Published by the Centre of Sociological Research, Poland

ISSN: 1795-6889

Human TECHNOLOGY

Volume 21, Number 3, December 2025

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Editors in Chief

https://ht.csr-pub.eu/

Human
TECHNOLOGY

Volume 21, Number 3, December 2025

DOI: https://doi.org/10.14254/1795-6889.2025.21-3

Contents

ISSN: 1795-6889
https://ht.csr-pub.eu/

Submission: https://ht.csr-pub.eu/index.php/ht/about/submissions

Human Technology is an interdisciplinary, scholarly journal publishing innovative, peer-reviewed articles exploring the issues and challenges within human–technology interaction and the human role in all areas of ICT-infused societies.

Human Technology, published by the Centre of Sociological Research, Poland, is distributed without a charge online.

Human
TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 21(3), December 2025, 469–473

ECOLOGICAL AND SECURE ELECTRICITY MICROGRIDS - MONITORING AND FORECASTING CHALLENGES

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Abstract: *Reliable, low-carbon power systems depend on high-granularity, short-horizon forecasting, especially within islandable microgrids where consumers and prosumers shape real-time balance. Ultra-short-term (15-minute) forecasts support storage scheduling, demand response, and secure operation amid renewable intermittency and growing cyber risk. Forecasting approaches are classified into black-box, gray-box, and white-box methods, highlighting trade-offs in accuracy, explainability, and deployability. Operational use-cases are aligned with forecasting time scales, and current literature shows notable gaps: limited 15-minute multi-step studies, inconsistent evaluation protocols, insufficient attention to explainability, and restricted access to representative datasets. Design principles are outlined for deployable forecasting and control: standardised metrics and horizons, privacy-preserving data pipelines, explainability-first modelling, and transferable domain-specific hyperparameters. Addressing these gaps can increase renewable penetration, lower imbalance costs, strengthen cybersecurity compliance, and enhance resilience, delivering cleaner energy at reduced cost with higher quality of service. Researchers who want to support effective energy management technologies with their research should be aware of the current challenges.*

Keywords: *energy, anomaly detection, forecast, modelling, microgrids, cybersecurity*

DOI: https://doi.org/10.14254/1795-6889.2024.21-3.0

INTRODUCTION

Problem Statement

Electricity has become a critical resource with profound effects on economic growth and household living costs. Rising demand, combined with the imperative to reduce greenhouse gas emissions, has driven a steady expansion of renewable generation. Yet renewables are inherently intermittent because output depends heavily on weather and other exogenous factors. At the same time, the threat of cyberattacks on energy infrastructure is increasing, making secure and efficient system operation particularly challenging. Climate policy has introduced a range of regulations that influence both energy prices and the composition of generation (the energy mix). The tight coupling between weather-dependent renewables and traditional thermal sources, whose ramping capabilities are limited, creates persistent difficulties in balancing supply and demand across time and location. These pressures heighten the need for grid flexibility, including storage, demand response, and high-resolution forecasting, so that operators can anticipate short-term fluctuations and maintain reliability at reasonable cost.

The balance of supply and demand in a country-level power system ultimately aggregates the behavior of individual consumers and prosumers, yet it shapes the entire delivery chain. Effective microgrid management, ideally with the capability to operate in islanded (off-grid) mode when needed, can reduce the need for macro-scale interventions by absorbing local disturbances. Such off-grid operation demands agile, data-driven adjustments to both supply and demand, which in practice are only feasible with high-quality operational forecasting and planning. Management efficiency enabled by forecasting is reflected both in a higher feasible share of renewable generation and in the avoidance of critical events (overloads, voltage excursions, unserved energy). Importantly, different prediction horizons serve different purposes: second-to-minute horizons support protection and fast controls; 15-minute to intraday horizons enable dispatch, storage scheduling, and demand response; day-ahead and multi-day horizons inform procurement, maintenance, and market participation. In all cases, short- and medium-term, high-granularity forecasts are the backbone of reliable control and automation.

Accurate energy-consumption forecasting has operational, financial, and technological implications. On the operational side, it underpins continuity of service and system stability by aligning demand with available supply and flexibility resources. Financially, it improves procurement and bidding, reduces imbalance penalties, and guides investment in storage and efficiency. Technologically, it enables process control, grid diagnostics (e.g., anomaly detection that affects system stability), and quantification of energy-saving potential. Together, these capabilities translate directly into cost reduction while enhancing security and resilience of national power systems (Vasylieva et al., 2025; Mukhtarov et al., 2023).

Energy forecasts approaches

While long-term forecasts are adequate for strategic planning, short-term forecasts pose tactical challenges and are essential for stable system operation. For example, in April 2025 the Iberian Peninsula experienced a blackout linked to a local imbalance in an already overloaded grid, an event that underscores the critical role of timely, high-resolution forecasting.

Forecasting models are commonly grouped into three categories:

- Black-box models: classic top-down approaches that use only inputs and outputs to learn system behaviour.
- Gray-box models: systems are decomposed into logically separate components (e.g., PV, HVAC), each treated as a black box but differentiated at component level.
- White-box models: bottom-up, physics-based approaches that build detailed component models and aggregate them into a system representation.

A well-known paradox is that white-box models, while invaluable at the design stage, often diverge from operational reality due to construction tolerances, ageing, maintenance practices, and unforeseen interactions. Black-box models therefore dominate operations because they require little prior knowledge; however, the trade-off is reduced explainability and potentially limited accuracy outside the training domain. Against this backdrop, gray-box methods strike a pragmatic middle ground, offering manageable complexity with improved interpretability and reliability.

System scale matters: forecasting a single building is difficult due to non-stationary and highly variable demand patterns. Aggregation at city or metropolitan scales yields smoother, more cyclic trends - but large interconnected grids can be vulnerable to cascading effects triggered by local disturbances. This makes stability at the level of islandable microgrids (off-grids) especially important: local stability supports global stability.

These considerations highlight the need for ultra-short-term operational forecasting, predicting demand and supply shifts before they escalate into widespread disruptions. Such forecasts are foundational for real-time IT/OT operations (SCADA/EMS/DMS). The literature typically classifies time horizons as: (i) ultra-short-term/operational: minutes to tens of minutes, (ii) short-term: one hour to one week, (iii) medium-term: one week to one year, (iv) long-term: beyond one year.

Granularity is equally important: operational decisions are often taken at intervals of a few to several minutes. Despite widespread minute-level metering and settlement in 15-minute blocks across much of Europe, there is a shortage of studies that actually forecast at 15-minute resolution or that push multi-step forecasts 2, 12, or 24 hours ahead at that granularity (e.g., Somu et al., 2021). Most research still targets hourly (or coarser) horizons and sampling (e.g., Olu-Ajay et al., 2023; Demir & Gunal, 2025). Short-term and operational forecasts underpin demand management and storage scheduling. Regional systems and microgrids - particularly those serving large consumers such as hotels, public buildings, and industrial facilities - depend on operational planning for stability (Klyuev et al., 2022). Exogenous drivers are critical: common predictors include calendar/time features, building operations, macroeconomic indicators, occupancy, building parameters, weather, and historical consumption. Weather variables appear in about 80% of studies, while occupancy features are considered in roughly 20% and others even less frequently (Olu-Ajay et al., 2023). Incorporating space-use signals (e.g., motion detectors) can materially improve operational forecasts by capturing real utilisation patterns.

Prediction reliability and explainability are increasingly important amid rising cybersecurity requirements. The EU’s NIS 2 Directive (European Parliament & Council, 2022) mandates robust monitoring and incident reporting, including anomaly detection, while the

Cyber Resilience Act (European Commission, 2023) obliges manufacturers to ensure cybersecurity across the product lifecycle. Reliable operational forecasting enhances observability and risk mitigation, supporting compliance. Nevertheless, few academic studies explicitly address these regulatory dimensions.

Model transparency and robustness also matter in practice. Deep neural networks, though powerful, can lack explainability, complicating causal interpretation and operator trust. A viable alternative is decomposition with interpretable models (gray-box): separate, instrumented models for air-handling units, heat pumps, thermal loops, machinery, and other subsystems. In parallel, classical machine-learning methods, e.g., decision trees and random forests, offer greater transparency, lower resource requirements, and improved robustness to adversarial risks (e.g., poisoned data, tampered models). Explainability is a prerequisite for safe autonomous control, and without it, confidence in automated decision-making will remain limited.

Methodological consistency and data availability. The literature varies widely in datasets, treatment of time-series structure, and evaluation metrics. Although MAE, MAPE, MSE, RMSE, and R^2 are common, they are often used in isolation without domain-aware interpretation. Normalised measures (e.g., N-MSE, N-RMSE) offer a path toward comparability but remain underused. Data scarcity is another constraint: even popular repositories (e.g., Kaggle) lack representative, comprehensive datasets for benchmarking. Sparse or fragmented data encourages overfitting and weak generalisation. Because energy data are strategic - and, in the context of ongoing hybrid warfare in Eastern Europe, unlikely to be broadly shared - there is a need for universal, adaptable control frameworks that can be rapidly tailored to specific microgrids without disclosing sensitive datasets. It is also worth defining domain-specific hyperparameters and protocols that standardise model configuration, measurement granularity, and evaluation, enabling fair comparison and safer deployment prior to real-world operation.

CONCLUSIONS

Scientific work on electricity monitoring and modelling is strategically important, particularly in the current geopolitical context, because reliable energy systems underpin the functioning of entire societies and economies. Despite notable progress, critical gaps remain, especially in ultra-short-term, high-granularity forecasting; reproducible evaluation protocols; explainability; and access to secure, representative datasets.

Meeting these challenges requires more than algorithmic advances. It calls for regulatory harmonisation, rigorous and transparent methodology (including standardised metrics and time-scale definitions), and trustworthy data pipelines that protect confidentiality while enabling learning, e.g., through privacy-preserving or federated approaches. At the system level, a balance between black-box performance and gray/white-box interpretability is essential to support operator trust, cybersecurity, and safe automation.

By closing these gaps, the community can deliver technologies that increase grid resilience, raise the feasible share of renewables, and lower operational and capital costs. The payoff is significant: cleaner energy, reduced volatility, and tangible improvements in quality of life.

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Authors' Note

The author (Y. Bilan) express their gratitude to the project titled "Cluster for innovative energy" in the frame of the program "HORIZON-MSCA-2022-SE-01" under the Grant agreement number 101129820

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 21(3), December 2025, 474–510

NEUROSOCIOLOGICAL PERSPECTIVES ON VIDEO GAMES: A NARRATIVE REVIEW

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Abstract: *This research explores the neurosociological dimensions of video games, focusing on their evolution, social impact, and neurological effects. Using a narrative review, we first examine their progression from playful activities to digital and connected experiences. We assess potential risks such as youth vulnerability, excessive screen time, lack of physical presence, gaming disorder, and aggressiveness. Conversely, we highlight positive aspects, including self-expansion, social play, flow states, excitement and relaxation, neurophysiological and psychological effects, and mental health applications. We further analyze gaming's role in socialization, high-stimulation environments, disembodied interactions, and as a source of fun in modern society. Finally, we synthesize these themes through three key perspectives: the allure of screen flow among youth; the balance between digital and physical play for healthy development; and the importance of understanding both the risks and benefits of video games. This study frames video games as a cultural and cognitive technological force shaping human development.*

Keywords: *video games, gaming, neurosociology, mental health, digital society, culture*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.1

INTRODUCTION

Here, we investigate the flourishing field of neurosociology to explore the interplay between the brain and culture in analyzing the social phenomenon of video gaming.

The Nexus of Two Sciences: A Neurosociological Perspective

Neurosociology highlights the interaction between neurosciences and sociology, showing how social experiences shape neuroplasticity and influence neural processes (Kalkhoff et al., 2016; Tang & Tang, 2015). Neurosociology operates on two levels: micro, focusing on brain functions during interpersonal dynamics; and macro, involving collective frameworks like ideologies and class awareness (TenHouten et al., 2023). The emerging field exploring the social and cultural dimensions of neuroscience offers valuable insights into how societies differ in their value systems and the underlying mechanisms that drive these differences (Shkurko, 2024). Neurosociology bridges neuroscience's experiments with sociology's field research on sociocultural phenomena (Lende et al., 2021). Neuroscientific tools like functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) analyze brain function (Dong et al., 2018), while sociological methods (e.g., surveys, interviews, and ethnography) examine the impact of social factors on behavior (Pearce, 2012). In neurosociology, innovative methods like hyperscanning measure brain activity (e.g., EEG) during real-time multiple social interactions (Czeszumski et al., 2020; TenHouten et al., 2023), virtual reality (VR) creates environments for behavior studies (Auriemma, 2023), and neurostimulation modulates brain activity to examine social cognition (Bell & DeWall, 2018). Video games also simulate social interactions in controlled research settings (Kourtesis et al., 2020; Parsons, 2015).

Thus, we aim to examine, through a neurosociological lens, how the social phenomenon of video gaming influences and is influenced by the brain and how it shapes and is shaped by culture and society.

Social Phenomenon of Video Gaming

Social phenomena encompass collective behaviors and interactions among individuals, forming key events for scientific analysis (Sampaio & Andery, 2010). The social phenomena of video games involve examining behaviors that both shape and are shaped by video games. With the advancement in digital culture, analog games have been transformed into digital formats, particularly video games (Esposito, 2005). Human development has been mediated by the new digital media (Kyshtymova & Skorova, 2024), and modern leisure now includes the integration of digital gaming into daily life worldwide (Muriel & Crawford, 2018). By 2022, video gaming reached nearly 3.2 billion players globally, with the majority in Asia, followed by regions such as the Middle East, Africa, Europe, Latin America, and North America (Newzoo, 2023). A North American study found the average gamer age to be 33, with three-quarters under 44, and players spending an average of 13 hours per week gaming (Entertainment Software Association, 2022). As video games have become central to modern culture, understanding their impact on the brain and society is crucial, and the focus of this research.

THE TRANSFORMATION OF GAMES

Games differ from other forms of play (Caillois, 2001) and have evolved into video games through digitalization (Esposito, 2005) and connectedness (Wijman, 2018).

Playful Activities

Discussion of games dates back to 1938 with historian Johan Huizinga, who emphasized the significance of play in human civilizations and its ludic role in fostering voluntary joy (Huizinga, 1980; Şentuna & Kanbur, 2016). However, Huizinga blurred the lines between play and games, a distinction later clarified by Roger Caillois (Caillois, 2001; Encheva et al., 2023). Caillois categorized play into two types: "paidia," which is spontaneous and imaginative (e.g., doll play), and "ludus," which involves disciplined, rule-governed activities (e.g., board games).

From a contemporary perspective, despite efforts to define games, their growing diversity in type and context has made them more complex (Arjoranta, 2019). A review of over 60 game definitions highlighted recurring themes like rules, purpose, separation from reality, interconnectedness, player engagement, competition, and goals (Stenros, 2017). However, one simplified definition from a game designer describes games as playful activities occurring in a pretended ludic reality, where participants aim to achieve nontrivial goals by following rules (Adams, 2014).

Digitalization

Advances in digital culture and audiovisual technology transformed analog games into digital formats, notably video games (Esposito, 2005). With technological growth and video game commercialization, the gaming industry has evolved rapidly. The debut of Pong in 1972 and Space Invaders in 1979 signaled the rise of video games (McKernan, 2013). As technology evolved, new forms of leisure emerged, including television, radio, personal computers (PCs), gaming consoles, and later smartphones and tablets (Pizzo, 2023). Video games emerged, leading to the "ludification" of culture, where gaming surpassed traditional film and music industries (Carvalho & Coelho, 2022; Raessens, 2006). However, video games have not always been the same.

Before the mid-2000s, gaming was mainly offline, played solo or in local multiplayer on consoles and computers, but the rise of online play and open-world gaming in the mid-2000s allowed people to connect with both friends and strangers in virtual environments (Dale & Shawn Green, 2017). Initially, gaming sessions were confined to leisure time and space, separated from social obligations like work or school (Brooks et al., 2016). Old portable consoles, like Gameboy, allowed gaming mobility but were rarely used in structured settings like schools (Angell, 1998). A Brazilian study revealed that 67% of youth aged 12-15 played in LAN (Local area network) houses (i.e., connected computers within a localized area, typically sharing a central internet connection), but the spread of broadband internet and smartphones eventually shifted gaming to home and mobile environments (Trammel, 2019). Post-2000s, fast internet, and smartphones reshaped global digital consumption and behavior (Naughton, 2016).

Connectedness

After the 2000s, online video games gained widespread popularity, and by 2012, some markets, such as the Japanese online game market, surpassed traditional home video games (Koizumi, 2016). Still, according to the gaming research, by 2014, online games captured 64% of Japan's total video game market, reaching $5.527 million, while conventional games remained at $3.112 million. Players could now connect with virtual friends or strangers online, without needing in-person interactions (Lou et al., 2019).

Fast internet allowed global connectivity, while smartphones and tablets expanded this by enabling gaming anywhere, anytime (S. Choi, 2016). Unlike gaming on consoles or computers, which required specific locations, smartphones made gaming more mobile. By 2018, mobile video games had become the top segment in the gaming industry, reflecting a market shift (Wijman, 2018). While portable consoles focused solely on gaming, smartphones performed multiple functions, like communication and media consumption, alongside gaming (Hjorth & Richardson, 2017; McCrea, 2011). By 2023, nearly 7 billion smartphones were in use globally (Ericsson, 2023), highlighting their integration into daily life. Mobile gaming, though not replacing PC or console gaming, complements it (Cai et al., 2022). The spread of smartphones and the fast internet allowed people to game anytime, anywhere, whether solo or with others worldwide, blurring the distinction between leisure and responsibilities, like work (Pink et al., 2018) and school (Allaby & Shannon, 2020). Figure 1 summarizes this section.

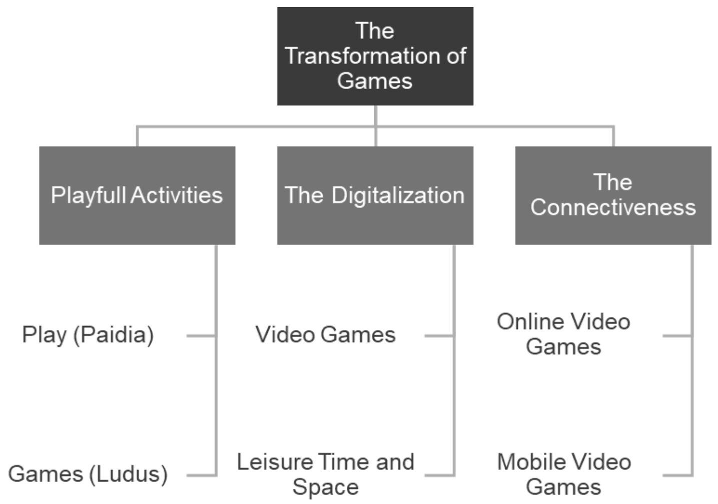

Figure 1: The Transformation of Games

THE DARK SIDE OF GAMING

Video games can pose risks to neurodevelopment and society, particularly through problematic behaviors like addiction, with children and adolescents being especially vulnerable due to their ongoing brain development (Darvesh et al., 2020; Marzola et al., 2023).

The Generation of Virtual Bonds and Human Gaps

In today's fast-paced world, technology and digital environments deeply shape culture. Cyberculture, driven by digital technology and internet use, erases traditional boundaries between individuals, communities, and information, fostering creativity and new social structures within cyberspace (Lévy, 2001). Virtual environments, like social media and video games, facilitate globalized interactions, integrating diverse cultures into daily life and forming a global cultural structure (Durmus, 2021). The spectacle society highlights media and consumer culture's influence, where life becomes appearance (Debord, 2021). This blurring of physical and virtual realms expands entertainment (Davies & Innocent, 2017). Hypersociety theory points to digital connectivity's transformative impact, keeping people constantly connected yet disconnected from true human interactions (Castells, 2011). Screen use has shifted communication from face-to-face bonding to mediated exchanges via technologies like smartphones (Ball et al., 2019). Video games blend spectacle and cyberculture, immersing players, such as children and adolescents, in immersive screen experiences.

Youth Vulnerability in a Digital Age

Neurodevelopment is a highly orchestrated process during which the nervous system forms complex networks of neurons and synaptic connections through the interplay of genetic programming and environmental stimuli (Chakraborty et al., 2021). Neuroplasticity is the nervous system's natural response to environmental changes, enabling the functional restructuring of nerve cells and forming new, stable neural connections (Spytska, 2024). Neuroplasticity is crucial during childhood and adolescence (Lende et al., 2021). While neuroplasticity remains present in adulthood, it is most malleable during early developmental windows, shaping cognitive, motor, and sensory functions, and is significantly influenced by external experiences that can either strengthen or prune neural pathways (Chakraborty et al., 2021; Marzola et al., 2023). As individuals age, neuroplasticity declines, as neuroplasticity is tightly controlled by cellular and molecular processes, which tend to decline over time (Voss et al., 2017). During childhood and adolescence, socialization plays a significant role in shaping cultural identity by instilling societal norms and values (Checkel, 2017). Media and information and communication technologies (ICT) now mediate socialization, creating environments where individuals engage in work, school, leisure, and communication (Kellner, 2004, 2020). Technological advances have brought about new cyberspaces, reshaping culture and centralizing information control (Kellner & Share, 2019), and video games, as a form of media and activity within ICT environments, serve as mediators of culture

The industry uses these games for surveillance, gathering player data for behavioral insights, and monetization (Deleuze, 2017). Video games, seen as cultural artifacts, reflect this consumer data-driven approach (Švelch, 2022). These games, while offering joy or escape, often create an illusion of freedom, as players may have the freedom to make decisions within a game, but only within the constraints of a system deliberately designed by the industry. In a postmodern context, capitalism fuels consumerism and globalization (Harvey, 2020). Hyperconsumption fuels a relentless pursuit of material goods and experiences for fleeting happiness, ultimately leading to dissatisfaction (Lipovetsky, 2009; Lipovetsky et al., 2002). The video game industry, like many others, is thus driven by consumer data to maximize revenue through fleeting pleasures (Marchand & Hennig-Thurau, 2013). This poses a potential societal risk for youth, whose habits developed during this key period of neuroplasticity may lead to addiction or harmful behaviors (Kim et al., 2022).

Screen Time and Video Gaming

Excessive video game use leads to increased screen time, raising mental health concerns. Studies show that extended screen exposure at age two can harm neurodevelopment (Sugiyama et al., 2023). Both the American Academy of Pediatrics (AAP) and the World Health Organization (WHO) recommend limiting screen time to one hour per day for 2-5-year-olds (McArthur et al., 2022). Meanwhile, the Australian Government recommends a maximum of two hours of recreational screen time daily for young people aged 5–17 years, excluding school-related activities (Joshi & Hinkley, 2021). However, 3–6-year-old children now average almost four hours daily on screens, including TVs, phones, and computers (Konca, 2022). For children aged 8-12, screen time often exceeds five hours daily (Nagata et al., 2022). Adolescents aged 17-18 average six hours per day (Twenge et al., 2019). A Canadian study of nearly 30,000 adolescents, averaging 14.9 years old, found that from 2019 to 2022, daily screen time increased by 129 minutes, rising from 320 minutes (5.3 hours) to 449 minutes (7.5 hours), with adolescents in 2022 spending almost equal time on screens as they did sleeping (Poirier et al., 2024). Research shows players spend an average of 13 hours per week gaming, with 70% playing on smartphones (Entertainment Software Association, 2022). Over 90% of children aged two and older play video games, with 75% of American households owning a console, and children aged 8-17 spend around 1.5 to 2 hours per day gaming (Alanko, 2023). Boys typically spend more time than girls playing video games, especially on consoles or computers, while girls engage more with social media (Leonhardt & Overå, 2021).

A Swedish study linked high smartphone screen time (over 4 hours daily) with increased mental health problems in adolescents, while TV and computer screen time showed no significant impact (Lundin-Emanuelsson, 2021). This suggests that smartphones, which allow constant content consumption, contribute more to mental health issues. The International Classification of Diseases (ICD-11) recognizes both online and offline video games as potential sources of gaming disorder (Paschke et al., 2020), while the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) highlights only the risks of online gaming (Luo et al., 2022), emphasizing how the proliferation of smartphones and the internet (Ericsson, 2023) has led to increased concerns.

Diminished Physical Presence and Dark Participation

In today's digital society, long parental work hours push children toward digital escapes, fostering family-work conflicts and digital abuse behaviors, while leisure activities may offer essential breaks from screens, providing face-to-face interactions (Abreu, 2022). Digital media serves as a modern pacifier for young children, with parents using screen time as a coping strategy to alleviate parenting stress (Brauchli et al., 2024). In today's stressful society, people turn to the comfort of digital media, and parents often rely on digital babysitters to entertain their children (Abreu, 2023; Bar Lev et al., 2018). Free play supports socio-emotional, cognitive, linguistic, and self-regulation skills, aiding stress management and healthy development (Yogman et al., 2018). Leisure activities like outdoor walking and conversation also positively impact mental health (Weng & Chiang, 2014). However, youth now prioritize digital media, including video games and social media, over nature-based play (Larson et al., 2019). A study highlights a generational decline in children's connection to nature, replaced by a preference for digital media, and this shift from physical to virtual experiences has reduced free play and led to more sedentary lifestyles (R. C. Edwards & Larson, 2020). The transition to smartphones has further diminished genuine social connections, fostering self-alienation and constant consumption (Harmon & Duffy, 2022). Additionally, dark participation (i.e., toxic online behaviors like harassment and fake news) is rampant in gaming environments, with over half of gamers experiencing harassment (Kowert, 2020). A study even found that online gaming is viewed as more toxic than social media, posing risks, particularly for minors (Alanko, 2023; Cook et al., 2023).

The Gaming Generation Grows Up

A 12-year longitudinal analysis of individuals from ages 6 to 18 revealed that those raised in pro-environmental contexts were more likely to engage in similar behaviors as adults, illustrating how childhood socialization influences later adult behavior (G. W. Evans et al., 2018). Similarly, due to socialization, those raised in highly digital environments, marked by extensive screen time and video games, may display similar behaviors in adulthood, seeking more digitized experiences (Yun, 2023). Video games popularly surged in the 1980s (McKernan, 2013), potentially influencing those born during or after. This helps explain why nearly three-quarters of U.S. players are under 44, with an average age of 33 (Entertainment Software Association, 2022). As these generations mature, video games may drive the gaming industry and cultural "ludification" from leisure (Carvalho & Coelho, 2022; Raessens, 2006), extending different formats (e.g., serious games and gamification) into education (Coelho et al., 2024; Coelho, Rando, et al., 2025; Sailer & Homner, 2020), work (Coelho & Abreu, 2023), and healthcare (Coelho, Gonçalves, et al., 2025; Damaševičius et al., 2023). In today’s hyperconnected world (Castells, 2011), digital habits have become global, and it is crucial to understand the risks of excessive childhood gaming for the generation born into video games.

