cooperation & communication consists of specific communication as well as cooperation in digital environments. These include, for example, the capability of being careful with things one says or writes online since these information is not revocable on the one hand and on the other hand one can be easier misunderstood in e.g. Online-Chats. Compared to the construct presented in table 3 this factor does not include items 16 - 19 but item 7 that was assigned to factor 2 in table 3. Integrative knowledge generation deals with the ability of structuring, recombining and using digital information for solving complex tasks as well as for one's own improvement. Compared to table 3, this facet does not include item 20. Last but not least, Co-creative problem solving consists of capabilities such as the use of digital information for solving individual as well as problems in teams but also the ability to combine digital information with other offline information sources. Here item 26 and item 30 are missing compared to the solution in Table 3.

3.2 Scale Validity

To validate the scale by means of construct validity we formulated hypotheses and tested them by employing correlational designs and mean value comparisons.

H1: There is a significant negative correlation between digital competences and technostress.

We test this hypothesis by using sample 5 (N=203). Stress that results from working in digitalized work environments is called technostress (Dragano & Lunau, 2020; Salanova et al., 2014; Wang et al., 2022). As digital competencies are intended to enable individuals to cope better with digital job demands, we argue that there is a negative relationship between technostress and digital competencies. We use the technostress questionnaire (Ragu-Nathan et al., 2008; Westermann, 2017), which consists of the three factors techno-overload, techno-invasion and techno-complexity to measure stress. Techno-overload is concerned with the higher workload that stems from constantly having to deal and get familiar with novel and unknown technologies. Techno-invasion refers to the greater availability resulting from the use of digital technologies and techno-complexity addresses the technical complexity of digital tools and the individual's inability to deal with it properly.

As can be seen in Table 9 confident handling of digital resources as well as effective information handling & generation are significantly negatively correlated with all three facets of technostress. For techno-complexity the correlation coefficient is even around -0.5. Techno-complexity is significantly negatively correlated to all facets of digital competencies except for sustained cooperation & communication. Overall, the results presented in Table 9 partly support hypothesis 1 (H1).

H2: Workers who maintained working virtually beyond the first COVID-19 related lockdown rated own digital competencies to be on average significantly higher than those who only experienced a minimal or short increase of virtual work during the lockdown.

To test hypothesis H2 we use the COVID-19 related sample 4 with N=633. Here, we distinguish between three clusters of workers depending on their virtual working hours before, during and after the first COVID-19 related lockdown in Germany:

Cluster 1: minimal exceptional virtualization

Cluster 2: substantial exceptional virtualization

Cluster 3: substantial sustainable virtualization

We argue that workers who belong to cluster 3, and thus have had more experience with virtual work than workers who experienced a minimal or short increase of virtual work, rate their digital competences to be averagely higher than those in cluster 1 or cluster 2. We use the one-way ANOVA to test the hypotheses. The results are illustrated in Table 11.

As can be seen in Table 11, the ANOVA is significant for the two competencies farsighted & critical information handling as well as co-creative problem solving. The effect-size estimator η^2 indicates that the magnitude of the mean differences is rather small ($.01 \leq \eta^2 \leq .06$) which can be seen as an indicator for a rather small effect (Cohen, 1988; Okada, 2013). This partly supports hypothesis H2.

H3: There is a significant positive correlation between space-time flexibility and digital competencies.

This hypothesis is tested on sample 3 (N=145). Space-time flexibility refers to time and location flexibility at work. The five item scale is concerned with employees' possibility of working independently of time

Tab. 9. Correlation coefficients between technostress and digital competencies

	(1) Effective usage of technologies and tools	(2) Farsighted & critical information handling	(3) Sustained cooperation & communication	(4) Integrative knowledge generation	(5) Co-creative problem solving
Techno-overload	-.276**	--	--	--	-.202**
Techno-complexity	-.544**	-.301*	--	-.311**	-.433**
Techno-invasion	-.272**	--	--	--	-.272**

Tab. 10. Virtualization clusters

	Number	%
Cluster 1	182	37.3
Cluster 2	179	36.7
Cluster 3	127	26.0

Tab. 11. ANOVA Results

	Cluster 1	Cluster 2	Cluster 3	F	df	Significance	η^2
(1) effective usage of technologies and tools Mean SD	6.289a 0.694	6.301a 0.663	6.412a 0.598	1.432	2	0.239	0.01
(2) farsighted & critical information handling Mean SD	5.198a 1.011	5.334a 0.912	5.640b 0.910	8.170	2	< 0.001	0.03
(3) sustained cooperation & communication Mean SD	5.746a 0.861	5.823a 0.797	5.916a 0.741	1.668	2	0.190	0.01
(4) integrative knowledge generation Mean SD	5.397a 0.863	5.445a 0.882	5.562a 0.883	1.337	2	0.264	0.01
(5) co-creative problem solving Mean SD	5.353a 1.586	5.497a 1.493	5.785b 1.395	10.138	2	< 0.001	0.04

Note: a,b Mean values that don't share the same subscript within one row are significantly different (significance calculated with the help of post-hoc Tests).

and space constraints and is measured on a 7-point Likert scale (Poethke et al., 2019). We argue that there is a positive relationship between space-time flexibility and digital competencies.

As one can see in Table 12 hypothesis H3 is supported.

H4: There is a significant positive correlation between the digital competence facet sustained cooperation & communication and availability.

This hypothesis is tested on sample 3 (N=145). Availability is concerned with workers' readiness of being available through digital tools during non-official working hours. It is measured by five items that deal with the extent to which a person can be reached by cell phones, e-mail, etc. while being e.g. on vacation or outside working hours (Poethke et al., 2019). Availability is measured on a 7 point Likert scale. We argue, that there is a positive relationship between availability beyond ones working hours and digital communication competencies.

The correlation coefficient between sustained cooperation & communication and availability amounts to $r = .221$, $p = .011$. This supports hypothesis H4.

4. Discussion of the results

The further advancements in digitalization in professional work environments create new competence demands for workers that need further specification and validation. Instruments or scales for measuring digital competence are less developed so that even researchers are forced to follow rather pragmatic approaches for conducting empirical investigations (Bartolomé et al., 2022; Golz et al., 2021). One of the very few but more comprehensive and widely recognized approaches of gathering digital competence of workers has been introduced by van Laar et al. (2018, 2020) who developed an extensive 21st century digital skill framework for creative industries. However, the authors point out some peculiarities of their framework as it consists of frequency scales instead of usually used self-assessment scales and that the approach refers to a wider range of different competencies and skills not having a clear focus on digital competence as such which results in a comparably long measurement instrument. In general, it can be stated that the individual level of workers' competence as the unit of analysis is still underrepresented in scientific writing about digital transformation and sustainable digital enhancements in organizations. This article is one among the first introducing an empirical-based validation of a self-assessment scale of digital competence for frontline employees in sales & service (N=1,283). With respect to the guided research question "What are key dimensions of a not all-encompassing but context-specific scale of digital competence for frontline employees in sales & service work and how can these dimensions be measured?" we introduced

Tab. 12. Correlation coefficients between digital competencies and flexibility

	(1) Effective usage of technologies and tools	(2) Farsighted & critical information handling	(3) Sustained cooperation & communication	(4) Integrative knowledge generation	(5) Co-creative problem solving
Space-time flexibility	.272**	.256**	.305**	.332**	.262**

*: p<0.05; **: p<0.005

Tab. 13. Correlation coefficients between digital competencies and availability

	(1) Effective usage of technologies and tools	(2) Farsighted & critical information handling	(3) Sustained cooperation & communication	(4) Integrative knowledge generation	(5) Co-creative problem solving
Availability	.143	.124	.211*	-.017	.149

*: p<0.05; **: p<0.005

a five-dimensional scale of digital competence consisting of (1) effective usage of technologies and tools, (2) farsighted & critical information handling, (3) sustained cooperation & communication, (4) integrative knowledge generation, and (5) co-creative problem solving. As statistical analysis among various sub samples revealed, this 19 item scale (Appendix A) shows good reliability and internal consistency. Regarding validation, we referred to the variable of employee related technostress as well as the context related variable of virtualization and digitalization of the work environment. As expected, the results of the validation with technostress show highly significant negative correlations with four of the five dimensions of digital competence. This is in line with state-of-the art research arguing that specific digital competencies may equip employees to better cope with technology-induced stress. However, further empirical analysis is needed in that regard. The contextual variable of space-time flexibility, which is a typical characteristic for frontline workers, shows highly significant positive correlations for all five dimensions of the digital competence scale introduced. This can mean, that e.g. due to selective processes in the work environment or ongoing workplace learning frontline workers show higher degrees of digital competence in the five dimensions introduced. However, as the construct of technostress the contextual variables do not allow interpretation of causalities based on the empirical data analyzed in this article.

Nevertheless, we argue that based on the five dimensions of digital competence, which we regard as a not all-encompassing but context-related validation of specific competencies we make a substantial contribution for reducing the scientific-practice gap when it comes to work-related evaluation of digital competencies among employees (2020). The present article might be considered as a starting point to close this gap. Based on the validated digital competence scale for frontline employees in sales & service we provide more specific knowledge about key competencies employees may need to interact more effectively with modern digital tools and technologies like generative AI and other highly knowledge intensive systems. Within the context of professional work, we except that not all of the five dimensions of digital competence we derived will be equally important as this might be the case for rather basic competencies. We find it more likely that based on various job roles and contextual demands there will be distinct configurations consisting of a set of complementary competence levels with regards to each of the five dimensions. However, much more empirical knowledge is required in that area, e.g. to enable and support more advanced competence management for human-computer interaction in professional work.

From our point of view future research in the field of digital competence should consider more explicitly the causalities between different variables, e.g. focusing on the question about how different digital competencies affect efficiency, effectivity as well as adaptability, sustainability or innovative output of human-computer interaction at work. With a specific focus on digitalization in the professional filed of frontline sales & service workers further investigations about the impact of employee's digital competence on the short-, mid- and long-term success of sustainable sales success, customer satisfaction or economic growth might be of interest. Also, the question about how digital leadership may foster digital competence development in professional work environments is considered as highly relevant in organizations. Other aspects we regard as highly important are how digital competence can be defined and measured on a group and team level, especially when considering virtual teams including human-agent teaming as well as how the perception of social isolation in a highly digitalized work and society may be addressed by digital competence.

In summary the objective of this research article is to enable similar and other research initiatives by providing one of the first validated scale of digital competence which is clearly not all-encompassing, but an entrance point into a more systematic understanding in future research about the causes and effects of digital competence in professional human-computer interaction. The final questionnaire of the validated scale can be found in Appendix A.

Conclusions

This study advances the discourse on digital competence in professional contexts by introducing one of the first empirically validated self-assessment instruments specifically designed for frontline employees in sales and service. Drawing on existing conceptual frameworks, we developed a five-dimensional model encompassing proficient use of technologies and tools, anticipatory and critical information management, sustained collaboration and communication, integrative knowledge creation, and co-creative problem solving. The resulting scale exhibits strong reliability and internal consistency, providing a context-sensitive means of assessing digital competence at the individual level. This study offers an empirically substantiated starting point for more systematic inquiries into digital competence within professional human–computer interaction. By introducing a validated and contextually sensitive measurement scale, it establishes a foundation for advancing both scholarly research and organizational competence management, with the aim of preparing employees for work environments that are becoming progressively more digitalized and knowledge-intensive.

The validation analyses demonstrated that higher levels of digital competence are significantly associated with lower levels of technostress, thereby reinforcing the proposition that advanced digital skills equip employees to manage technology-related demands more effectively. Furthermore, the positive associations with contextual factors such as space–time flexibility suggest that frontline employees may enhance their competence through experiential workplace learning and adaptation to increasingly digitalized environments. Although causal inferences cannot be drawn at this stage, these findings underscore the scale's practical utility in narrowing the divide between scholarly research and organizational practice.

The presented digital competence self-assessment scale is considering the increasing relevance of frontline work in sales & service in the era of digitalization. However, a task for future studies is to test and respectively extend the instrument with respect to a more specific set of distinct work systems. Another aspect that has to be pointed at is that the mean values for the presented sample are relatively high which could be explained by the fact that the majority of people in our sample is working in highly-digitalized environments and has an academic background. In addition, more than 90 % of the respondents in the sample are between 18 and 37 years old (see Table 5). This means that a majority of people in our sample can be allocated to the so-called "digital generation". Furthermore, other studies have also revealed that self-assessment scales are more likely to produce higher mean values. Additional empirical investigations with a different and extended sample structure are planned as one of the next important steps to compare and evaluate the presented findings. One expected outcome of such studies could be that the manifestation of distinct competencies could be different when comparing industries, job roles, socio-demographic factors, latest technologies in the field of artificial intelligence or various implementations of the new work approach.

Disclosure of interest

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

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Appendix A

The use and application of digital technologies in your everyday working life

The following questions are dedicated to your personal use of digital tools and technologies during daily work. You will find a list of statements on the use and application of digital tools and technologies. Please assess the extent to which each statement applies to you personally. In your assessment, please select on a scale from 1 = "strongly disagree" to 7 = "strongly agree".

		1	2	3	4	5	6	7
(1) Effective usage of technologies and tools	I can confidently handle the functions and opportunities of digital platforms, websites or other digital tools.							
	I easily find the relevant information I need by exploring the internet							
	I'm well able to search effectively for relevant information online.							
(2) Farsighted & critical information handling	I constantly evaluate the information provided by the internet or by digital media.							
	I critically reflect about digital information provided online.							
	I critically compare digital information from various providers or sources.							
	I critically evaluate the authenticity of sources of digital information.							
(3) Sustained cooperation & communication	I am careful about how I say things online so they don't come across the wrong way.							
	If I disagree with people online, I watch my language so it doesn't come across as mean.							
	I think about making sure that things I say and post online will not be something I regret later.							
	I obey rules and regulations in online environments even when no one is watching.							
	I take steps to try to prevent problems with other workers during online collaboration.							
(4) Integrative knowledge generation	I structure complex information and problems with the help of digital tools and methods.							
	I can develop new problem solutions with the help of information provided by the internet							
	I recombine information from various digital sources to solve complex problems.							
	I use online information and digital tools particularly for my own development and improvement.							
(5) Co-creative problem solving	I'm well able to use digital information to solve individual problems.							
	I'm well able to use digital information to solve problems in teams.							
	I'm well able to use digital information in combination with other sources of information (e.g. books).							

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Assessment of product quality risks by qualimetric methods using functionally dependent statistics

Roman Trishch
Vladislavas Petraškevičius
Agnė Šimelytė
Olena Cherniak
Kostiantyn Lomanov

ABSTRACT
In modern production systems, ensuring high product quality while minimising risk is a critical challenge. Traditional quality assessment methods often rely on expert judgment or complex models, which may introduce subjectivity or require large datasets. This study aims to develop a universal methodology for assessing product quality risks using a mathematically grounded approach that eliminates the need for expert-based evaluations and can be easily implemented in various industrial contexts. A qualimetric method based on nonlinear mathematical dependence using the error function "erf" is proposed. The method transforms measured quality indicators into a dimensionless scale and derives functionally dependent statistics under the assumption of a uniform distribution. The model is validated through analytical derivations and numerical experiments on piston components in precision mechanical engineering. A new mathematical model was established to calculate the probability density function of transformed quality indicators. The methodology enables the estimation of the probability that a quality indicator will fall within a risky range near tolerance limits. Numerical experiments confirmed the validity of the model, demonstrating its applicability to real-world production scenarios and its alignment with known principles of qualimetry. The proposed method provides a universal, objective, and practical tool for risk-based quality assessment. It can be applied across different industries, integrated into existing quality management systems, and used to support decision-making in production control. Future research should expand the model to accommodate non-uniform distributions and explore its integration with real-time quality monitoring systems.

KEY WORDS
qualimetry, quality of life, risk, risk assessment, quality risk, sustainability criteria, error function, functionally dependent statistics, multicriteria quality assessment

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Olena Cherniak
National Aerospace University "Kharkiv Aviation Institute", 17 Vadym Manko st., 61000 Kharkiv, Ukraine
ORCID 0000-0001-6167-8809
Corresponding author:
e-mail: olena-cherniak@ukr.net

Roman Trishch
National Aerospace University "Kharkiv Aviation Institute", 17 Vadym Manko st., 61000 Kharkiv, Ukraine
Mykolas Romeris University, 20 Ateities st., Vilnius, Lithuania.
ORCID 0000-0002-9503-8428
e-mail: trich_@ukr.net

Vladislavas Petraškevičius
Vilnius Gediminas Technical University, 11 Saulėtekio al., 10223 Vilnius, Lithuania
ORCID 0000-0002-6131-1318
e-mail: vladislavas.petraskevicius@vilniustech.lt

Agnė Šimelytė
Vilnius Gediminas Technical University, 11 Saulėtekio al., 10223 Vilnius, Lithuania
ORCID 0000-0002-9475-9645
e-mail: agne.simelyte@vilniustech.lt

Kostiantyn Lomanov
V. N. Karazin Kharkiv National University, 4 Svobody sq., 61022 Kharkiv, Ukraine
ORCID 0009-0000-7124-7607
e-mail: klomanov0320@gmail.com

Introduction

The development of the public production of any country, its position in the global trade market, as well as the growth of national prosperity and living standards, are all closely connected to maintaining a high level of quality in products, services, and the functioning of socio-economic systems such as education, healthcare, environmental protection, and labour safety. Since the beginning of social production, mankind has been managing product quality. The quality of products and services offered by a national producer significantly influences foreign

Trishch, R., Petraškevičius, V., Šimelytė, A., Cherniak, O. & Lomanov, K. (2025). Assessment of product quality risks by qualimetric methods using functionally dependent statistics. *Engineering Management in Production and Services, 17*(3), 68-82. doi: 10.2478/emj-2025-0020

policy, national security, and the overall stability of the national currency. It also plays a key role in determining the standard of living and quality of life within the country.