Pathological Behaviors

The constant pursuit of digital excitement, like video games, can become habitual and potentially lead to health issues such as addiction and gaming disorder (Darvesh et al., 2020), together with increased stress and aggressive behavior (Mitsea et al., 2023).

Addiction and Gaming Disorder

While video games often provide fleeting pleasure, they can also pose risks of addiction, as during gameplay, brain regions such as the ventral striatum, nucleus accumbens, and cingulate cortex activate, correlating with habit and reward-related behavior, similar to addiction patterns (Benady-Chorney et al., 2018, 2020; Koepp et al., 1998). Gaming and substance addiction share similar neurobiological mechanisms (A. M. Weinstein, 2010), involving dopamine release, which is also seen in gambling and drug abuse (A. Weinstein & Lejoyeux, 2015). The addictive nature of video games may stem from the brain's reward system, as dopamine plays a role in learning and motivation, with habitual gaming engaging this neurotransmitter (Wise & Jordan, 2021). Repeated gaming behaviors can form habits that risk addiction (van Elzelingen et al., 2022).

Dopamine also influences risk-taking, with interactions between the prefrontal cortex and limbic system playing a role in addiction (Kohno et al., 2015). The prefrontal cortex is crucial for managing emotional, cognitive, and behavioral changes related to addiction, particularly in areas such as response inhibition, self-control, and decision-making (Ceceli et al., 2022). Video games can disrupt dopamine balance, impairing the interaction between the prefrontal cortex and limbic system, which may lead to addiction and impaired emotional regulation (A. Weinstein & Lejoyeux, 2015). Adolescents are especially vulnerable due to ongoing prefrontal cortex development, given a peak in dopaminergic innervation and receptor density in this brain region (Chini & Hanganu-Opatz, 2021).

Gaming disorder, now recognized as a mental health condition, primarily affects children and adolescents (Darvesh et al., 2020) and has serious negative consequences (Feng et al., 2017). Introduced in DSM-5 in 2013 as Internet Gaming Disorder (Luo et al., 2022), it was expanded in ICD-11 in 2018 to include both online and offline gaming (Paschke et al., 2020). A meta-analysis reported a 3.3% prevalence of disordered gaming, with higher rates among adolescents aged 8-18 (6.7%) and young adults (12-40 years) at 6.3% (Kim et al., 2022). Gaming disorder, as defined by the ICD-11, involves a persistent gaming habit lasting at least 12 months, leading to impaired control, prioritization over other activities, and negative effects on personal, occupational, and social life (Xiang et al., 2020).

Gaming addiction, particularly in adolescents, is associated with issues like social anxiety, depression, loneliness, and poor mental health (J.-L. Wang et al., 2019; S. Zhu et al., 2021). It can also affect sleep quality, stress levels, and physical activity, and increase the risk of obesity (Handayani et al., 2021). Excessive gaming may delay verbal intelligence development (Takeuchi et al., 2016), impair academic performance (S. Das et al., 2023), increase distractibility and difficulty in sustaining attention (Alho et al., 2022), and affect working memory and decision-making (Billieux et al., 2020; Irak & Soylu, 2023).

Nonetheless, it is important to differentiate recreational gamers from those with gaming disorder, as the latter exhibit weakened connections in reward and executive control systems (greater inhibition of the putamen-middle frontal gyrus-insula pathway), leading to heightened cravings and diminished executive control (M. Wang et al., 2020). Another study with EEG also suggests potential biomarkers for identifying gaming disorder, especially in visuospatial processing, i.e., activation of the right parieto-occipital area (Hosseini et al., 2021). Thus, addiction affects executive functions and visuospatial processing, with the striatum-prefrontal cortex pathway potentially serving as a biomarker for addiction risk.

Stress and Aggressive Behavior

Aggressive behavior is linked to disruptions in the frontolimbic region, which controls emotions (Klasen et al., 2019). While aggression is often associated with violent video games, studies frequently mix violence with competitiveness, difficulty, and intensity, complicating interpretations (Adachi & Willoughby, 2011). Meta-analyses consistently suggest that violent video games increase aggression, aggressive thoughts, and emotions while reducing empathy and prosocial behavior (C. A. Anderson et al., 2010; Greitemeyer & Mügge, 2014). Another meta-analysis found violent video games linked to physical aggression modulated by cultural factors, with Eastern cultures emphasizing social responsibility, mitigating negative effects, while Western cultures promoting individualism heighten desensitization (Prescott et al., 2018). A longitudinal meta-analysis showed a U-shaped curve for violence-related aggression, peaking in early adolescence (Burkhardt & Lenhard, 2022). Game addiction has also been linked to aggressive behavior (Uçur & Dönmez, 2023), likely due to frontolimbic dysfunction and serotonin imbalance affecting emotion regulation and impulsivity (Çetin et al., 2017; Klasen et al., 2019). Beyond violent content, video game addiction correlates with impulsive behaviors, including aggression and emotional eating (Caner & Evgin, 2021).

Stress and cortisol levels can be associated with aggressive behaviors (Figueiredo et al., 2020), and they can be enhanced by exposure to violent content in video games (Mitsea et al., 2023). Even background music, such as pop/techno, can raise cortisol (Hébert et al., 2005). An increase in cortisol and alpha-amylase, both involved in the stress circuit (Tammayan et al., 2021), and a decrease in oxytocin, which is associated with empathic behavior (Barchi-Ferreira & Osório, 2021), have also been observed in response to games with scary content (Aliyari et al., 2023). The amygdala and hypothalamus activate during stressful gameplay, triggering fear and anger responses (Aliyari et al., 2018). Figure 2 summarizes this section.

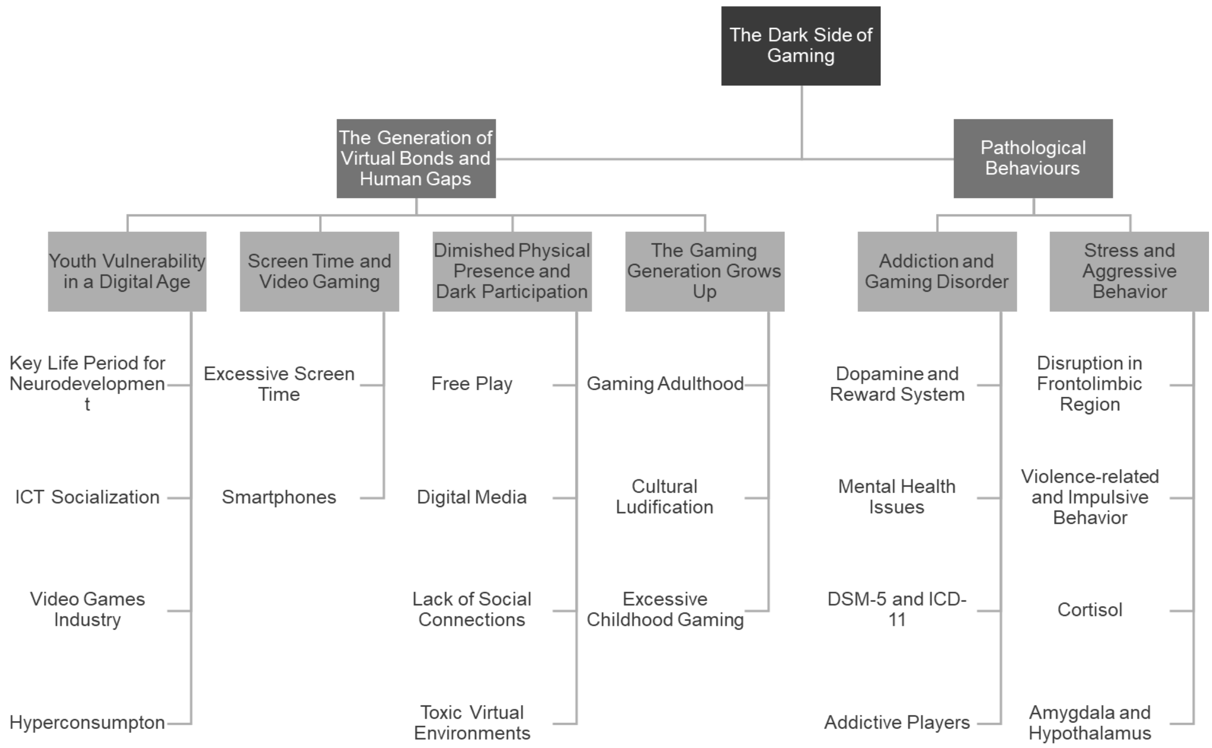

Figure 2: The Dark Side of Gaming

THE BRIGHT SIDE OF GAMING

Video games have evolved from non-digital to widespread digital, online, and mobile experiences (Cai et al., 2022; Esposito, 2005), posing risks, but also offering benefits when played healthily during leisure moments (Stenseng et al., 2021).

Gameful Leisure Experiences

Stress is widespread in modern society, making effective coping strategies vital, with leisure activities playing a key role by evoking positive emotions, well-being, and overall quality of life and offering a constructive escape from daily pressures (Auger, 2020; Denovan & Macaskill, 2017). Leisure, essential for health and well-being, provides restorative moments of excitement (Elias & Dunning, 1986; Thing, 2016). Technology has transformed leisure activities (López-Sintas et al., 2017), elevating video games to the same cultural status as film and music (Carvalho & Coelho, 2022; Raessens, 2006).

Self-Expansion and Coping Activities

Leisure activities, often viewed as escapism, can be positive when they involve self-expansion (linked to mastery and self-growth, promoting psychological well-being), but self-suppression (which seeks to avoid negative emotions, often in response to life stressors) is prejudicial to long-term mental health (Stenseng et al., 2012). Although gaming for self-suppression is strongly related to pathological gaming, gaming for self-expansion positively correlates with intrinsic psychological needs like autonomy and competence (Stenseng et al., 2021), being associated with well-being and intrinsic motivation in self-determination theory (Ryan & Deci, 2020). Gaming can also serve as a coping mechanism, offering distraction through interactive, manageable challenges, which, though not solving problems, can provide a sense of progress and purpose (Iacovides & Mekler, 2019).

Research comparing screen activities found that while weekday television time was linked to poorer academic performance, video gaming, and weekend television were not (Sharif & Sargent, 2006). Video games engage the fronto-parietal networks, enhancing attention and associative learning, unlike passive media like television, which primarily activate the default mode network, related to mind-wandering and resting (D. R. Anderson & Davidson, 2019). Thus, considering the recommended daily screen time and the range of digital leisure activities, such as television, video games can be a more active and less harmful option compared to other forms of screen media. However, we must be alert for those using games to escape real-life issues (Prinsen & Schofield, 2021).

Playing Together, Having Fun Together

Engaging in digital leisure activities like watching films or playing video games can strengthen family bonds, improve communication, and foster mutual respect (Belmonte et al., 2021). Data from the National Statistical Institute (NSA) shows that families commonly engage in digital leisure, with video games playing a significant role (de Los Dolores Gil García et al., 2024). "Couch co-op" games, where players collaborate or take turns in multiplayer or single-player (i.e., tandem play) games, encourage social interaction and teamwork, particularly when experienced players guide novices (Consalvo, 2017). Nonetheless, the gaming industry has transitioned from traditional "couch co-op" play, where players gather in the same room, to online and mobile gaming, where people can connect to others from different places and time zones (Koizumi, 2016; Wijman, 2018).

Online games now create global networks, enabling social connections and a sense of belonging through virtual interactions and gaming communities (Saldanha et al., 2023). Gaming has given rise to entrepreneurial streamers who broadcast live gameplay on platforms like Twitch, where viewers can financially support them, fostering dynamic online gaming communities (Bingham, 2020). Participating in online gaming can reduce isolation and foster a sense of belonging by creating social connections through gameplay and gaming communities, but virtual interactions do not replace physical ones, offering an additional opportunity to initiate conversations and connect with others (Iacovides & Mekler, 2019). Gaming also promotes real-world connections through events like E-sports and gaming meetings, reflecting its cultural impact (Reitman et al., 2020). E-sports fosters emotional bonds among team members, providing social support through friendships or romantic relationships within the community (Freeman & Wohn, 2017). Similarly, gaming jams - meetings where participants collaborate to create video games - promote belonging, offering work opportunities, and fostering friendships (Saldanha et al., 2023).

Gaming also encompasses metagame activities, i.e., those connected to the game but not part of playing it directly, that foster social connection, including off-screen interactions like organizing gaming sessions with friends, discussing and seeking information with peers, creating and sharing content, or engaging in game-related outdoor play (Kahila et al., 2021). Additionally, as the gaming industry grows, it shapes unique consumption patterns, creating online networks and communal identities like cosplay (Aljanahi & Alsheikh, 2021). Cosplay, where individuals dress as characters from popular media, has become a mainstream fan activity with the rise of the internet, offering support and socio-emotional connections while fostering collaboration and friendships (Vardell et al., 2022). In Japan, cosplay reflects a deep cultural heritage, while otaku culture has spread globally, influencing the consumption of Japanese cultural goods (Ito & Crutcher, 2014; Kam, 2013).

Flow and Immersion

Flow is a state of deep concentration and enjoyment often experienced during gaming (Caroux et al., 2015; Csikszentmihalyi, 1975). Video games promote flow through immersive experiences, balancing the player's skills with the game's challenges, resulting in intense focus, a loss of time perception, and reduced self-awareness (Brown & Cairns, 2004). Flow is closely linked to narrative engagement and enjoyment in games, as all these psychological states involve emotional immersion (Sherrick, 2021). Flow is associated with reduced self-referential processing and increased arousal, with participants experiencing greater absorption and perceiving time as passing more quickly (Khoshnoud et al., 2022). This state is linked to mindfulness, and both states foster relaxation, concentration, improved mood, and reduced stress (Cruea, 2020). Nonetheless, during the COVID-19, quarantine was associated with poorer well-being, but flow moderated this effect, with those experiencing high levels of flow showing little or no decline in well-being, whereas mindfulness did not moderate well-being (Sweeny et al., 2020).

Flow deactivates the default-mode network, which is typically active in passive states (Ulrich et al., 2014). Optimal game difficulty enhances flow, increasing oxygenated hemoglobin in the frontoparietal network, and personal autonomy in choosing game challenges further enhances activation of the frontoparietal regions, highlighting the connection between flow, attentional resources, and personal autonomy (de Sampaio Barros et al., 2018). A study found that intermittent rewards in gaming were associated with lower hippocampal GABA levels (the brain's inhibitory neurotransmitter), compared to consistent or no rewards, suggesting that intermittent rewards may induce a flow state, balancing skill and challenge, and boosting hippocampal activity (Prena et al., 2020). This suggests a link between intermittent rewards, flow, and improved in-game learning through hippocampal activation (Adcock et al., 2006; S. Li et al., 2003; Ostrovskaya et al., 2014).

Exciting and Relaxing Moments

Excitement-based flow occurs when challenges exceed player skills, while relaxation-based flow arises from easier, controllable challenges (Chang et al., 2020). As noted in the previous research, goal-oriented players prefer relaxation flow for results and confidence, while behavior-oriented players seek excitement during the process to apply advanced skills. Exciting gameplay can raise heart rates through cardiovascular responses involving adrenaline release (Behnke et al., 2020). A study found a positive relationship between game rewards and arousal, with more rewards increasing arousal, measured by skin conductance and heart rate (Ravaja et al., 2006). Conversely, puzzle games can reduce cortisol and stress levels (Mitsea et al., 2023), while immersive games, i.e., making use of virtual reality, boost alpha and theta brain activities, promoting relaxation (Beitle, 2021; GomezRomero-Borquez et al., 2023). After gameplay, individuals may feel deep calm and well-being, likely from endorphin release (Snodgrass et al., 2011). Research shows casual gaming can improve mood more effectively than meditation or guided relaxation (Stanhope et al., 2016), similar to the endorphin-driven relaxation found in exercise, yoga, and meditation (Suri et al., 2017).

Brain Boosters

Video games offer diverse audiovisual stimuli that require user interaction (D. (D. R. Anderson & Davidson, 2019), and engage the brain (Bateman & Nacke, 2010; Siviy, 2016).

Neurophysiological and Psychological Benefits

Video games activate the prefrontal cortex, facilitating decision-making, problem-solving, attention, memory, spatial reasoning, and visuomotor tasks (Buelow et al., 2015; Y. Li et al., 2018). They also engage the somatosensory cortex and superior parietal lobule, aiding hand movement, coordination, and motor learning by integrating sensory stimuli (Momi et al., 2018). The limbic system, including the ventral striatum, nucleus accumbens, and anterior cingulate cortex, is activated during gameplay, influencing habit and behavior development through rewards and pleasure (Benady-Chorney et al., 2018, 2020; Koepp et al., 1998). This leads to excitement, pleasure, and dopamine release (Benady-Chorney et al., 2018, 2020; Koepp et al., 1998; Phan-Hug et al., 2011). Experienced action video game players (who play regularly each week) compared to individuals with little or no experience show higher gamma waves during motor imagery, linked to improved memory and perception (Sepúlveda et al., 2014), while extended gaming sessions elevate beta waves, associated with focus and cognitive processing (S. S. and J. K. Das, 2017). Video games can lower cortisol levels, reducing stress (Mitsea et al., 2023), and immersive video games promote relaxation through endorphin release and enhanced alpha and theta brain activity (Beitle, 2021; GomezRomero-Borquez et al., 2023; Snodgrass et al., 2011).

In social gaming, video games can promote prosocial behavior, linked to oxytocin release, which fosters trust and cooperation (Annett & Berglund, 2015; De Dreu & Kret, 2016). Cooperative play enhances sociocognitive processes like attention orientation, agency perception, self-other discrimination, and perspective-taking (Liu et al., 2021). Additionally, male participants in the intergroup competition showed increased testosterone levels, suggesting that multiplayer games simulating cooperative competition are particularly appealing to young men, as they replicate male–male competition (Oxford et al., 2010).

A positive association between video game play and cognitive enhancement has been demonstrated, but generalizing these findings is limited by variability in game genres and individual player experience (E. Choi et al., 2020). Video games improve attention and working memory (Huang et al., 2017). Video games enhance coordination and motor learning, and integrate sensory information (Momi et al., 2018). They also improve the perception and manipulation of visual stimuli (Palaus et al., 2017) and promote probabilistic learning by encouraging efficient problem-solving (Schenk et al., 2017; Shute et al., 2015). Additionally, video games can be set up in a foreign language, providing immersive environments for second language acquisition (Zhang et al., 2017) and activating memory for versatile knowledge (Schenk et al., 2017). Video games are positively associated with well-being (Johannes et al., 2021), with studies showing that playing for up to two hours daily is correlated to higher life satisfaction (Yamaguchi, 2023), although not showing direct causal effects.

Most of the experimental research on video games discussed here has been conducted in controlled settings and lacks long-term real-life analysis, yet the data still suggest potential benefits. Additionally, video games have also been used as treatments and interventions to improve mental health in clinical settings (Schuurmans et al., 2018).

Mental Health Buffer and Treatments

Depression and anxiety are the most common mental health disorders globally, and video games, with their controlled scenarios and engaging features, can complement traditional therapies by enhancing cognitive skills like attention and information processing, offering an accessible, affordable, and stigma-free way to tackle mental health issues (Kowal et al., 2021).

Concerning anxiety, research found that specific video games reduce symptoms, alleviate social anxiety, and support anxiety prevention (Zayeni et al., 2020). Another study showed that web-based video games reduced anxiety in adolescent boys (Ohannessian, 2018). Casual video games, when prescribed, have been effective in lowering both state and trait anxiety in individuals with depression and anxiety (Fish et al., 2014). A comparison study found that playing Plants vs. Zombies four times a week (30-45-minute sessions) resulted in greater anxiety reduction than traditional anxiolytic medication (Fish et al., 2018). Additionally, a study showed that video games can help reduce children's anxiety during preoperative preparation for day-case surgery in hospitals (Dwairej et al., 2020).

Regarding depression, controlling working memory is key to preventing rumination of persistent negative thinking, common in individuals with depression (Joormann, 2010). Action games like Boson X improve cognitive abilities and help reduce rumination (Kühn et al., 2018). Casual games like Bejeweled 2 have been shown to lower depression and anxiety symptoms with just short daily sessions (Pine et al., 2020). Video games also offer adaptive coping strategies, enhance well-being, and foster social engagement, helping manage moods and alleviate depressive symptoms (Colder Carras et al., 2018). Video games like Animal Crossing: New Horizons reduce loneliness and depressive symptoms by maintaining social interaction (L. Zhu, 2021), while World of Warcraft fosters emotional regulation by allowing players to manage various avatars with unique skills and social roles, helping them develop flexibility and reappraisal strategies (Granic et al., 2014). Also, the video game Mario Kart has been shown to improve mood among adolescents by boosting positive emotions and reducing negative feelings (Rieger et al., 2014).

Video games show therapeutic potential, particularly for children and the elderly with health or neurodiverse conditions (Yang et al., 2021). Video games can improve cognition, including reading skills, attention, and planning in typically developing children from 8-12 years old (Pasqualotto et al., 2022). For the elderly, video games enhance cognitive function, slow age-related decline, and improve quality of life (Abd-alrazaq et al., 2022). They also benefit those with neurodiverse conditions, aiding in general health promotion, rehabilitation, cognitive therapy for disorders like Alzheimer’s, and influencing health behaviors in mental disorders such as autism (Damaševičius et al., 2023). For physical health, video games help children with obesity improve exercise adherence and cardiovascular health (Comeras-Chueca et al., 2022). They also match traditional therapies like Constraint-Induced Movement Therapy in stroke rehabilitation, reducing the need for therapist involvement (Gauthier et al., 2022). Figure 3 summarizes this section.

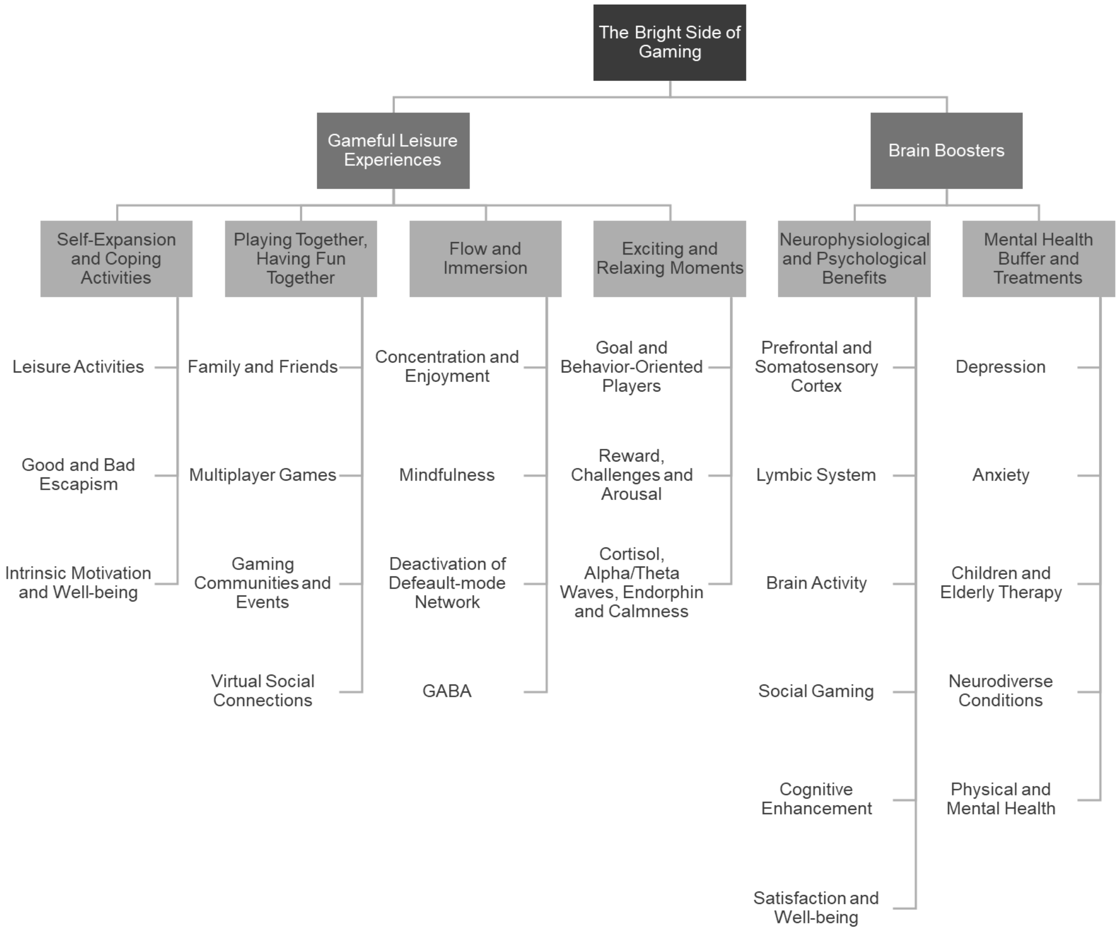

Figure 3: The Bright Side of Gaming

THE RISE OF GAMING IN EVERYDAY LIFE

Video games have become a significant part of everyday life (Muriel & Crawford, 2018), mediating socialization as they integrate media and ICT into modern culture (Kellner, 2004, 2020; Raessens, 2006). Socialization involves the interplay between individual actions and social structures, shaping cultural identity through internalizing societal norms, values, and behaviors (Bourdieu, 1990; Checkel, 2017; Costa & Murphy, 2015; Roksa & Robinson, 2017). Socialization influences neuroplasticity, affecting thoughts, behaviors, and emotions (Colagè & d'Errico, 2020). Neuroplasticity allows the brain to adapt and grow, while culture influences the stimuli that affect cognitive abilities such as literacy and tool use (Lende et al., 2021). Cultural differences impact neural patterns and brain structures (Domínguez Duque et al., 2010). The literature suggests viewing society and individuals through phylogenetic, ontogenetic, and cultural lenses to understand the ongoing interaction between biology, individual development, and society (Fabry, 2020; Gelfand & Kashima, 2016; Han & Ma, 2015; Kashima, 2016), as shown in Figure 4. Understanding this interaction is key to recognizing how and why video games have become integral to daily life.