Risk is a critical factor in decision-making and is essential for making effective management choices. In a market economy, businesses achieve competitiveness through innovation, which inherently carries risks. Risk-based decisions lead to more efficient production processes, benefiting entrepreneurs, consumers, and society at large (Crawford & Jabbour, 2023).

Risk is both a cause of possible losses and a source of possible profit. The primary objective of risk management is not to avoid risk altogether, but to make risk-related decisions based on objective criteria. Risk reduction is possible by improving the reliability of goods and systems, reducing the possible intensity of undesirable factors (for example, limiting the stock of hazardous substances), and increasing the protection of facilities from their impact. Risk reduction is possible (Settembre-Blundo et al., 2021):

- at the stage of planning an operation (project) or designing samples - by introducing additional reliability elements and other necessary measures;
- at the decision-making stage - by using appropriate criteria for evaluating the effectiveness of a decision, such as the Wald or Savage criteria ("expect the worst");
- at the stage of technical systems operation - by observing operating modes and their control.

Within each of the areas, the measures taken will have different effectiveness. These measures are costly and need to increase as the complexity of the systems increases. Therefore, under certain conditions, it may be more economically feasible to spend money not on preventing or reducing the degree of risk, but on compensating for possible losses, using the insurance mechanism.

Production risks include, in particular, the risks of defective products. In the context of mass production, enterprises have technical control departments, quality bureaus and other units that control product quality. In the machine building industry, the average cost of control operations is approx. 10 % of the cost of production. Part of the risk losses can be compensated for by maintenance services for products that are already in the hands of consumers (Ha et al., 2022).

Another group of production risks is related to the performance of existing technological processes - accidents of varying severity, which lead to production reduction and stoppage. Production reduction and stoppage are the consequences of an accident or equipment breakdown, leading to direct losses of profit due to a decrease in production output and indirect losses due to the non-delivery of products to customers (Raian et al., 2023).

The production of high-quality products is linked to the quality of technological processes at all stages of the production life cycle. Any technological process is associated with the risk that standardised product quality indicators will deviate from the ideal values provided in regulatory documents and technical regulations (Pirbalouti et al., 2023).

Many scientific fields, such as game theory, probability, mathematical statistics, decision-making, psychology, military sciences, economics, demography, medicine, biology, law, and others, study the concept of risk. Modern scientific achievements allow for considering risk at two levels: theoretical, where it is studied as a social phenomenon with its own essence and patterns of development and management under conditions of uncertainty, and applied, which arises from specific research in various scientific fields (Fleurbaey & Zuber, 2022).

In the field of qualimetrics, a crucial aspect when evaluating the quality of objects is understanding the type of relationship between the measured quality indicators and their corresponding scores on a dimensionless scale. This is significant because the relationship between quality indicators and their scores may not always be linear. Statistical methods are often employed to effectively manage and assess the quality of qualimetric objects. In this context, it is important not only to have information on the distribution of the quality indicators in their original measurement units but also to understand how these indicators are distributed on a dimensionless scale. This article presents research focused on identifying the patterns and regularities of the distribution of quality indicator scores when mapped onto a dimensionless scale.

The purpose of the article is to develop and validate the effectiveness of a universal methodology for assessing the risks associated with products of a specified quality using nonlinear mathematical dependencies.

The article presents the results of a literature review on existing approaches to product quality risk assessment and the justification for developing a universal methodology based on nonlinear mathematical dependencies. The research methodology is described in detail, including the transformation of quality indicators into a dimensionless scale and the determination of probability density functions. The results of applying the proposed method to the evaluation of high-precision mechanical parts are presented and discussed, highlighting its advantages over traditional expert-based approaches. Generalisations of the findings are provided, along with an explanation of the study's limitations and potential applications in various industries. The conclusion and recommendations for future research directions are outlined in the final section.

1. Literature review

1.1. Risk essence and methods of risk assessment

As outlined in EN IEC 31010:2019, IDT Risk Management - Risk Assessment Techniques (ISO 31010, 2019), and the ISO Guide 73:2009 Risk Management - Terminology - Guidelines for Use in Standards (ISO Guide 73, 2009), risk is defined as the likelihood and frequency of adverse impacts within areas of human activity. It serves as a crucial factor in decision-making, forming the foundation for effective management strategies. In a competitive market economy, innovation plays a pivotal role in driving business success; however, it inherently involves taking risks. Businesses can achieve more efficient production processes by embracing risk-oriented approaches, benefiting entrepreneurs and consumers, and positively contributing to society as a whole.

Risk refers to the probability of losses or a shortfall in income compared to anticipated outcomes. It serves as a tool for addressing uncertainty - essentially, the absence of reliable information or assurance. In practice, risk often involves decision-making in situations where choices are unavoidable. In such cases, it becomes possible to quantitatively and qualitatively assess the likelihood of achieving desired outcomes, encountering failures, or deviating from established goals.

Globally and locally, over 30 methods for general risk assessment are employed, as outlined in the standard ISO 31010 (2019). These methods enable decision-makers and stakeholders to gain a clearer understanding of potential risks that could impact goal achievement, as well as to evaluate the adequacy and effectiveness of existing controls.

This standard expands on the principles outlined in ISO 31000:2018, IDT "Risk Management - Guidelines" (ISO 31000, 2018), offering practical guidance on selecting and applying systematic methods for comprehensive risk assessment. It supports broader risk management activities by providing insights into various methodologies and references to international standards that detail their concepts and applications. Notably, this standard is not intended for certification, regulatory compliance, or contractual use.

This standard does not define specific criteria for determining when risk analysis is necessary, nor does it mandate the use of any particular method for a given application. Additionally, it does not cover all possible risk analysis methods; the absence of a method in the standard does not imply its invalidity. The applicability of a method to a specific situation does not automatically make it the optimal choice for use.

A comprehensive risk assessment empowers decision-makers and stakeholders to gain deeper insights into risks that could impact the achievement of objectives and the effectiveness of existing controls. This understanding serves as a foundation for choosing the most suitable risk management strategies. The results of the assessment become integral to the organisation's decision-making processes, ensuring informed and strategic actions (Ismail et al., 2024; Glette-Iversen et al., 2023).

Comprehensive risk assessment involves a collaborative approach to identifying, analysing, and evaluating risks. The application of this process varies based on the context of the risk management framework, as well as the specific methods and techniques employed. Given the diverse nature of risks and their potential causes and impacts, this process often necessitates a multidisciplinary approach to ensure all relevant factors are thoroughly addressed (Fraume et al., 2020; Hu et al., 2023).

Risk analysis is a critical step in gaining a deeper understanding of potential risks. It supports the overall risk assessment process and informs decisions about whether action is required and which strategies or methods are best suited for addressing the risks. This process involves identifying potential outcomes of risk events and their probabilities, considering the presence and effectiveness of existing controls. By combining these outcomes and probabilities, the analysis determines the overall level of risk, serving as a foundation for effective risk management (Aven, 2023).

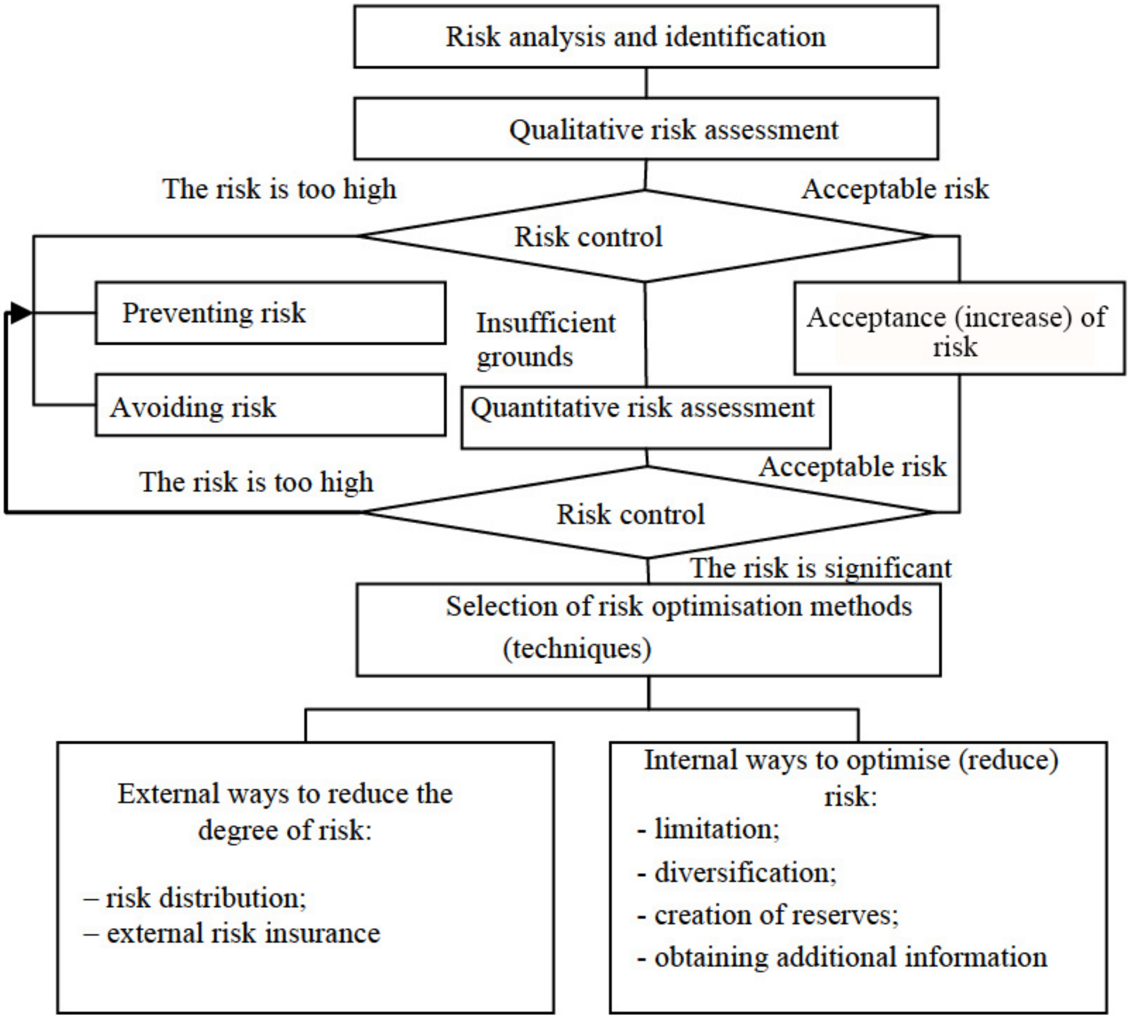

Fig. 1. Generalised risk management process flowchart

Risk analysis involves examining the causes and sources of risks, their potential consequences, and the likelihood of these consequences. It is essential to identify the factors that influence these outcomes and probabilities. A single event may have multiple consequences, impacting various objectives. The analysis should also consider the available controls and their effectiveness. In more complex cases, it may be necessary to use multiple methods to fully assess the risk. Risk analysis often involves quantifying a range of possible outcomes resulting from an event, situation, or circumstance, along with their associated probabilities, to assess the level of risk. However, in certain cases - such as when the consequences are minimal or the likelihood of occurrence is extremely low - it may be sufficient to evaluate just one parameter in order to decide (Simpson, 2024; Nateghi & Aven, 2021).

In certain situations, a consequence may arise from multiple events or conditions, or a specific event might remain unidentified. In such cases, the overall risk assessment concentrates on evaluating the importance and vulnerability of system elements to determine the appropriate risk management approaches, which may involve protection levels or recovery strategies (Li, 2020).

Risk analysis methods can be qualitative, semi-quantitative, or quantitative, depending on the specific needs of the application, the availability of reliable data, and the organisation's decision-making requirements. In some cases, certain methods and levels of analysis may be mandated by law. A qualitative assessment categorises consequences, likelihood, and risk levels using descriptive terms such as high, medium, or low. The consequence and likelihood are then combined to determine the resulting risk level according to qualitative criteria. Semi-quantitative methods use numerical scales to assess consequences and probabilities, which are then combined using a formula to calculate the overall risk level. These scales may follow linear, logarithmic, or other types of relationships, and the formulas may differ based on the method used (Tzanakakis, 2021).

Quantitative analysis evaluates the practical significance of consequences and their probabilities, calculating risk levels in specific units identified during the environmental assessment. However, a full quantitative analysis may not always be feasible or appropriate due to factors such as insufficient information, lack of data, human factors, or because the costs associated with quantitative analysis may not be justified or required. In such cases, a comparative semi-quantitative or qualitative risk ranking, involving specialists with expertise in the relevant fields, can be an effective alternative (Elhammady & Fischmeister, 2023; Urbano et al., 2023).

A risk object refers to an economic system whose efficiency and operational conditions are not predetermined. A risk subject is an individual or entity with an interest in the outcomes of managing the risk object and the competence to make decisions regarding it (Lee, 2021). A risk source is any factor (such as a phenomenon or process) that introduces uncertainty into the expected outcomes or creates conflict. In economics, the classical theory of entrepreneurial risk equates risk to the mathematical expectation of losses resulting from the selection of a particular decision, meaning that risk represents the cost associated with implementing that decision (Kilström & Roth, 2024).

The term "risk" is applied differently across various social and natural sciences, each with its own focus and research methods. In the context of sustainable development, the concept of "risk" gives rise to different types, such as economic, social, psychological, political, biomedical, legal, natural, man-made, environmental, and more. The international standard ISO 31010 (2019) provides a comprehensive list of risk assessment methods that can be applied in different fields of sustainable development. It also outlines the advantages, disadvantages, and application principles of each method. By using this standard (ISO 31010, 2019), one can select the most appropriate method for risk assessment in any area of sustainable development or combine methods to create custom approaches tailored to specific applied risk assessment challenges.

The concept of risk is utilised across a wide range of social and natural sciences, each with its own focus, subject matter, and research methods. This enables the identification of various aspects of risk, including economic, social, psychological, political, biomedical, legal, natural, man-made, environmental, and others.

Risk assessment methodology is heavily influenced by the industry in question, as it is shaped by several key factors, such as the specifics of technological and product sales cycles, the nature of business entities' assets, the dynamics of scientific and technological advancements, economic development models, and information and communication support, among others. To effectively analyse risk, it is essential to first understand it. Risk analysis provides the necessary inputs for evaluating the degree of risk and guides discussions on whether risk management is needed, as well as the appropriate strategies and methods for managing those risks.

1.2. Modern approaches to assessing industrial risks

Production risks encompass the risk of defective products. In mass production settings, companies typically have dedicated departments, such as technical control departments, quality bureaus, and other units, to oversee product quality. In the machine-building industry, the average cost of control operations is about 10 % of production costs. Some of the risk losses can be offset through maintenance services for products already in the hands of consumers.

Another category of production risks is associated with the execution of existing technological processes, including various severity accidents, from minor disruptions to catastrophic events with human casualties. Such incidents can occur at industrial facilities due to various factors: natural causes (earthquakes, floods, and lightning), man-made factors (wear and tear of buildings, equipment, design errors, human mistakes, or equipment damage during repairs), or mixed causes (such as disruptions to the natural balance due to human activity, like the emergence of an oil and gas fountain during well drilling). In such cases, environmental risks may arise, such as accidental discharges of process fluids into rivers or gas emissions into the atmosphere. For these incidents, companies may face fines imposed by environmental authorities. Accidents or equipment breakdowns lead to reduced production or even shutdowns, resulting in direct profit losses due to decreased output and indirect losses from product delivery delays and lawsuits from consumers.

"Failure Mode and Effects Analysis (FMEA)" is a widely recognised and effective method used to assess risks in the operation of technological processes across various industries (Ouyang et al., 2020). This method is effective in reducing the number of potential risks in production; however, it has its limitations. The primary drawback of FMEA is that it focuses on the results rather than the causes that lead to an unfavourable situation. Moreover, FMEA relies heavily on expert assessments, which can introduce subjectivity into the process.

Ouyang et al. (2020) introduced an alternative approach to the FMEA method by applying fuzzy set theory, enabling the estimation of risk probabilities within specified intervals. This method reduces the influence of expert opinion on subjective risk assessments and allows for the comparison of probabilities across different risks, offering more nuanced information for improved risk management. The authors also compared various methods for analysing the causes and consequences of failures, providing insights into their effectiveness in selecting the most appropriate risk assessment method for specific applications.

Stødle et al. (2024) examined the use of artificial intelligence in risk analysis, emphasising the importance of combining automated algorithms with human oversight. They demonstrated that modern AI approaches enhance the description of consequences, management of uncertainties, and knowledge handling, thereby opening new possibilities in the field. At the same time, the authors highlighted the limitations of full automation, noting that critical risk management decisions cannot be entirely delegated to algorithms. They thus presented AI as a tool that strengthens analytical capabilities and improves decision-making efficiency rather than replacing human expertise.