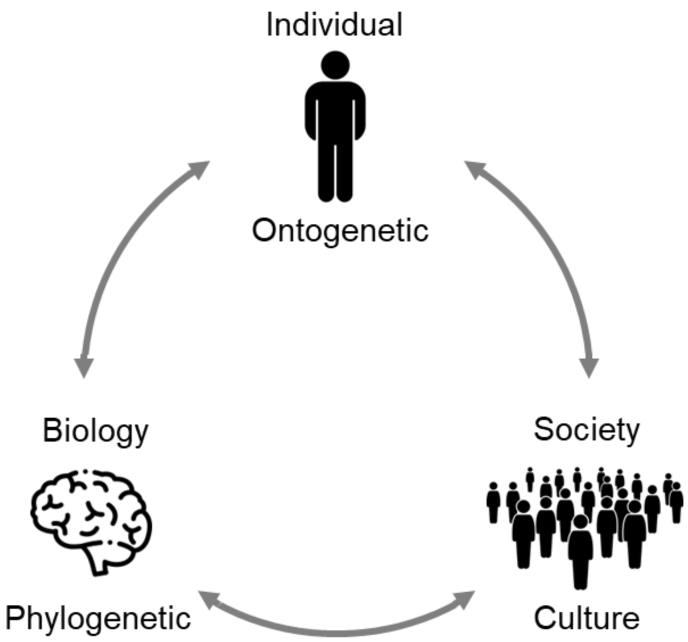

Figure 4: The Socialization Process

Boredom in a High-Stimulation Society

Neuroplasticity peaks during childhood and adolescence, making the brain highly sensitive to external stimuli (Lende et al., 2021). Immersive activities like video games engage the brain's dopamine system, crucial for reward processing and motivation (A. Weinstein & Lejoyeux, 2015). Dopamine regulates functions like locomotion, attention, and cognition, and changes in its availability during childhood can harm neurodevelopment, impacting brain structure and behavior (Areal & Blakely, 2020). Constant stimulation from video games and digital media makes the brain increasingly dependent on dopamine-driven pleasurable experiences (Guan & Chen, 2023). Frequent gaming can develop into habitual behaviors that may lead to addiction (van Elzelingen et al., 2022). Cyberculture, the spectacle society, and the ludification of culture immerse individuals in a digital environment, accessible anytime (Debord, 2021; Lévy, 2001; Raessens, 2006). This overstimulation, especially in youth, desensitizes the brain's reward system, leading to a preference for immediate rewards and weakening attentional capacities (Verma et al., 2024). The relentless pursuit of fleeting happiness fosters dissatisfaction (Lipovetsky, 2009; Lipovetsky et al., 2002). Boredom plays a crucial role in human functioning by reducing attention to tasks, increasing arousal, and motivating a desire for change, which leads to the pursuit of alternative goals and new opportunities for stimulation (Bench & Lench, 2013). It signals dissatisfaction and prompts the need for escape or change (Elpidorou, 2023). As society becomes more reliant on highly stimulating digital media, the cycle of seeking more stimulation intensifies, reinforcing the brain's dependence on immediate rewards and leaving little room for boredom.

Playing Brains and Resting Bodies

Play activities are essential for developing physical, social, communicative, and personal potential during socialization, especially in childhood (Serykh et al., 2021). Unlike traditional play, which involves physical presence and movement (Børve & Børve, 2017), video games are structured with set rules (Adams, 2014; Esposito, 2005). Non-active video games, more common than active ones that demand physical activity, are linked to increased sedentary time (Simons et al., 2015), reduced physical activity (Haug et al., 2022), and increased body mass, though the effect is small (Marker et al., 2022). The brain minimizes effort by avoiding tasks with higher demands (Patzelt et al., 2019) and evaluating costs and benefits through regions like the ventral striatum, anterior insula, and prefrontal cortex (Sescousse et al., 2013; Westbrook et al., 2019). Physical effort reduces an action's value (Kurniawan et al., 2010), making video games appealing due to their low physical demands and high rewards from dopamine release (Benady-Chorney et al., 2020). Interactions in virtual environments involve unique forms of embodiment and presence, where avatars enable interaction independent of the physical world, with social engagement being a key factor in creating presence (S. Evans, 2012). Video game avatars serve as tools for players, acting in virtual worlds as disembodied minds (Black, 2017), while modern relationships increasingly rely on screen-mediated interactions (Lemma, 2015). As video games advance, posthuman empathy examines the relationship between avatars and players, and machines and humans, focusing on aligning subjective and embodied experiences (Wilde & Evans, 2019). Digital experiences are becoming physically effortless, with humanized digital bodies, leading society toward interactions where the brain is active, but the body remains still.

Fun as Relief in a Stressful Society

As human civilization evolved from hunter-gatherer groups to modern societies, stress shifted from physical threats to self-inflicted psychosocial pressures due to societal expectations and productivity demands, leading to self-stress (Orquiza, 2024). Modern society grapples with wicked problems like climate change, global poverty, and systemic racism, which resist solutions and challenge policymakers, researchers, and citizens (Hipólito & Khanduja, 2024). These factors, along with social media and distressing news, have fueled anxiety and depression among youth (Brunette et al., 2023). Relieving stress is neurologically crucial to preventing chronic activation of the hypothalamic-pituitary-adrenal (HPA) axis, which otherwise leads to increased glucocorticoid levels, depression, cardiovascular issues, and cognitive decline (Ulrich-Lai et al., 2016). Preventing depression and anxiety is essential for brain health, as these conditions can impair the prefrontal cortex, which is responsible for emotional regulation and cognitive control (Zheng et al., 2024). Screens, including video games, are linked to mental health problems like stress and anxiety (Santos et al., 2024), though they also offer coping as a distraction and relaxation (Khalili-Mahani et al., 2019). Video games, while providing relief from daily stress and restoring mental well-being (Iacovides & Mekler, 2019; Stenseng et al., 2012), can harm mental health when used for self-suppression or addiction (Kim et al., 2022; Stenseng et al., 2021), blurring the line between healthy escapism and disconnection from reality as individuals may seek refuge from the complexities of society. Figure 5 summarizes this section.

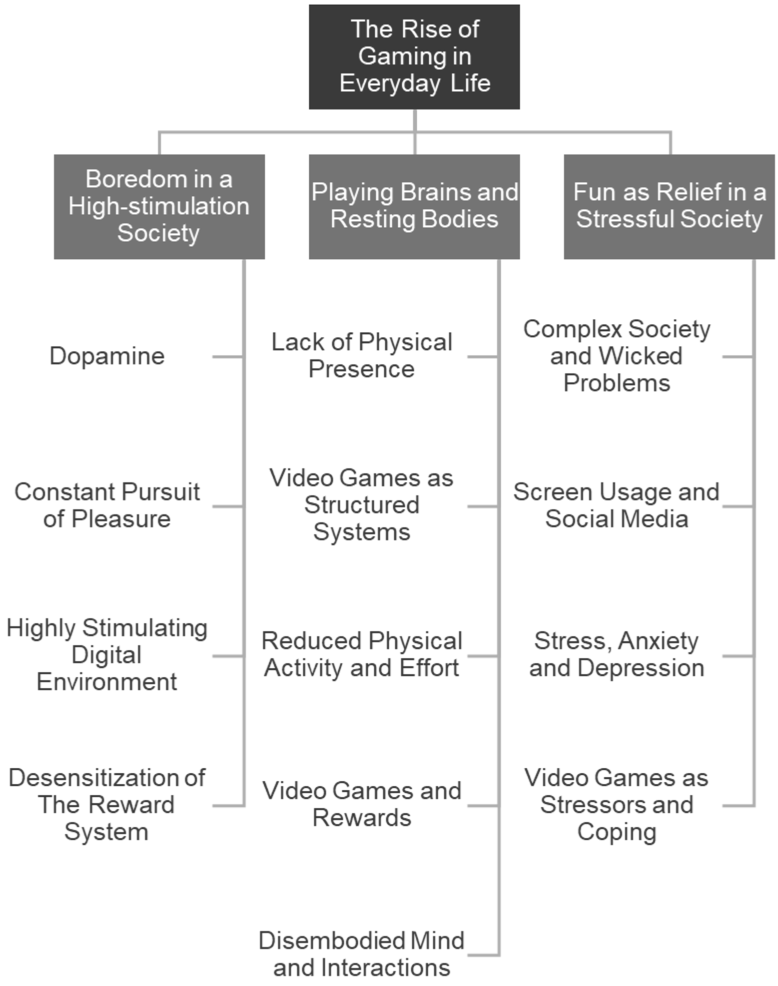

Figure 5: The Rise of Gaming in Everyday Life

DISCUSSION AND CRITICAL EVALUATION

The appeal of screens in youth presents societal risks, requiring attention from families, schools, governments, and companies. Balancing digital and physical play, while recognizing both the risks and benefits of video games, is crucial.

The Allure of Screen Flow on Youth

Given the critical neurodevelopmental stages of children and adolescents (Marzola et al., 2023) and the risk of addiction from excessive gaming (A. Weinstein & Lejoyeux, 2015; Wise & Jordan, 2021), monitoring gaming behavior and implementing protective measures is essential. Digital literacy is crucial for understanding technology's mental health impact (Lazonder et al., 2020). Open discussions among families, schools, governments, and companies are needed to foster healthy tech habits (Coelho & Abreu, 2025).

Parents shape child development (Terras & Ramsay, 2016), so setting recreational screen time limits according to guidelines (no screen time until 2 years, 1 hour for ages 2-5, and 2 hours for 5-17 years) is key (Joshi & Hinkley, 2021; McArthur et al., 2022). As digital tools integrate into education (Otterborn et al., 2019; Secretaria-Geral da Presidência et al., 2023), it is also necessary to consider this school screen time. It is crucial to mitigate the development of addictive behaviors, which often stem from habitual actions (van Elzelingen et al., 2022), avoiding repeating the same behavior in recurring contexts (Wood & Rünger, 2016) and limiting constant stimulation to prevent dopamine dependence (Guan & Chen, 2023). We recommend taking breaks during gameplay and avoiding making it a fixed habit by varying intervals and times. Since violent content can influence pathological behavior (Greitemeyer & Mügge, 2014), supervision through age ratings like the Entertainment Software Rating Board (ESRB) is crucial to prevent problematic content consumption (Duffy & Derevensky, 2022). Also, healthy behaviors should be adopted by parents and educators, not just children, as screens are often used for stress relief in front of children (McDaniel & Radesky, 2018; Whitbourne et al., 2013), reinforcing unhealthy behaviors (G. W. Evans et al., 2018).

Monetization in video games is evolving rapidly, raising concerns about digital consumption and mental health, especially regarding gambling-like elements (Denoo et al., 2024). Therefore, governments must regulate video games, which pose addiction risks, by enforcing transparency, setting age restrictions, regulating in-game money transactions, and controlling gambling elements, especially for minors (Lischer et al., 2022). Regarding companies, while making games less addictive could be a positive social contribution, this might reduce their appeal, enjoyment, and profitability (Király et al., 2018), making it an unrealistic option. However, video game companies can tackle these issues by promoting healthier gaming habits, such as rewarding breaks instead of extended gameplay, fostering collaborative digital environments, penalizing toxic behavior, enhancing parental controls and age restrictions, and encouraging real-world interactions, such as movement detection and GPS use. Figure 6 links the topics discussed previously.

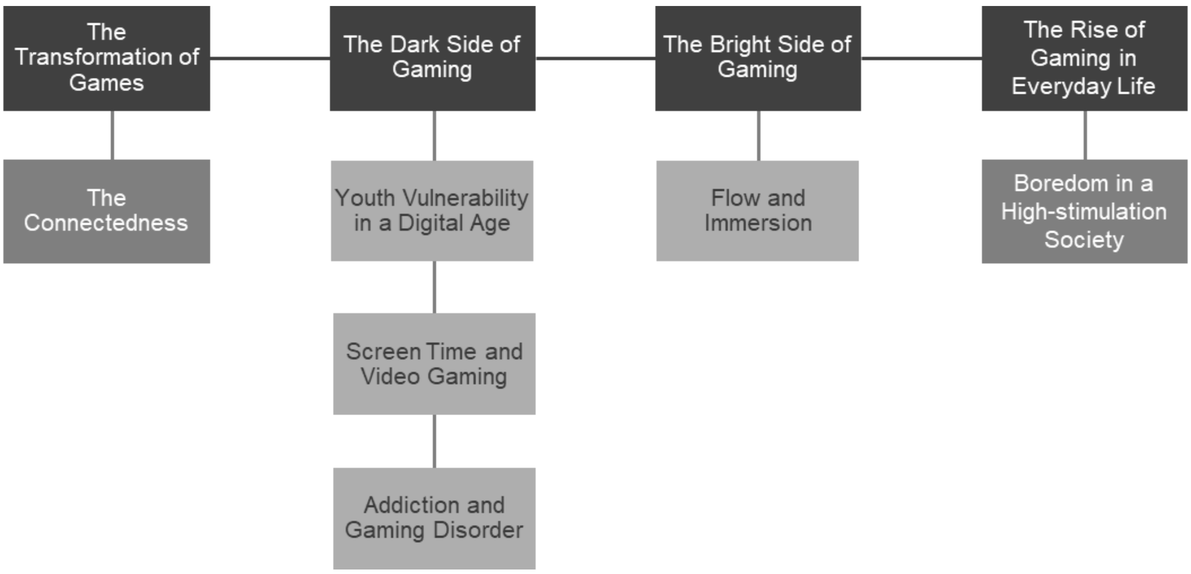

Figure 6: The Allure of Screen Flow on Youth

Balancing Digital and Physical Play

The decline in physical play is concerning, as free play is crucial for socio-emotional and cognitive development (Yogman et al., 2018). To balance this, physical activity and real-world interactions are crucial for mental health, helping offset the effects of digital culture (Abreu, 2022) and reducing anxiety (Weng & Chiang, 2014). Ensuring that gaming does not overshadow in-person activities is crucial, balancing technology use with real-life experiences. Physical presence and human interaction help reduce stress by boosting oxytocin and lowering cortisol (Estapé, 2021; Heinrichs et al., 2003). While gaming behavior appeals due to its low physical effort and high dopamine rewards (Benady-Chorney et al., 2020; Kurniawan et al., 2010), it is important not to let gaming encourage idleness and social isolation, prioritizing in-person interactions and free play whenever feasible. When that is not feasible, selecting active video games that involve physical movement (Simons et al., 2015) or those that promote positive social connections, such as "Couch co-op" games (Consalvo, 2017), can serve as suitable alternatives. Balancing digital and physical play fosters a healthier relationship with the world. Figure 7 links the topics discussed previously.

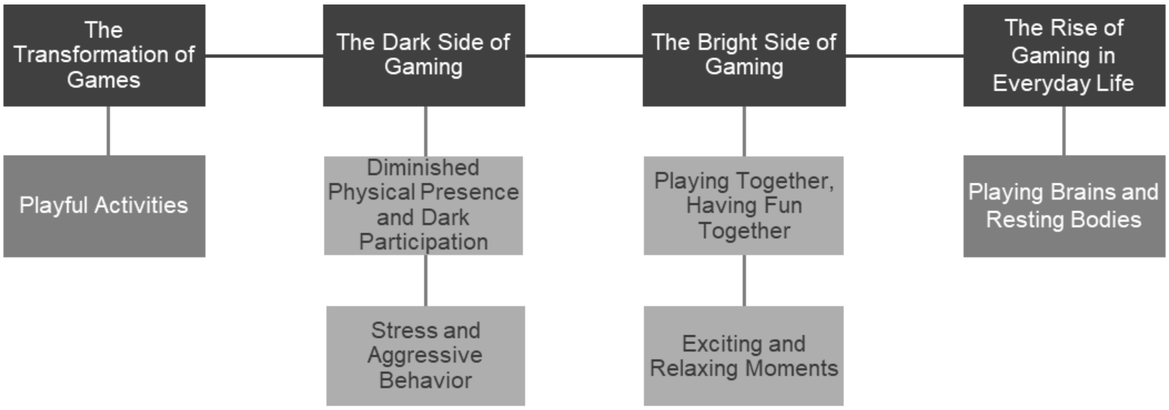

Figure 7: Balancing Digital and Physical Play

Navigating the Video Gaming World

In a stressful society facing social, economic, and health challenges (Orquiza, 2024), video games offer moments of relief and enjoyment (Iacovides & Mekler, 2019; Stenseng et al., 2012). Video games can enhance cognitive functions (Buelow et al., 2015; Momi et al., 2018), reduce stress (Beitle, 2021), offer therapeutic benefits for anxiety and depression (Ohannessian, 2018; Zayeni et al., 2020), cognitive rehabilitation for the elderly (Abd-alrazaq et al., 2022), and neurodiverse individuals (Damaševičius et al., 2023). However, video games can easily shift from beneficial to addiction (A. Weinstein & Lejoyeux, 2015), being associated with sedentarism (Simons et al., 2015), poor sleep (Handayani et al., 2021), compulsive eating (Caner & Evgin, 2021), self-suppression (Stenseng et al., 2021), and loneliness (J.-L. Wang et al., 2019). To prevent these negative effects, it is crucial to balance gaming with physical activities, avoid late-night sleeping, excessive screen time, and habit-forming gaming, while maintaining healthy eating, prioritizing social interactions, and responsibilities. Gaming without these harmful behaviors can be seen as a healthy form of fun that promotes several cognitive benefits. However, since video games can be associated with such issues, it is essential to recognize problematic behaviors early on and address them before they escalate into pathological behaviors. Figure 8 links the topics discussed previously.

Figure 8: Navigating the Video Gaming World

CONCLUSION

This research examines the evolution of video games and their impact on the brain and society from a neurosociological perspective. We interconnected several themes in three key areas: first, the appeal of video games among youth raises concerns about addiction, especially during neurodevelopment. Second, we stressed the importance of balancing digital and physical play, as video games should not replace essential human interaction. Third, we advocate for a cautious yet open integration of video games into society, recognizing both the problematic behaviors and the cognitive and social benefits they offer. In each area, heightened awareness is essential, leading to carefully considered recommendations that address the roles of families, schools, governments, companies, and the players themselves. This research underscores the crucial role of new digital media and technology in mediating human development (Kyshtymova & Skorova, 2024), emphasizing the importance of recognizing video games as both a significant cultural phenomenon and a cognitive influence in contemporary society.

LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Much of the existing research has been conducted in controlled settings, which may not fully translate to real-world scenarios. We recommend future research using randomized controlled trials and meta-analyses for a further rigorous evaluation of insights discussed in this paper, but we advocate for studies in more ecological environments, integrating neuroscience and social sciences to better understand video games' impact beyond the lab. The lack of neurosociological research about video games using advanced tools like hyperscanning highlights the need for such methods to analyze such social contexts, benefiting both neuroscience and sociology. Finally, although we did not focus on extended realities (XR) and artificial intelligence (AI), these technologies are poised to transform gaming by offering more immersive experiences and AI-driven content (Demers et al., 2020; G. Edwards et al., 2021; Newzoo, 2023). As these technologies evolve, they present both opportunities and risks, including addiction and disorders, requiring urgent interdisciplinary research to consider benefits and harms and prescribe safe and healthy guidelines.

IMPLICATIONS FOR RESEARCH, APPLICATIONS, AND POLICY

From a research and theoretical perspective, this study advances neurosociology by exploring how video games shape human interactions, neural processes, and behavioral patterns. Viewing video games as both a cultural and cognitive force, particularly for youth, provides insight into habit formation, reward mechanisms, and the socio-emotional impact of digital play. In practice, fostering healthier gaming habits requires cooperation among families, educators, game developers, and policymakers. Implementing digital literacy education, setting balanced screen time guidelines and habits, and promoting active or cooperative gaming can reduce risks like addiction and social isolation while enhancing cognitive and emotional well-being. At the policy level, governments should regulate monetization strategies, ensure transparency in in-game transactions, and enforce age-appropriate content guidelines. Meanwhile, gaming companies can integrate responsible design choices that promote healthier gaming behaviors without diminishing engagement. A holistic approach integrating research, education, and regulation is necessary to harness the positive potential of gaming while preventing its adverse effects on youth and society.

ACKNOWLEDGEMENTS

We express our sincere gratitude to FCT (Fundação para a Ciência e a Tecnologia) for the financial support. This work is financially supported by National Funds through FCT, I.P., under the projects UID/04279 - Centro de investigação Interdisciplinar em Saúde (CIIS) (https://doi.org/10.54499/UID/04279/2025); and 2022.10688.BD - Franz Coelho (https://doi.org/10.54499/2022.10688.BD)

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 21(3), December 2025, 511–529

UNVEILING SCHOLARLY NARRATIVES ON HUMAN TECHNOLOGY: A STRUCTURAL TOPIC MODELING APPROACH

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Abstract: *This study systematically maps the thematic evolution of human–technology research from 2020 to 2025 using Structural Topic Modelling (STM) applied to over 2,000 abstracts from the Web of Science Core Collection. The analysis identifies six dominant themes: Industry, AI and Sustainability; Education and Human-Centred Design; Public Health, Community and Equity; Robotics, HRI and Ergonomics; Philosophy and Ethics of Technology; and Clinical mHealth and Usability. The results reveal a structural realignment from pandemic-driven experimentation to institutionalised, interdisciplinary research embedded in industrial, clinical, and community systems. Thematic inequality declined while diversity stabilised, indicating a mature and balanced research ecosystem. Methodologically, the study introduces a reproducible STM-based workflow integrating Gini and Shannon indices. Empirically, it provides a data-driven map of cross-disciplinary convergence. Conceptually, it demonstrates that human–technology inquiry increasingly operationalises ethics and sustainability through design, governance, and applied practice.*

Keywords: *human technology; structural topic modeling (STM); bibliometric analysis; research mapping*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.2

INTRODUCTION

Technological change in the twenty-first century is rapidly reshaping healthcare, education, work, governance, and communication. The spread of artificial intelligence (AI), robotics, data-driven systems, and digital platforms not only alters how people use tools, but also how those tools configure human action, values, and institutions (Shneiderman, 2022; Tiutiunyk et al., 2021). Technologies are not neutral artefacts; they are components of socio-technical systems that embody values, distribute agency, and co-produce social norms and everyday practices (Winner, 1980; Bijker et al., 2012; Blok, 2022). A practical illustration is transport and logistics telematics, where real-time monitoring and analytics reshape operational decisions and human work practices (Szcześniak & Gorzelańczyk, 2024). Within these systems, the human role is not fixed but negotiated in practice: people appropriate, workaround, and domesticate systems through routines of use, repair, and adaptation, while algorithmic decision-making redistributes agency and accountability across humans and artefacts (Johannessen et al., 2023). These lived interactions help explain why similar technologies yield uneven benefits and harms across contexts (Schürkmann & Anders, 2025). Assessing whether ongoing change advances well-being, equity, and sustainability - or reproduces asymmetries and vulnerabilities - therefore requires inquiry that bridges social sciences, engineering, ethics, and design. As the literature expands at speed and across disciplines, even specialists struggle to retain analytical orientation, underscoring the need for systematic, cross-disciplinary mapping of human–technology studies.

Over the past two decades, a vast and heterogeneous body of human–technology research has emerged across diverse fields. In healthcare, the rise of mHealth, telemedicine, and data-driven remote care has generated thousands of studies exploring usability, accessibility, and patient engagement (Kallander et al., 2013; Zhao et al., 2024). In education, human-centred design and design thinking approaches have transformed pedagogical models and learning environments (Liedtka, 2018; Mishchuk et al., 2025). Meanwhile, robotics and ergonomics research has expanded toward collaborative human-robot systems emphasizing safety and usability (Goodrich & Schultz, 2007; Ajoudani et al., 2018), while philosophical and ethical debates have deepened around embodiment, technological mediation, privacy, and responsibility (Floridi et al., 2018; Tutar et al., 2025). Yet these communities often operate in parallel, which hampers cumulative knowledge and policy-relevant synthesis. In this context, bibliometric and scientometric approaches offer transparent tools for mapping intellectual structures. Unlike narrative reviews, they rely on systematic data collection and computational methods that reduce selection bias and enable scalability (Donthu et al., 2021). We leverage these advantages to provide a data-driven map of the human – technology literature over 2020–2025 – a period spanning the pandemic shock and the subsequent acceleration of digitalization – based on abstracts retrieved from the Web of Science Core Collection (WoSCC) using a carefully constructed query.

Our objective is to identify the field's leading themes and trace their evolution. We apply Structural Topic Modeling (STM), which uses document-level metadata to estimate how topic prevalence varies over time and across contexts. To characterize structural balance, we complement STM with the Gini and Shannon indices to capture concentration and diversity. Using a corpus of more than 2,000 abstracts, we (i) map dominant thematic clusters for 2020

–2025, (ii) analyze their temporal dynamics before and after the pandemic, and (iii) assess whether the field is diversifying or fragmenting.

This study contributes in three ways. Methodologically, it advances a transparent, reproducible STM-based workflow for cross-disciplinary mapping. Empirically, it assembles a scalable corpus and analytic framework that synthesises dispersed subfields. Structurally, it introduces indicators and visualisations that diagnose thematic organisation and change, offering a transferable template for comparative analyses.

The remainder proceeds as follows: Section 2 describes data, corpus construction and methods; Section 3 presents results on dominant themes, temporal evolution and diversity metrics; Section 4 discusses implications for interdisciplinarity and theory; Section 5 concludes with future research directions and policy relevance.

METHODS

Data

A fundamental prerequisite for any bibliometric study is the construction of a well-defined and consistently curated bibliographic database. Establishing a reliable dataset is the first critical step that determines the transparency, comparability, and reproducibility of subsequent analyses. Our database is created based on records in the Web of Science Core Collection (WoSCC) is widely regarded as the gold standard for bibliometric and scientometric research due to its rigorous curation of peer-reviewed journals and consistent metadata structure (Pranckutė, 2021). Compared to other databases such as Scopus or Google Scholar, WoSCC offers higher transparency, stability of indexing, and compatibility with advanced analytical tools for citation and text analysis. The Web of Science Core Collection includes the Science Citation Index Expanded (SCIE), which covers the natural and technical sciences since around 1900 (webofscience.help.clarivate.com); the Social Sciences Citation Index (SSCI) for the social sciences (guides.library.queensu.ca); and the Arts & Humanities Citation Index (AHCI), which includes the arts and humanities from approximately 1975 (lib.montana.edu). In addition, it contains conference proceedings, book citation indexes, and the Emerging Sources Citation Index (ESCI) (guides.lib.umich.edu).