Gul et al. (2024) proposed an innovative SBBWM model that combines stratification, the Bayesian approach, and TOPSIS sorting, which significantly improves the accuracy and adaptability of professional risk assessment. However, the study is limited to the case of flour production, which calls into question the universality of the results for other industries. Although the method considers the uncertainty and conflict of expert assessments, it requires significant resources to collect and process data from several experts. Thus, the model is promising but needs further testing and optimisation for practical use in different production environments.

Arroyo-Montaño et al. (2025) used a mixed methodology, combining quantitative data (surveys) and documentary analysis, and found a positive attitude towards the use of monitoring for risk identification, strategic alignment and quality, although they identified challenges related to staff training, policy updates and the effectiveness of alerts.

Tetelepta et al. (2025) demonstrated the practical application of the HIRARC methodology in the logistics company PT XYZ, covering 12 typical operations with injury potential and proposing realistic control measures such as training, PPE, and technical instructions. Cheng et al. (2024) developed a fall-risk assessment model that accounts for both geographical location and physiological factors to improve prediction accuracy. They created a real-time algorithm enabling rapid identification of high-risk situations and immediate warnings, which has strong potential in occupational safety, healthcare, and public safety.

Different economic sectors employ distinct methods for assessing product quality and associated risks, which depend on several factors. Riabchykov et al. (2022) investigated the probabilities associated with actual cavity sizes of porous materials when converted into foam, using them as quality indicators. Elmadhoun et al. (2025) devoted their work to the implementation of quality risk management at the final operational stage of sterile drug production (at the stages of sterilisation, packaging, labelling, inspection, and storage), using the ICH Q9 methodology and FMEA analysis for the systematic identification and mitigation of risks in a pharmaceutical context. Articles by other authors (Riabchykov et al., 2023a; Riabchykov et al., 2023b) demonstrated that the efficiency of medical materials is influenced by the size of the scattering field of actual quality indicators.

Several scientific studies (Wang et al., 2025; Burduk et al., 2025) explored methods for assessing production risks, specifically the probability of unexpected results. This approach is applied across various sectors of the national economy, including energy and nuclear facilities (Hovorov et al., 2025; Khomiak et al., 2025; Khomiak et al., 2024), the oil industry (Tang et al., 2024), the chemical industry (He et al., 2025), and construction (Cai et al., 2024; Zhao, 2024).

In assessing complex indicators as combined values of individual quality indicators, various methods are used. Wickramaratne (2024) described the use of weighted average values for combining individual quality indicators into complex metrics.

Bubela et al. (2025) assessed the risks of cyber-physical systems, in particular, researching potential vulnerabilities in the integration of physical devices and digital components. The authors analyse how factors related to security, reliability and data management can affect the smooth operation of such systems, emphasising the need for proactive risk management to ensure stable functioning.

Guliyeva (2021) developed a system of indicators for measuring quality of life, integrating both objective and subjective factors to capture the well-being of the population. The author argued for a multidimensional approach, which proved more effective than traditional one-dimensional assessments, and provided practical guidance for policy and management improvement.

Dyadyura et al. (2023), Cherniak et al. (2024), and Rudyk et al. (2024) examined statistical methods for relating the actual values of individual quality indicators for various qualimetry objects to their dimensionless assessments, facilitating integration into a comprehensive quality measure. Hovorov et al. (2025), Hrinchenko et al. (2019), and Panda et al. (2024) proposed a nonlinear mathematical relationship for assessing energy efficiency in the energy sector, demonstrating the universality of such an approach across different measurement units and indicator ranges.

An alternative mathematical model is proposed for a comprehensive evaluation of quality indicators for manufacturing parts, such as bodies of revolution, in the machine-building industry. This model is flexible, allowing its shape to vary based on the chosen shape parameter, which is determined by an expert.

When assessing sustainable development indices, mathematical dependencies are employed that do not rely on expert methods but instead focus solely on the maximum permissible values of the quality indicator (Fedorovich et al., 2023; Fedorovich et al., 2024; Komari et al., 2023). It is recommended to follow the requirements outlined in the international standard ISO 9001 (2015) to ensure the quality of measurements for individual indicators. A methodological analysis of the requirements of this standard is provided in publications (Trishch et al., 2024).

Risk assessment is mandatory when implementing international standards for quality management systems of testing and calibration laboratories. One of the requirements of this standard is the development and maintenance of a procedure for estimating measurement uncertainty. Recent scientific papers consider the extended measurement uncertainty in product quality assurance (Vasilevskyi, 2021; Vasilevskyi et al., 2021; Vasilevskyi et al., 2022; Vasilevskyi et al., 2023; Vasilevskyi et al., 2024). The fundamental requirements of this standard are presented by Trishch et al. (2019).

AI-driven risk assessment tools can predict the probability of manufacturing low-quality products by continuously monitoring process parameters and identifying deviations from optimal conditions. These systems leverage machine learning algorithms to provide rapid, detailed insights into process health, supporting proactive interventions to prevent quality issues. The integration of AI in risk management frameworks has demonstrated significant improvements in the accuracy and speed of risk detection compared to traditional methods (Canon et al., 2023; Sureshkumar et al., 2024; Palakurti, 2025; Yazdi et al., 2024).

An analysis of several publications related to quality assessment of various qualimetry objects and quality risk assessment demonstrates that most existing methodologies rely on the involvement of experts. Based on the findings from these scientific publications, the development of a universal methodology for assessing quality risks in any qualimetry objects without expert involvement appears to be a pressing challenge. Moreover, determining the probabilities of product quality risks in the production process using objective methods is an urgent task. This can be addressed through the application of mathematical statistics methods.

2. Research methods

2.1. Mathematical nonlinear functional dependence

Any product manufactured through a technological process is characterised by a set of quality indicators, which are governed by regulatory documents or customer requirements outlined in agreements. Product quality is defined as the set of characteristics that meet consumer expectations. It is essential to know the values of individual quality indicators in quantitative terms, or as measured values, to manage technological processes effectively. This information is crucial for controlling a technological operation.

To provide a comprehensive assessment of the quality of a technological system, it is necessary to determine a composite quality indicator, which combines all individual quality indicators into a single value. For this combination to be meaningful, the quality indicators must share a common scale and evaluation range. This is achieved using nonlinear mathematical dependencies, which convert individual quality indicators into dimensionless terms. By applying mathematical statistics methods, these quality indicator values are transformed into functionally dependent values or statistics.

Based on an analysis of existing mathematical dependencies used in qualimetry to assess the quality of various objects, it is evident that these methods have limitations. Therefore, the authors propose an alternative mathematical relationship, grounded in the error function. The error function, denoted as erf(x) in mathematical statistics, is commonly used in statistical processing methods. It has the following form:

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2}\, dt \qquad (1)$$

The error function (1) is defined in scientific literature as follows: "If a random variable x has a mean of 0 and a variance of 1/(√2), and it follows a normal distribution, then applying the mathematical dependence (1) to it yields the probability that Y will fall within the interval [-x, x]" (Cherniak et al., 2024). The graphical representation of this mathematical relationship is shown in Fig. 2.

The mathematical dependence (1) takes an exponential form and has an inflexion point at x = 0. This aligns with established principles in qualimetry. According to the qualimetry theory, quality indicators at the edges of the tolerance field have a lower probability density compared to those in the middle. The tolerance field represents the range between the smallest and largest acceptable values for a quality indicator. These limits and the tolerance field are typically defined by regulatory documents that govern product quality requirements.

Therefore, mathematical dependence (1) is reasonable and can be considered a universal tool for assessing single quality indicators of any qualimetry object with established permissible limits and a tolerance field. However, since the tolerance field and permissible limits vary for each qualimetry object, the mathematical dependence (1) cannot be universally applicable as the evaluation range (-6, 6) is predefined on the (X) axis.

To address this, it is proposed to apply mathematical transformations that allow for the creation of a universally applicable mathematical dependence. This is achieved by using the principle of dividing a segment into specified proportions. The transformations result in a new mathematical dependence that can be universally applied to any qualimetry object.

$$y(x) = \frac{1}{2} + \frac{1}{2} erf\left(-2 + 4\frac{X - X_{min}}{X_{max} - X_{min}}\right) \qquad (2)$$

where erf(x) - the error function, X_{min} and X_{max} - allowable values of single quality indicators; and X - the measured value of the quality indicator.

The graphical form of the mathematical dependence (2) is shown in Fig. 3, provided that the unit quality indicator has the following boundary constraints: X_{min} = 10, X_{max} = 20.

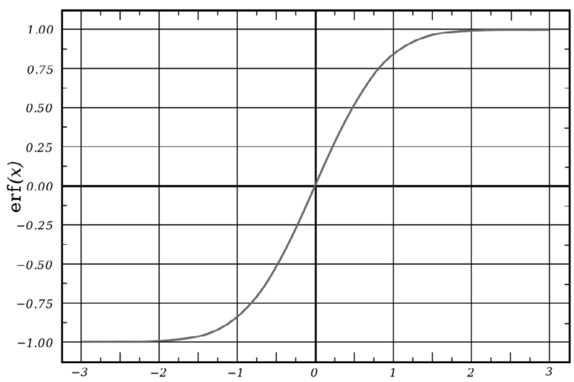

Fig. 2. Graphical view of mathematical dependence (1)

Source: (Cherniak et al., 2024).

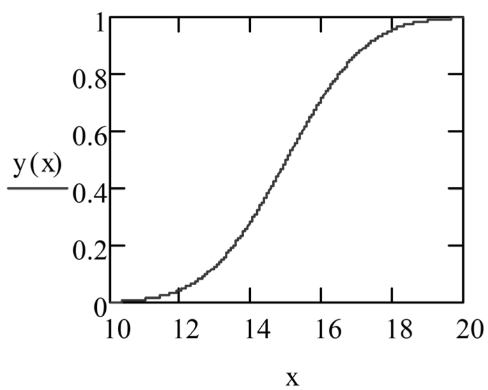

Fig. 3. Graphical view of the mathematical dependence (1) at X_{min} = 10, X_{max} = 20

The proposed mathematical dependence (2) presents several advantages over existing methods used in qualimetry:

1. Nonlinear Nature. The nonlinear character of dependence (2) aligns with the theoretical principles of qualimetry. It is supported by the fact that quality indicator estimates change minimally at the edges of the evaluation scale. This property makes the method particularly suitable for assessing quality indicators that exhibit such behaviour.

2. Ease of Use. Unlike existing methods that require complex calculations and expert assessments, the proposed dependence utilises the error function, which is already built into Microsoft Excel. This eliminates the need for specialised software, making it easier to automate the assessment process. As a result, the method can be applied to a wider range of objects, including processes, products, and knowledge across various sectors of the economy.

3. Practical Application. The proposed mathematical dependencies offer a practical tool for evaluating the quality of diverse objects. They can also be incorporated into regulatory documents at the organisational or enterprise level to standardise and streamline the quality assessment process. This enhances the flexibility and accessibility of the method in different industries and applications.

2.2. Assessing the probability of product quality risks

Modern technological systems must incorporate risk assessment procedures, as understanding the risk of producing low-quality products allows for influence over process control and the implementation of corrective actions. This enables ongoing monitoring of individual quality indicators and corrective measures to ensure their actual values remain within the established permissible limits. As existing international regulations do not provide specific methods for risk assessment, each company is required to develop its own approach based on the quality indicators, production volume, and the availability of skilled personnel.

The development of methods for assessing the risks associated with low-quality products should be grounded in the concept of "risk". The risk of producing low-quality products is understood as the probability that the quality indicators of the products will approach the permissible limits within the tolerance field. Since the calculation of probabilities is a key aspect of mathematical statistics, suitable mathematical tools must be utilised for risk evaluation.

Assume that the distribution of random values for any quality indicator follows a uniform distribution law with the corresponding density function.

$$f(x)=\begin{cases} 0 & at \quad x<a \\ \frac{1}{b-a} & at \quad a\le x\le b \\ 0 & at \quad x>b \end{cases} \tag{3}$$

where a and b are the parameters of the distribution law.

In this case, the area under the surface of the distribution law takes the value 1.

$$\int_{-\infty}^{+\infty} f(x)dx=\int_a^b \frac{1}{b-a}dx=1$$

The substitution of the actual value of a single quality indicator of any product (qualimetry object) and the permissible values in the mathematical dependence (2) results in an estimate of this quality indicator on the dimensionless scale OY. Many such values provide statistics of quality indicator estimates in the form of random variables. The use of the mathematical apparatus of mathematical statistics obtains the probability density function of random variables of quality indicator estimates q(y):

$$q(y)=f(C_2(y))\cdot|C_1(y)| \tag{4}$$

where:

$$C_1(y)=\frac{1}{2}\cdot(\frac{1}{4}X_{max}-\frac{1}{4}X_{min})\pi^{\frac{1}{2}}\begin{bmatrix}2+\frac{1}{2}\pi\cdot(2y-1)^2+\frac{7}{48}\pi^2\cdot(2y-1)^4+ \\ +\frac{127}{2880}\pi^3\cdot(2y-1)^6\end{bmatrix}$$

$$C_2(y)=\frac{X_{\max}-X_{\min}}{4}\left[\frac{\sqrt{\pi}}{2}\begin{bmatrix}(2y-1)+\frac{\pi(2y-1)^3}{12}+\frac{7\pi^2(2y-1)^5}{480}+ \\ +\frac{127\pi^3(2y-1)^7}{40320}\end{bmatrix}+2\right],$$

Fig. 4 shows a graph of the probability density function (4).

The determined probability density function of random variables pertaining to numerical values of single quality indicator assessments on a dimensionless scale makes it possible to find the probability that the value of a random variable Y can be in a certain range (c, d):

$$P(c<y<d)=\int_c^d q(y)dy, \tag{7}$$

where q(y) - probability density function of the distribution of a random variable Y.

If the tolerance field of a quality indicator is divided into zones, it is evident from the principles of

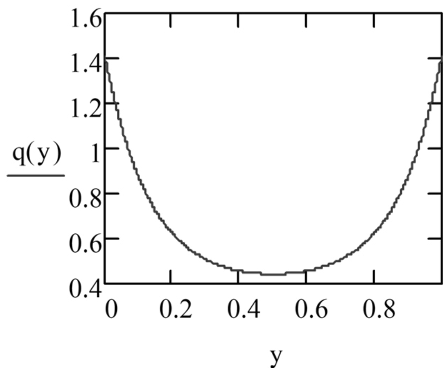

Fig. 4. Graph of the probability density function of random variables (4)

qualimetrics that manufacturers aim for the actual values of the quality indicator to be centrally positioned within the tolerance field. Values at the edges of the tolerance field are considered risky, as random factors affecting the technological system may cause the actual quality indicator to fall outside the tolerance field, leading to a product defect. Therefore, it is crucial for decision-makers to understand the probability of the actual value of the quality indicator falling within a certain range, which equates to the probability of producing low-quality products.

The likelihood that a random value of quality indicator estimates falls within a specified interval is calculated to determine this probability. This is done by determining the integral based on the formula (7).

Table 1 is constructed based on the results of the calculations.

The integration results demonstrate that the sum of the areas of the intervals from 0 to 1 equals one, which validates the accuracy of the scientific research. For further development of the methodology for assessing the quality risks of qualimetry objects, it is essential to determine the distribution law of the random variables Y. This means selecting an appropriate distribution law with which the random variables will align. Understanding the distribution law will enhance the efficiency of solving practical risk assessment tasks.

3. Research results

To validate the effectiveness of the proposed risk assessment method, it is suggested to apply it to evaluate the quality of industrial production, specifically in the manufacture of high-precision parts in mechanical engineering. Internal combustion engines are critical components of vehicles, and the parts of the piston group (piston and cylinder liner) are among the most precise components in these engines. Thus, the proposed method was tested by using it to assess the risks associated with producing a low-quality piston part.

In mechanical engineering, high-quality parts are those whose dimensions are as close as possible to the centre of the tolerance field. The tolerance field is defined by the difference between the minimum and maximum acceptable values for the part, as outlined

$$\int_0^{0.1} q(y)\,dy = 0.111; \quad \int_{0.1}^{0.2} q(y)\,dy = 0.073; \quad \int_{0.2}^{0.3} q(y)\,dy = 0.056;$$
$$\int_{0.3}^{0.4} q(y)\,dy = 0.048; \quad \int_{0.4}^{0.5} q(y)\,dy = 0.045; \quad \int_{0.5}^{0.6} q(y)\,dy = 0.045;$$
$$\int_{0.6}^{0.7} q(y)\,dy = 0.048; \quad \int_{0.7}^{0.8} q(y)\,dy = 0.056; \quad \int_{0.8}^{0.9} q(y)\,dy = 0.073;$$
$$\int_{0.9}^{1} q(y)\,dy = 0.111;$$

Tab. 1. Probability of a random variable Y falling into the interval (c, d)

Range (c, d)	0-0.1	0.11-0.2	0.2-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1	Σ
Probability P(c<Y<d)	0.111	0.073	0.056	0.048	0.045	0.045	0.048	0.056	0.073	0.111	0.666

$$\int_{-\infty}^{0} q(y)dy = 0.168; \qquad \int_{1}^{\infty} q(y)dy = 0.168.$$

$$\sum P(c < y < d) = 0.168 + 0.666 + 0.168 = 1$$

Tab. 2. Experimental data for assessing the quality indicators of the "piston" parts in the order of their manufacture

No.	d_1 = 82.867 ± 0.005 mm	d_2 = 82.238 ± 0.005 mm	d_3 = 81.704 ± 0.005 mm	d_4 = 21.979 ± 0.005 mm
	x_{min}=82.862 mm	x_{min}=82.233 mm	x_{min}=81.699 mm	x_{min}=21.974 mm
	x_{max}=82.872 mm	x_{max}=82.243 mm	x_{max}=81.709 mm	x_{max}=21.984 mm
	Evaluation y(x) of a quality indicator on a dimensionless scale			
1	0.213	0.170	0.935	0.893
2	0.480	0.813	0.002	0.976
3	0.997	0.436	0.037	0.993
4	0.009	0.138	0.036	0.004
5	0.040	0.254	0.969	0.217
6	0.026	0.460	0.503	0.018
7	0.133	0.970	0.777	0.984
8	0.210	0.145	0.995	0.106
9	0.824	0.108	0.995	0.993
10	0.011	0.976	0.039	0.989
11	0.026	0.060	0.996	0.953
12	0.474	0.875	0.314	0.080
13	0.361	0.023	0.092	0.063
14	0.053	0.998	0.320	0.570
15	0.363	0.293	0.346	0.950
16	0.617	0.286	0.003	0.400
17	0.394	0.081	0.067	0.706
18	0.984	0.975	0.072	0.961
19	0.004	0.995	0.110	0.004
20	0.950	0.169	0.073	0.828
21	0.938	0.082	0.983	0.698
22	0.992	0.481	0.008	0.098
23	0.891	0.006	0.970	0.992
24	0.998	0.474	0.535	0.009
25	0.739	0.621	0.668	0.988
26	0.046	0.113	0.655	0.055
27	0.014	0.305	0.563	0.974
28	0.005	0.649	0.979	0.167
29	0.963	0.993	0.013	0.859
30	0.171	0.797	0.978	0.297

in the technical documentation. Therefore, if the dimensions of a part approach the edges of the tolerance field, this signals that the manufacturing process may need correction or adjustment.

When manufacturing high-precision parts, statistical methods and mathematical statistics are used for quality control. The law governing the distribution of part dimensions, treated as random variables, is typically a uniform distribution, based on the principles of mechanical engineering technology.

A numerical experiment will be conducted to apply the proposed risk assessment method for evaluating the production of a low-quality piston part, specifically focusing on the risk that the dimensions of the part may fall at the edges of the tolerance field.

The quality of the "piston" part is largely characterised by the accuracy of the diameter dimensions: d_1 = 82.867 ± 0.005 mm; d_2 = 82.238 ± 0.005mm; d_3 = 81.704 ± 0.005 mm; and d_4 = 21.979 ± 0.005 mm. A measurement experiment is carried out, which consists of measuring the listed quality indicators of parts in the order of their manufacture in the form of deviations from the middle of the tolerance field. According to formula (2), the assessment of the qual-

Tab. 3. Probability of finding the value of estimates of a random variable Y in the range (c, d)

Range (c, d)	0-0.1	0.1-0.2	0.2-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1.0	∑
Probability P(c<Y<d)	0.17	0.11	0.1	0.07	0.05	0.05	0.07	0.1	0.11	0.17	1

ity indicator is determined by y(x) on a dimensionless scale. The results of the assessment are summarised in Table 2.

Substituting the results of the measurement experiment from Table 1 into formulas (4), (5) and (6) provides the experimental (empirical) probability density function q(y).

Applying formula (7) obtains the probabilities of falling into the assessment range (c, d). The results of the calculations are presented in Table 3.

The integration results demonstrated that the sum of the probabilities for the estimates of the random variable Y equals one, providing experimental confirmation of the reliability of the scientific research.

The next stage in advancing the proposed qualimetric method involves determining the distribution law of functionally dependent statistics along the OY axis and deriving effective estimates for its parameters. This will necessitate further scientific investigation to ensure accuracy and applicability.

4. Discussion of the results

The proposed method of assessing product quality risks using functionally dependent statistics based on the error function complements and enhances existing risk assessment methodologies. In contrast to traditional approaches such as FMEA (Ouyang et al., 2020), which rely heavily on expert judgment and often focus on the consequences rather than the causes of defects, the presented approach enables the calculation of quality risks based on mathematical formalism. This reduces subjectivity and enhances reproducibility.

The use of a nonlinear error function aligns with the theoretical principles of qualimetry, as supported by studies by Khomiak et al. (2025; 2024), which propose similar nonlinear transformations in the energy sector. Furthermore, the application of a dimensionless scale, as developed in this article, corresponds with the findings by Cherniak et al. (2024) and Trishch et al. (2024), where quality indicators are evaluated without reference to measurement units, making cross-comparison possible across various domains.

Unlike methods based on fuzzy logic (Gul et al., 2024; Irfan et al., 2022) or artificial neural networks (Canon et al., 2023; Palakurti, 2025; Yazdi et al., 2024), which require either expert-defined membership functions or large datasets for training, the proposed method is based purely on objective statistical distributions. This allows for its application even in data-scarce environments, such as in high-precision engineering or pilot-scale production, where real-time decision-making is crucial.

As such, the proposed method fills a significant methodological gap by offering a universal, mathematically rigorous, and easily implementable approach to quantifying quality risks. It can be integrated into existing quality management systems (e.g., ISO 9001 and ISO/IEC 17025) and used to enhance product quality monitoring, particularly in industries where standardisation and risk minimisation are critical.

Conclusions

This study presents and validates a universal methodology for assessing the risk of manufacturing products of a given quality by applying nonlinear mathematical dependencies derived from the error function. The proposed approach enables the transformation of measured quality indicators into a dimensionless scale and the construction of functionally dependent statistics. The key theoretical contribution lies in substantiating the applicability of the error function to qualimetric assessments under the assumption of uniform distribution of quality indicators.

From a theoretical standpoint, the developed model contributes to the field of qualimetry and statistical quality control by offering a mathematically grounded, non-subjective approach to evaluating quality risk. Unlike traditional expert-based methods (e.g., FMEA), this methodology allows for analytical determination of risk intervals without human bias. The application of nonlinear functional dependence provides a more accurate reflection of quality variation near tolerance boundaries, aligning with the core principles of qualimetry.

Practically, the model can be integrated into quality assurance procedures in high-precision industries such as mechanical engineering, metrology, and manufacturing of critical components. The implementation of the proposed method in spreadsheet tools (e.g., Excel) allows for easy adoption in real production environments without the need for complex software or AI systems. It also enables continuous monitoring of product quality and early detection of trends leading to defects.

One key limitation of the current study is the assumption of a uniform distribution of quality indicators. While this assumption is reasonable in certain manufacturing contexts, it may not hold universally, especially in processes characterised by systematic deviations or multimodal distributions. Another limitation is the use of synthetic data in testing, which, although illustrative, requires further validation on large-scale real production datasets across multiple industries.

Future research should focus on extending the methodology to account for other statistical distributions, such as normal or beta distributions, which may better represent quality variation in different sectors. Additionally, integrating this model with real-time data acquisition systems and developing automated software tools for dynamic risk visualisation could enhance its practical value. Comparative studies involving industry-standard methods (e.g., Six Sigma, AI-based prediction models) will help position this methodology more clearly within the landscape of quality management tools.

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Organisational identification-based model of job performance in the IT sector: mediating role of work engagement and organisational citizenship behaviour

Katarzyna Żak

ABSTRACT
High employee job performance is considered one of the key factors contributing to a company's commercial success, especially in such service-oriented sectors as IT. Researchers recognise a significant role of employee organisational identification, work engagement, and organisational citizenship behaviour in improving job performance; however, a complex model showing the relationship between those variables has not been provided so far. Moreover, a discrepancy exists between the theoretical conceptualisation and definition of organisational identification and its empirically proven measurements. In this context, the article aims to develop a holistic measurement for organisational identification and analyse the roles of organisational identification, work engagement, and organisational citizenship behaviour in improving job performance of the IT sector employees.
An empirical study was conducted with 246 employees from IT sector organisations in Poland and Germany. The study was performed using the CAWI technique. The research tool was a questionnaire. The gathered data were analysed using IBM SPSS Statistics (descriptive statistics, scale reliability testing, and EFA) and IBM SPSS AMOS (CFA and path analysis) to verify the model.
The analysis results show a positive influence of organisational identification on job performance through work engagement and organisational citizenship behaviour, i.e., organisational identification has a strong, positive and statistically significant effect on work engagement; work engagement has a positive and statistically significant impact on job performance and organisational citizenship behaviour; and organisational citizenship behaviour has a positive and statistically significant impact on job performance of the IT sector employees.

KEY WORDS
organisational identification, work engagement, job performance, organisational citizenship behaviour, IT sector

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Katarzyna Żak
Wrocław University of Science and Technology,
Wybrzeże Stanisława Wyspiańskiego 27,
50-370 Wrocław, Poland
ORCID 0000-0002-1793-1034
Corresponding author:
e-mail: katarzyna.zak@pwr.edu.pl

Introduction

In the modern economy, the IT industry contributes to all sectors by providing innovative solutions such as digitalisation, automation, IoT, AI, data storage and computing, software development, and many others (Atkinson, 2022; Budrowski, 2023). The technology industry in Europe constitutes more than 8 % of the economic output. It continued to grow even during the COVID-19 pandemic and is expected to grow more than 5 % every year until the end of the decade (Esser et al., 2022). Although the projected growth of the IT industry seems to be stable, the sec-

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tor faces difficulties caused by the Russian invasion of Ukraine, high inflation rates and energy prices, supply chain constraints, and the uncertain job market (Business Reporter, 2024; Sladden, 2022). The issues in other economic sectors result in a squeeze of tech funding, which, in turn, causes layoffs in the IT industry (Sladden, 2022). Those challenges were forecasted to be overcome in 2024, with a projected sector growth of 5.1 %, driven mainly by software growth (Business Reporter, 2024; O'Grady, 2024). Despite sector stabilisation predictions, employment in IT continues to face challenges due to the squeeze on tech funding and the shift towards AI. Geopolitical factors and challenges influence the whole European IT sector, including both emerging and developed economies. Hence, a selection of Poland and Germany as study objects is based on a contrast between the two economies: the former is a rapidly developing post-transformation economy in Central and Eastern Europe, and the latter is a mature Western European economy. Although both countries represent a specific economic context (Poland is a fast-growing IT sector, integrating with Western countries as a nearshore centre and adapting to Western standards; and Germany is a mature and stable Western economy with well-developed HR practices), studies have shown relative cultural similarities within the IT sector, in particular in key factors in organisational behaviour, job performance, work engagement and employee identification: a similar approach to project teamwork, a moderately low power distance, and a high communication competence in English as the primary business language. Those similarities are strengthened by wide professional norms and practices in the European IT sector, which reduce differences in everyday work life, as well as by competition and companies' expectations that employees contribute to their overall success by performing to the best of their abilities (Britenet, 2024; Hofstede et al., 2010; House et al., 2004; Irascu, 2024; ITDS, 2024; Kmieciak et al., 2018; Kowal et al., 2019; Piątkiewicz, 2024)

Job performance is a notion that brings benefits to individuals and organisations. On the one hand, highly performing individuals have a wider career, recognition, promotion opportunities, higher job satisfaction, and a sense of success (Barling & Cooper, 2008). On the other hand, for the organisation, high job performance of employees gives a competitive advantage thanks to increased productivity, efficiency and quality (Rich, 2010). Strong advantages of high individual performance have directed the researchers' attention to the job performance concept since the 90's (Barling & Cooper, 2008). Currently, job performance, next to job satisfaction, is said to be the key outcome of sustainable HRM (Davidescu et al., 2020; Law et al., 2017).

According to many researchers and business consultants, competitive advantages can also be an effect of employee engagement (Rich, 2010). Work engagement is often argued to lead to high job performance (Jagannathan, 2014; Rich, 2010). This means that the employees who are engaged can go above and beyond their duty, thus delivering more than expected (Tims et al., 2015). The behaviours and attitudes that adhere to the company's values and goals, such as intrapreneurial behaviour and organisational citizenship behaviour, can be predicted by the notion of organisational identification (Bergami & Bagozzi, 2001; Cheema et al., 2020; De Roeck et al., 2016; Moriano et al., 2014). Organisational identification, as "a key psychological state reflecting the underlying link or bond that exists between the employee and the organisation" (Edwards, 2005), is of vital importance in ensuring employee satisfaction, commitment, and engagement in the success of the company (Johnson et al., 2012).

Although researchers and practitioners recognise the importance of the concepts of organisational identification (OI), work engagement (WE), organisational citizenship behaviour (OCB), and job performance (JP), and those factors have been widely researched, some questions remain unanswered in the subject literature. First, despite the overall agreement on the positive outcomes, there is still a disagreement regarding the conceptualisation and measurement of OI (Edwards, 2005). Most researchers focus on the cognitive dimension of OI, neglecting the affective one (Johnson et al., 2012). Second, the link between OI and its non-attitudinal outcomes, such as OCB and JP, has not often been researched (Johnson et al., 2012). Third, despite a plethora of research on OI, WE, OCB, and JP, a literature review shows a lack of a cohesive model sufficiently explaining the relationship between them. In this context, a research gap has been identified.

This paper aims to fill the identified research gap by finding a synthetic construct for OI and examining the role of OI as a predictor of JP by proposing a structural model with the indirect influence of OI on JP with WE and OCB as mediators of this relationship. To achieve the goal, the OI construct and OI-based model have been verified empirically, based on factor analysis and path analysis.

1. Literature review

1.1. Organisational identification

Organisational identification (OI) is often confused with organisational commitment, loyalty, and internalisation (Ashforth & Mael, 1989; Edwards, 2005). Some researchers perceive OI as a part of organisational commitment, while others even consider them to be synonyms (Ashforth & Mael, 1989). For example, O'Reilly et al. stated that "identification or involvement based on a desire for affiliation" is one of the dimensions of commitment (O'Reilly & Chatman, 1986). Based on a literature review, Hall et al. (1970) proposed a definition which treats identification as a process where the values of employees and their organisation become more compatible.

In an attempt to "restore some coherence to organisational identification", Ashforth and Mael (1989) introduced social identity theory as a theoretical background for OI, suggesting that OI is a specific form of social identification. They defined social identification as a "perception of oneness with a group of persons", which acts as a facilitator of the internalisation of the organisational values and beliefs and enabler of the feeling of loyalty and commitment (Ashforth & Mael, 1989). Meanwhile, the social identity theory gives a basis for the affective aspect of identification, and the self-categorisation theory gives a basis for the cognitive aspect of identification (Johnson et al., 2012). Moreover, the literature proposes two additional components: evaluative (positive assessment of the organisation) and behavioural (current behaviour) (van Dick, 2003).

In line with the social identity theory, Rousseau (1998) connects OI with the employee perception of being a part of an organisation and denotes two aspects of OI: situated and deep structure identification. Situated identification is a feeling of being a part of the larger whole that occurs when individuals contribute their efforts to the goals of a group. In this context, the situational cues create a sense that "I" is a part of "we". This kind of identification "is most likely to occur where cues signal common interests and where outcomes are shared, integrative, and not distributive" (as a response to a catalyst) (Rousseau, 1998). When the situational factor is removed, the situational identification also ceases to exist. Deep structure identification is a higher level of identification that can be developed over time, provided that situated identification is already established. Deep structure identification occurs when an employee incorporates the organisation's value into their self-image and exists even when the role or circumstances change (Rousseau, 1998).

Edwards (2005) concluded his extensive OI literature review by stating that despite similarities and overlaps in the last 50+ years of OI research, some significant differences also exist in the OI definitions and approach. He summarised that over the years, the notion of OI has been connected with a sense of belonginess, loyalty, involvement, attraction to the organisation, consistency of organisational and individual goals, reference of self to organisational membership, shared characteristics, perceived similarity of characteristics, individuals' acceptance of the organisation's goals and values, integration of the organisational goals and values as the individual's own, emotional commitment, emotional attachment, self-categorisation or social identification, self-referential or self-defining beliefs, cognition of self in relationship to the organisation and a feeling of solidarity. In conclusion, a recent research approach underlines the importance of considering affective and cognitive elements as basic OI components.

The cognitive OI aspect reflects a sense of pride and a sense of belongingness to the organisation, while also reflecting the perceived value of the identity (Whetten & Godfrey, 1998). Edwards (2005) proposed that the cognitive OI aspect has two dimensions: self-categorisation and value and goal sharing. Through cognitive processes of categorisation, an employee forms a view (or a self-image) of being a member of the organisation. The processes are based not only on looking for similarities with colleagues in the organisation, but also on dissimilarities with members of other organisations. With the increasing sense of identification with the organisation, the employees perceive themselves as representatives of the social unit, i.e., an organisation (Turner, 1985). According to Ashforth and Mael (1989), OI leads to experiencing the organisation's successes and failures on a personal level; however, it is not necessarily connected with behaviour or emotional state. This means that identification is a concept that differs from internalisation, i.e., a person who identifies with an organisation may not incorporate its values, principles, attitudes or goals (Ashforth & Mael, 1989).

The affective aspect emphasises an emotional OI component. The dimensions of affective identification are emotional attachment, belonging, and membership (Edwards, 2005). Johnson et al. (2012) suggested that the affective dimension is "generally positive", including feelings of joy, pride, excitement or even love. This is connected with a wish to have positive feelings related to the membership and being able to feel pride even in a stigmatised group. Based on that, they define affective identification as "an individual's positive feelings about being one with a group" (Johnson et al., 2012). According to Meyer and Allen (1991), the affective dimension of OI is connected not only with emotional attachment, but also with identification and involvement.