The query in the Web of Science Core Collection (WoSCC) was conducted on 20 May 2025. The search was limited to document types including articles, proceedings papers, early access papers, book chapters, and books published from the years 2020 to 2025. Additionally, only abstracts written in English were included in created database, as they provide the most content-rich descriptions of research focus and ensure the relevance of texts for subsequent topic modeling. The query was constructed around the core expression “human technology”, including its direct orthographic variants such as “human-technology” and compound forms like “human technology interaction” or “human-technology interaction”. To capture semantically equivalent terms commonly employed in the field, the query further incorporated “human-centered/centred technology”, “human-centered/centred design”, and “human-centered/centred computing”, thereby accounting for both American and British orthography as well as syntactic variations. This design enhanced recall while maintaining precision, since all selected expressions directly relate to the conceptual nucleus of human-centred technological development and interaction. By systematically including these lexical variants, the search minimized the risk of omitting relevant publications due to orthographic or stylistic differences, while avoiding overly broad or tangential terms that could introduce noise into the corpus. The final query was:AB (abstracts)=("human technology" OR "human-technology" OR "human technology interaction" OR "human-technology interaction" OR "human-centered technology" OR "human-centred technology" OR "human-centered design" OR "human-centred design" OR "human-centered computing" OR "human-centred computing").

The final dataset comprised 2,022 abstracts retrieved from the Web of Science Core Collection, spanning 1,223 distinct journals and authored by approximately 1,993 unique researchers. This wide coverage underscores the highly interdisciplinary nature of human–technology scholarship.

Methodology

We employ Structural Topic Modeling (STM) – a probabilistic text mining technique designed to uncover latent thematic structures in large textual corpora while simultaneously accounting for document-level metadata (Roberts et al., 2014). STM assumes that each document d is represented as a mixture of K latent topics, and each topic corresponds to a probability distribution over the vocabulary. In contrast to classical Latent Dirichlet Allocation (LDA), STM enables topic prevalence and content to vary systematically as a function of observed covariates, such as author attributes, publication year, or institutional affiliation.

Prior to model estimation, the corpus was pre-processed through tokenization, stopword removal, lowercasing, and stemming. Rare words and documents with extremely low word counts were excluded to improve convergence and interpretability. All analyses were conducted in R using the stm package (Roberts et al., 2019). The estimation procedure proceeds in five main steps (Roberts et al., 2016):

1) Initialization: Each document d is initially assigned random topic proportions θ_d representing a mixture over K topics. These serve as starting values for the subsequent optimization routine.

2) Expectation – Maximization Updates: STM employs a variational Expectation–Maximization (EM) algorithm to iteratively update latent assignments. During each iteration, the model compares observed word frequencies to the current estimates of topic–word distributions. Words that are strongly associated with a topic increase the posterior probability of that topic in the document's composition.

3) Incorporation of Metadata: Topic prevalence is linked to document-level covariates through a logistic–normal regression structure. The latent variable n_d follows a multivariate normal distribution with a mean determined by the covariates

$$X_d: n_d \sim \mathrm{N}(X_d, \Gamma, \Sigma) \tag{1}$$

where X_d is the vector of metadata, Γ is the matrix of regression coefficients, and Σ denotes the covariance matrix.

4) Transformation into Topic Proportions: The latent vector n_d is then mapped onto the simplex of valid topic proportions using the softmax transformation:

$$\theta_{dk} = \frac{exp\ (n_{d_k})}{\sum_{j=1}^{K} exp\ (n_{d_k})} \quad (2)$$

ensuring that all topic proportions are positive and sum to one.
5) Convergence: The iterative updates continue until convergence, yielding posterior topic proportions θ_d that jointly capture the observed word co-occurrences and the systematic variation explained by document-level metadata.

A crucial step in the Structural Topic Model approach is determining the optimal number of topics (K). This decision is not purely algorithmic but requires balancing statistical diagnostics with substantive interpretability. Following established guidelines by Roberts et al. (2014; 2016), three complementary criteria were jointly evaluated. First, held-out likelihood measures predictive accuracy on data excluded from estimation. It increases rapidly for small K and then flattens, indicating diminishing returns from additional model complexity. Second, semantic coherence captures how consistently high-probability words co-occur across documents. It is typically highest for smaller K and decreases as the number of topics grows, reflecting the fragmentation of semantically meaningful clusters. Third, exclusivity assesses topic distinctiveness through the uniqueness of top words. It tends to increase with K, as rarer terms form separate clusters, although excessive segmentation may produce overly narrow or analytically trivial topics.

Taken together, these diagnostics indicate that selecting K = 6 provides a balanced compromise (Figure 1)

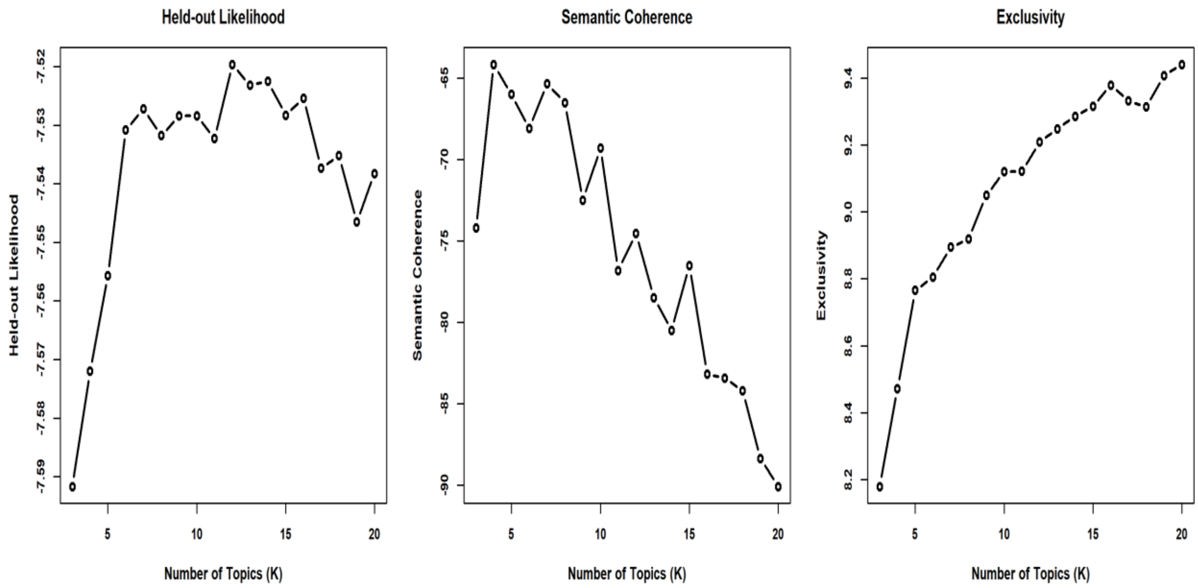

Figure 1. Diagnostic Metrics for Selecting the Optimal Number of Topics
[Authors' computation based on STM diagnostic framework by Roberts et al. (2016)]

At K =6, the held-out likelihood is near its maximum, coherence remains sufficiently high for reliable human interpretation, and exclusivity is strong enough to yield clear thematic separation without undue granularity. Substantively, the six-topic configuration maps cleanly onto the major strands of the human–technology literature, avoiding both under-aggregation and over-fragmentation. Hence, K=6 is both statistically defensible and substantively grounded, balancing predictive validity, semantic interpretability, and thematic distinctiveness, qualities valued in empirical research in economics and related social sciences.

RESULTS

Building on the methodological choices outlined above, this section presents the empirical results of the Structural Topic Modeling analysis. Figure 2 presents a visual summary (word clouds) of the six dominant topics identified through Structural Topic Modeling (STM) applied to abstracts published between 2020 and 2025. Each word cloud displays the top 40 terms associated with a given topic, selected according to the FREX metric. FREX combines frequency (the prevalence of a word within a topic) and exclusivity (its distinctiveness to that topic), thereby highlighting terms that are simultaneously common and specific. In the visualizations, larger and darker words indicate higher importance in characterizing the topic.

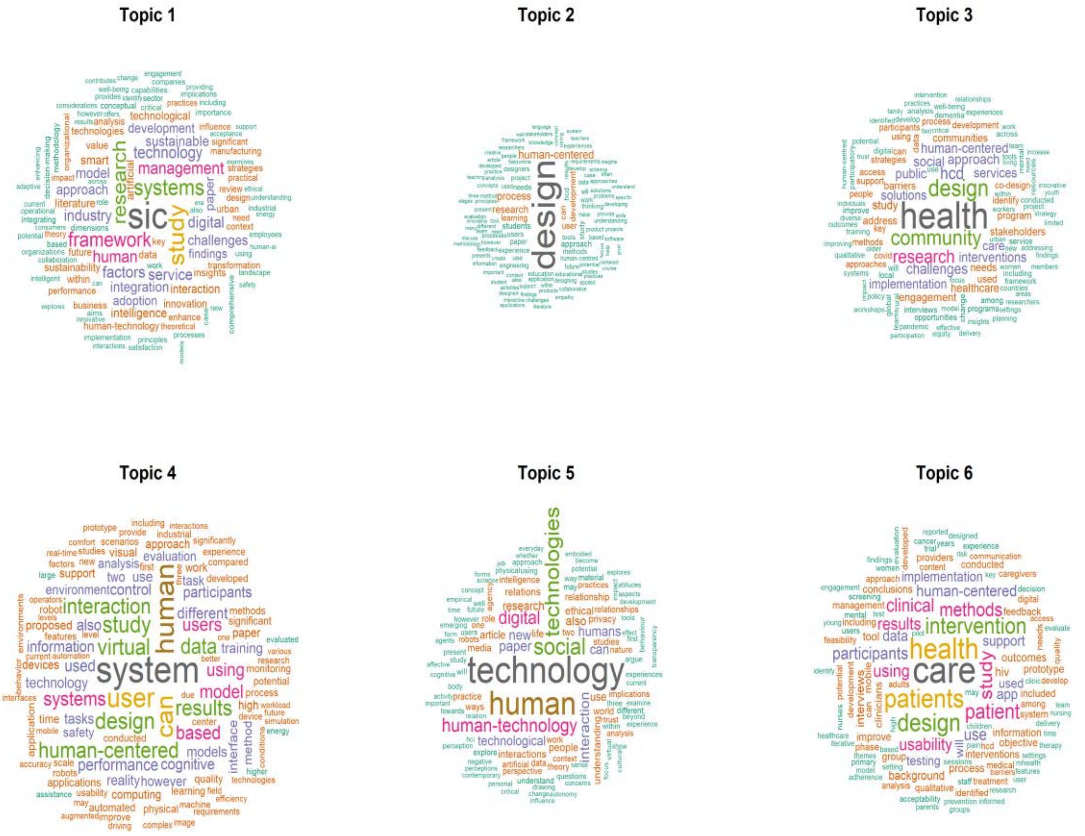

Figure 2. Word clouds representing the six dominant topics identified through Structural Topic Modeling (STM) of human–technology abstracts (2020–2025)
[Source: Authors' computation based on STM output]

The six word clouds in Figure 2 provide a concise visual representation of the dominant thematic clusters identified through STM. Each cloud highlights the most distinctive vocabulary used within a topic, revealing the conceptual breadth of human–technology research. Collectively, they show a balanced distribution between applied and theoretical domains - ranging from industrial transformation and design education to public health, robotics, ethics, and clinical usability - thereby illustrating the multidimensional nature of the field. We provide table 1 with a precise, textual summary of the most representative terms, formally defining each topic according to the STM algorithm.

Table 1. Top 15 FREX terms describing the thematic composition of the 2020–2025 human–technology corpus [Source: Authors' computation based on STM output]

Topic	Top 15 FREX Words	Label
Topic 1	transformation; sustainable; business; sustainability; industry; manufacturing; smart; companies; consumers; framework; IoT; maturity; adoption; HCAI; innovation	Industry, AI & Sustainability
Topic 2	students; teachers; engineering; design; learning; creativity; course; problems; product; prototyping; thinking; user; testing; education; feedback	Education & Human-Centred Design
Topic 3	communities; vaccine; dementia; vaccination; equity; covid; pandemic; programs; public; rural; aging; disparities; equitable; co-design; care	Public Health, Community & Equity
Topic 4	flight; accuracy; motion; neural; vehicles; task; experiment; automation; simulation; ergonomics; human-robot; comfort; sensors; prototype; HRI	Robotics, HRI & Ergonomics
Topic 5	relations; embodied; agency; mediated; moral; philosophical; non-human; shops; animals; argue; privacy; alcohol; media; humans; animal	Philosophy & Ethics of Technology
Topic 6	patients; clinical; HIV; nurses; cancer; pain; mHealth; clinic; medication; CDS; chronic; usability; intervention; pediatric; accessibility	Clinical mHealth & Usability

Topic 1 – Industry, AI & Sustainability. This topic explores how digital transformation and AI reshape human work within industrial systems, redefining the roles of operators, engineers, and managers, and their interactions with HMIs, IoT infrastructures, and HCAI tools, as well as the implications for safety, trust, and decision quality. Research connects operational metrics (OEE, defect rates, energy intensity, carbon footprint) with human-centred indicators (usability, cognitive load, transparency, acceptance). Data from connected devices and user feedback support co-design processes and continuous improvement. Governance discussions address bias and privacy in HCAI, interoperability across platforms, and the alignment of ESG objectives with workplace constraints and employee well-being.

Topic 2, titled "Education and Human-Centred Design," explores how learners, teachers, and external users co-create technologies through human-centred practices. Instruction connects theory to application through problem framing, prototyping, and user testing, with students acting as co-designers who translate user needs into requirements and refine solutions based on feedback from studies and field trials. Programmes assess human outcomes such as usability, workload, accessibility, trust, and explainability alongside technical performance, using rubrics, evaluations, and structured test protocols. Courses include ethical safeguards for generative tools related to attribution, bias, privacy, and consent, and promote inclusion through universal design and accessibility. Stakeholders such as patients, teachers, operators, and community partners provide context, validate use cases, and help ensure that solutions function in real settings. Capstone studios and living lab projects expose learners to realistic constraints, including safety, cost, and maintenance, while reflection and peer critique help develop responsible innovation skills. Overall, the topic highlights human agency in design and demonstrates how education connects engineering decisions with user value, equity, and social responsibility.

Topic 3 – "Public Health, Community and Equity" highlights the central role of human agency in shaping technologies for health, care, and community well-being. Research in this cluster examines how patients, caregivers, and local actors use, adapt, and reinterpret technologies in contexts such as vaccination programmes, pandemic response, dementia care, and rural health delivery. Rather than treating technology as an external intervention, studies frame it as a social interface where relationships of trust, reciprocity, and responsibility are negotiated. Human-centred and participatory design approaches enable communities to articulate priorities, co-create prototypes, and evaluate usability and fairness in real-life settings. Through these practices, people act not merely as users but as co-designers and stewards of digital and organisational systems that mediate care and distribute resources (Yakymova et al., 2022). Equity frameworks and anti-racist design principles guide how technologies are implemented, ensuring they respect cultural values, accessibility needs, and diverse forms of knowledge. Overall, this topic emphasises that the effectiveness and legitimacy of public health innovation depend on recognising people as active participants who co-produce technologies, governance processes, and ethical standards for equitable care.

Topic 4 – “Robotics, HRI & Ergonomics” . This topic presents robots and automated systems as partners that co-shape human work, rather than as standalone tools. Studies investigate how operators, pilots, and drivers allocate attention and authority with machines in flight simulators, motion-tracking tasks, and automated-vehicle testbeds, and how these interactions influence safety and performance. Human agency is central: operators monitor, negotiate handovers, and recover from edge cases; designers translate sensory and neural signals into interfaces that support transparency, predictability, and trust; participants’ feedback calibrates control policies and comfort thresholds. Outcome measures connect human experience– workload, situational awareness, trust calibration, embodiment, and comfort– with technical metrics such as accuracy and precision. The literature regards automation as both an opportunity and a risk: it can reduce physical strain and improve consistency, yet it requires ergonomic principles and governance that preserve attention, appropriate reliance, and meaningful human control. Overall, the research demonstrates that future industrial and transport systems depend on HRI designs that prioritise human performance and well-being while responsibly leveraging robotic capabilities.

Topic 5 – Philosophy and Ethics of Technology. This topic explores how people and technologies co-constitute each other in everyday and institutional contexts. Contributions analyse embodied experience, agency, and mediation, drawing on postphenomenology and socio-technical network perspectives to explain how artefacts shape perception, choice, and responsibility. The literature addresses privacy, surveillance, manipulation, alienation, and the limits of intervention, showing how these issues are negotiated in ordinary settings such as media platforms and retail environments, as well as in public institutions. Designers, users, and regulators co-define acceptable practice through consent, transparency, explainability, accountability, and audit mechanisms, embedding ethics in design and governance procedures rather than treating them as stand-alone reflection. Debates also consider non-human actors and heritage contexts, where technology acts as a mediator and active participant in networks of relations. Overall, the focus is on human agency and value conflict, and on maintaining human dignity and fairness as technologies are specified, deployed, and governed.

Topic 6, labeled "Clinical mHealth and Usability," This topic examines how mobile health tools and clinical decision support (CDS) systems are designed, implemented, and governed within real care pathways. Research focuses on patient groups such as people living with HIV, oncology patients, and those with chronic conditions, highlighting the roles of clinicians, nurses, and caregivers in selecting, configuring, and using digital tools. Studies assess human outcomes alongside clinical ones, including usability, learnability, workload, trust, explainability, adherence, and safety. Methods include co-design with patients and staff, think-aloud usability tests, workflow observations on wards and in clinics, and field trials tracking adherence and symptom reporting. A recurring theme is integration with existing infrastructures. Work addresses EHR interoperability, alert fatigue, data quality, privacy, and consent management, as well as accessibility for users with low literacy, children, and minority populations. Designs that support shared decision-making, plain-language prompts, multilingual interfaces, and inclusive visual cues improve engagement and equity. Governance is treated as part of design: teams calibrate CDS thresholds, audit algorithmic bias, and set procedures for human override. Overall, the literature shows how human-centred design translates into clinical practice by aligning digital tools with routines, responsibilities, and values in care delivery, thereby improving effectiveness while protecting dignity, safety, and fairness.

Building on the thematic composition shown in Figure 2, the next analysis examines how the prevalence of the six topics changes over time. By tracking their annual distribution from 2020 to 2025, we can identify shifts in scholarly attention and moments when specific domains gain or lose prominence. Figure 3 visualizes these temporal dynamics and shows how the field of human–technology interaction responds to social, technological, and policy developments.

The temporal evolution of topics between 2020 and 2025, as shown in Figure 3, reveals a substantial restructuring of research priorities in the human–technology domain. Topics 2 ("Education and Human-Centred Design") and 4 ("Robotics, HRI and Ergonomics"), which are most prominent in 2020–2021, record the steepest subsequent declines. Their early salience aligns with the global pivot to remote education and the rapid, experimental deployment of automation during the initial COVID-19 response. As emergency adaptation gave way to normalization, and with typical publication lags moving clinical and implementation studies into later years, research attention shifted from short-term instructional and ergonomic challenges toward systemic questions of integration, governance, and social impact. The decline of these topics therefore reflects the waning of crisis-driven innovation and the absorption of human-centred methods into broader design and policy frameworks.

By contrast, Topic 6 ("Clinical mHealth and Usability") shows the strongest growth and becomes the most prevalent theme by 2025. This expansion parallels the institutionalization of digital health infrastructure, the consolidation of telemedicine practices, and the global policy emphasis on healthcare resilience. Initiatives such as the European Health Data Space and national digital-health strategies have legitimized mHealth research as a permanent component of health-system modernization. Similarly, Topics 1 ("Industry, AI and Sustainability") and 3 ("Public Health, Community and Equity"), which were marginal in 2020, advance into the top tier by 2025. Their rise mirrors wider socio-political trends: the European Green Deal, the AI

Act, and post-pandemic recovery programs have redirected research funding and corporate strategies toward sustainable industry, ethical AI, and social well-being.

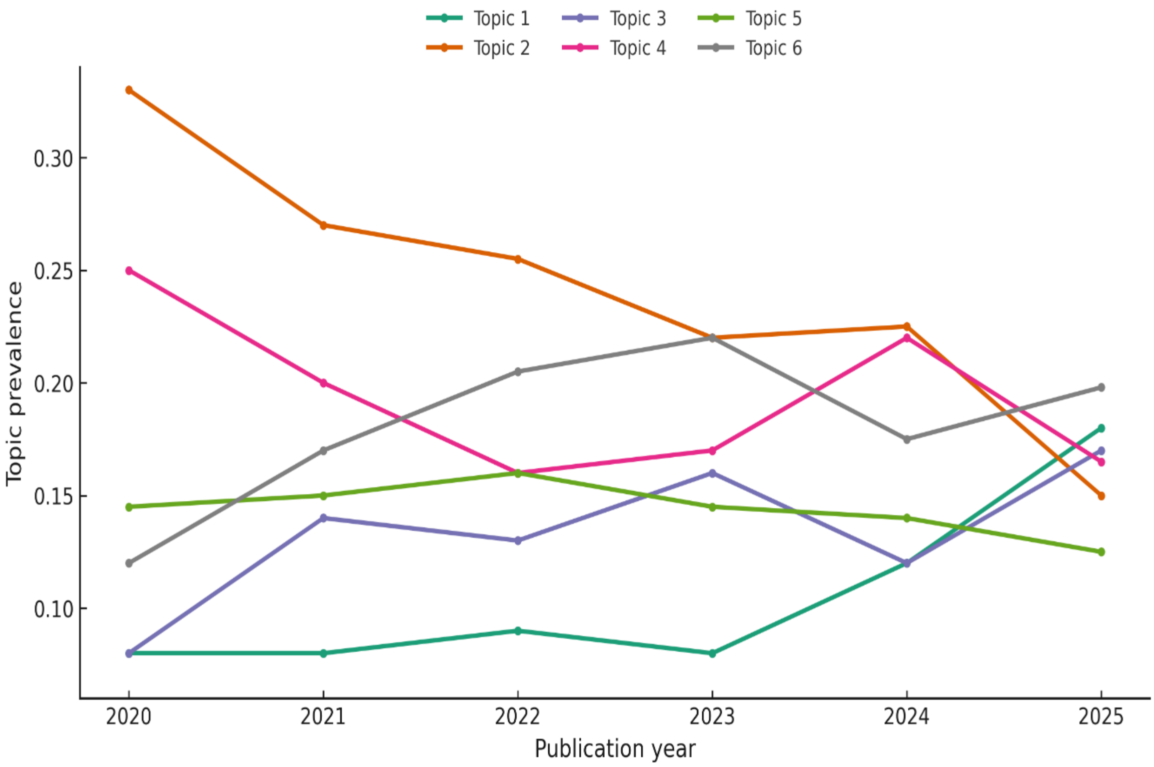

Figure 3. Trends in topic prevalence across the human–technology corpus (2020–2025).
[Source: Authors' computation based on STM output]

Together, these shifts mark a transition from reactive, pandemic-specific research to more strategic and institutionalized agendas that embed digital technologies within industrial, medical, and community systems. The human–technology field thus moves beyond early experimentation to address long-term priorities such as resilience, inclusiveness, and governance, reflecting how global crises, sustainability imperatives, and regulatory initiatives reshape both the content and direction of scientific inquiry.

To test whether these observed trends were statistically significant rather than random fluctuations, we conducted inferential comparisons of topic prevalence before (2020–2021) and after (2022–2025) the onset of COVID-19 using independent-sample t-tests with Benjamini–Hochberg correction for multiple testing (Figure 4). The results confirm both substantive and statistical realignment of the field. Topics T2 and T4, dominant before the pandemic (mean prevalence 0.30 and 0.22), declined significantly to 0.21 and 0.18 (BH-adjusted $p < 0.05$). Conversely, Topics T1 and T6 increased significantly (from 0.08 to 0.12 and from 0.15 to 0.20; BH-adjusted $p < 0.05$), while Topic T3 showed a moderate but robust increase ($0.11 \rightarrow 0.14$; $p < 0.05$). Topic T5 remained statistically unchanged ($0.15 \rightarrow 0.13$; n.s.), indicating its stable yet secondary role. Overall, the inferential evidence confirms a structural realignment from short-term pandemic responses to diversified, policy-oriented, and socially embedded lines of inquiry.

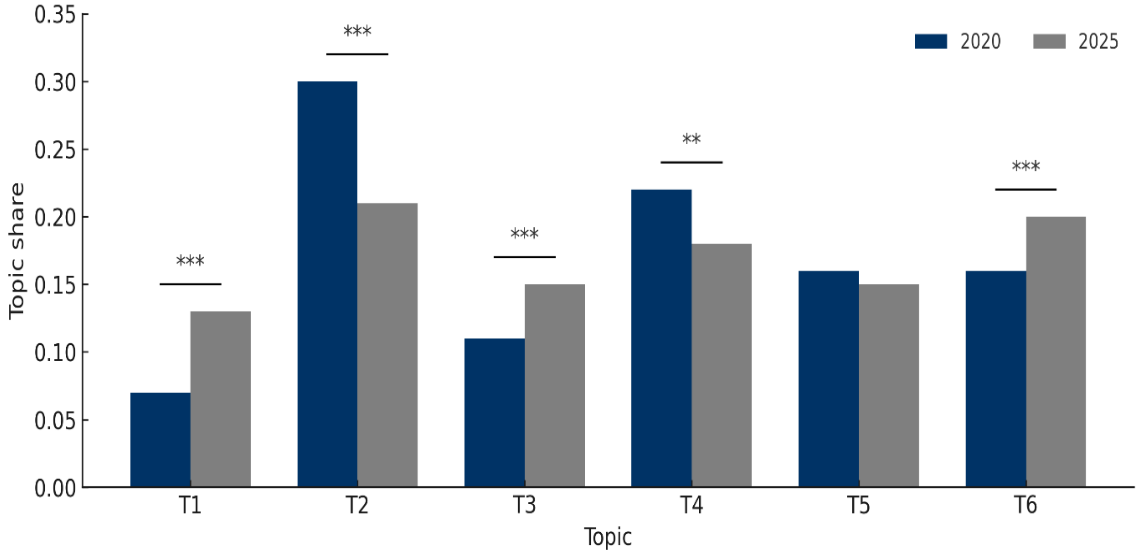

Figure 4. The comparison of topic prevalence before (2020–2021) and after (2022–2025).
[Source: Authors' analysis]

In the next step we analyse the correlation matrix of topic proportions, which illustrates how frequently the six topics co-occur within the same abstracts (see Figure 5).