The researchers recognise that cognitive and affective aspects may be difficult to separate in practice (Edwards, 2005). As a consequence, some of the researchers recognise both dimensions while conducting a study; however, they include scale items belonging only to the cognitive dimension (Johnson et al., 2012). Moreover, it has been stated that organisational identification depends on the contextual factors like Eastern/Western setting, national cultural differences, sector specifics, etc. (Mazumder et al., 2017, 2022). For example, models of OI based on an assumption of a relational self-concept rather than an individualist one may be more representative in relationship-oriented Eastern countries (Mazumder et al., 2022). Regarding the sector specifics, the majority of employees of the organisations in the fast-paced IT industry are knowledge workers. Knowledge workers prefer to control their work, thrive under empowering leadership, constantly pursue growth of knowledge, and tend to be more loyal to the occupation instead of the employer (Zhan et al., 2013). Based on those characteristics of the IT sector employees in Poland and Germany, one of the research objectives of this study is to develop an OI scale that is suitable for this particular context.

1.2. Work engagement

The term work engagement (employee engagement, WE) was coined by Kahn (1990) as the "harnessing of organisation members' selves to their work roles: in engagement, people employ and express themselves physically, cognitively, emotionally and mentally during role performances". In contrast, disengagement is a state of uncoupling from work, i.e., withdrawal and defending oneself (Kahn, 1990). Later, a WE definition as "a positive, fulfilling, affective motivational state of work-related well-being that is characterised by vigour, dedication, and absorption" has been introduced (Bakker et al., 2008, p. 188). Understanding job burnout as the opposite of WE, Schaufeli et al. (2002) explained the three WE factors as follows:

- vigour - high level of energy and mental resilience, the willingness to invest effort, and persistence even in the face of impediments;
- dedication - sense of significance, enthusiasm, inspiration, pride, and challenge;
- absorption - full concentration, deep immersion in work, difficulties with detaching from work.

The employees who are engaged can stay focused and truly present as well as work hard towards the assumed goals (Barbars, 2015). They put a lot of effort into their work because they identify with it. Hence, many researchers see WE as a two-dimensional, psychological construct (energy and identification) (Bakker et al., 2008). However, the term has also been conceptualised in a broader scope, e.g., as an umbrella term for trait engagement (i.e., proactiveness), state engagement (involvement), and behavioural engagement (organisational citizenship behaviour) (Macey & Schneider, 2008).

1.3 Job performance

As per the early definition proposed by Campbell (1993), "performance is what the organisation hires one to do, and do well". Job performance (JP) is a core concept of organisational psychology, which consists of two aspects: behaviour and outcome (Campbell, 1990; Campbell et al., 1993; Sonnentag & Frese, 2005). While the behavioural aspect refers to employee actions at work, which can be measured and are relevant to the organisation's goal, the outcome aspect refers to the results of employee behaviour. It is noteworthy that those two aspects are related in practice, but not completely overlapping, e.g., because of the outcomes being not fully dependent on the individual (Campbell et al., 1993; Motowidlo et al., 1997; Sonnentag & Frese, 2005). However, Campbell et al. also suggested that job performance can be solely referred to the behavioural aspect, defining JP as behaviours and actions which support the organisation's goals (Campbell et al., 1993). Campbell (1990) proposed a JP framework where JP is modelled as an eight-dimensional construct (job-specific task proficiency, non-job-specific task proficiency, written and oral communications, demonstrating effort, maintaining personal discipline, facilitating peer and team performance, supervision, management, and administration).

Motowidlo et al. (1997) underlined that JP is a behavioural, episodic, evaluative, and multidimensional construct. According to them, one can distinguish between task performance and contextual performance. Task performance is directly related to the organisation's technical core by executing technical processes (activities such as selling, operating a machine, teaching, performing surgery, etc.) or maintaining technical requirements (activities such as restocking, distribution of products, providing control, supervision and staff-related functions, etc.). Task performance corresponds to Campbell's dimensions of job-specific task proficiency and non-job-specific task proficiency. Contextual performance maintains the organisation's organisational, social and psychological environment by activities, such as maintaining psychological context, following rules and procedures, volunteering to carry out extra tasks, etc. Contextual performance corresponds to Campbell's dimensions of written and oral communications, demonstrating effort, maintaining personal discipline, facilitating peer and team performance, supervision, and management and administration.

The literature review also shows approaches that add to the two main dimensions. One of the additional dimensions considers counterproductive work behaviours, including absenteeism and presenteeism (Bakker et al., 2004; Burton et al., 2004), downtime and destructive/hazardous behaviours (Murphy, 1989), off-task behaviour, unruliness, theft and drug misuse (Hunt, 1996). Adaptive performance includes the ability to adapt to changes, creative problem solving, dealing with unpredictable work situations and the ability to learn and is sometimes mentioned as the fourth JP dimension (Allworth & Hesketh, 1999; Pulakos et al., 2000; Sinclair & Tucker, 2006). Koopmans et al. (2001) presented a comprehensive conceptual framework with four dimensions of performance and their indicators:

- task performance - completing job tasks, work quantity, work quality, job skills, job knowledge, keeping knowledge up-to-date, working accurately and neatly, planning and organising, administration, decision-making, solving problems, oral and written communication, and monitoring and controlling resources;
- contextual performance - extra tasks, effort, initiative, enthusiasm, attention to duty, resourcefulness, industriousness, persistence, motivation, dedication, proactivity, creativity, cooperating with and helping others, politeness, effective communication, interpersonal relations, and organisational commitment;
- adaptive performance - generating new, innovative ideas, adjusting goals and plans to the situation, learning new tasks and technologies, being flexible and open-minded to others, understanding other groups or cultures, showing resilience, remaining calm, analysing quickly, and acting appropriately;
- counterproductive work behaviour - off-task behaviour, too many or longer breaks, presenteeism, absenteeism, complaining, tardiness, doing tasks incorrectly, accidents, insulting or gossiping about coworkers, fighting or arguing with coworkers, disregard of safety, misusing privileges, aggression, theft, and substance use (Koopmans et al., 2011).

1.4. Organisational citizenship behaviour

Organisational citizenship behaviour (OCB), firstly introduced by Cheney et al. (1983), refers to the behaviour of employees which is voluntary, goes beyond the job requirements and contract, and is not recognised by the organisation's formal reward system (Podsakoff et al., 2000). Engaging in OCB means that an employee is willing to go an extra mile on their own volition without expecting an official reward; on the other hand, an employee who is not engaging in OCB faces neither negative consequences nor disciplinary punishment. The literature captures seven OCB dimensions:

- Helping behaviour - helping others at work, including solving and preventing problems before they occur;
- Sportsmanship - tolerating the inevitable inconveniences and impositions of work without complaining;
- Organisational loyalty - spreading positive word of mouth, promoting, protecting and defending the organisation, and remaining committed to the organisation;
- Organisational compliance - internalisation and acceptance of the organisation's rules, regulations, and procedures and complying with the organisation's rules even when no one is watching;
- Individual initiative - voluntarily engaging in tasks which go beyond the role description (creative approach, innovation, enthusiasm, extra effort and responsibilities, encouraging other employees to act similarly;
- Civic virtue - showing a macro-level interest in or commitment to the organisation as a whole (willingness to participate in the organisation's governance, e.g., attending meetings, monitoring

risks, discussing strategy, and reporting fire hazards and suspicious activities);
- Self-development - developing one's skills, knowledge, and abilities (Podsakoff et al., 2000).

1.5. Hypothesis development

As proven by empirical research, job performance is a notion that depends on job-related attitudes, i.e., job satisfaction, motivation, engagement, commitment, and involvement (Bieńkowska & Ignacek-Kuźnicka, 2019; Habeeb et al., 2017; Shahab & Nisa, 2014). In the context of the IT sector knowledge workers, high work engagement is a crucial attitude because it leads to a competitive advantage based on employee innovativeness, critical thinking, and initiative - behaviours that are necessary for job performance supporting the organisational goals (Toth et al., 2020). Thus, when analysing the phenomenon of the influence that organisational identification has on job performance in the IT sector, it is also necessary to consider the mediating role of work engagement. An appropriate level of work engagement is generally considered to be an important factor determining high-quality job performance (Yao et al., 2022). Empirical studies show the positive relationship between work engagement and job performance (Yongxing et al., 2017). Kim et al. examined 20 empirical studies and found that nine reported a relationship between work engagement and performance, one was direct and indirect, and only one was indirect. In seven other studies, the engagement was found to be a mediating factor between other constructs and performance (Kim et al., 2013).

Organisational identification is believed to lead to positive organisational outcomes relating to employees, such as commitment, motivation, goal achievement, qualitative performance, and job satisfaction (Ashforth & Mael, 1989; De Roeck et al., 2016; Likert, 1967; Stryker & Burke, 2000). Although the research showing the direct link between organisational identification and work engagement is limited, the organisational behaviour literature supports the statement that organisational identification determines the attitude of employees towards work (Karanika-Murray et al., 2015). Employees who identify with the organisation are more likely to internalise its values, be concerned about its future and well-being, as well as better perform their tasks (Dutton et al., 1994; Ötken & Erben, 2010). The desire of an employee to better perform the tasks reinforces the willingness of an individual to engage in work (Karanika-Murray et al., 2015; Ötken & Erben, 2010).

Strongly engaged employees who are enthusiastic and involved in their job perform their assigned tasks with higher quality and are more likely to get involved in additional, voluntary activities (Wahyu, 2013). Based on the social exchange theory and the principle of reciprocity, organisational citizenship behaviour (OCB) is a result of a positive emotion towards the organisation, which is driven by favourable treatment of employees by the organisation (Miles et al., 2002; Sun, 2019). Positively engaged individuals devote themselves completely, are more excited about working beyond expectations and generally go an extra mile by manifesting creativity and willingness to take extra tasks (Rahman & Karim, 2022; Smruti Rekha & Sasmita, 2019). Although extra efforts of performing OCB are neither formally included in the job description nor in the rewarding system, the research shows that it is taken into consideration in the process of managerial evaluation of employees (Podsakoff et al., 2000). This shows that OCB is believed to be an important performance factor, both individual and organisational (Organ et al., 2006), and can play a mediating role in the relationship between work engagement and job performance.

Based on the above, a hypothesis for this study has been formulated as follows:

H1. There is a positive influence of organisational identification (OI) on job performance (JP) through work engagement (WE) and organisational citizenship behaviour (OCB).

A hypothesis overview is presented in Fig. 1.

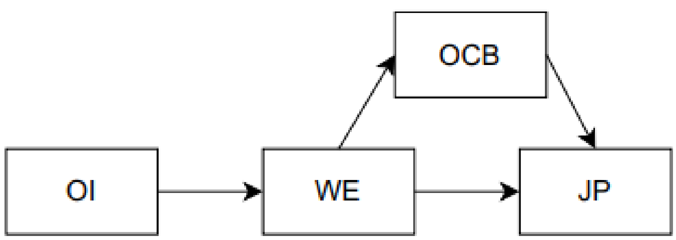

Fig. 1. Hypothesis H1

2. Research methods

2.1. Data collection and sample description

An empirical study has been conducted to achieve the aim of this article and verify the hypotheses. Before conducting the main study, the questionnaire was presented to 15 specialists from the IT sector in Poland to check if the questions were fully comprehensible and perceived as adequate (February 2023).

The quantitative research was carried out among the IT sector employees in Poland and Germany in March-June 2023 using the CAWI method. The criteria for the research sample were the country of employment (Poland or Germany) and the sector of employment (IT). The anonymity of the responses was guaranteed. It took ca. 12-15 minutes to complete the survey. The total size of the sample was 246 knowledge workers in the IT sector.

Tab. 1. Socio-demographic characteristics of the sample

Characteristic	Value	Frequency	Per cent
Country	Germany	35	14.2
	Poland	211	85.8
Age	< 27	50	20.3
	27-35	90	36.7
	36-42	68	27.6
	43-50	32	13.0
	51-58	6	2.4
Gender	Female	90	36.6
	Male	155	63.0
	Other	1	0.4
Work experience (overall)	0-3	47	19.1
	10-15	51	20.7
	3-6	45	18.3
	6-10	43	17.5
	> 15	60	24.4
Work experience (current company)	0-1	71	28.8
	1-3	66	26.8
	3-6	57	23.3
	6-10	23	9.3
	> 10	29	11.8
Current position	Developer / Software Engineer	87	35.5
	Manager / Leader	40	16.3
	Consultant / IT Support	30	12.2
	Business Analyst / System Analyst	26	10.6
	Software Tester	21	8.5
	DevOps Engineer	14	5.7
	PMO	7	2.8
	Business / Technical Architect	6	2.4
	HR	3	1.2
	UX Designer	3	1.2
	Administrative / Assistance Role	2	0.8
	Research Assistant	2	0.8
	Scrum Master	2	0.8
	Other	3	1.2
Company size	Big (> 250 employees)	231	93.9
	Medium (< 250 employees)	9	3.7
	Small (< 50 employees)	5	2.0
	Micro (< 10 employees)	1	0.4
Company type	Global	187	76.0
	Multinational	53	21.5
	National	6	2.5

The research tool, a questionnaire prepared based on the literature review, was divided into two parts. Part I consisted of general questions and aimed to obtain information about the characteristics of the sample. All questions from this part were answered by the respondents. Part II contained questions regarding the studied constructs, i.e., organisational identification (OI), work engagement (WE), job performance (JP), and organisational citizenship behaviour (OCB). However, not all respondents answered all questions in the second part, which led to excluding invalid answers (as further described in the respective step of the analysis). The selection of the sample was made in a non-probability manner; however, the sample description (Tab. 1) shows a sample diversity, allowing for drawing conclusions and performing statistical testing.

Most of the respondents currently work for a big company (nearly 94 %). However, the company type is less homogeneous in the sample, i.e., 76 % are global companies and 21.5 % are multinational. The sample was dominated by men (63.3 %), which is not surprising considering the fact that, according to Eurostat data, in 2021, women only accounted for ca. 19.1 % in the IT sector in Europe (De Luca, 2023). A significant number of the surveyed employees belong to the Millennial generation (around 64 %), which, together with the younger Gen Z generation, constitutes the significant majority of the sample: 84 %. As for the current position, the technical roles were reported by ca. 75 % of the respondents (developers, engineers, consultants, analysts, testers, and DevOps engineers), whereas managerial/leadership positions are held by ca. 16 % of the respondents. The sample shows a discrepancy between German (14.2 %) and Polish (85.8 %) respondents, which is caused by difficulties in reaching the target group of IT specialists in Germany. The issue of low response rate in organisational research, especially among IT professionals who have tight schedules and may perceive surveys as low priority, has been previously reported by other researchers (Baruch & Holtom, 2008; Smith et al., 2013). However, a literature review shows significant similarities between Polish and German IT labour market, especially in the areas of skills and education (high technical skills, higher education, and English proficiency), cultural proximity (geographical closeness, frequent cooperation on projects, similar approach to teamwork, and the emphasis on knowledge sharing), market challenges and specifics (shortage of qualified IT specialists, remote work, multinational projects, quality pressure to compete with cheaper offshore suppliers, HR practices, technological turbulence, and innovations), and the last but not least - employees' attitudes and expectations towards the employers, which vary in the macroeconomic and not the motivational dimension (Britenet, 2024; Irascu, 2024; ITDS, 2024; Piątkiewicz, 2024). The above factors and the diversity within the combined sample enable a meaningful statistical analysis despite the quota imbalance between German and Polish subsamples.

2.2. Overview of measures and variables

Considering the characteristics of the IT sector knowledge workers in Poland and Germany, this study questioned whether all the OI scales' items existing in the literature are relatable to the IT sector employees. Above all, the tendency to be more loyal to the occupation than to the organisation challenges the legitimacy of self-categorisation items (e.g., "Being an employee at this organisation is the most significant dimension of me"), and the strong need individualist self-concept challenges the legitimacy of some value and goal sharing items (e.g. "I have attributes, traits, and features that are typical for an employee at this organisation").

To find a synthetic construct for organisational identification (OI) of the IT sector organisation employees, a literature review for cognitive and affective dimensions of organisational identification has been conducted. While the first dimension was divided into two sub-dimensions - self-categorisation and value and goal sharing, the latter was not divided into sub-dimensions. It was assumed that the affective identification is one dimension containing emotional attachment as well as belonging and membership. The results of the literature overview and items constructing the OI variable are presented in Tab. 2.

Organisational identification (OI) items were measured on a five-point Likert scale, from 1 - "Strongly disagree" to 5 - "Strongly agree" with a neutral point 3 - "Neither agree nor disagree".

To build a structural model and test hypotheses, three variables: work engagement, job performance, and organisational citizenship behaviour, were measured using existing and previously validated scales (Tab. 3).