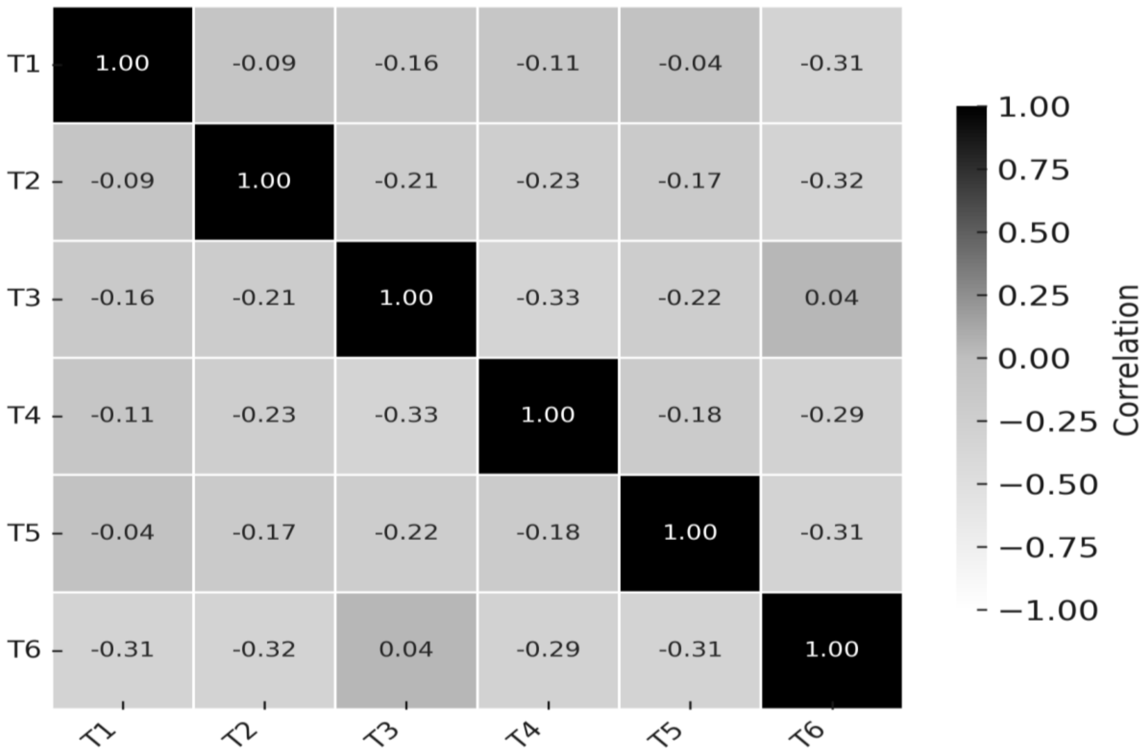

Figure 5. Correlation matrix of topic proportions.
[Source: Authors' computation based on STM output]

As shown in Figure 5, the overall correlations are weak and predominantly negative, indicating a relatively distinct thematic separation between topics. The absence of strong positive correlations suggests that most papers are clearly associated with a single dominant thematic area rather than combining multiple ones.

The highest negative correlations occur between Topic 6 (Clinical mHealth and Usability) and Topics 1, 2, 4, and 5 ($r \approx -0.3$), implying that clinical and health-related studies tend to be conceptually and empirically isolated from research on industry, education, robotics, and ethics. Topic 3 (Public Health, Community and Equity), however, shows a weak positive link with Topic 6 ($r = 0.04$), reflecting their shared focus on health and social well-being. The moderate negative correlations among the remaining topics (−0.1 to −0.3) indicate specialization without fragmentation: while subfields are distinct, they coexist within a coherent intellectual structure. Overall, the correlation matrix confirms that the six-topic configuration captures meaningful thematic boundaries, supporting the internal validity of the STM model and reinforcing the interpretation that human–technology research has evolved into a diversified yet integrated domain.

To complement the descriptive analysis of topic prevalence, two indices were employed to capture the structural characteristics of the thematic distribution: the Gini index and Shannon entropy. Both indices were computed using normalized topic prevalence scores obtained from the STM posterior estimates. The Gini index (Figure 6) quantifies the degree of inequality in topic prevalence. It is derived by comparing the differences between all pairs of topic shares and normalizing them by the mean share across topics. In intuitive terms, the index measures how unevenly research attention is distributed: values close to 1 indicate strong concentration, where a few topics dominate the field, while values near 0 reflect a more balanced thematic structure.

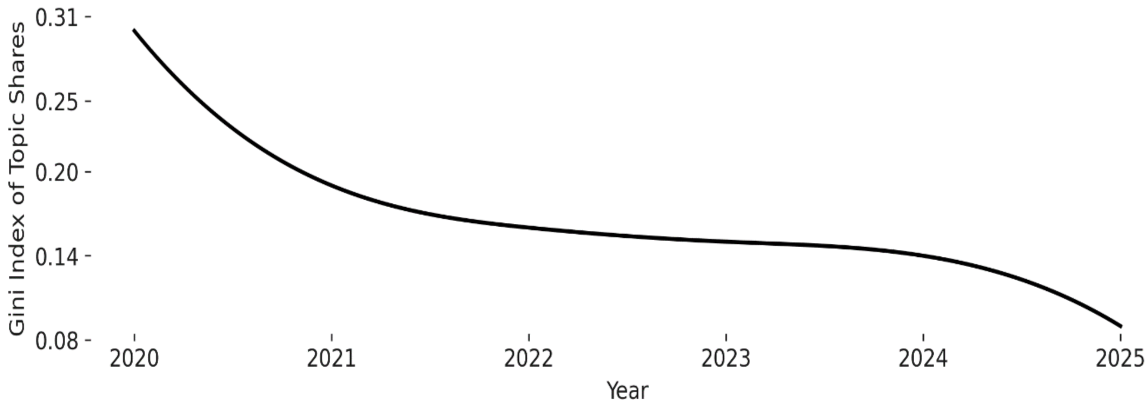

Figure 6. Evolution of Thematic Inequality (Gini Index, 2020–2025. [Source: Authors' analysis]

The decline in the Gini index indicates a gradual equalization of topic shares between 2020 and 2025, meaning that research attention became more evenly distributed across themes. In relation to Figure 3, this trend reflects a shift from the early dominance of Topics 2 (Education and Human Centered Design) and 4 (Robotics, HRI and Ergonomics) toward the growing importance of Topics 1 (Industry, AI and Sustainability), 3 (Public Health, Community and Equity), and 6 (Clinical mHealth and Usability). The decrease in inequality corresponds with the diversification and institutionalization of the human technology field, as studies expanded from short term responses during the pandemic to broader systemic and policy oriented agendas. The pattern is also consistent with the correlation matrix in Figure 4, where weak and mostly negative correlations indicate specialization without fragmentation. Overall, the declining Gini index shows that the field evolved toward a more balanced and mature configuration in which diverse research areas coexist within an integrated structure.

The Shannon entropy, in turn, measures the overall diversity of topic distribution, with higher values indicating a more balanced and pluralistic research landscape and lower values reflecting concentration around a few dominant themes. It is calculated by multiplying each topic's share by the natural logarithm of that share, summing the results for all topics, and taking the negative of that sum. While the Gini coefficient showed a steady decline from 0.3 in 2020 to 0.1 in 2025, indicating a gradual reduction in thematic inequality, the entropy measure reveals a more complex dynamic. (Figure 7) .

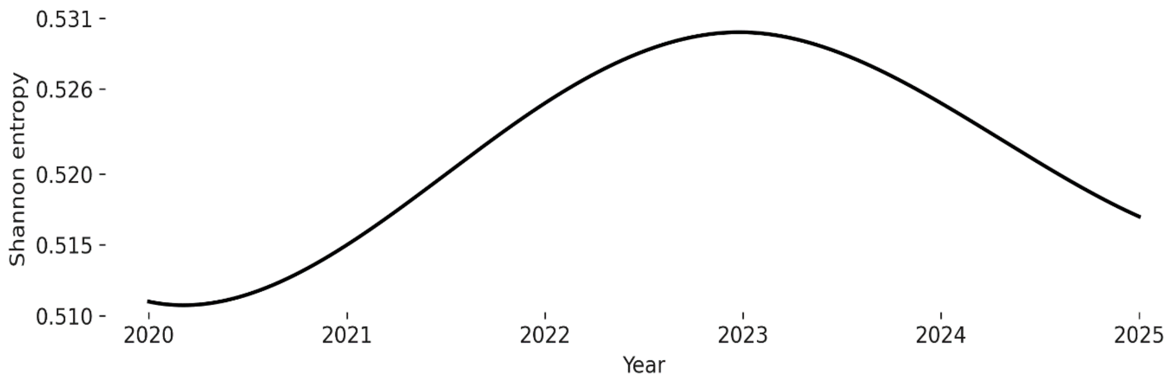

Figure 7. Changes in Research Diversity Over Time: Shannon Entropy Index, 2020–2025.
[Source: Authors' analysis]

Entropy increased from 0.512 in 2020 to a peak of about 0.530 in 2023, marking a period of growing diversification and balance across research streams. After this peak, a mild decline to 0.517 in 2025 suggests a partial reconsolidation of scholarly attention, likely around new dominant themes that emerged during the earlier expansion. Taken together, the Gini and Shannon indicators depict a research field that initially diversified and then began to stabilize into a moderately pluralistic yet more coherent configuration.

DISCUSSION

This study systematically mapped the thematic evolution of human–technology research from 2020 to 2025 using a Structural Topic Modelling (STM) approach. The model identified six dominant topics: Industry, AI and Sustainability; Education and Human-Centred Design; Public Health, Community and Equity; Robotics, HRI and Ergonomics; Philosophy and Ethics of Technology; and Clinical mHealth and Usability. The findings reveal a significant structural realignment in the field after 2020. The early pandemic period was characterised by rapid, practice-oriented responses in education and ergonomics, while subsequent years saw a marked shift towards applied, solution-oriented, and interdisciplinary research streams embedded in industrial, clinical and community systems. Thematic inequality, measured by the Gini index, declined steadily from 0.30 in 2020 to 0.10 in 2025, while Shannon entropy increased to a peak in 2023 and then mildly declined (0.512 → ~0.530 → 0.517), indicating a pluralistic yet increasingly balanced field. Together, these indicators suggest a maturing research ecosystem that has moved beyond disciplinary silos towards a more integrated configuration of applied subfields.

The shift from crisis-driven, short-term responses to practical and institutionalised application reflects both societal and institutional pressures shaping knowledge production. Global crises such as COVID-19 accelerated the adoption of digital tools in health care, education, and industrial organisation (Shneiderman, 2022; Zhao et al., 2024). Consequently, scholars prioritised empirical evaluation and design optimisation over abstract theorisation. The increasing prominence of Industry, AI, and Sustainability mirrors the widespread diffusion of industrial AI and the IoT as drivers of green and digital transitions (Phatthanachaisuksiri et al., 2025). This strand connects human-centred artificial intelligence (HCAI) with corporate sustainability frameworks, echoing the call for socially aligned innovation emphasised by Shneiderman (2022). This institutional embedding is also reflected in the maturation of sustainability reporting research, which maps how disclosure and accountability practices become standardized governance mechanisms (Agama & Zubairu, 2022). In parallel, Clinical mHealth and Usability has emerged as the fastest-growing domain, reflecting intensified investment in digital health infrastructure and patient-centred care (Deniz-García et al., 2023). Consistent with these shifts, Education and Human-Centred Design and Robotics, HRI, and Ergonomics declined from their early-pandemic prominence, while Public Health, Community, and Equity registered a moderate increase. Overall, these transformations indicate that the human–technology nexus has entered an era of institutional embedding, where the "human" is defined through design protocols, usability standards, and governance requirements rather than philosophical debate.

Conversely, Philosophy & Ethics of Technology did not change significantly, suggesting that value-sensitive inquiry is increasingly diffused into adjacent applied domains rather than marginalised. Ethical considerations are now integrated into AI governance, user-experience design, and data management (Batool et al., 2025). This aligns with Floridi (2023), who argues that ethics is increasingly enacted through design choices and algorithmic audits rather than stand-alone philosophical argumentation. By contrast, Education & Human-Centred Design declined from its early-pandemic prominence, indicating that while pedagogical reform remains influential (Hu & Chan, 2025), its relative share has diminished as attention shifted toward institutionalised industrial, clinical, and community agendas. Collectively, these shifts illustrate a movement from debating the "why" of human–technology relations to optimising the "how" of human-centred implementation.

The trends observed in our analysis are in line with earlier mapping efforts. García-Fernández et al. (2024) found that research on digital human resources shifted from conceptual discussion to managerial implementation, while Zhao et al. (2024) observed a similar shift in healthcare HCI. The current analysis extends these insights by quantifying not only topic prevalence but also structural balance, showing that the expansion of applied domains does not lead to fragmentation. Moderate negative correlations among topics indicate specialisation without isolation: health-oriented studies rarely overlap with robotics or educational design, yet all coexist within a coherent network of shared methods and ethical vocabularies. At the same time, the persistence of philosophical inquiry at a stable level, together with the diffusion of ethical reasoning into adjacent applied areas, resonates with what Blok (2022) calls the "re-embedding of creativity" in human–technology relations. Similar findings appear in bibliometric analyses of AI ethics, where clusters on fairness, transparency, and accountability increasingly merge with applied computer-science venues (Qiu et al., 2025). Hence, this pattern reflects not a retreat of philosophy but its integration into pragmatic domains that internalise ethical reasoning.

Our findings contribute to broader theoretical debates on how human agency and technological mediation co-evolve. The diversity of topics supports the socio-technical systems perspective emphasizing that technologies are not external tools but nodes in networks of human and non-human actors (Bisconti et al., 2024). The rise of practice-based research in design and robotics corroborates postphenomenological accounts that view interaction as mutual shaping rather than one-way influence (Gray et al. 2025). Empirical evidence from STM shows that humans increasingly appear not as abstract users but as situated agents - operators, patients, students, and consumers - who negotiate functionality and meaning through participation and feedback loops. This evolution resonates with Johannessen et al. (2023), who describe "multi-site domestication" of technologies across institutions, illustrating how agency is redistributed through everyday appropriation and repair.

Moreover, the convergence of industrial AI and sustainability indicates a paradigmatic shift towards "responsible automation", where efficiency gains are assessed against social and environmental outcomes (Shabur et al., 2025). By quantifying how these topics emerge and interact, this study empirically substantiates theoretical claims about the co-production of technological and normative orders. It also demonstrates that resilience in socio-technical systems depends not only on technological robustness but also on institutional capacity to integrate ethical and participatory feedback.

CONCLUSIONS

This study systematically mapped the thematic evolution of human–technology research from 2020 to 2025 using a Structural Topic Modelling approach. By analysing over 2,000 abstracts from the Web of Science Core Collection, six dominant research clusters were identified: Industry, AI and Sustainability; Education and Human-Centred Design; Public Health, Community and Equity; Robotics, HRI and Ergonomics; Philosophy and Ethics of Technology; and Clinical mHealth and Usability. Collectively, these topics delineate a field that has shifted from early, crisis-driven and experimental implementations towards empirically grounded, solution-oriented, and institutionally embedded inquiry integrating design, ethics, and governance. Ethical reasoning remains present but is increasingly operationalised within applied domains.

The findings indicate a structural realignment after the COVID-19 pandemic. Thematic inequality (Gini index) declined steadily from 0.30 in 2020 to 0.10 in 2025, while Shannon entropy peaked in 2023 before mildly declining, suggesting a pluralistic yet increasingly coherent configuration of subfields. Early practice-oriented agendas in education and ergonomics were replaced by applied domains combining human-centred AI, digital health, and sustainability frameworks, marking a measurable maturation of the field.

Quantitatively, convergence toward lower inequality alongside sustained diversity shows that research attention is redistributing rather than collapsing into a few dominant strands, preserving pluralism without fragmentation. Substantively, the co-evolution of design protocols, usability standards, and governance practices demonstrates that the “human” dimension is increasingly specified through auditable procedures rather than abstract ethical claims. This consolidation of a shared methodological vocabulary - user studies, living labs, algorithmic audits - enables cumulative learning and methodological comparability across contexts. The study thus provides both a reproducible diagnostic for monitoring structural balance over time and a framework for identifying where integrative research is already consolidating versus where disciplinary boundaries persist.

Methodologically, the STM-based workflow combining topic modelling with diversity metrics (Gini and Shannon entropy) offers a transferable tool for assessing consolidation and fragmentation in interdisciplinary domains. Theoretically, the results support sociotechnical and postphenomenological perspectives by showing that technologies operate as co-evolving nodes in networks of human and nonhuman actors, with humans functioning as situated agents who shape systems through feedback and adaptation.

Despite its strengths, the study is limited by reliance on English-language abstracts from WoSCC and a focus on co-occurrence rather than causal mechanisms. Future work should integrate citation and co-authorship networks, embedding models, and multilingual corpora to validate cross-domain comparability and include non-Western epistemologies.

Ultimately, this research contributes a reproducible, data-driven framework for mapping structural maturity and inclusiveness in interdisciplinary knowledge fields, offering a transferable model for evaluating how ethical and sustainable design principles become institutionally embedded within the evolving human–technology nexus.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

The field’s partial reconsolidation after 2023 points to actionable next steps. For research, the STM-plus-diversity workflow should be reused to monitor thematic balance, compare subfields, and evaluate how funding reshapes trajectories. Priorities include extending beyond English, integrating citation and co-authorship networks to map epistemic communities, and testing embedding models to sharpen topic boundaries and detect drift. For application, the growing institutionalization of ethics in design, mHealth, and industrial AI argues for operationalizing ethics via usability benchmarks, governance checklists, audit trails, human-override procedures, and documentation of data stewardship, accessibility, and equity. For policy, alignment with Horizon Europe and the Digital Decade suggests favouring cross-disciplinary consortia that link engineering, social science, and ethics, require pilots or living labs, and evaluate outcomes with human-centred metrics safety, trust, inclusion, and environmental impact. Overall, these implications shift emphasis from abstract principles toward verifiable practice, measurable standards, and funding criteria that reward responsible, socially grounded innovation.

ACKNOWLEDGMENTS

The project in Poland is financed by the Ministry of Science and Higher Education in Poland under the program "Regional Excellence Initiative".

Regionalna Inicjatywa Doskonałości

Ministerstwo Nauki i Szkolnictwa Wyższego

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 21(3), December 2025, 530–547

DOES VIDEO GAME PLAYING STIMULATE MINDFULNESS?

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Abstract: *The video game industry is a thriving sector where the effects derived from its consumption are studied, among other aspects. This research analyzes the possible incidence of commercial video games on the mindfulness trait of players. To this end, a survey was carried out on a sample, mostly Spanish, of 225 people aged 17 to 66 years. The measure used to assess the mindfulness trait is the Five Facets of Mindfulness Questionnaire (FFMQ). Among the main results obtained, the length of time spent playing video games is slightly and directly associated with a higher mindfulness trait among non-meditating players. On the other hand, a positive association is also detected between the greater experience with video games, except for meditating players, with the FFMQ dimensions: not-judging inner experience dimension (particularly strong correlation in ADHD players), describing and non-reactivity to inner experience dimension.*

Keywords: *video games, mindfulness, psychological effects, attention, meditation.*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.3

INTRODUCTION

The video game industry is a booming sector. Taking the Spanish case as a reference, nearly 40% of the population plays video games and spends more than 7 hours per week on this activity (AEVI, 2022). Although the most common users are teenagers and young adults, more and more children and older adults are playing (ISFE-EGDF, 2021). Given their prominence, it is understandable that there is considerable research on video games effects. Among other psychosocial aspects, they favor mental flexibility (Mayer, Parong and Bainbridge, 2019), attention (Dale and Green, 2016; Quwaider, Alabed and Duwairi, 2019; Villafuerte-Holguín, 2022), emotional regulation (Di Blasi et al., 2019; Kosa and Uysal, 2020), socialization (Pitic and Pitic, 2022) or well-being (Vyas, 2021).

There is currently much research on the health benefits of mindfulness. And because both in video games and in mindfulness attention is essential, specific videogames have also been developed for the study of mindfulness (Patsenko et al., 2019) or for its stimulation (Kowert, 2020). However, studies addressing the potential of commercial videogames to induce mindfulness are really scarce (Gacken-bach & Bown, 2011), despite the fact that this technique can also be conceived as a trait (Hülsheger, Alberts, Feinholdt, & Lang, 2013) to be measured (Baer, 2020).

Video game consumption in Spain

The pandemic has boosted the digitalization process, consolidating the videogame industry as a widespread consumer good and consequently placing Spain in the top 10 worldwide in the sector in terms of market size (AEVI, 2020). According to the 2022 yearbook on The Video Game Industry in Spain published by the Spanish Association of Video Games (AEVI), 2,012 million euros were invoiced by this section of audiovisual and cultural leisure, representing 12.09% more than in the previous year. With regard to the sale type, the general trend over the last decade has been positive for both physical and online channels, especially for the latter, which in 2020 managed to surpass its predecessor in sales (AEVI, 2020).

An important section within this industry is the way of consuming video games, focusing on the different devices used on the one hand and, on the other, on the time of use. Currently, the most commonly used devices in Spain are desktop consoles with 29%, followed closely by the smartphone, with 26%. This is followed by the computer with 22%, the tablet with 14% and the portable console with 9% (AEVI, 2022). The average time spent now playing games per week stands at 7.42 hours (AEVI, 2022), representing a slight decrease compared to the previous year, when the highest figure recorded to date in Spain was 8.1 hours (AEVI, 2021). In the combination between time spent per week and device used, consoles top the ranking with 4.93 hours, with men being predominantly (66%) those who use this method the most. Equal percentages of women and men use smartphones and tablets 4.37 hours. And finally, the computer gets 3.84 hours, this time with a higher percentage of women, 72% (AEVI, 2022). The frequency with which games are played is another parameter to take into account. 72% of gamers say that they play every week, representing some 13.1 million people in Spain, another 18% play at least once a month and the remaining percentage plays sporadically (AEVI, 2022).

Another relevant issue is the players' profile. According to the statistics collected, there are gamers of all ages, obtaining data between 6 and 64 years of age (ISFE-EGDF, 2021).

During 2022, of the 18.2 million people who confirm themselves as video gamers in Spain, it is still mainly adolescents, with 84% of the population between 11 and 14 years of age, who consume the most video games. A significant increase is seen in childhood, with 79% of children between 6 and 11 years of age playing video games. Young people between 15 and 24 years old maintain their numbers at 71%, while the older age groups are gaining more and more followers every year, accounting for 60% between 25 and 34 years old, 42% between 35 and 44 years old and 31% between 45 and 64 years old (AEVI, 2022). In reference to the device chosen by each age group, it is worth noting that 62% of gamers between 6 and 10 years of age prefer to use desktop consoles, as do 76% of gamers between 11 and 14 years of age. Gamers between 15 and 24 years of age choose indistinctly, 49%, both smartphones and desktop consoles. The same is true for the 25-34 age group, but the percentage is reduced to 34% for both devices. The smartphone prevails at 24% for those aged 35 to 44. And finally, the 45-64 age group breaks the trend, as their most used devices are the smartphone, with 15%, and the computer, with 14% (AEVI, 2022). By gender, the number of women playing video games is increasingly similar to that of men, reaching the highest percentage in Spain in 2021, with 48%. In figures, this means 8.6 million female gamers out of a total of 18.1 million (AEVI, 2021).

Finally, according to the number of sales, it should be emphasized which genres are preferred by the Spanish population today. Leading the ranking with 1,786,554 units is action, followed by role-playing games with 1,449,099 and sports games with 1,114,50. Adventure, with more than half the sales of the previous ones, followed by racing, FPS or shooter and strategy, with around half a million units each. And closing the list are family games with 280,313, 68,253 for casual games and arcade games with 1,170 that are adding new regulars every year (AEVI, 2022).

Psychosocial effects of video games

Scientific research on video games is sometimes contradictory, presenting both favorable and unfavorable results (Moncada & Chacón, 2012). This may be partly due to the high overload of cognitive abilities required by various genres of video games, as they seem to demand a paradigm shift in how cognitive neuroscience examines their impact (Dale, Joessel, Bavelier & Green, 2020). Be that as it may, the current scientific production on the psychosocial effects of video games is high.

The literature on favorable effects has been classified into four blocks: stimulation of psychological skills, emotional management, social skills and aspects associated with well-being. In relation to the first block, some studies indicate that video games can favor executive functioning in general (Dale & Green, 2016; Xu, Liang, Baghaei, Berberich & Yue, 2020), or some of the executive functions in particular, such as working memory, decision-making or self-control (De Pasquale, Chiappedi, Sciacca, Martinelli y Hichy, 2021; García-Naveira, Jiménez, Teruel & Suárez, 2018; Villafuerte-Holguín, 2022). Likewise, video games can stimulate self-confidence, motivation, inteligence and creativity (García-Naveira et al., 2018; Bowman, Kowert, & Ferguson, 2015; Xu et al., 2020). Furthermore, action games in particular seem to foster the ability to focus on visual details and make correct decisions under pressure (Bavelier & Green, 2016).

Two aspects within this first block on positive psychological skills, also linked to executive functioning, deserve special consideration: attention and cognitive flexibility. In relation to the latter aspect, there are studies that mention this effect through commercial video games (Mayer, Parong, & Bainbridge, 2019) or in those used as training with the aim of improving some cognitive abilities (García-Naveira et al., 2018). Regarding the item of attention, there are several studies that show benefits in this ability due to video games (Dale & Green, 2016; Quwaider, Ala-bed & Duwairi, 2019; Villafuerte-Holguín, 2022). There are also papers that focus attentional gain on shooter (Bavelier and Green, 2016) or action video games (Antzaka et al., 2017), as well as studies confirming that attention improves significantly due to video games compared to other cognitive processes (Parada, Raposo-Rivas & Martínez-Figueira, 2018) or explaining the player's attentional improvement as a learning curve in new video games (Moncada & Chacón, 2012).