Work engagement (WE) as well as job performance (JP) were measured on a five-point Likert

Tab. 2. Organisational identification: dimensions, subdimensions, and items

Dim	Sub	Name	Item	Source
Cognitive identification	Self-categorisation	IS01	I identify myself as a member of this organisation	Adapted from: (Stoner et al., 2011) (van Dick et al., 2004)
		OIS02	When I talk about the organisation, I usually say “we” rather than “they”	(Mael & Tetrick, 1992) (Tyler & Blader, 2001)
		OIS03	I feel as though I belong at work	Adapted from: (Tyler & Blader, 2001) (Stoner et al., 2011)
		OIS04	Being an employee at this organisation is the most significant dimension of me	(Stoner et al., 2011)
		OIS05	Overall, being a member of this organisation has very little to do with how I feel about myself (R)	Adapted from: (Cameron, 2004) (Harris & Cameron, 2005)
	Value and goal sharing	OIV01	What the organisation stands for is important to me	Adapted from: (Edwards & Peccei, 2007)
		OIV02	I share the goals of the organisation	Adapted from: (Edwards & Peccei, 2007)
		OIV03	I find that my values and the values of this organisation are similar	(Vandenberg et al., 1994)
		OIV04	I have attributes, traits, and features that are typical for an employee at this organisation	Adapted from: (Mael & Tetrick, 1992) (Stoner et al., 2011)
		OIV05	I have attitudes and behaviours that are typical for an employee at this organisation	Adapted from: (Stoner et al., 2011)
Affective identification	Emotional attachment + belonging and membership	OIE01	This organisation means a lot to me	Adapted from: (Boen et al., 2006)
		OIE02	I like being a member of this organisation	(Stoner et al., 2011)
		OIE03	When someone criticises the organisation, it feels like a personal insult	(Mael & Tetrick, 1992) (Tyler & Blader, 2001)
		OIE04	I have warm feelings towards this organisation as a place of work	Adapted from: (Cheney, 1983)
		OIE05	The organisation’s successes are my successes	(Mael & Tetrick, 1992)
		OIE06	When someone praises the organisation, it feels like a personal compliment	(Mael & Tetrick, 1992) (Tyler & Blader, 2001)
		OIE07	I am proud that I can work for this organisation	Adapted from: (Boen et al., 2006) (Cheney, 1983)
		OIE08	I like to work for this organisation	(van Dick et al., 2004)
		OIE09	I am glad I chose to work for this organisation rather than another company	(Cheney, 1983)

scale, from 1 - “Strongly disagree” to 5 - “Strongly agree” with a neutral point 3 - “Neither agree nor disagree”. For the organisational citizenship behaviour (OCB) construct, a modified five-point Likert scale was used, with the possible choices of 1 - “Never”, 2 - “Once or twice”, 3 - “Once or twice per month”, 4 - “Once or twice per week” and 5 - “(Almost) every day”. This questionnaire was validated for internal consistency using IBM SPSS Statistics v. 28.0.1.0.142. The analysis showed the reliability (Cronbach’s alpha coefficient) for each scale as follows: WE - 0.708; JP - 0.817; OCB - 0.879.

The collected data were analysed using descriptive statistics, factor analysis, and structural equation modelling using IBM SPSS Statistics v. 28.0.1.0.142 and IBM SPSS AMOS v. 28.0.0. In the analysis, all p-values less than 0.05 were accepted as statistically significant.

Tab. 3. Summary of the constructs and the corresponding items: WE, JP, and OCB

Variable	Name	Item	Source
Work engagement (WE)	WE01	At my work, I feel bursting with energy	(Schaufeli et al., 2019)
	WE02	I am enthusiastic about my job	
	WE03	I am immersed in my work 211	
Job performance (JP)	JP01	I always complete the duties specified in my job description and all the formal performance requirements of my job	(Bieńkowska & Tworek, 2020; Panayiotou et al., 2009; Phan et al., 2022; Yu et al., 2018)
	JP02	I always fulfil all responsibilities required by my job	
	JP03	I appropriately complete the work duties allocated to me	
	JP04	I perform my work duties precisely	
	JP05	I follow through on tasks to completion	
	JP06	I am rarely absent from my work	
	JP07	I make few mistakes at work	
	JP08	I always do all the tasks entrusted to me on time	
	JP09	I create new ideas and original solutions for improvements in my field	
Organisational citizenship behaviour (OCB)	OCB01	I took time to advise, coach, or mentor a coworker	(Spector et al., 2010)
	OCB02	I voluntarily helped a coworker learn new skills or shared job knowledge	
	OCB03	I voluntarily helped new employees get oriented to the job	
	OCB04	I lent a compassionate ear when someone at work had a work problem	
	OCB05	I offered suggestions to improve how work is done	
	OCB06	I helped a coworker who had too much to do	
	OCB07	I volunteered for extra work assignments	
	OCB08	I worked after-hours, weekends or other days off to complete a project or task	
	OCB09	I volunteered to attend meetings or work on committees in my time	
	OCB10	I gave up meal and other breaks to complete work	

3. Research results

3.1. Factor analysis

The first step of the analysis tested the data for normality. K-S test indicated that the distributions are deviating from normality ($p < 0.001$). For this reason, the further analysis used the exploratory factor analysis (EFA) with the maximum likelihood estimation method as a method relatively robust to the deviation from normality (Fuller & Hemmerle, 1966).

For EFA, a subset of 123 observations was randomly chosen from the total set of 246 responses. In this step, two models were estimated:

- Three first-order factor model - three sub-dimensions of OI as separate factors ("Sub" column in Table 3): self-categorisation (OIS), value and goal sharing (OIV), and emotional attachment + belonging and membership (OIE) correlated with each other. All three factors (OIS - five items; OIV - five items; OIE - nine items) were analysed separately for communalities lower than 0.5. After removing values lower than 0.5, for further analysis (CFA), ten items were accepted: OIV01-OIV03, OIE01, OIE02, OIE07, OIE08, OIS01, OIS03 and OIS05. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy for those three factors: KMO(10) = 0.925, $p < 0.01$ and total variance explained by them at the level of 71.737 %. The three first-order factor model accepted for further testing is shown in Fig. 2.
- One first-order factor model - one first-order factor accounting for all the common variance. In the first iteration of EFA, the values of communalities after the extraction of items OIE03-OIE06, OIE09, OIS02, OIS04, and OIV03-05 were lower than 0.5. Hence, those were excluded from further analysis. The second iteration for the remaining ones: OIS01, OIS03, OIS05, OIV01, OIV02, OIE01, OIE02, OIE07 and OIE08 showed no communalities values lower than 0.5; KMO test result: KMO(9) = 0.921, $p < 0.01$ and total variance explained by one factor at the level of 62.827 %. Those nine items were thus accepted for further analysis (CFA). The one first-order factor model accepted for further testing is shown in Fig. 3.

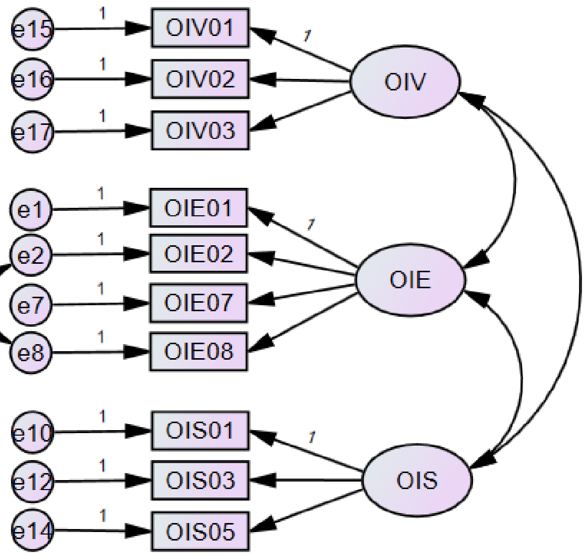

Fig. 2. Three first-order factor model

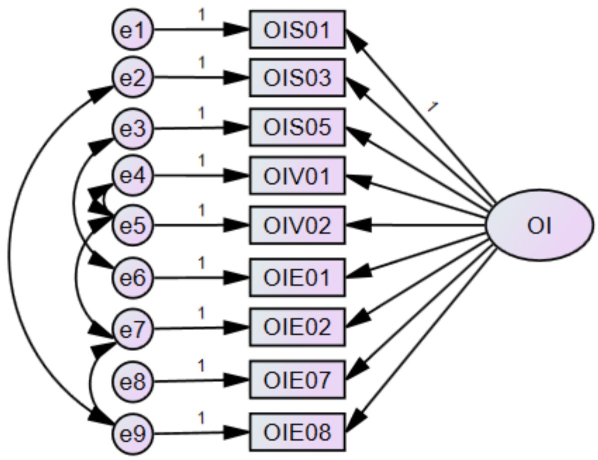

Fig. 3. One first-order factor model

Tab. 4. Fit summary for the tested models

Statistic	Three first-order factor model	One first-order factor model
Chi-square (CMIN)	38.767	25.326
df	31	22
CMIN/df	1.251	1.151
RMR	.034	.026
GFI	.946	.958
AGFI	.903	.914
NFI	.952	.965
TLI	.985	.992
CFI	.990	.995
SRMSR	.0371	.0264
RMSEA	.045	.035

For confirmatory factor analysis (CFA) of the two models, a subset of the remaining 123 observations was assumed (from the total set of 246 responses). The detailed results of the analysis are presented in Tab. 4.

The CFA results presented in Table 4 indicate a good fit of the proposed model, with a slightly better match of the one first-order factor model. The CMIN/df ratios of 1.251 and 1.151 are lower than the acceptable threshold of 2 (Ullman & Bentler, 2003). The GFI (Goodness-of-Fit) and AGFI (Adjusted Goodness-of-Fit) indices, which are relatively resistant against normality and measure how much the models jointly account for the variances and covariance, are also greater than the recommended threshold of 0.9 (Hair et al., 2010; Somers et al., 2003). The good model fit is also justified by values of CFI (Confirmatory Fit Index) and TLI (Tucker-Lewis Index) above 0.9 (Bentler, 1990) as well as of SRMSR (Standardised Root Mean Square Residual) and RMSEA (Root Mean Square Error of Approximation) below 0.08 (Hu & Bentler, 1998).

3.2. Structural Equation Modelling

The research hypothesis was tested with the use of Structural Equation Modelling (SEM) in AMOS on the sample of n=173. One-factor organisational identification (OI) was assumed as an independent variable, with work engagement (WE) and organisational

Tab. 5. Path coefficients of the structural equation model

Hypothesis	Path	Standardised estimate	S.E.	C.R.	p-value	Hypothesis acceptance
H1	OI to WE	.636	.095	6.220	< .001	Accepted
	WE to JP	.210	.075	2.296	.022 < .05	
	WE to OCB	.339	.096	3.472	< .001	
	OCB to JP	.210	.070	2.488	.013 < .05	

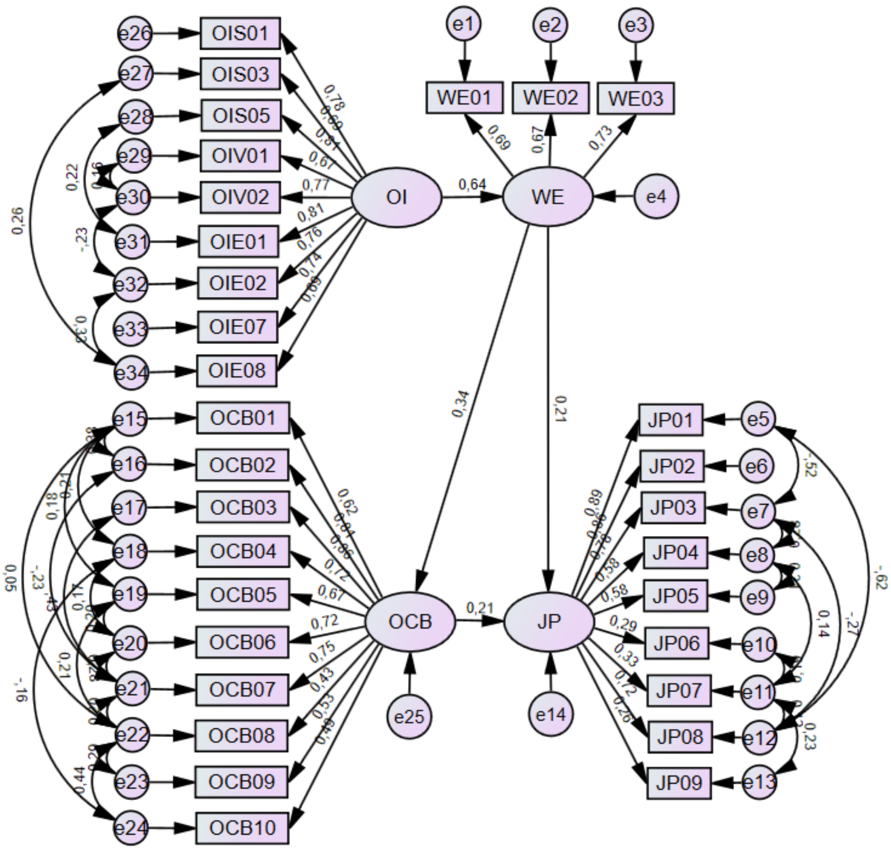

Fig. 4. Tested model

citizenship behaviour (OCB) as intermediate variables, and job performance (JP) as the dependent variable. The tested model with latent variables is shown in Fig. 4. For the final model, meeting the following criteria of the model's goodness-of-fit still enables the conclusion that the model is well-fitted: CMIN/df = 1.416 < 2.0; CFI = 0.938 > 0.9; TLI = 0.929 > 0.9; RMSEA = 0.049 < 0.08.

- The analysis results show that OI has a strong, positive and statistically significant effect on WE (path factor = 0.636, p-value < 0.001). The impact of WE on JP (path factor = 0.210, p-value = 0.022) is positive and statistically significant. The results also show a positive and statistically significant impact of WE on OCB: path factor = 0.339, p-value < 0.001, as well as OCB on JP: path factor = 0.210, p-value = 0.013, which means that the assumed hypothesis H1 has been confirmed.

Analysis of indirect effects shows that OI affects JP indirectly via two paths:

- OI -> WE -> JP: Indirect effect: 0.636*0.21=0.1336 (positive, statistically significant),
- OI -> WE -> OCB -> JP: Indirect effect: 0.636*0.339*0.21=0.0453 (positive, statistically significant).

3.3. Summary of the results

The conducted statistical analysis aimed to assess two models of organisational identification (OI) and an indirect influence of OI on job performance (JP), based on a sample of IT-sector specialists in Poland and Germany. The results showed:

- a good fit of the multidimensional model, emphasising cognitive identification (self-categorisation and value and goal sharing), and affective identification (emotional attachment as well as belonging and membership),
- a slightly better fit of the unitary model, emphasising a strong correlation between the theoretical dimensions,
- a good fit of the model assessing the influence of Organisational Identification (OI) on Job Performance (JP) via Work Engagement (WE) and Organisational Citizenship Behaviour (OCB), with all direct effects between variables shown in Table 5 being statistically significant. Additionally, two specific indirect effect pathways are identified: (1) the mediation of WE in the relationship between OI and JP, and (2) the serial mediation of WE and OCB between OI and JP.

4. Discussion of the results

This paper aimed to build a synthetic construct for organisational identification (OI) and analyse the role of OI in strengthening job performance (JP) in the IT sector. This aim was fulfilled by a literature review followed by empirical research. The literature review allowed for the finding of items belonging to affective and cognitive dimensions of OI, thus building a theoretical OI scale for the IT sector. The conducted literature review was also a basis for the hypothesis development. The theoretical OI construct and hypothesis were verified in the empirical research. In the conducted research, two new scales for organisational identification have been verified: a three first-order factor scale and a one first-order factor scale. The final scales comprise items reflecting affective and cognitive dimensions, which is consistent with the theoretical conceptualisation of the term (Edwards, 2005; Johnson et al., 2012). The analysis confirmed that not all the items mentioned in the subject literature are appropriate for the IT sector knowledge workers. As expected, only the items that support IT employees' sense of individualism and need for empowerment can build the final models, which is consistent with the characteristics of IT sector knowledge workers (Zhan et al., 2013). Although three- and one-factor models are both well-fitted, the latter has demonstrated better fit indices. This result is consistent with previous research depicting OI as a unitary construct, which provides a simplified, but still reliable measurement across different types of organisations. Likewise, Edwards (2005) concluded that such an approach can be justified by strong empirical correlations between the dimensions, which makes it reasonable to use a single-factor approach in practice. Hence, the unitary construct was used for further path analysis. However, the multidimensional model offers valuable theoretical insights. It may help distinguish how the particular dimensions predict, e.g., attitudes and behaviours (Edwards, 2005).

Moreover, the analysis confirmed the main research hypothesis that there is a positive influence of organisational identification (OI) on job performance (JP) through work engagement (WE) and organisational citizenship behaviour (OCB). The direct effect of OI and WE in the collected data goes in line with previous findings stating that OI determines employee attitudes towards work and reinforces the willingness to be engaged (Karanika-Murray et al., 2015; Ötken & Erben, 2010). In the conducted research, WE has been proven to have a positive and statistically significant impact on JP, with partial mediation of OCB. Generally, this result is consistent with previous empirical studies that also confirm a positive relationship between WE and JP (Yongxing et al., 2017), the willingness of highly engaged employees (WE) to engage in voluntary activities (OCB) (Rahman & Karim, 2022; Smruti Rekha & Sasmita, 2019; Wahyu, 2013), and that engaging in OCB leads to higher JP (Organ et al., 2006). The indirect effect of OI on JP through WE also turned out to be positive: employees who identify strongly with the organisation tend to be more engaged in their work, which, in turn, translates into higher job performance. The results may be perceived as an approach to build on Kahn's psychological conceptualisation of WE. In Kahn's model, performance is fostered by psychological conditions closely linked to identification (meaningfulness, safety, availability, belonging, and meaning at work) via the mediating role of personal engagement (energy, motivation, and commitment) (Kahn, 1990). Moreover, a statistically significant, serial mediation pathway OI -> WE -> OCB -> JP shows that OI positively affects work engagement, which then stimulates greater organisational citizenship behaviour. This increased OCB further improves job performance. This indirect path empirically shows how OCB emerges from underlying psychological concepts of OI and WE, and ultimately strengthens JP. Therefore, the research gap has been filled by developing a measurement for the OI construct, finding a link between OI and building a model explaining the relationship between OI, WE, OCB, and JP.

Conclusions

The obtained results contribute to the human resources management field, especially to the ongoing debate regarding the conceptualisation of OI, by introducing a three-factor OI scale that synthetically represents cognitive and affective OI dimensions, as well as a one-factor OI scale that underlines the closeness of the dimensions in practice. The presented approach advances the understanding of OI by providing a holistic, empirically validated model of both affective and cognitive components, which are traditionally examined separately in the literature (with an emphasis on the cognitive dimension).

The results also add to the existing literature by not only proving an influence of OI on JP through WE, but also emphasising the partially mediating role of OCB in the relationship between WE and JP. To the best of the author's knowledge, such an influence has not been directly shown in any of the existing theoretical JP models. Given the rapid, project-based work environment, the results provide empirical support for the hypothesis that OI remains a driver of WE, OCB, and ultimately JP, not only in traditional, process-based corporate environments. By modelling these mediating relationships, the study clarifies the psychological and behavioural mechanisms linking identification to performance, offering a refined framework for the IT sector.

The developed OI scale and OI-based job performance model also have a practical significance, especially in the IT sector. As employee job performance is a crucial factor in the overall performance of the organisation, it should be reinforced and stimulated by management. The results of this study indicate that management can influence job performance by nurturing employees' sense of belonging, emotional attachment and self-categorisation as a part of an organisation. Moreover, the results show the importance of recruiting employees who share the organisation's goals and values. Such employees, who are compatible from the beginning, are more likely to identify themselves with the organisation, be more engaged, and, in consequence, get involved in voluntary activities and perform well.

Although the aim of this paper has been successfully fulfilled and theoretical and practical implications have been recognised, the results have certain limitations. The first limitation is the study sample, which is relatively small and was purposively collected only in Poland and Germany, in the IT sector. Second, the research was conducted only once, yet employee views tend to vary in time (e.g., they reflect the current economic and political situation). Third, a literature review shows a plethora of factors that can influence employee job performance, and this study considered only organisational identification, work engagement and organisational citizenship behaviour.

The above limitations can be a starting point for future research. The research could be replicated with a bigger sample that would be more geographically diverse and not limited to the IT sector. Appropriateness of a unitary versus multidimensional model may vary across industries and cultural settings. Future research may benefit from testing multidimensional

OI models in other sectors or national contexts where organisational cultures are less cohesive than in IT, as this might reveal meaningful distinctions between various facets of identification. Such exploration could provide a deeper theoretical understanding and increase the generalisability of measurement models for Organisational Identification. In further research, it would also be worth considering other factors influencing job performance, like leadership, training and other HRM solutions. Finally, it could be beneficial to check if there are some moderating factors to the described relationships, e.g., the type of employment, gender, company size, sector, etc.

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Foreign direct investment and technology transfer: unlocking Serbia's growth potential

Sonja Pejić
Ana Nešić Tomašević

ABSTRACT
This paper examines the effects of foreign direct investments (FDIs) on economic development and the transfer of knowledge and technology (technology spillover) in developing countries, specifically focusing on the Republic of Serbia.
The analysis is based on a comparative review of EU countries and Serbia in terms of statistical data on R&D activities and patent applications. The study synthesises existing research and proposes a methodological framework for future empirical studies.
Findings indicate that technology spillover - horizontal and vertical - has not yet reached the desired levels in Serbia. Despite the presence of FDIs, the anticipated improvements in domestic innovation and technological advancement remain limited.
This study contributes to the literature by contextualising technology spillover in Serbia and identifying gaps in its realisation. It also provides a foundation for future research on the mechanisms by which FDIs influence domestic enterprise performance and national economic development.
The paper offers insights for policymakers and business leaders seeking to maximise the FDI benefits. It suggests the need for strategic policies to enhance technology transfer, support domestic R&D, and foster stronger linkages between foreign investors and local firms to accelerate economic development.

KEY WORDS
foreign direct investments, technology spillover, knowledge, technology, Serbia, EU

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Sonja Pejić
University of Novi Sad,
Trg Dositeja Obradovića 6,
21000 Novi Sad, Serbia
ORCID 0000-0002-8349-8339

Corresponding author:
e-mail: anael@uns.ac.rs

Ana Nešić Tomašević
University of Novi Sad,
Trg Dositeja Obradovića 6,
21000 Novi Sad, Serbia
ORCID 0000-0002-8386-4669
e-mail: ana.nesic@uns.ac.rs

Introduction

Foreign direct investments (FDIs) are often regarded as catalysts for economic and social development, particularly through knowledge diffusion, innovation, and technology transfer (Solow, 1956; Arrow, 1962; Romer, 1986; Stiglitz & Greenwald, 2014). In developing economies, FDIs can enhance the competitiveness of domestic firms by introducing new capital, fostering research and development, and facilitating the acquisition of managerial and technical skills. This process, also known as technology spillover, occurs through mechanisms such as intel-

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lectual property protection, labour mobility, supplier linkages, and the demonstration effect. However, empirical research suggests that FDIs do not uniformly translate into economic growth (Carkovic & Levin, 2005; Herzer et al., 2008), with horizontal spillover effects often limited (Aitken & Harrison, 1999).

The extent to which FDIs contribute to development depends on a country's ability to absorb and utilise external knowledge. Acemoglu (2014) identified four key factors influencing economic growth: geography, culture, institutions, and happiness. While geography and cultural values shape economic behaviour and social trust, institutions - laws, policies, and governance structures - are the most adaptable and play a critical role in economic reforms. Institutions determine the incentives for investment in technology and human capital, influencing a society's capacity for innovation and long-term growth.

In the context of Serbia, understanding the interplay between FDIs, technology spillover, and institutional frameworks is crucial for shaping policies that maximise economic and social benefits. This paper aims to analyse the impact of FDIs on domestic enterprises and the broader economy through knowledge diffusion, applying historical, comparative, and descriptive methods based on secondary data. Given that productivity gains stem from capital accumulation and technological progress (Stiglitz & Greenwald, 2014), this study underscores the need for institutional strategies that enhance knowledge absorption and innovation capacity in Serbia's evolving economic landscape.

This paper is structured as follows: Section 1 provides a literature review of foreign direct investments and technology transfer in Serbia. Section 2 briefly presents the research methods applied in the study. Section 3 reports the research results, emphasising R&D trends and patent activity. Section 4 discusses these findings in relation to Serbia's institutional and economic context. Finally, the conclusion summarises the key insights and provides limitations of the study, practical implications, and directions for future research.

1. Literature review

Developing countries, including Serbia, face structural constraints such as capital shortages, limited technological capacity, and gaps in engineering expertise. FDIs are often viewed as a strategic avenue to address these deficiencies and stimulate economic growth. However, the impact of FDIs remains a subject of extensive research due to their dual effects. While FDIs can enhance production, wages, employment, and technological transfer, they may also contribute to unemployment, increased market competition, and environmental degradation (Sredojević et al., 2016).

In Serbia, scholars have critically examined these dynamics. Šabić and associates (2012) found that while FDIs contributed to economic growth, their concentration in non-tradable sectors (banking, insurance, telecommunications, real estate, and retail) limited export potential and industrial productivity. Hadžić and Pavlović (2011) emphasised the importance of supporting high-growth "gazelle" companies to strengthen the competitiveness of Serbian SMEs. Lehnert, Benmamoun, and Zhao (2013) highlighted FDIs' role in fostering human capital development and technological advancement, while Narula (2012) underscored the need for sustainable financing strategies that integrate economic, environmental, and social considerations into investment decisions.

For Serbia and other developing nations, the challenge lies in maximising FDIs' developmental potential while mitigating their adverse effects. A growth model that prioritises sustainable investment - ensuring intergenerational equity and long-term economic resilience - should be a core policy objective.

Highly educated labour is increasingly recognised as a key factor in attracting FDIs, positioning education as a critical individual and societal investment. In developing countries like Serbia, however, weak linkages between higher education institutions and the labour market contribute to brain drain, as skilled professionals seek opportunities abroad. The relationship between labour and foreign investors is fundamentally investment: individuals invest in their education and skills, while investors allocate capital in anticipation of future returns.

Beugelsdijk, Smeets, and Zwinkels (2008) distinguished between vertical and horizontal FDIs, each with distinct implications for human capital formation. Vertical FDIs, driven by cost-efficiency, typically target countries with cheap labour, offering low wages that discourage further education (Zeng & Eastin, 2012). In contrast, horizontal FDIs, focused on market expansion, incentivise education by offering higher wages for skilled workers (Wang & Zhao, 2008). Serbia's FDI landscape is dominated by vertical investments, which prioritise low-cost, unskilled labour with limited opportunities for upskilling. This structural imbalance is reflected in Serbia's low proportion of highly educated workers (6.5 % per the 2011 census) and high unemployment rates among university graduates (24 %) (Pejić, 2012; Labour Force Survey, 2019). The absence of policies fostering knowledge-based job creation through FDIs exacerbates these challenges, highlighting the need for institutional reforms that align foreign investment with human capital development.

Serbia has emerged as a leader in FDIs within the region, with Russia, Kazakhstan, Azerbaijan, Turkmenistan, and Serbia accounting for 81 % of the FDI inflows in Southeast Europe and the Commonwealth of Independent States in 2017 (UNCTAD World Investment Report, 2018). Over the period from 2006 to 2017, Serbia experienced its highest FDI inflows in 2006, 2007, 2008, and 2011, followed by a downturn starting in 2012. This decline can be attributed to the global economic crisis, diminished privatisation revenues, and a lack of greenfield investments (Ignjatijević, 2015). However, FDI growth rebounded in 2017, with a 22 % increase compared to 2016, reaching a total of USD 2.9 billion. Despite this, investment in new projects fell by nearly 50 % in 2017, dropping from USD 505 million in 2016 to USD 281 million in 2017 (UNCTAD World Investment Report, 2018).

The sectoral distribution of FDIs in Serbia is notably concentrated in the automotive industry, agriculture, food and beverages, textiles, construction, electrical engineering, electronics, machinery, and furniture. The EU countries, particularly Italy, Germany, Austria, Slovenia, France, and Greece, along with the United States, remain the dominant FDI sources in Serbia. However, there has been a noticeable shift towards greater diversification, with increasing participation from investors in the Asia-Pacific and Middle East regions (Dugalić, 2017). Structural reforms, including simplified property registration procedures, streamlined building permit processes, new subsidy regulations, competitive labour costs, and access to the EU market under the Stabilisation and Association Agreement, have all contributed to making Serbia an increasingly attractive destination for foreign investment. These shifts reflect broader social and economic transformations that underscore the importance of FDIs in shaping Serbia's development trajectory within the context of regional integration and global economic shifts. Some recent studies highlighted the importance of FDIs in Serbia's economy by analysing their relationship with GDP, the unemployment rate, and the global competitiveness index (GCI), providing insights for shaping future investment and public policies (Vukmirović et al., 2020). While FDIs play a crucial role in Serbia's economic growth, their impact on innovation remains limited, as local firms primarily engage in imitation rather than novel creation, underscoring the need for stronger institutional frameworks and leadership strategies to enhance knowledge generation and long-term competitiveness (Vujanović, 2022).

2. Research methods

This study employs a comparative and descriptive methodology, relying on secondary data analysis of statistical reports, international databases, and academic research. These methods were chosen to highlight Serbia's position relative to EU countries in terms of FDI inflows, R&D investment, and patent activity, and to identify patterns of technology transfer and spillover. The analysis focuses on long-term trends (2006–2023), drawing from Statistical Yearbooks, Eurostat, UNCTAD, and related research studies.

3. Research results

Between 2018 and 2023, Serbia's foreign direct investment experienced notable fluctuations. In 2018, FDI inflows reached USD 4.12 billion. This upward trend continued, with investments totalling USD 4.27 billion in 2019 and USD 4.60 billion in 2021. In 2022, FDIs slightly increased to USD 4.61 billion, followed by a 6.06 % rise in 2023, amounting to USD 4.89 billion (Serbia Foreign Direct Investment 2007–2025).

Technological progress has been a key factor in improving living standards in the 20th and 21st centuries, with the application of scientific and technical knowledge driving economic and societal development. Knowledge is fundamental to progress, acting as both a societal goal and a meritocratic principle (Pejić & Radivojević, 2018). GDP disparities between countries are largely due to differences in technological development, innovation, and investment in research and development. FDIs are crucial for development, as they foster technology spillover. However, Miroslav Antevski suggested that such spillovers are unlikely when there is a significant technological gap between countries (Antevski, 2011).

When a spillover occurs, questions arise regarding the ownership and conditions for utilising new knowledge. Greenhalgh and Rogers identified several perspectives on innovation: (1) knowledge as a public good (Solow, 1957); (2) innovation as a private good with positive externalities; (3) innovation as uncertain and costly, potentially leading to under-investment; (4) market competition that results in redundant discoveries (Greenhalgh & Rogers, 2010). While fundamental knowledge can be a public good, innovations that threaten profits require intellectual property protection. For countries with limited capital, such as Serbia, incremental innovations - small improvements to existing processes - are more common than radical innovations, which involve entirely new products or production methods (Greenhalgh & Rogers, 2010).

For technology spillover to be successful, information about new processes or products must be transferred to potential buyers, and decisions on innovation adoption must be made to achieve market saturation. Under the influence of FDIs, local companies may be compelled to adopt more efficient technologies or face competitive pressures that threaten their survival. Foreign companies often transfer knowledge to local suppliers, raising technical standards and productivity, which can lead to vertical backward spillovers where suppliers improve productivity, as well as vertical forward spillovers where domestic firms benefit from higher quality inputs, better technical instructions, and more timely deliveries (Zildović et al., 2016). However, the success of these spillovers depends on the technological distance between countries and the absorptive capacity of the follower country (Greenhalgh & Rogers, 2010; Gerschenkron, 1962; Gugler & Vanoli, 2015).

Serbia, as a developing country, faces numerous social and systemic challenges in achieving sustainable economic growth. To attract FDIs, the government offers subsidies conditioned on the employment of a set number of workers for a minimum period, based on the investment value (Decree on establishing criteria for the allocation of incentives to attract direct investments, 2019). These subsidies cover 50 %, 60 %, and 70 % of project costs for large, medium, and small companies, respectively. Importantly, subsidies are granted based on the development level of the municipality, regardless of whether the investor is foreign or domestic. However, the government does not address the specifics of employee roles or wages, nor the extent of cooperation with the local economy. While the government expects technology spillovers, foreign investors primarily seek profit. Thus, the government must facilitate the transfer of technology and knowledge to ensure domestic businesses can benefit from foreign investments.

Research and development (R&D) activities are key indicators of a country's technological spillover capacity and its ability to absorb and apply new knowledge (Yip & McKern, 2014). A country seeking accelerated economic development must have a robust scientific and research workforce, which plays a crucial role in driving societal progress. The number of researchers in the EU-28 has steadily grown, reaching 1.88 million in 2016, i.e., 32.2 % more than in 2006. A similar trend is seen in rapidly developing non-EU countries. By 2014, China (1.52 million researchers) had surpassed the USA (1.27 million), while Turkey doubled its researcher count from 2005 to 2014. Researcher distribution correlates with country size and development level. In 2016, 49.3 % of EU researchers worked in business, 38.6 % in higher education, and 11.2 % in government. More developed EU countries have a higher share of researchers working in business, while in less developed states, they are more concentrated in academia. Leading nations include Germany (360,300), France (365,200), and the UK (259,300), followed by Spain, Italy, Sweden, the Netherlands, Poland, Austria, Switzerland, and the Czech Republic.

Serbia faces significant challenges in research and development (R&D) activities. In 2017, according to the Statistical Office of the Republic of Serbia, the distribution of R&D organisations was as follows: 38.2 % in the non-financial (business) sector, 19.3 % in the governmental sector, 39.6 % in higher education institutions, and 2.9 % in the non-profit sector (Statistical Yearbook 2018: 367). The number of researchers in R&D decreased by more than 2.4 % in 2017 compared to 2016. Despite this decline in personnel, the number of research papers increased, with 46 % classified as fundamental, 37 % as applied, and 17 % as development research. This suggests that in Serbia, research has primarily grown as an academic pursuit rather than a societal or economic necessity.

An analysis of the funding structure of research and development (R&D) in Serbia over the period 2008–2023 reveals significant changes in the relative contributions of different funding sources (Table 1). Government funds represented the dominant source of R&D financing in the early years of the observed period, peaking at 63.4 % in 2011. However, this share has gradually declined over time, reaching 37.4 % in 2021 and stabilising at around 40 % in 2023.

In contrast, the share of own funds has exhibited a general upward trend. After fluctuating between 20.86 % and 26.83 % from 2008 to 2011, own contributions increased markedly in 2012 to 33.7 %, and peaked at 45.7 % in 2021. Although a decline followed in 2023 to 28.2 %, this still represents a significant increase compared to the beginning of the period.

Enterprise funding remained relatively stable in the range of 7–9 % through 2014, with a notable increase to 12.8 % in 2015. However, this source experienced a steady decline, thereafter dropping below 1 % in 2021–2023, indicating a weakening role of the business sector in R&D investment.