Two of the reasons why people play video games, escapism and stress relief (Pitic & Pitic, 2022), are associated with improvements in emotional management. The escapism (avoidance of the real) offered by video games can reduce stress levels after stressful activities (e.g., work) (Kosa & Uysal, 2020). Likewise, commercial video games are also a promising resource for coping with other negative states such as depression and anxiety (Kowal et al., 2021). And they can also, in the case of intensive players of violent video games, significantly reduce their verbal and physical aggression (Ferguson et al., 2022). In addition, video games may constitute a healthy coping strategy for some players (it is common for many to use them to avoid negative moods and induce positive ones) (Kosa & Uysal, 2020) or as a resource to improve their emotional regulation through the game experience itself (Di Blasi et al., 2019; Kosa & Uysal, 2020).

Regarding the benefits associated with social skills, they are also linked to another of the reasons why people play video games: socialization (Pitic & Pitic, 2022). Videogames enable social skills development (García-Naveira et al., 2018), favor positive social interaction (online video games) (Arbeau, Thorpe, Stinson, Budlong & Wolff, 2020), are associated with increased peer support and prosocial behavior (case of interpersonal and prosocial video games) (Shoshani Braverman & Meirow, 2021) and, stimulate cooperation in general (Quwaider, Alabed & Duwairi, 2019).

The last block on favorable effects associated with well-being, is also linked to other motives explaining their use: entertainment, achievement and fun (Pitic & Pitic, 2022). Online video games constitute a very rewarding experience due to social interactions (Arbeau et al., 2020), an aspect that may be associated with video games being slightly, but favorably, correlated with affective well-being (Johannes, Vuorre & Przybylski, 2021). This technological amusement constitutes a useful resource for generating well-being (Vyas, 2021) or subjective well-being (Shoshani Braverman & Meirow, 2021), and may enhance psychological well-being by teaching skills associated with happiness and life satisfaction (Kowert, 2020).

From a negative perspective, the unfavorable effects detected in the literature on video games are grouped into four blocks: psychological abilities impairment, dependence, negative emotions and well-being deterioration. Regarding the first aspect, the literature indicates that they do not facilitate learning to think (Machargo, Luján, León, López & Martín, 2003). Intensive gaming is also linked to poorer memory and attention, as well as to cognitive and academic skills impairment (Farchakh et al., 2020) and this last aspect matches another study (Gómez-Gonzalvo, Devís-Devís & Molina, 2020). In relation to dependence, there is no consensus among scholars as to whether or not the possible addiction generated by video games is a mental health problem, or if it represents a gambling disorder (Ferguson & Colwell, 2020).

It is noteworthy that males appear to be more addicted than females, although dependence, in both sexes, decreases with increasing educational level (Esposito et al., 2020).

Video games provoke feelings of guilt for having invested too much time in them or implying the loss of school classes (Graner, Sánchez-Carbonell, Beranuy & Chamarro, 2008). They are also associated with higher anxiety levels (De Pasquale et al., 2021), negativity and aggressiveness (Quwaider, Alabed & Duwairi, 2019). Regarding this last mentioned aspect, some studies link aggressiveness to exposure to violent video games (Ferguson et al., 2022; Quwaider, Alabed & Duwairi, 2019). In relation to well-being deterioration, players themselves point out that the use of video games can be detrimental and affect their physical, mental and social well-being (Cisamolo, Michel, Rabouille, Dupouy & Escourrou, 2021).

Mindfulness and video games

The concept of mindfulness is strongly rooted in Buddhist psychology, although it shares conceptual parallels with ideas from various philosophical and psychological traditions (Brown, Ryan & Creswell, 2007). This word derives from the Pali word sati translated, on the one hand, as memory and, on the other, as consciousness, awareness or knowledge (the latter term also translated from sati as mindfulness) (Shulman, 2010). Consciousness, from this perspective, is the conscious registering of stimuli, including the five physical senses, the kinesthetic senses and the activities of the mind (Thera, 1973).

From the Western psychological perspective, mindfulness is usually defined as the maintenance of attention on the experiences happening in the present moment, accepting them as they occur or, in other words, without judging them. These experiences can occur both internally, whether mental or bodily, and externally. This type of disposition is often contrasted with a an autopilot state, in which behavior occurs mechanically and without attention to it (Baer, 2020). Among other aspects, mindfulness implies a renunciation of direct control, i.e., it does not aim for the person to control his or her reactions, feelings or emotions, but to experience them as they occur (Vallejo, 2006).

Definitions of mindfulness usually refer to a state of consciousness, but it can also be understood as a personality trait. In the first case, it refers to the degree to which a person pays attention and is truly aware of the stimuli occurring in the present (Brown & Ryan, 2003). Whereas the meaning of mindfulness as a trait represents the duration, frequency and intensity with which a person tends to engage in mindful states (Hülsheger, Alberts, Feinholdt & Lang, 2013). The mindfulness trait can be measured with various instruments, primarily self-report questionnaires (Baer, 2020).

The benefits associated with mindfulness are diverse. To cite some specific ones, it reduces the intensity of emotional disorders (Brown & Ryan, 2003), improves emotional regulation (Baer, Smith & Allen, 2004), stimulates creativity (Vargas, 2014) and benefits social relationships (Bihari & Mullan, 2014). In terms of well-being, its potential to promote both health and psychological well-being in the work environment (Goilean, Gracia, Tomás & Subirats, 2020), health and well-being in children and adolescents (Semple & Burke, 2019), physical well-being, especially in populations with pain (Creswell, Lindsay, Villalba & Chin, 2019), as well as psychological well-being in general (Tang et al., 2019), has been evidenced. Mindfulness has also been shown to be useful in relation to the negative effects of video games. There are studies that have found a negative association between mindfulness and an obsessive passion for video games (Mills, 2019), specific intervention designs have been developed to treat video game addiction with mindfulness presence (Li et. al, 2018) and there are research that has detected a lower association with mindfulness, among other variables, in people with Internet gaming disorder and/or depression (Marchica, Mills, Keough & Derevensky, 2020).

Do video games have the potential to generate mindfulness? Considering non-commercial proposals, virtual relaxation spaces have been created with games to maintain sustained attention that energetically recharged participants (Asati & Miyachi, 2019); interventions with games and mindfulness have been designed to increase patients' engagement with their therapy (Birk, 2019); games have been developed to improve mindfulness with immediate results (Kowert, 2020); phone and virtual reality-based games have been created to teach mindfulness to people recovering from post-traumatic stress disorder (Birk, 2019); video games based on meditation, have been devised/implemented to study mindfulness at brain level explaining why it is associated with improvements in performance on an attentional task (Patsenko et al., 2019); and gamified applications and experimental games have been developed for participants to define their mindfulness experience in the video game (Hamilton, DiSalvo & Fullerton, 2021).

On the other hand, there are also several studies showing that virtual reality systems and their applications help induce mindfulness or increase people's mindfulness skills (Kosa and Uysal, 2018); that playing video games can enhance applied mindfulness practice (when performing a task) (Newell, 2021); and that video game players, relative to yoga practitioners, obtain more prominent mindfulness scores (Ray, 2022).

The only localized study that offers results on the relationship between co-marketing video games and mindfulness, among other variables, was developed by Gackenbach and Bown (2011) on a sample of young American adults. According to this work, the conscious experience of the present moment and the mindful awareness state, both during the game, as well as the ability to act without judgment during the day are found to be more accentuated in intensive players than in occasional ones.

The Present Study

This study evaluates the potential of commercial video games to generate mindfulness through their association with video game consumption variables. In the evaluation of each hypothesis, we consider whether players suffer from attention deficits or engage in a meditation practice as extraneous factors that may affect the results.

The hypotheses that finally articulate the study are:

Hypothesis 1 (H1): Higher consumption of video games is directly and positively associated with higher scores on all dimensions of the mindfulness trait.

More specifically:

Hypothesis 1a (H1a): greater length of time playing video games is directly and positively associated with higher scores on all dimensions of the mindfulness trait.

Hypothesis 1b (H1b): Greater frequency of playing video games is directly and positively associated with higher scores on all dimensions of the mindfulness trait.

Hypothesis 1c (H1c): Longer duration of video game playing sessions is directly and positively associated with higher scores on all dimensions of the mindfulness trait.

METHODS

Participants

The sample consisted of 225 participants, of whom 125 (55.6%) were women, 55 were men (42.2%), the rest -5, 2.2%- being of other options (prefer not to say, agender, other, etc.).

The average age of the participants was slightly over 28 years, as can be seen in Table 1.

Table 1. Descriptive statistics of the age variable

Media	Median	Minimum	Maximum	Standard Deviation
28,14	24,00	17	66	11,006

Instruments

Mindfulness trait. It was measured through the Five Facets of Mindfulness Questionnaire (FFMQ), original by Baer, Smith, Hopkins, Krietemeyer and Toney et al. (2006) and adapted to Spanish by Cebolla et al. (2012). It is an instrument of 39 items, rated on a Likert scale from 1 (*never or very rarely true*) to 5 (*very often or always true*). The tool measures five dimensions of mindfulness (Baer et al., 2008): observing (noticing or attending to inner and outer experiences, such as sensations, cognitions emotions, images, sounds, and smells), describing (labeling inner experiences with words), acting with awareness (attention to in-the-moment activities and can be contrasted with behaving mechanically with attention focused elsewhere), nonjudgment of inner experience (taking a stance toward thoughts and feelings without evaluation of them), and nonreactivity to inner experience (tendency to allow thoughts and feelings to come and go without getting caught or carried away by them). It also provides a general measure of mindfulness.

The obtained reliability of the scale determines its validity, without being outstanding (Cronbach's alpha = 0.777). Further analysis of the scale shows, according to Table 2, that all dimensions obtained normal distributions except for the fifth dimension (*non-reactivity to interior experience*).

Table 2. Kolmogorov-Smirnov test for the FFMQ scale

		Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5
N		225	225	225	225	225
Normal pameters						
	Media	27,3822	25,2444	17,0489	17,6356	22,8489
	Desv. típica	5,46300	6,98326	6,82448	7,58114	4,21459
More extreme differences						
	Absolute	,067	,063	,058	,063	,101
	Positive	,059	,062	,040	,055	,058
	Negative	-,067	-,063	-,058	-,063	-,101
Kolmogorov-Smirnov Z		1,002	,948	,876	,938	1,515
Asympt. Sig. (bilateral)		,268	,330	,427	,343	,020

Note. The contrast distribution is the Normal.

For all mean comparison tests, a Bonferroni posthoc was carried out.

Video games consumption. The sample was asked if they usually play video games, with a dichotomous response; how long they have been playing, with different alternatives for a single response (1 year or less, between 1-3, between 3-5, between 5-10, between 10-20 and more than 20); frequency, again with a single response between different options (daily, almost daily, some days of the week, weekly, monthly and occasional or very occasional); average time spent per game session, also with a single possible choice (1-30 min, 30 min.-1h, 1-2h, 2-3h, 3-4h and more than 4h); genre or genres played, with multiple choice (action, shooting, strategy, simulation, sport, racing, adventure, role-playing, musical, puzzles and others); and platforms played, also with multiple choice (computer, tablet, console connected to screen, portable console and cell phone, etc.); and platforms played, also with multiple choice (computer, tablet, console connected to screen, portable console and cell phone, etc.).

Meditation practice. The members of the sample were asked if they practiced any type of meditation, with a dichotomous response alternative, as well as their frequency of meditation practice, with different options for a single response (daily, several times a week, once a week or occasionally with no defined frequency). This is an odd variable, considered because of its possible incidence in the interpretation of the results.

Reduced attention span. The study participants were also asked whether they had been diagnosed with any type of attention deficit disorder or deficit (such as ADD or ADHD), with different alternatives for a single answer (yes, no and not sure). Again, this is an odd variable, considered because of its possible impact on the interpretation of the results.

Sociodemographic aspects. Participants were asked their age, gender (male, female or other) and country of residence (Spain, Latin America or other).

Procedure

When the research design was presented to the Research Ethics Committee (REC) of the main institution promoting the study (UEMC), the REC indicated that since clinical data were not collected, informed consent was not necessary and a favorable report from the REC would not be required. In any case, consent was required from the study participants at the beginning of the questionnaire through four items *(I understand that my participation is voluntary and I am free to participate or not in the study; I understand that the information obtained will only be used for the specific purposes of the study; I understand that I can withdraw from the study whenever I want, without having to give explanations and without any negative repercussions; I freely give my agreement to participate in the project).*

To obtain data, an initial investigation was carried out on the main associations related to the video game sector in Spain in order to find out their role and contact details (27 associations were located). Subsequently, the associations were contacted to present the study to them and to find out their willingness to participate in it.

Each of the ten entities that finally participated in the research was provided with a possible text to formalize the invitation to their members. The data were collected during the months of June to September. In addition, through Whatsapp and e-mail, the research team complemented the sample with its network of direct and indirect contacts, especially with the aim of expanding the presence of sporadic video game players and non-gamers.

All data were collected online through the Google Forms tool.

RESULTS

General information

By way of introduction, it should be noted that the sample analyzed who regularly play video games (53.3% of the total, 37% of women and 63% of men) have extensive experience in their use, since according to the data shown in Table 3, slightly more than 70% of the total report experience of more than 10 years (60% of women and 81.6% of men).

Table 3. How long ago did you start playing?

	Frequency	Valid percentage
1 Year or less	4	3,2
Between 1 and 3 years	5	4,0
Between 3 and 5 years	6	4,8
Between 5 and 10 years	21	16,7
Between 10 and 20 years	45	35,7
More than 20 years	45	35,7
Total playing	126	100,0
Not playing	99	
Total	225	

On the other hand, there is also a predominance of a frequency of use that can be described as high, since the majority declare that they play weekly (33.6% -32.4% in the case of women and 34.2% in the case of men) or even daily (46.2% -36.3% of women and 50% of men) -Table 4-.

Table 4. How often do you play?

	Frequency	Valid Percentage
Very occasionally (occasionally or very occasionally)	9	7,2
Some days or a few days a month (monthly)	16	12,8
Some single day every week (weekly)	20	16,0
Two or three days a week (some days a week)	22	17,6
Almost every day of the week (almost daily)	32	25,6
Every day of the week (daily)	26	20,8
Total playing	125	100,0
Not playing	100	
Total	225	

It should also be noted that gaming sessions usually last less than two hours (67% of the total, 73% in the case of women and 61.3% in the case of men) -Table 5-.

Table 5. How much time do you spend on average on the video games you like?

	Frequency	Valid Percentage
1 to 30 minutes	12	9,6
30 minutes to 1 h	32	25,6
1 to 2 h	40	32,0
Between 2 and 3 h	21	16,8
Between 3 and 4 h	14	11,2
More than 4 h	6	4,8
Total playing	125	100,0
Not playing	100	
Total	225	

Finally, with respect to two central questions in this study, the meditation practice and ADHD presence, it should be noted that only 25.1% practice meditation (74.9% of the total sample does not -71% in the case of women and 78.7% of the total sample of men-), and that the intensity of meditation, when occurring, is less than a week (54.1% in the case of women and 60% in the case of men), as can be seen in Table 6.

Table 6. How often do you practice meditation?

	Frequency	Valid Percentage
Occasionally or at a lower frequency than the following	33	55,9
Once a week	7	11,9
Several times a week	13	22,0
Daily	6	10,2
Total meditating	59	100,0
Not meditating	166	
Total	225	

With regard to ADHD, the data obtained from the sample rule out its presence in the majority (87.9% of the total, in similar proportions according to sex).

FFMQ scale scores

The mean scores obtained from the sample with respect to the five dimensions and the total scale are shown in Table 7.

Table 7. Descriptive dimensions FFMQ scale

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Total
Feminine						
Media	28,12	24,61	16,91	16,59	22,22	108,45
Median	28	24	18	17	23	22
Typ. Dev.	5,53	7,47	6,57	7,32	4,31	6,24
Masculine						
Media	26,29	26,09	17,49	18,74	23,83	112,44
Median	26	26	18	19	24	22,6
Typ. Dev.	5,29	6,34	7,02	7,74	3,9	6,058
Total						
Media	27,38	25,24	17,05	17,64	22,85	110,16
Median	27	26	18	17	23	22,2
Typ. Dev.	5,46	6,98	6,82	7,58	4,21	6,21

The comparison tests of the mean scores of the FFMQ scale dimensions obtained for players and non-players did not yield statistically significant differences (p=.292, F=24.307, T-test). That is, playing or not playing did not determine significant differences in the mean scores obtained from the FFMQ scale.

Thus, no significant differences were observed between men and women (p=.133, F=2.513, T-test) in the overall score. Considering the dimensions of the scale separately, significant differences were observed in dimensions 1, 4 and 5 (p=.014, ,037 and ,011, F=.773, ,919, T-test in dimensions 2 and 4, Mann Whitney U=4754.500 in dimension 5), and no significant differences were observed in the rest of them (p=.121 and ,528, F=5.155 and ,257 respectively, T-test).

Finally, no significant differences were detected between meditators and non-meditators (p=.168, F=5.070, T-test, X non-meditators=109.17, X meditators=113.34,) or between ADHD and non-ADHD (p=.371 ANOVA 1 factor, posthoc Bonferroni, X ADHD=102.72, X non-ADHD=111.97). That is, both meditating and noting having ADHD do not imply significantly higher scores on the FFMQ scale.

Contrast of hypotheses

The hypotheses proposed and their contrast with the data obtained for this study are as follows:

Hypothesis 1 (H1): Higher video game consumption is directly and positively associated with higher scores on all dimensions of the mindfulness trait.

The contrast of this hypothesis is reached by adding the subsequent hypotheses. Thus, and considering the evidence obtained for the working hypotheses H1a, H1b and H1c, it can be generally affirmed that greater consumption of video games is not directly and positively associated with higher scores in the dimensions of the mindfulness trait.

This situation holds in different subgroups of the sample: meditators and non-meditators, and sample with ADHD and without ADHD.

More specifically:

Hypothesis 1a (H1a): greater length of time playing video games is directly and positively associated with higher scores on all dimensions of trait mindfulness.

The correlation coefficients in Spearman's Rho test show a direct and significant relationship between the length of time playing video games for dimensions 2, 4 and 5, an inverse and significant relationship for dimension 1, and no significant relationship for dimension 3 (Table 8). Consequently, it cannot be affirmed that more time playing video games is associated with higher scores on the FFMQ mindfulness scale.

Table 8. Rho Spearman test between seniority playing video games and PPMQ scale dimensions

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5
Coef. Corr.	-0,26	0,30	0,16	0,32	0,20
Sig.	0,00	0,00	0,08	0,00	0,03
N	126,00	126,00	126,00	126,00	126,00

However, considering this question in relation to the part of the sample that meditates and the part that does not meditate, significant correlations should be highlighted in general in the group of non-meditators -inverse in dimension 1 (p=.001, Coef. Corr=-.326) and direct in the rest except dimension 3 (p=.001 , ,000 and ,041, Coef. Corr=.332, ,367 and ,206 respectively), where there is no statistical significance (p=.248 and Coef. Corr=.117) - with respect to the group of meditators - where no significant relationships are observed in any dimension. In other words, in the group of non-meditators there is a certain relationship between length of time playing video games and higher scores on the FFMQ scale. This cannot be affirmed in the group of meditators.

Regarding the sample with presence and absence of ADHD, it should be noted that in the case of non-ADHD direct and significant relationships are observed in dimensions 2, 4 and 5 (p=.007, .001, and .037, Coef. Corr=.273, .328 and .312). In the case of the sample with ADHD, a direct and significant relationship was observed only in dimension 4 (p=.007 and Coef. Corr=.780).

Hypothesis 1b (H1b): Higher frequency of playing video games is directly and positively associated with higher scores in all dimensions of the mindfulness trait.

In this case, the correlation coefficients in Spearman's Rho test highlight the absence in all the dimensions of the FFMQ scale of a significant relationship with the frequency of playing, thus affirming that the greater frequency of playing video games is not associated in any case with higher scores in all the dimensions of the mindfulness trait. The specific data can be seen in Table 9.

Table 9. Rho Spearman test between frequency of playing video games and PPMQ scale dimensions

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5
Corr. Coeff.	0,10	0,10	-0,21	-0,09	0,01
Sig.	0,26	0,25	0,02	0,32	0,90
N	126,00	126,00	126,00	126,00	126,00

Unlike the previous case, a certain homogeneity should be noted in the data between non-meditators (where only an inverse and significant relationship was observed between frequency of gambling and dimension 3 of the FFMQ scale -p=.002 and Coef. Corr=-.312-) and mediators (where no significant relationship was observed).

On the other hand, and in homogeneity with the data presented above, the presence or absence of ADHD does not make any difference to the general findings, since, in the same way as mentioned above, no significant relationships of any kind could be established between the frequency of gambling and the scores of the FFMQ scale dimensions.

Hypothesis 1c (H1c): Longer duration of video game playing sessions is directly and positively associated with higher scores on all mindfulness trait dimensions.

In this case, it cannot be affirmed that there is no association between the duration of video game sessions, since the statistical test only highlights a significant relationship between dimension 3, which is also inverse in nature (Table 10).

Table 10. Rho Spearman test between duration of gaming sessions and dimensions of the PPMQ scale

	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5
Corr. Coeff.	0,05	-0,02	-0,21	-0,16	0,07
Sig.	0,56	0,86	0,02	0,08	0,44
N	126,00	126,00	126,00	126,00	126,00

Considering again the difference between meditators and non-meditators, we highlight a similar situation to that described above. Here we only observe an inverse and significant relationship between meditators and duration of game sessions in dimensions 3 and 4 (p=.008 and .041 and Coef. Corr=-.265 and -.207 respectively). As in the previous case, no relationship was observed between meditators and duration of game sessions.

Finally, the samples without ADHD and with ADHD also showed homogeneity in this regard, since in both cases only significant differences were observed between the duration of the sessions and the scores obtained in dimension 3, although both were inverse (p=.027 and .048 and Coef. Corr=-.228 and .-610).

DISCUSSION

According to the results, no differences were observed in the mindfulness trait for playing or not playing video games, although the length of time spent playing video games was directly associated with a higher mindfulness trait among non-meditators. In this sense, if one does not meditate, continuing to play video games seems to stimulate the mindfulness trait to some extent.

Particularly, on the dimensions of mindfulness, the ability of players to attend to internal and external experiences (*observing*) seems to be slightly reduced, to a greater degree among non-meditators, as the length of time spent playing video games increases. Similarly, the ability to *act with awareness* with respect to the duration of games in meditators and in ADHD and non-ADHD players, as well as with the playing frequency in non-meditating players. Both dimensions, closely related to attention in our opinion, are in line with the studies indicating that intensive gaming reduces this capacity (Farchakh et al., 2020). The negative association with game duration is particularly strong among players with ADHD, which seems to indicate that the regular playing of video games in this group favors mechanical behavior with their attention focused elsewhere (Farchakh et al., 2020). The negative association with game duration is particularly strong among players with ADHD, which seems to indicate that the habitual playing of video games in this group favors mechanical behavior with their attention focused elsewhere.

The ability to label internal experiences with words (*describing*) is, on the contrary, positively associated with greater seniority in video games (except in the ADHD group where this relationship is not detected). This link could perhaps be explained through a possible identification that players establish between the content of the screens and the internal vision of their consciousness, so that the greater experience with these devices could lead to a greater ability to name what is happening in the mind. This direct relationship with seniority in video games also occurs with the ability *to be non-judgmental* about the inner experience, especially intense in the case of ADHD players. Stance towards inner thoughts and feelings that presents syntony with the development of the capacity to act without judging in intensive players detected in another study (Ga-ckenbach & Bown, 2011). However, this link with seniority is inverse in the case of meditating gamers, something that could perhaps be explained by the greater development of the capacity for *non-judgment of inner experience* through meditative practice than through video games, with the result that this second activity reduces this capacity in meditating gamers.

Finally, *non-reactivity to inner experience* is positively related to seniority in video games. A result that, in our opinion, presents correspondence with studies pointing out that video games stimulate cognitive flexibility (Mayer, Parong, & Bainbridge, 2019), considering that this is applied to some degree in the non-evaluative stance towards inner thoughts and feelings.

CONCLUSIONS

This study represents a contribution to the study of commercial video games with the aim of generating mindfulness, a practice with many associated benefits. Although more studies are needed in this line of research to provide robust results, it is considered that the results achieved in this work could be useful for the industry. In the sense, that they could favour their ability to design commercial video games with the capacity to stimulate mindfulness. In addition, the results could also be interesting for those gamers interested in stimulating certain skills associated with this meditative practice: the ability to label internal experiences with words (except in players with ADHD), the ability to not judge the internal experience (in players who do not meditate) and non-reactivity to the internal experience.

LIMITATIONS AND FURTHER STUDIES

The study shows some limitations, such as not being carried out with a larger sample and not contrasting the findings with a longitudinal study. In future research on the topic addressed, it could be interesting to study whether the different platforms from which games are played or the different video game genres have a particular impact on the mindfulness trait or some of its dimensions.

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Authors' Note

The authors wish to give special thanks to the following entities for their collaboration in the collection of data for the study: La Fundación Museo do Videojuego (Fundación MUVI), Red Española de Excelencia en Videojuegos (RiDiVi), Asociación Canaria de Desarrollo de Videojuegos (ACADEVI), Asociación Valenciana de Realidad Extendida (AVRE), Asociación Granada Jam, Asociación Española de Empresas Productoras y Desarrolladoras de Videojuegos y Software de Entretenimiento (DEV), and Asociación GAMELX.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 21(3), December 2025, 548–575

HOW SERIOUS ARE SERIOUS GAME ASSESSMENTS OF READING AND READING-RELATED SKILLS?