The contribution of foreign funds has shown a substantial and consistent increase, particularly after 2014. From 9.03 % in 2008, foreign sources accounted for more than 19 % annually between 2017 and 2019, reaching 21.6 % in 2018 and 30.3 % by 2023 - the highest share in the observed period. This trend highlights the growing importance of international collaboration and external financing mechanisms in Serbia's R&D landscape.

Funding from non-profit institutions has remained marginal throughout the period, never exceeding 0.76 %, and registering 0.0 % in several years.

Overall, the data indicate a shift from predominantly public-sector financing toward increased reliance on own and foreign funds, alongside a declining contribution from enterprises. This transformation suggests a changing landscape of R&D funding in Serbia, shaped by both domestic policy shifts and international engagement.

In 2021, Business Enterprise Expenditure on R&D (BERD) in Serbia amounted to 0.4 % of GDP, significantly below the EU average of 1.49 % for the same year, indicating a comparatively low level of the business sector's investment in research and development relative to the national economic output (ERA Country Report 2023: Serbia). In Serbia, the largest number of researchers in R&D activities are employed in the state and higher education sectors. According to the Statistical Office of the Republic of Serbia, a total of 22,782 researchers (full-time and part-time) were employed in R&D in 2017. Of these, 14,156 were in higher education, 5,262 in the state sector, 3,340 in the non-financial sector, and 24 in the non-profit sector (Statistical Yearbook, 2018).

Despite the increase in foreign direct investments (FDIs) in Serbia, it appears that FDIs have not significantly influenced the employment of more researchers in the non-financial sector. However, there was a noticeable increase in funds from foreign clients for R&D activities between 2011 and 2017. This suggests that while FDIs have not directly boosted employment in the non-financial sector's R&D workforce, it

Tab. 1. Sources of funds for R&D in Serbia (% share)

Year	Own funds (%)	Gov. funds (%)	Enterprise funds (%)	Non-profit inst. (%)	Foreign funds (%)
2008	22.33	60.15	7.77	0.72	9.03
2009	20.86	62.87	8.33	0.76	7.18
2010	26.83	59.4	8.62	0.04	3.58
2011	21.8	63.4	9.1	0.1	5.5
2012	33.7	51.3	5.8	0.1	9.2
2013	25.1	59.5	7.5	0.0	7.8
2014	25.9	53.5	8.2	0.0	12.5
2015	24.0	50.6	12.8	0.0	12.6
2016	32.3	45.6	9.2	0.0	13.0
2017	23.5	46.6	10.0	0.0	19.9
2018	25.3	43.1	10.0	0.0	21.6
2019	25.0	45.9	9.1	0.1	19.7
2020	44.4	43.4	2.1	0.2	9.6
2021	45.7	37.4	0.5	0.1	15.9
2022	41.7	39.3	1.3	0.0	17.5
2023	28.2	40.2	0.9	0.2	30.3

Source: author's elaboration on the basis of (*Statistical Yearbooks*, 2008–2024).

has had some positive effect on funding for research and development. In 2022, Serbia reported approximately 2,350 researchers per million people (Serbia - Researchers in R&D). Serbia's R&D growth is partly driven by rising FDIs and increasing collaboration between Serbian and foreign companies, particularly in IT. Serbian IT experts are increasingly contributing to global product development. In 2018, Serbia's software exports (USD 1.198 billion) doubled its imports, surpassing transport and tourism (NBS, 2019). However, research and economic projects remain scarce, with universities focusing on basic research that attracts little FDIs. In 2017, FDIs in R&D saw only a modest net increase of USD 5.5 million.

Science and technology professionals play a key role in societal advancement. In the EU-28, 78 million people (32.1 % of the workforce) were employed in these fields in 2016. Leading countries include Luxembourg (50.9 %), Sweden (42.8 %), and Switzerland (41.6 %), while Romania (20.0 %) and Greece (20.2 %) lag behind. In Serbia, 96,800 people (3.4 % of total employment) worked in professional, scientific, and technical sectors in 2017.

As of 2022, Serbia's professional, scientific, and technical activities sector employed approximately 78,600 individuals, accounting for 3.5 % of the nation's total employment, which is not considered a significant increase compared to 2017 (Annual Bulletin 2023 - the Chamber of Commerce and Industry of Serbia).

The structure of R&D funding and the participation of personnel within the business sector in Serbia from 2008 to 2023 reveal evolving trends that reflect broader shifts in national and international engagement with industrial research and innovation (Table 2).

Throughout the observed period, own funds consistently represented the primary source of R&D financing in the business sector, peaking at 83.98 % in 2010. However, their share fluctuated in subsequent years, declining to 22.0 % by 2017, before rising again to 63.5 % in 2021 and then dropping sharply to 30.3 % in 2023. This volatility suggests varying levels of internal capacity and willingness among enterprises to invest directly in R&D activities. The contribution of government funds to business-sector R&D remained modest across the entire period, ranging from a high of 26.69 % in 2009 to a low of 2.6 % in 2011. In recent years, government funding remained below 5.5 %, highlighting the limited role of direct public investment in stimulating private-sector R&D. Enterprise funds, defined here as R&D investment sourced from other enterprises, showed modest contributions with a notable increase in 2014–2017, peaking at 27.4 % in 2015. However, in 2021–2023, their share had dropped to below 2 %, indicating reduced inter-enterprise collaboration or outsourcing in R&D investment. Foreign funding emerged as a particularly dynamic component of business R&D financing. Initially modest, foreign sources accounted for 19.1 % in 2011 and increased significantly thereafter. By 2023, foreign funds constituted 64.2 % of business R&D financing, marking a substantial shift toward international dependence and possibly reflecting increased participation in cross-border research programmes, foreign ownership, or donor-funded initiatives. The number of R&D personnel in the business sector generally increased over time, rising from 1,344 in 2008 to 5,435 in 2023. While fluctuations occurred, particularly a drop to just 517 personnel in 2011, the overall growth suggests a strengthening of human capital within the sector. When expressed as a share of total national R&D personnel, the business sector's contribution grew from 6.96 % in 2008 to 20.07 % in 2023, more than tripling over the 15-year period. This rise signals a growing institutionalisation of R&D within enterprises and reflects the gradual alignment of Serbia's innovation system with international trends, emphasising the role of the private sector.

Collectively, these trends illustrate a transition in Serbia's business R&D landscape: from one primarily self-financed and modest in scale to a more externally funded and personnel-intensive sector. Nevertheless, the still relatively low share of enterprise funds and modest government involvement point to structural challenges in building a robust, self-sustaining innovation ecosystem led by domestic industry.

Strong R&D is key to patent competition, as new products and innovations boost a company's edge. Developed countries tend to register more patents due to their robust R&D, but many firms keep innovations as trade secrets to avoid exposing them to competitors. Patent competition arises when two firms develop the same solution, and the profits go to the first to patent and market it. Innovation success depends on R&D investment, geography, and technology spillover, which enhances firms' ability to innovate (Cincera, 1997; Jaffe, 1986).

Technology spillover occurs in two forms: competitive, where firms in the same field compete to patent first, and diffusion, where one company's research benefits another. Measuring spillover

Tab. 2. R&D funding and personnel in the business sector in Serbia (2008–2023)

Year	Own funds (%)	Gov. funds (%)	Enterprise funds (%)	Foreign funds (%)	R&D personnel (business sector)	Total R&D personnel	Business sector share (%)
2008	72.63	12.34	6.05	7.57	1344	19321	6.96
2009	57.84	26.69	10.36	4.4	2052	20087	10.22
2010	83.98	9.66	4.23	2.07	1193	19341	6.17
2011	67.5	2.6	10.6	19.1	517	19742	2.62
2012	74.5	2.7	1.5	21.3	776	19646	3.95
2013	63.8	11.6	4.8	19.7	1121	21044	5.33
2014	37.1	11.6	19.8	31.4	3182	21880	14.54
2015	31.6	9.0	27.4	31.9	3334	23629	14.11
2016	41.7	7.3	22.4	28.6	3849	23542	16.35
2017	22.0	7.0	25.2	45.8	3340	22782	14.66
2021	63.5	5.3	0.6	30.7	3735	23977	15.58
2022	61.0	4.1	1.7	33.2	4056	24838	16.33
2023	30.3	4.5	0.9	64.2	5435	27078	20.07

Source: author's elaboration on the basis of (*Statistical Yearbooks*, 2008–2024).

involves tracking innovation transfer via patent activity and citations (Verspagen, 1997; Leoncini & Montresor, 2003). Studies show foreign patents are frequently cited, suggesting they drive domestic innovation (Malebra et al., 2007).

According to data from the European Patent Office, Germany led the EU-28 in patent applications in 2018, with 26,734, followed by France (10,317), the Netherlands (7,140), and Great Britain (5,736) (European Patent Application 2009–2018 per Country of Residence of the Applicant, 2019). In terms of R&D investment, Germany allocated 2.9 % of its GDP (approximately USD 109.56 billion), France had 2.3 % (USD 60.59 billion), the Netherlands had 2 % (USD 16.4 billion), and Great Britain followed with 1.7 % (USD 43.81 billion). Serbia, by comparison, invested only 0.9 % of its GDP in R&D activities (Global Innovation Index, 2018). This disparity in R&D spending is closely linked to a country's success in patent creation and innovation.

A significant portion of R&D spending in developed countries is directed towards the business sector, which is crucial for successful innovation. For instance, in 2018, the top 20 patent applicants globally included major corporations such as Siemens, Huawei, Samsung, LG, and others, reflecting the high level of investment and innovation within these businesses (Top 100 Applicants, 2018, 2019).

Serbia, however, invests minimally in R&D within the business sector, which highlights the country's reliance on technology spillover for potential economic growth. Patent activity in Serbia is limited, with data from the European Patent Office indicating only nine patents from Serbia that were registered in the EU in 2018. This has been a consistent trend, with the exception of a dramatic dip in 2016, where only one patent was registered. These patents, classified in fields of chemistry, mechanical engineering, and civil engineering, are few compared to those of more developed nations.

National patent registrations in Serbia are also low and show minimal yearly variation (Statistika - Patenti, 2019). When compared to FDI trends, there is no significant correlation between increased FDIs and a rise in national patent applications. However, Serbia has seen a higher number of extended European patents, suggesting that foreign companies are more inclined to protect their intellectual property in Serbia than to engage in technology spillover. Unfortunately, due to the lack of detailed data on the sectoral distribution, exploitation, and citation of patents, it is difficult to ascertain the true impact of spillover from foreign patents in Serbia. Between 2019 and 2023, Serbia experienced fluctuations in the number of patent applications filed by residents. In 2019, there were 23 patent grants, marking a 23.3 % decrease from the previous year. The total number of patents in force during that period was approximately 9,000, positioning Serbia 56th globally (Intellectual property statistics - Serbia).

4. Discussion of the results

The potential for foreign investment spillovers in Serbia is influenced by key factors such as the absorptive capacity of national firms and the institutional framework of the host country (Farole & Winkler, 2015). While empirical studies have generally identified technology spillovers as a primary benefit of FDIs, the actual effects vary across countries. Ideally, spillovers enable the recipient country to match the growth rates of the investing country, but formal models suggest that GDP per capita convergence is unlikely, meaning the recipient's growth, though aligned, will not reach the same level (Greenhalgh & Rogers, 2010).

In Serbia, Stojanović (2018) found a strong positive relationship between FDI and GDP growth, with a correlation coefficient of 0.732. Despite this, Serbia faces several obstacles that hinder the full exploitation of FDIs' potential, including insufficient investment in R&D, a lack of R&D teams within foreign companies, limited labour mobility, and low patent activity. Additionally, the absorptive capacity of Serbian firms remains limited, preventing them from fully leveraging external knowledge and technology. The productivity gap between domestic and foreign firms is exacerbated by macroeconomic instability, financing challenges, non-performing loans, and weak corporate governance (Zildović et al., 2016).

To overcome these challenges, investing in education and R&D within the business sector, while fostering stronger collaboration between academic institutions and economically significant projects, is vital for Serbia's long-term development. Akin and Vlad (2011) supported this approach by using the Zhang-Markusen (ZM) theory to demonstrate the relationship between education and FDIs. The ZM theory suggests an inverted U-shaped relationship between FDIs and human capital, where countries with low income and human capital are less successful in attracting FDIs. Multinational companies (MNCs) prioritise skilled workers over low wages, recognising the importance of expertise and skills in modern business operations (Šabić et al., 2012). Akin and Vlad's findings affirm that FDIs are significantly higher in countries with higher levels of education, particularly in middle-income nations.

Serbia's long-term economic growth and competitiveness require institutional reforms that enhance the collaboration between education, domestic firms, and foreign investors to stimulate R&D and innovation. While FDIs improve technological efficiency, their impact varies across industries, necessitating targeted policies and strategic leadership to foster knowledge creation and ensure sustainable integration into the EU (Nikolić, 2021).

Conclusions

Serbia's experience with foreign direct investments (FDIs) reveals a complex dynamic between economic growth, technology transfer, and structural limitations. While often seen as a catalyst for development, FDIs' impact is neither automatic nor evenly distributed. Serbia has yet to fully capitalise on its potential for sustainable technological progress (Voica et al., 2015).

Limited technology spillover stems not just from policy gaps but also from structural constraints like weak institutions, labour market imbalances, and low R&D investment. The dominance of vertical FDIs reinforces Serbia's reliance on foreign capital without fostering local innovation, mirroring global economic inequalities. Also, it is crucial to highlight the critical role of managerial styles in overcoming structural barriers, fostering innovation, and driving sustainable development, whether in leveraging FDIs for economic transformation in Serbia or enhancing organisational performance (Nešić Tomašević et al., 2025).

Weak ties between universities, domestic firms, and multinational corporations fuel brain drain, depriving Serbia of skilled talent and deepening social disparities. To move beyond passive reliance on foreign capital, Serbia must enhance its capacity for technology absorption through institutional reforms, stronger R&D investment, and policies favouring knowledge-based industries. Also, to move beyond low-cost production, Serbia must foster education-industry linkages, support SMEs in high-tech sectors, and leverage regional trade agreements like the Open Balkan initiative to enhance knowledge spillovers. Ultimately, Serbia's ability to harness FDIs for lasting progress depends on aligning investment with domestic capacity-building. A more integrated approach - linking economic policy with social development - is key to ensuring that technological growth benefits society as a whole.

While FDIs bring advanced technology, their influence varies across sectors. Knowledge spillovers are strongest where local firms can integrate foreign innovations. In Serbia, industries like ICT and automotive manufacturing have benefited from technology transfer, whereas traditional sectors lag due to weaker linkages with foreign firms. Strengthening these connections through policy support is essential for maximising FDIs' transformative potential. However, the geopolitical dimension of FDI inflows should not be overlooked. The increasing role of Chinese investments in infrastructure projects presents an alternative model of technology transfer that diverges from Western European norms. This dynamic poses both opportunities and risks, requiring further exploration into whether Serbia's technological development trajectory is aligned with long-term economic diversification goals.

Despite the advantages FDIs offer, they remain concentrated in labour-intensive industries, leading to a dual labour market where foreign firms provide high-tech employment opportunities while domestic enterprises struggle with low productivity. Serbia's low wages make it an attractive destination for investors, yet they may also hinder long-term development if wage stagnation discourages innovation. Experiences from economies such as South Korea and the Czech Republic highlight the importance of aligning FDIs with human capital development to ensure sustainable growth.

While Serbia has made progress in improving its investment climate, challenges persist in areas such as contract enforcement, intellectual property protection, and bureaucratic inefficiencies. Additionally, the country's geopolitical position plays a significant role in shaping FDI patterns, with competing interests from EU, Chinese, and Russian investors influencing its economic strategy. Successfully balancing these external influences while aligning with EU integration goals is essential for securing stable, long-term investment.

By addressing these issues, this study aims to refine the understanding of the FDIs' role in Serbia, ensuring a more nuanced assessment of its developmental impact. FDIs have fuelled Serbia's growth; however, the country's long-term success depends on strengthening domestic innovation, addressing sectoral imbalances, and refining investment policies. A strategic shift toward an innovation-based economic model will be essential for sustaining development beyond foreign capital inflows.

This study is limited by its reliance on secondary data sources, including statistical yearbooks, international databases, and published research. While these provide valuable insights into long-term trends, they do not allow for detailed analysis of sector-specific or firm-level spillover effects. In addition, the limited availability of patent data restricts the assessment of innovation diffusion in Serbia. Establishing a clear causal link between foreign direct investment and domestic technological advancement is, therefore, difficult without micro-level, longitudinal evidence. The findings highlight the need for stronger institutional frameworks that support knowledge absorption and innovation in Serbia. Policymakers should prioritise building closer ties between universities, domestic enterprises, and foreign investors to enhance technology transfer. Practical steps that could significantly improve the developmental impact of FDIs include supporting SMEs in high-tech sectors, aligning education and labour market policies to reduce brain drain, and encouraging multinational companies to engage in collaborative R&D activities.

Further research should focus on firm-level analyses of how foreign and domestic enterprises interact in Serbia, particularly in sectors where technology spillovers are most likely to occur. Comparative studies with other emerging economies could help to benchmark Serbia's performance and identify best practices. In addition, the growing role of Chinese and other non-EU investors warrants closer investigation to understand how different FDI models influence Serbia's long-term technological and economic trajectory.

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