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Abstract: ***Purpose****: This study examined the validity of serious game–based assessments (SGAs) for measuring Finnish primary school children's (Grades 1–4; n = 735) reading, spelling, and related cognitive skills.* ***Methods****: Performance in the digital SGAs was compared with corresponding paper-and-pencil tasks assessing word and pseudoword reading, sentence reading fluency, spelling, and underlying skills including phonological processing, rapid automatized naming, short-term memory, receptive vocabulary, and associative learning.* ***Results****: The SGAs showed good concurrent and construct validity for reading fluency, reading accuracy, spelling, rapid automatized naming, and vocabulary. The SGA tasks explained 72–80% of the variance in traditional reading fluency measures and 51–66% in reading accuracy.* ***Conclusions****: The findings indicate that serious game–based assessments provide a valid and engaging alternative to traditional literacy assessment tools. Implications for digital assessment and intervention in reading development are discussed.*

Keywords: *reading fluency, digital serious game assessment, assessment of reading and reading-related skills, transparent orthography, GraphoLearn.*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.4

INTRODUCTION

Around 5–15% of school-aged children face difficulties in learning to read (American Psychiatric Association, 2013). The importance of early intervention of reading difficulties is indisputable: the earlier the identification and adequate support, the less time and effort is needed to reduce the risk of later reading problems (see Fletcher, Francis, Foorman, & Schatschneider, 2021 for summary). Early identification and support to prevent learning disabilities is also at the core of the Response to Intervention (RTI) framework (Fuchs & Fuchs, 2005), a model that has also been applied in Finland where the current study was conducted (Björn, Aro, Koponen, Fuchs, & Fuchs, 2016). Though teachers in Finland have a central role in providing support for students in this three-tiered support system, they can often struggle to find time to provide support adequately to all in need, a task that also involves the completion of accompanying documentation (Eklund, Sundqvist, Lindell, & Toppinen, 2021). Crucially providing early and adequate support requires valid and practical skill assessments. Although some standardised paper-and pencil assessments exist, they require a qualified administrator and usually take up a plenty of time with one-to-one assessments and for scoring the data. What is urgently needed is a reliable and practical assessment tool applicable to teachers (Virinkoski, Lerkkanen, Holopainen, Eklund, & Aro, 2018).

One way to enable practical skill assessment is to use digital versions of standardised skill assessments. Indeed, studies investigating comparability of digital assessments to pencil and paper tasks have shown that although the differences between the two modes are evident the digital versions of the assessments can be a valid way to assess skills (e.g., Kroehne, Buerger, Hahnel, & Goldhammer, 2019). A benefit of digital assessment over traditional one-to-one assessment is that at best it can provide a cost-effective way to secure, scientifically valid, and reliable assessment data without requiring a professional administrator as it also saves time by scoring and interpreting data automatically (e.g., Wang, Jiao, Young, Brooks, & Olson, 2008). Digital assessments can also provide new kinds of methods for assessment, data analyses, and feedback at both the individual and institutional levels that have been virtually impossible via traditional tools (Bennett, 2015). Furthermore, some usability studies have also indicated that both teachers and students seem to prefer digital assessments over the traditional assessment method (e,g., Paleczek, Seifert, & Schöfl, 2021; Seifert, & Paleczek 2021).

In the present study, we took two further steps to critically examine the potential of digital skill assessment specifically in terms of reading and reading related skills in Finnish speaking primary school students. First, instead of merely digitalising existing standardised paper and pencil tasks (PP) we designed and developed tasks directly applicable into the serious game GraphoLearn[1] (e.g., Richardson & Lyytinen, 2014). In other words, our aim was to develop serious game assessment (SGA) tasks that utilised the multimodality of a digital gaming format at the same time as assessing the skills assessed in the standardised PP tasks. Second, we critically examined whether the developed tasks provided similar assessment data as in their counterpart paper and pencil tasks using different validity constructs. Thus, our aim was to investigate if and to what extent the SGA tasks provide comparable and valid data to PP tasks. To our knowledge, investigations of validity of reading and reading-related skill assessments within a serious-game framework does not exist prior to our investigation. The closest alternative to SGA are computerised assessments. Therefore, next we will provide a short background to our study by looking into previous research evidence provided by studies on computerised assessment of reading and related skills.

Computerised Assessment of Reading and Related Skills

The majority of the studies concerning digital, computerised assessment (CA) of reading and literacy skills have investigated reading comprehension skills of high school or university students, and only a relatively small number of studies have explored CA of basic literacy skills, such as decoding and spelling in younger school-aged children (for reviews, see Blok, Oostdam, Otter, & Overmaat, 2002; Kingston, 2008; Wang et al., 2008). In addition, most of the studies have been conducted in the opaque English orthography (Carson, Boustead & Gillon, 2014; Clemens et al., 2015; DeGraff, 2005; Ma et al., 2025; Merrell & Tymms, 2007; Sainsbury & Benton, 2011; Singleton, Thomas & Horne, 2000; Yeatman et al., 2024), for which the emphasis of reading assessment is mostly on reading accuracy, reading comprehension and phonological skills. In transparent orthographies like Finnish, German, Italian, and Greek, learners obtain high reading accuracy already during first Grade (Seymour, Aro, & Erskine, 2003). What is more challenging for Finnish and other learners in transparent orthographies, however, is the development of reading fluency (Eklund, Torppa, Aro, Leppänen, & Lyytinen, 2015; Landerl & Wimmer, 2008), which highlights the need for CA methods to assess fluency as well as accuracy (Protopapas & Skaloumbakas, 2007). Some previous studies have successfully developed CA methods for reading fluency assessment for French (Auphan, Ecalle, & Magnan, 2019), Greek (Protopapas & Skaloumbakas, 2007; Protopapas, Skaloumbakas, & Bali, 2008) and Finnish (Authors, 2020; Heikkilä et al., 2023; Niskakoski, Määttä, Korpivaara, & Westerholm, 2020; Paananen et al., 2019).

To deepen our understanding of reading skill development, assessing also reading-related skills may be important. Specifically reading-related assessments can broaden the understanding of the potential cognitive underpinnings of reading difficulties (Furnes & Samuelsson, 2011; Parrila, Kirby, & McQuarrie, 2004; Vaessen & Blomert, 2010). Some recent studies have addressed the digital assessment of reading related skills in Greek (Zygouris, Vlachos, Styliaras, Tziallas, & Avramidis, 2025), but they did not iclude latency-data nor reading itself. Some currently available CA methods serve as a more comprehensive battery for assessing reading and reading-related skills, but are administered on a one-to-one basis (Jiménez, García, & Balade, 2024; Nergård-Nilssen & Friborg, 2022). While this approach allows for close observation of the child’s performance, it is time-consuming and resource-intensive, and does not take full advantage of the efficiency and scalability offered by group-administered digital assessments..

As in reading, accuracy measures for many underlying skills, such as letter knowledge, phonological awareness, and spelling accuracy, are prone to the ceiling effect in transparent orthographies, which highlights the need to assess fluency in addition to accuracy in these measures (Georgiou et al., 2020; Torppa, Georgiou, Niemi, Lerkkanen, & Poikkeus, 2017; Vaessen, Gerretsen, & Blomert, 2009). Conveniently CA provides an opportunity to measure response times for individual responses, which we will utilise in this study to measure fluency for reading and spelling. Next, we will briefly review the connection between reading and underlying skills from the perspectives of reading development and orthography, and of previous studies on the CA of reading-related skills.

Poor readers typically make spelling errors, yet to a lesser degree in transparent than in more opaque orthographies (Furnes & Samuelsson, 2010). Previous studies on CA of spelling skills have shown weaker correlations between CA and PP tasks in transparent (.40-.42; Protopapas et al., 2008) than in opaque orthography (.60-.71; DeGraff, 2005). However, adding latency data may expand the accuracy of discrimination in transparent languages (Zygouris et al., 2025).

Letter knowledge skills of pre-school children have been shown to be a strong predictor of later reading and spelling skills across orthographies (e.g. Caravolas, 2004; Lervåg & Hulme, 2010; Torppa et al., 2013) but seems to lose its discriminatory power as soon as basic reading skills have been acquired (Leppänen, Niemi, Aunola, & Nurmi, 2006). CA letter knowledge, however, has previously been found to serve as a highly sensitive measure for screening later risk for reading problems measured in kindergarten (Puolakanaho & Latvala, 2017).

Phonological awareness (PA) refers to an individual's ability to understand the sound structure of a word. PA has been consistently shown to predict reading skills, especially reading accuracy (e.g. Melby-Lervåg, Lyster & Hulme, 2012) and word and pseudoword spelling (e.g. Landerl & Wimmer, 2008; Lervåg & Hulme, 2010; Torppa et al., 2013). However, the connection between PA and reading seems to vary depending on orthographic complexity and other variables (Landerl et al., 2019) and diminish as children learn to decode words accurately (e.g. de Jong & van der Leij, 1999; Juul, Poulsen, & Elbro, 2014). Phonological skills might still, however, differentiate those with reading difficulties to a small degree (Eklund et al., 2015) and predict spelling accuracy (Furnes & Samuelsson, 2010; Lervåg & Hulme, 2010). Previous studies of PA assessments have reported generally moderate or low correlations (< .60) between CA and PP tasks (Singleton et al., 2000; DeGraff, 2005). In a semi-transparent Norwegian orthography, individually administered PA measures have shown at least acceptable reliability (Nergård-Nilssen & Friborg, 2022). To our knowledge, validated CA of PA accuracy has not been studied in transparent orthographies, which highlights the need for further development and validation of such tasks.

Rapid automatised naming (RAN), the ability to retrieve and fluently name serially presented familiar items, is a known precursor of reading skills, especially fluency (for reviews, see e.g. Kirby, Georgiou, Martinussen, & Parrila, 2010; Norton & Wolf, 2012). The connection between RAN and reading fluency seems to be consistent across orthographies (e.g. Landerl et al., 2019) and remains strong across age groups (Furnes & Samuelsson, 2010; Torppa, Lyytinen, Erskine, Eklund, & Lyytinen, 2010; Van den Bos, Zijlstra, & Spelberg, 2002). To our knowledge, no previous studies comparing CA and PP RAN exist, probably because RAN is problematic for a CA presentation domain, as it essentially requires naming items aloud. For our study, however, we did include RAN CA tasks by developing and employing a speech-recognition system for the tasks.

Studies on the association between short-term memory (STM) or verbal STM (VSTM) and reading skills suggest that STM taps the verbal processes that are connected with reading and that children with poor reading skills often have difficulties in domain-specific STM tasks (Swanson, Zheng, & Jerman, 2009). In some studies, with transparent orthographies, STM has also differentiated between average and poor spellers (Brandenburg et al., 2015; Lervåg & Hulme, 2010; Wimmer & Schurz, 2010; Zygouris et al., 2025). In previous CA studies on STM, the CA span task was associated with reading and spelling accuracy (Protopapas &

Skaloumbakas, 2007), and the PP and CA tasks were moderately correlated (r=.53; Paul et al., 2005). However, STM was not among the best discriminators between good and poor readers (Protopapas et al., 2008).

There are not many studies on the connection between receptive vocabulary and reading, but the results refer to a stronger connection in opaque (Ouellette, 2006) than transparent orthographies (Torppa et al., 2013). The CA and PP versions of vocabulary tasks are typically very similar, requiring a user to recognise an auditorily presented target and select a corresponding picture out of four alternatives. A very strong correlation of 0.82 has been reported between CA and PP assessments with differing test items (Merrell & Tymms, 2007; but for opposite evidence, see DeGraff, 2005).

Finally, learning to read requires forming new associations, such as between letters and speech sounds and between orthographic, phonological, and semantic word representations. Evidence suggests that paired associative learning tasks, especially in a visual–verbal domain, explain reading performance on top of the other well-known reading subskills, such as phonological skills (Hulme, Goetz, Gooch, Adams, & Snowling, 2007; Wimmer, Mayringer, & Landerl, 1998), even after controlling for IQ (Ho, Chan, Tsang, Lee, & Chung, 2006; Windfuhr & Snowling, 2001). Associative learning is typically assessed by repeated presentation of visual–auditory item pairs with corrective feedback, similarly in both CA and PP domains. In adults, moderate to strong correlations with a range of r =.51–.76 between CA and PP domains in associative learning tasks have been obtained (Fratti, Bowden & Cook, 2017; Paul et al., 2005). To our knowledge, there are no studies with children comparing CA and PP domains in paired associative learning.

Purpose of the Study

The aim of this study is to develop and validate digital assessment methods (serious game assessments, SGA) for reading and reading-related skills suitable for a transparent orthography. These measures are integrated in a serious game (GraphoLearn) to serve early identification of reading difficulties and specifically to individually target the intervention according to the assessment results. The assessment tasks are designed so that they are simple enough to be used independently and are concise and child-friendly enough to maintain the children’s interest, even those with low-end attentional and scholastic capabilities. An important feature of our SGA method is that immediate feedback on accuracy for each response is provided to direct the attention towards learning objectives (Black & Wiliam, 1998) and to serve learning opportunities in a style of dynamic assessment.

The first analyses on this assessment battery showed that with a set of reading and spelling SGA measures, the children with a risk for reading difficulties could be identified with very high specificity and sensitivity (91% and 95%, respectively; Authors, 2020). The aim of the present study is to explore and develop this SGA method further by investigating the validity of the measures more thoroughly as well as analysing the skills known to be related to reading that have previously not been broadly assessed in the context of CA (i.e., vocabulary, PA, RAN, STM, phonological memory, and associative learning). The specific research questions are (1) What is the validity of SGA measures compared to the PP assessment methods? and (2) To what extent do the SGA tasks assess reading accuracy and fluency?

We focus our investigation on the three aspects of validity, concurrent, construct and criterion validity. Concurrent validity informs to which extent two tasks designed to measure the same skill correlate with each other. In our study the goal is to obtain high correlation between a novel SGA measure and the established corresponding PP measure. The construct validity refers to the phenomenon that several tasks measure partly the same underlying skill or ability. In this case, these tasks load on the same factor reflecting the underlying skill. The goal in our study is that both SGA and PP versions of a task load on the same underlying factor and that the identified factors fit on theoretical understanding of reading skill. For example, theoretical understanding is that reading accuracy and fluency are somewhat separate skills, as well as memory and vocabulary. Criterion validity informs whether a sufficient degree of variance in a skill is captured by either a single measure or set of measures. Here the goal is to obtain a very high level of variance explained in PP measureswith combined SGA measures.

METHODS

Participants

The participants of this study consisted of 735 Finnish speaking monolinguals first- to fourth-grade children (aged 6 to 11, females 54%) from 17 different elementary schools in the central Finland area. Written consent to participate in the study was obtained from the children as well as their guardians. There were no differences in the parental education level or family gross earnings between the grades and schools. Therefore, the participating children represent Finnish L1 children attending typical public schools in Finland. Finnish schools are basically inclusive; thus, it is supposed that the normal variation of reading skills is represented in this sample. The description of the procedure of the data collection is provided elsewhere (Authors, 2020).

Measures

Paper and Pencil (PP) Measures

Reading was measured with three widely used tasks: lists of words (Häyrinen, Serenius-Sirve, & Korkman, 2013) and pseudowords (adapted from Salmi, Eklund, Järvisalo, & Aro, 2011) with increasing difficulty were read aloud. The third task was a Finnish adaptation of the Woodcock-Johnson sentence reading fluency test (Woodcock, McGrew, & Mather, 2001), in which the child has to verify written sentences (e.g. Strawberries are blue) as true or false. The child was instructed to read as quickly and accurately as possible. The percentage of correctly read or selected items and reading fluency (i.e., the number of items read correctly in one minute) were used as outcome scores. A more detailed description of the reading measures is reported elsewhere (Authors, 2020).

Reading-related skills were measured with standardised tests when available. We measured word spelling (Häyrinen et al., 2013), pseudoword spelling (created for this project, described below), letter knowledge (naming the Finnish letters), PA (phonological processing subtask of the *Developmental Neuropsychological Assessment NEPSY II*; Korkman, Kirk & Kemp, 2007), phonological memory (phonological memory subtask of NEPSY; Korkman, Kirk, & Kemp, 1998), STM (digit span forward subtest from the Wechsler Intelligence Scale for Children; Wechsler, 2010), associative learning (name learning subtask of NEPSY II; Korkman et al., 2007), RAN (letters and objects subtests from Ahonen, Tuovinen & Leppäsaari, 2003), and receptive vocabulary (shortened version of the Peabody Picture Vocabulary test PPVT; Dunn, Dunn, Bulheller, & Häcker, 1965; Lerkkanen et al., 2010). The descriptions of the standardised tasks are available from the manuals of the tests. The only measure with no such information is pseudoword spelling, which was created for the purposes of this study. In this task, the items with increasing difficulty (n = 10; from four to 15 letters, e.g., *siul, tuupposristekka*) were matched to the SGA items in terms of syllable and word structures as well as the number of letters. The child was asked to spell the pseudowords based on recorded auditory stimuli. In all PP reading-related measures accuracy (either the percentage or the number of correct answers) and in RAN fluency (time) was also used as an outcome measure.

Serious Game Assessment (SGA) Measures

Word Reading. A child listened to a word and selected a corresponding written word from four alternatives comprising words and pseudowords. The alternatives were phonologically highly similar to the target word (e.g., *luuri* 'handset' vs. pseudowords *luuki, luri, ruuli*). In the case of an incorrect selection, the correct response was shown on the screen. The length of the words increased gradually from bisyllabic words (e.g., *myrsky* 'storm') up to 6-syllable inflected words (the maximum length was 16 letters, e.g., *tuomaristossakin* 'also in the jury'). The task was discontinued after four errors within six trials. The percentage of correct selections (max = 40) and the response fluency (i.e., the amount of correct selections per minute) were used as the outcome scores. The test–retest correlation was .74.

Pseudoword Reading. A task similar to the word reading was presented with pseudowords (30 target items). The task proceeded from monosyllabic (e.g., *sien*) to multisyllabic pseudowords (the maximum of four syllables and 13 letters, e.g., *souraannuttaa*). The test–retest correlation was .66.

Sentence Reading Comprehension (SRC). As in PP mode, a Finnish adaptation of the Woodcock-Johnson sentence reading fluency (Woodcock et al., 2001) was used. The sentences were presented individually on the screen accompanied by true (green) and false (red) response options. Before continuing to the next sentence, a correct response was shown in case the child selected an incorrect response. The test–retest correlation was .89. The children who completed the SGA task before the two-minute time limit with less than 60% accuracy were considered guessers and excluded from the analyses (n = 29). Exploration of these children's data showed that most of them were first graders whose reading performance in PP measures was poor – i.e., they were guessing most likely because they could not read the sentence.

Word Spelling. A set of sublexical written items, letters and/or syllables, were presented on the screen (Figure 1). A word was presented via an audio track, and the task was to construct this word by selecting the right letter and/or syllables from the items (including distractors) presented on the screen and putting them in the correct order. The task proceeded to the next word once the target word was constructed correctly. The length of the target words increased progressively (e.g., from *ei* 'no' to *geenimanipuloitu* 'gene manipulated'). The percentage of correctly constructed target words at the first attempt (of a maximum of 20 words) and the response fluency (i.e., the amount of correctly constructed target words per minute) were used as the outcome scores. The test–retest correlation was .60.

Figure 1. A Screen Capture from the SGA Word Spelling Task.

Pseudoword Spelling. A task similar to the word spelling task was used for assessing pseudoword spelling (24 target items). The task was to construct pseudowords that increased in length from two to 15 letters (e.g., *ri* to *laannusvastikko*). The test–retest correlation was .69.

Letter Knowledge. The sound (representing a phoneme) for a letter was presented via an audio track, and the task was to select the corresponding letter among all 23 Finnish letters presented in a fixed random order on the tablet screen. In case of an incorrect selection, the correct letter was shown before proceeding to the next item. The number of correct selections (maximum = 23) was used as the outcome scores. Due to the ceiling effect, no retest correlation was calculated for this task.

Phonological Awareness. Three different words (e.g., *puku* 'suit', *puhe* 'speech', *suvi* 'summer') were presented aurally in an odd-one-out paradigm. The task was to identify the word that started with a different sound (i.e., syllable) compared to the other two. Each word was paired with a button on the tablet's screen, and the odd one out was selected by pressing the corresponding button. A practice trial with corrective feedback was provided to ensure that the child understood the task. The number of correct responses (maximum = 20) was used as the outcome scores. The test–retest correlation was .46.

Phonological Memory. The child was asked to detect which of the three pseudowords auditorily presented was different from the other two by pressing a corresponding button representing the first, second, or third item. The sets increased in length gradually. The deviating item had the same length and syllable structure as the other two, but distinct phonological content (e.g., */heinostus/* ***/vuonostus/*** */heinostus/).* The number of correct responses (maximum = 18) was used as the outcome scores. The test–retest correlation was .44.

Short-Term Memory. A set of coloured buttons (red, yellow, blue, green, black, white) was presented on the tablet screen. The child heard a list of colours and was instructed to select the colours in the same order he or she heard them. Two consecutive trials consisted of the same number of colours to recall. The colours in each set increased gradually from two to six, and the task was discontinued after failing to recall both trials with the same number of colours. The number of correct responses (maximum = 10) was used as the outcome scores. The test–retest correlation was .30.

Associative Learning. The child's task was to learn associations between five arbitrary visual symbols and spoken syllables. First, the monosyllabic sounds (*/ma/*, */ha/*, */sa/*, */ka/*, */ra/*) paired with corresponding visual symbols were introduced. Then, a monosyllabic sound was presented via an audio track, and the child's task was to select the corresponding visual symbol from four options. Following an incorrect selection, the correct response was presented, and the child had to select it before continuing to the next trial. The task consisted of 25 trials in total. During the task, each sound-visual symbol pair was presented altogether five times. The score was the number of correct responses. The test–retest correlation was .75.

Rapid Automatised Naming. Two separate tasks, one for letters (*U, I, K, S, T*) and one for objects (*star, fence, hand, worm, button*), were presented in 10-item rows on the screen. Each set of items was replicated eight times in a random order but so that the items were not repeated successively. The naming performance was recorded with a computer application developed by our research team and was analysed by an open-source speech recognition program (Bolaños, 2012). Because the accuracy scores of the RAN task are typically high and do not discriminate between good and poor readers (e.g., Snyder & Downey, 1995), only the naming time for the whole list of items was used as the outcome score for each task.

Receptive Vocabulary. A new task in the style of the PPVT (Dunn et al., 1965) was developed. Four alternative pictures were presented on the screen, and the child was instructed to pick the alternative that matched the word he or she heard. The number of correct responses (maximum = 30) was used as the outcome scores. The test–retest correlation was .67.

Data analysis

The concurrent validity was analysed with inspecting paired correlations of corresponding PP and SGA tasks. The construct validity of SGA was analysed by an explorative factor analysis with the Oblimin rotation, allowing correlation of factors by analysing if the SGA measures were loading to the same factor as their supposed PP counterparts and therefore measured the same skills. To approach the frequently applied 10 observation per variable -ratio (Costello & Osborne, 2005), measures with low paired correlations or pairs loading inconsistently to factors were omitted. Finally, to analyse the criterion validity of the SGA measures explaining reading, stepwise regression analyses were conducted to find the best SGA predictors for the composite measures of reading fluency and accuracy as well as to show their explanatory power. In addition, we investigated whether and to which extent PP measures would add explanatory power above SGA measures.

RESULTS

The descriptive statistics on the background variables of participants, SGA measures, and PP measures for each school grade are provided in Tables 1 and 2. The results of comparing the performance between schools and school grades showed that there was no difference between the different schools and grades regarding either gender or socioeconomic status, and the performance level increased from grade to grade in each of the PP and SGA tasks. As was expected based on previous results from transparent orthographies, the differences were minor in most of the accuracy measures because of the ceiling effect.

Table 1. Descriptive Statistics of Paper and Pencil Measures in Grades 1-4.

	Grade 1 Mean (SD)	Grade 2 Mean (SD)	Grade 3 Mean (SD)	Grade 4 Mean (SD)	Effect Size	Post Hoc
Word reading accuracy %[a]	91.43 (9.97)	96.06 (4.18)	96.86 (3.20)	97.61 (2.52)		1 < 2, 3 < 4
Word reading fluency (words correct/min)	22.69 (10.67)	34.12 (8.36)	40.49 (8.11)	44.67 (7.38)	.416	1 < 2 < 3 < 4
PSW reading accuracy %[a]	77.92 (19.66)	89.11 (11.37)	84.31 (12.29)	88.42 (10.56)		1 < 2 < 3 < 4
PSW reading fluency (words correct/min)	17.95 (12.31)	30.17 (12.45)	23.53 (8.76)	28.49 (10.62)	.181	1 < 3 < 2, 4
SRC fluency (sentences correct/min)	6.73 (3.91)	12.07 (4.31)	16.40 (4.49)	20.37 (4.85)	.564	1 < 2 < 3 < 4
Word spelling accuracy %[a]	69.62 (25.92)	90.31 (13.31)	87.55 (10.33)	92.41 (6.30)		1 < 2 < 3 < 4
PSW spelling accuracy %[a]	59.89 (29.03)	79.40 (19.99)	89.94 (13.46)	92.72 (10.10)		1 < 2 < 3, 4
Letter knowledge (max 23) [a]	21.97 (1.25)	22.56 (.735)	22.77 (.572)	22.95 (.23)		1 < 2 < 3 < 4
Phonological awareness (max 53)	39.23 (5.90)	42.65 (5.16)	45.42 (3.54)	47.01 (3.29)	.262	1 < 2 < 3 < 4
Phonological memory (max 16)	9.35 (2.20)	9.94 (1.89)	9.93 (1.92)	10.18 (2.17)	.021	1 < 2, 3 < 4
Short term memory (max 16)	5.64 (1.20)	6.06 (1.24)	6.51 (1.26)	6.76 (1.37)	.102	1 < 2 < 3, 4
Associative learning (max 24)	10.45 (4.30)	12.40 (4.26)	13.41 (4.64)	14.36 (4.18)	.100	1 < 2 < 3 < 4
RAN objects duration (seconds)	63.67 (17.73)	57.66 (15.67)	52.49 (8.75)	47.49 (10.16)	.182	4 < 3 < 2 < 1
RAN letters duration (seconds)	41.03 (11.46)	32.41 6.93)	28.29 (5.76)	25.84 (5.34)	.375	4 < 3 < 2 < 1
Receptive vocabulary (max 30)	9.34 (4.75)	11.50 (5.99)	13.81 (5.63)	17.58 (5.65)	.228	1 < 2 < 3 < 4

Note. In tasks with a time limit, the number of correct responses is presented with accuracy percentage. In tasks without a time limit the number of correct responses is presented. PSW = pseudoword, SRC = Sentence reading comprehension, RAN = Rapid Automatised Naming

[a]Tests without effect sizes analyzed with non-parametric tests due to skewed distributions, all the tests significant at .01 level

Table 2. Descriptive Statistics of SGA Measures in Grades 1-4.

	Grade 1 Mean (SD)	Grade 2 Mean (SD)	Grade 3 Mean (SD)	Grade 4 Mean (SD)	Effect Size	Post Hoc
Word reading accuracy %	65.71 (14.71)	73.82 (10.78)	78.70 (11.14)	82.48 (8.48)	.228	1 < 2 < 3 < 4
Word reading fluency (correct/min)	8.90 (3.55)	12.03 (2.93)	13.44 (3.33)	15.35 (3.11)	.341	1 < 2 < 3 < 4
PSW reading accuracy	64.53 (17.28)	74.53 (10.10)	78.69 (9.32)	82.51 (8.92)	.236	1 < 2 < 3 < 4
PSW reading fluency (correct/min)	7.77 (3.10)	10.70 (2.49)	11.98 (2.80)	13.22 (2.68)	.343	1 < 2 < 3 < 4
SRC fluency (correct/min)	10.34 (5.62)	16.02 (5.15)	19.17 (4.83)	23.27 (5.13)	.400	1 < 2 < 3 < 4
Word spelling accuracy %	64.96 (17.24)	76.31 (13.36)	80.91 (12.04)	84.17 (9.56)	.198	1 < 2 < 3 < 4
PSW spelling accuracy %	60.95 (16.41)	70.45 (12.60)	76.13 (11.63)	78.44 (11.02)	.194	1 < 2 < 3, 4
Letter knowledge (max 23)[a]	20.73 (1.99)	20.92 (2.15)	21.23 (1.61)	21.35 (1.83)		1 < 3, 4; 2 < 4
Phonological awareness (max 20)[a]	13.46 (4.57)	14.91 (4.13)	16.38 (3.49)	17.25 (3.38)		1 < 2 < 3 < 4
Phonological memory (max 18)	10.27 (4.16)	11.12 (4.19)	12.44 (3.52)	13.80 (2.55)	.122	1 < 2 < 3 < 4
Short term memory (max 10)	6.01 (2.29)	6.51 (1.81)	7.35 (1.47)	7.73 (1.42)	.111	1, 2 < 3 < 4
Associative learning (max 25)	11.74 (4.29)	11.57 (4.71)	11.53 (5.08)	11.88 (5.13)		
RAN objects duration (seconds)	50.35 (12.46)	45.56 (9.52)	41.36 (7.24)	37.38 (7.24)	.227	4 < 3 < 2 < 1
RAN letters duration (seconds)	34.32 (9.88)	27.02 (5.88)	23.67 (6.08)	22.52 (5.11)	.217	4, 3 < 2 < 1
Receptive vocabulary (max 30)	19.09 (3.29)	20.34 (3.45)	21.38 (3.13)	22.88 (2.97)	.155	1 < 2 < 3 < 4

Note 1. In tasks with a time-limit or with a differing maximum score between school grades the outcome of correct answers is presented as accuracy percentage. In tasks without a time limit, the number of correct answers is reported and used as an outcome.
Note 2. [a]Tests without effect sizes analyzed with non-parametric tests due to skewed distributions, all the tests significant at .01 level.
Note 3. Main effect of grade was significant at the level < .01 except in associative learning < .05 level.
Note 4. SGA = Serious Game Assessment, PSW = pseudoword, SRC = Sentence reading comprehension, RAN = Rapid Automatised Naming.

Concurrent validity

Paired correlations between PP and SGA versions are presented in Table 3. Very strong (>.80) or strong (>. 60–.79) correlations were obtained for all reading fluency measures (word, pseudoword, and SRC), except for word reading fluency in Grade 3 (r = .59). Strong correlations were also obtained for spelling in Grade 1 and RAN Objects at Grade 4 and RAN Letters at Grade 1 and 3. Moderate (.40–.59) correlations were obtained for the rest of the RANs, spelling in Grades 2–4, PA in Grades 1–3, STM in Grade 2, and vocabulary in Grades 2–4. Weak (.20–.39) or very weak (< .19) correlations were obtained for letter knowledge, PA in Grade 4, phonological memory (Grades 1–4), and associative learning (Grades 1–4). These results indicate a high or moderate correspondence between PP and SGA in measures of reading fluency and RAN across the grades, whereas for reading accuracy, spelling and PA measures the correlations are high to moderate only in early grades. The rest of the reading-related skill measures, such as phonological memory, STM, and associative learning, seem to correspond with each other only to a moderate degree throughout the grades.

Consruct validity

For obtaining acceptable number of variables and an observation ratio, only subset of measures was selected into the factor analysis. First, measures with low concurrent validity (associative learning, phonological memory, letter knowledge) were omitted. In addition, word reading accuracy, PA and phonological memory measures did not consistently load on the same factor at each Grade and were therefore dropped from the final model. After these removals, five theoretical constructs of fluency, accuracy, RAN, short-term memory and vocabulary

Table 3. Paired Correlations Between Paper and Pencil and SGA Measures in Grades 1–4.

Variable	Grade 1	Grade 2	Grade 3	Grade 4
Word reading accuracy	.42	.41	.34	.31
Word reading fluency[1]	.81	.70	.59	.60
PSW reading accuracy	.60	.47	.50	.39
PSW reading fluency[1]	.76	.66	.69	.67
SRC fluency	.86	.74	.77	.70
Word spelling accuracy[2]	.73	.53	.44	.46
PSW spelling accuracy[2]	.66	.48	.42	.25
Letter knowledge[2]	.29	.13[3]	.09[3]	.20[3]
Phonological awareness	.55	.56	.45	.26
Phonological memory	.24	.29	.07[3]	.22
Short term memory	.35	.44	.22	.38
Associative learning	.24	.36	.24	.37
RAN objects	.58	.59	.58	.72
RAN letters	.70	.53	.61	.58
Receptive vocabulary	.36	.46	.51	.52

Note. SGA = Serious Game Assessment, PSW = Pseudoword, SRC = Sentence reading comprehension, RAN = Rapid automatised naming
[1] Reading accuracy included in fluency measures due to the ceiling effect.
[2] Analyzed with non-parametric methods (Spearman) due to the skewed distribution.
[3] n.s., while all other correlations were significant at the <.01 level.

Table 4. Summary of Exploratory Factor Analysis for Reading and Related Measures in Grades 1-4 Using Oblimin Rotation.

	Grade 1					Grade 2					Grade 3					Grade 4				
Measures	Acc	Flu	RAN	Voc	Mem	Acc	Flu	RAN	Voc	Mem	Acc	Flu	RAN	Voc	Mem	Acc	Flu	RAN	Voc	Mem
PP PSW reading %	.88					.74					-.61						.58			
SGA PSW reading %	.76					.58					-.59					-.70				
PP word spelling %	.86					.88					-.53	.40				-.69				
SGA word spelling %	.82					.68					-.83					-.47				
PP PSW spelling %	.82					.80					-.58					-.55				
SGA PSW spelling %	.66					.62					-.80					-.71				
PP word reading fluency		1.04					.86					.65					.79			
SGA word reading fluency		.87					.82					.59					.73			
PP PSW reading fluency		.84					.79					.72					.79			
SGA PSW reading fluency		.81					.84					.87					.78			
PP SRC fluency		.86					.69					.69					.77			
SGA SRC fluency		.68					.80					.86					.79			
PP RAN objects			.83					.71					.75					.73		
SGA RAN objects			.75					.71					.75					.76		
PP RAN letters			.64					.75					.75					.84		
SGA RAN letters			.81					.83					.82					.72		
PP Receptive vocabulary				.82					.82					.81					.84	
SGA Receptive vocabulary				.79					.84					.83					.82	
PP STM					.69					.74					.65					.77
SGA STM					.77					.73					.74					.84
Eigenvalues	1.47	9.72	1.72	1.23	1.03	2.05	7.48	1.83	1.43	.982	1.34	7.01	2.60	1.43	1.07	1.62	6.91	2.16	1.50	1.09
% of variance	7.32	48.61	8.61	6.16	5.13	10.25	37.05	9.16	7.13	4.91	6.71	35.07	13.00	7.17	5.36	8.08	34.56	10.80	7.47	5.46

Note. Acc = Accuracy, Flu = Fluency, RAN = Rapid automatised naming, Mem = Memory, Voc = Vocabulary, PP = Paper and pencil task, SGA = Serious Game Assessment, PSW = Pseudoword, SRC = Sentence reading comprehension, STM = Short-term memory remained, determining the number of factors to constant five. Table 4 provides the factor loadings for each grade separately. The factor analyses produced a very stable factor structure highly similar across grades. In each grade, the largest factor was Fluency and smallest factor was Memory, while the order of the rest of the factors varied. Overall, the factor loading of Accuracy for each task seems to decrease from first to fourth grade, which is apparently caused by accuracy measures approaching the ceiling. In other factors, the loading remained high in all grades.

Criterion validity

First, we computed a composite measure of reading fluency from PP word, pseudoword and SRC tasks (Cronbach's alphas were 0.85, 0.83, 0.81, and 0.80 for the Grades 1-4, respectively). This composite measure was then analysed in a hierarchical regression analysis with a stepwise selection of independent variables (Table 5). To study how much SGA measures can explain the dependent variable, all SGA measures were added at the first step. Then, to study what extent the remaining PP measures help in explaining additional variance in the dependent variable, these measures were added at the second step. For fluency the SGA measures of SRC, pseudoword reading, word reading, and RAN letters were the best predictors, explaining 83%, 76%, 71%, and 68% of reading fluency from first to fourth grade, respectively. The PP measures increased the explanation rate only marginally (three percent at best). Overall the results indicate that the SGA reading tasks are sufficient for predicting reading fluency and that only marginal benefit would be obtained by including SGA spelling and other reading-related tasks (RAN, letter knowledge and receptive vocabulary).

For the accuracy construct, we computed a composite from pseudoword reading and spelling, and word spelling measures (Cronbach's alphas were 0.90, 0.84, 0.77, and 0.59 for the Grades 1-4, respectively). The composite measure was first inverted and log-transformed to obtain normality and similar regression analysis was run as was the case for the reading fluency composite (Table 6). The composite was predicted with all SGA measures by 66%, 57%, 58%, 51% from first to fourth grade, respectively. The overall lower explanation ratio relative to reading fluency may reflect in part the ceiling effects, and on the other hand, the lower concurrent validity of the accuracy measures relative to fluency measures. The PP measures of reading related skills explained additional variance of 3%, 8 %, 6% and 6 %, respectively, mostly via the PP Word reading accuracy measure. In evaluating of other significant SGA predictors apart of the reading measures, at least spelling measures are needed for assessing accuracy skill. PA, Letter knowledge and RAN Letters also explained some variance but only at specific Grades so their inclusion in the assessment battery may not be justified.

Table 5. Stepwise Regression Analyses on Measures Predicting Reading Fluency in Grades 1-4.

Grade 1	SGA Measures	R^2	$R^2\Delta$	*p*	Grade 3	SGA Measures	R^2	$R^2\Delta$	*p*
	SGA SRC fluency	.718	.718	<.001		SGA SRC fluency	.526	.526	<.001
	SGA PSW reading fluency	.802	.084	<.001		SGA PSW reading fluency	.669	.144	<.001
	SGA PSW spelling	.816	.014	<.001		SGA RAN letters	.696	.027	<.001
	SGA RAN letters	.823	.007	.014		SGA Word reading accuracy	.713	.017	.002
	SGA Word reading fluency	.829	.006	.028		PP additions	R^2	$R^2\Delta$	*p*
	PP additions	R^2	$R^2\Delta$	*p*		PP Word writing accuracy	.733	.019	.001
	PP Letter knowledge	.835	.006	.022		PP RAN Letters	.746	.013	.004
	PP RAN letters	.840	.005	.030		PP Vocabulary	.754	.008	.019
Grade 2	SGA Measures	R^2	$R^2\Delta$	*p*	Grade 4	SGA Measures	R^2	$R^2\Delta$	*p*
	SGA SRC fluency	.619	.619	<.001		SGA SRC fluency	.456	.456	<.001
	SGA Word reading fluency	.705	.086	<.001		SGA PSW reading fluency	.593	.137	<.001
	SGA PSW reading fluency	.733	.028	<.001		SGA RAN letters	.628	.034	<.001
	SGA PSW accuracy	.747	.014	.002		SGA PSW reading accuracy	.669	.041	<.001
	SGA RAN letters	.756	.009	.012		SGA Word reading fluency	.680	.011	.020
	SGA Vocabulary	.762	.007	.029		Model 2: PP additions	R^2	$R^2\Delta$	p
	PP additions	R^2	$R^2\Delta$	*p*		PP RAN Objects	.691	.011	.018
	PP RAN letters	.769	.007	.027					

Note. SGA = Serious Game Assessment, PP = Paper and pencil task, SRC = Sentence reading comprehension, PSW = Pseudoword, RAN = Rapid automatised naming, STM = Short term memory

Table 6. Stepwise Regression Analyses on Measures Predicting Reading Accuracy in Grades 1-4.

Grade 1	SGA Measures	*R^2*	*$R^2\Delta$*	*p*	Grade 3	SGA Measures	*R^2*	*$R^2\Delta$*	*p*
	SGA PSW reading acc.	.515	.515	<.001		SGA PSW reading fluency	.342	.342	<.001
	SGA Word spelling acc.	.586	.071	<.001		SGA PSW spelling acc.	.518	.176	<.001
	SGA SRC fluency	.636	.050	<.001		SGA Letter knowledge	.554	.036	<.001
	SGA PSW reading fluency	.646	.010	.041		SGA SRC fluency	.578	.025	.002
	SGA RAN letters	.658	.012	.025		PP additions	*R^2*	*$R^2\Delta$*	*p*
	PP additions	*R^2*	*$R^2\Delta$*	*p*		PP Word reading accuracy	.620	.042	<.001
	PP Phon. awareness	.682	.023	.001		PP Phon. awareness	.639	.019	.004
	PP Vocabulary	.692	.011	.027	Grade 4	SGA Measures	*R^2*	*$R^2\Delta$*	*p*
Grade 2	SGA Measures	*R^2*	*$R^2\Delta$*	*p*		SGA PSW reading fluency	.337	.337	<.001
	SGA PSW reading acc.	.403	.403	<.001		SGA Word reading accuracy	.434	.098	<.001
	SGA Phon. awareness	.479	.076	<.001		SGA PSW spelling accuracy	.487	.053	<.001
	SGA PSW reading fluency	.529	.050	<.001		SGA Word spelling accuracy	.510	.023	.006
	SGA Word spelling	.565	.036	<.001		PP additions	R^2	$R^2\Delta$	p
	PP additions	*R^2*	*$R^2\Delta$*	*p*		PP Word reading accuracy	.540	.030	.001
	PP Word reading acc.	.635	.069	<.001		PP Phon. memory	.557	.016	.016
	PP Letter knowledge	.645	.010	.030		PP Phon. awareness	.569	.012	.034

Note. SGA = Serious Game Assessment, PP = Paper and pencil task, SRC = Sentence reading comprehension, PSW = Pseudoword, RAN = Rapid automatised naming, STM = Short term memory

DISCUSSION

The aim of this study was to develop and validate SGA measures for reading, spelling, and reading-related skills (PA, RAN, STM, phonological memory, receptive vocabulary, and associative learning) in the orthographically transparent Finnish language. Our results with children from the first four school grades demonstrated that the developed SGA measures of reading and spelling are valid methods for assessing reading fluency and accuracy, as reading measures alone were able to capture 68–83 % of the variance of reading fluency in each grade, and reading and spelling measures 51–66 % of variance in reading accuracy. Other reading related skills could explain only a marginal amount variance on top of these measures and in an inconsistent manner across different grades. Despite the clear benefits of SGA as a fast, cost-effective way of assessing reading skills, the measures and the methodology still have some further steps to take before SGA can fully replace the traditional paper and pencil methods of assessment. Next, we will discuss our results and the suggested further steps in more detail.

The Validity of the SGA Measures

The results showed that in general the concurrent validity of the SGA reading fluency measures (word/pseudoword reading and SRC) was high, as evidenced by the strong correlations (.59 – .86) between the paired SGA and PP tasks, while the correlation for most of the accuracy measures were high only at first grade but deteriorated towards higher grades. However, the rest of the reading related skills showed much weaker correlations with their PP counterparts – a finding that seems to emerge across studies (DeGraff, 2005; Merrell & Tymms, 2007; Protopapas & Skaloumbakas, 2007; Protopapas et al., 2008). There may be several reasons for the weak pairwise correlations in terms of reading-related measures between SGA and PP measures. First, the low correlations may be due to statistical issues caused by the ceiling effects found in the accuracy measures. Second, as our aim was not to develop SGA measures that are identical to PP measures, some of the low correlations may derive from the different demands of the tasks in SGA that will be discussed later in more detail.

We studied construct validity by investigating whether paired SGA and PP tasks measure the same underlying latent trait in a factor analysis. Indeed, the corresponding SGA and PP tasks loaded on the same stable factors (accuracy, fluency, RAN, vocabulary and STM) across the grades and vocabulary from the second grade onwards. However, the reading-related measures of phonological memory, PA, and associative learning failed to show consistent construct validity. Based on these findings, we conclude that the SGA measures for reading fluency, accuracy, RAN, vocabulary, and short-term memory measure the same skills as their PP counterparts across the grades. Despite notable methodological differences between studies, our results are in line with the previous validation study in opaque English orthography, where similar factors of decoding, fluency, and vocabulary were identified in Grades 1 and 3 (DeGraff, 2005). The loadings for the Accuracy factor showed a decreasing trend from first to fourth grade, which was apparently caused by most of the children learning to read and spell accurately; therefore, the ceiling effect was achieved (Aro & Wimmer, 2003; Seymour et al., 2003). Meanwhile, the loadings for the Fluency, Rapid Naming, Vocabulary and STM factors remained high in all grades, being indicative of the high discriminative capabilities of these measures over development (Eklund et al., 2015; Landerl & Wimmer, 2008; Verhoeven, van Leeuwe, & Vermeer, 2011; Gathercole, Service, Hitch, Adams, & Martin, 1999; Nithart et al., 2011; Siegel & Ryan, 1989).

Noting the limits of cross-sectional data, a comparison between the grade levels allowed us to consider some points related to the development of the skills assessed and come to some conclusions of the theoretical validity of the measures. As expected, all the raw scores of the tasks showed a trend for increasing skills from one grade to another unless the ceiling effect was reached (accuracy measures; see also Auphan et al., 2019 for similar results).

Why did some reading-related measures (e.g., PA, phonological memory, STM, associative learning) fail the test of concurrent and construct validity in correlational and factor analyses, respectively? Some explanations may derive from the methodological limitations of the measures mentioned above (e.g., the ceiling effects or the small number of items limiting the variation) or differences in the cognitive requirements between SGA and PP tasks (e.g., oral production, motor dexterity, visual search, or strategies used for fluent performance). These explanations cannot be reliably affirmed in this study, but some remarks on the possible reasons are warranted. First, the measures for PA did not reach the ceiling, yet the paired correlations dropped in the third and fourth grades. This may be because the standardised PP task used in this study extended to more complex phonological skills in Grades 3–4 relative to Grades 1–2, whereas the SGA task remained the same through the grades. Moreover, the SGA version required only the identification of a relatively large (easy) psycholinguistic segment, namely differing initial syllable, whereas the scope of the PP tasks was more diverse, requiring a child to pay attention to the middle parts of the words and phonemes in addition to syllables. Thus, SGA PA tasks clearly need to be developed further to increase the content validity of the measure.

The SGA tasks assessing phonological and associative learning did not correlate well with their PP counterparts, which may be partly due to the different demands of the tasks. PP version of the phonological memory assessment required vocal reproduction, while in the SGA, the response was simply made by selection. Further, as the items in the PP tasks were very difficult to pronounce, one could easily make an error in spite of fairly good memory representation of the item. Finally, the associative learning tasks both relied on learning with corrective feedback, yet in the PP domain, the task was to learn names for faces, but in the SGA, the task was to learn meaningless syllables for unfamiliar visual symbols. No prior studies explicate the correlation between these two learning domains of verbal–visual learning, yet one may assume learning names for faces may be based on at least partially different neuronal networks due to their special socio-emotional function.

In sum, the validity of SGA reading measures was good, forming a strong basis for game-based reading assessment for school-aged children. However, the converging findings on the lower validity of reading-related skills (DeGraff, 2005; Merrell & Tymms, 2007; Protopapas & Skaloumbakas, 2007; Protopapas et al., 2008) clearly suggest that more work needs to be done to develop a SGA system capable of reliably and efficiently assessing not only reading skills but also related cognitive skills, such as phonological processing.

To What Extent Do the Developed Serious Game Assessment Tasks Assess Reading Skills?

We studied the criterion validity of the SGA measures, that is to what extent they are able to explain PP reading skills. In the regression analyses, the large majority (68–83%) of the variance of reading fluency could be assessed with corresponding SGA reading tasks. Such a high level of explanatory power is comparable to those reported by a previous study comparing CA and PP assessment in the English language (DeGraff, 2005). No clear developmental trend between school grades was apparent in how well reading fluency could be assessed with the SGA tasks, indicating that SGA can be used to evaluate reading skills from the first grade onwards. It should be noted though that even with the assessment task with the best overall explanatory power, sentence reading comprehension (SRC), its power seemed to drop between third and fourth grade. This may be due to the developmental shift in older children when reading becomes more affected by reading processes other than those captured by the SRC task (Rasinski, Rikli, & Johnston, 2009). Taken together, these results indicate that first- to fourth-grade children's reading fluency can be reliably assessed by three short SGA tasks, namely word reading, pseudoword reading, and SRC tasks administrated for a whole class at the same time by using inexpensive tablet devices. Since no manual work for scoring is needed and results are immediately available, this makes the SGA assessment method highly time- and cost-efficient.

Also reading and spelling accuracy could be explained well (ca. 51-66 %) by the SGA reading and spelling measures. However, the explanatory power was clearly highest at first grade, suggesting that the practical applicability of the present SGA accuracy tasks may be limited to first grade assessments. It must be noted though that assessing reading accuracy is mostly needed in early grades in transparent orthographies before accuracy approaches the ceiling in later grades (Seymour et al., 2003). According to our results, assessing also reading accuracy, not only fluency, would require including pseudoword reading and word spelling tasks into the SGA battery to compensate the ceiling effect of word reading accuracy.

We were also interested in the correlates of reading (spelling, PA, RAN, STM, phonological memory, receptive vocabulary, and associative learning) explaining reading fluency in transparent orthography. Of these non-reading tasks, the RAN task seemed to work best. This result is in line with the consensus on the strong correlation between RAN and reading fluency (e.g., Kirby et al., 2010; Moll et al., 2014; Norton & Wolf, 2012). Even though the execution of SGA RAN as oral production working on speech recognition technology sets limitations for its practical utilisation in a classroom context, it casts promises to the further use of SGA RAN in the field of assessment of reading and related skills, not least for the automatised analysis of the speech data. With that said, however, adding the non-reading tasks in analyses increased the variance explained of reading fluency only marginally, RAN 1.5–3.8%, and the other non-reading tasks (e.g., letter naming accuracy) less than 2% each. This result is in accordance with the previous conclusions by Hammill and colleagues, who argued that the skills they called "nonprint abilities" (e.g., phonology, grammar, RAN) have a rather minor role in predicting and instructing reading in school-aged children compared to print-based skills – i.e., "actual reading" (Hammill, 2004; Hammill, Mather, Allen, & Roberts, 2002). Even though we agree with their conclusion, we add that our results do not trivialise the use of these non-reading measures as indicators of reading difficulties before reading instruction (i.e., when print-based assessment tools are not applicable; see de Jong & van der Leij, 2003; Lervåg & Hulme, 2009; Puolakanaho et al., 2007; Wolf, Bowers, & Biddle, 2000). Undoubtedly, non-reading measures are also of great use as tools for clinical work in analysing the background of reading skills more thoroughly (Hammill, 2004).

Limitations

This study focused on developing SGA technology of reading and related skills for an unselected sample of L1 children, not assessing the possible reasons behind low or high performance in the studied skills. Therefore, we did not assess children's general cognitive ability or the presence of neurological or developmental disorders. As a consequence, the present technology should be used only for screening and should not be used alone for diagnosing reading problems. Even though the generalisation of this study may be limited for some student groups (e.g., L2 or children with special needs), children of all reading levels were included in the study. This study thus provides important indications for the use of SGA for identification of children with a risk for reading difficulties in a transparent orthography, as also shown in another study investigating the specificity and sensitivity of these measures (Authors, 2020).

One of the drawbacks of SGA is the need to use multiple-choice tasks in assessment, which increases the temptation to guess the answers. However, features of the programme, such as corrective feedback provided for every item and the delay in presenting the next item after an incorrect answer, will probably reduce this tendency. Indeed, when the performance of children with low accuracy rates was analysed in more detail, it was shown that most of the children prone to guessing were actually poor readers who probably compensated for their inability to read with guessing. Finally, the research design was cross-sectional, therefore providing no information on how predictive the specific SGA measures are for future reading development.

Based on previous research regarding the significant moderator effect of adult interaction in computer-assisted instruction (not assessment) (McTigue, Solheim, Zimmer, & Uppstad, 2020), we would be cautious in administering the SGA without any adult supervision. However, based on the results of this study, the group administration with one or two supervisors seems to be sufficient for valid results, which is a great benefit compared to individual, professional-administered assessment.

CONCLUSIONS

The previous findings on computerised assessments, and here the extended findings of our study illustrate the applicability of serious game assessment tasks to assess reading and related skills (Authors, 2020; DeGraff, 2005; Merrel & Tymms, 2007; Protopapas et al., 2008; Puolakanaho & Latvala, 2017). These kinds of applications provide considerable benefits: there are no restrictions as to who can administer validated assessments, the assessments will be always equal since the assessment tasks in SGA will provide the very same instructions and feedback for those taking the assessments, due to the possibility of quick group assessments and exact data as well as results being immediately available valuable working time of practitioners will be saved. Adopting CA/SGA further increases the time efficiency of the assessment (see Merrell & Tymms, 2007; DeGraff, 2005).

In conclusion, our results support the use of serious game assessments for reading skills as a tool for detecting a risk for reading problems in transparent orthographies among elementary school children. Ready to be integrated in an educational serious game, this method serves as a tool for adaptive intervention as explicated next.

IMPLICATIONS FOR APPLICATION

Having validated the assessment methods, we can integrate the SGA methods into the digital intervention method, the serious game GraphoLearn, providing the needed extra tool for teachers for early identification and support of struggling readers. GraphoLearn (called Ekapeli in Finland) is already used by tens of thousands of children in Finland. GraphoLearn is also available in other languages for research purposes (see e.g., Borleffs et al., 2018). However, thus far, GraphoLearn has not included a validated reading assessment module. Therefore, based on the evidence of the current study, the next step is to develop language specific assessment content to other GraphoLearn versions that would form reliable, usable, and time-efficient SGA methods for everyone.

Furthermore, by directly applying validated digital assessment data, adaptive assessment systems integrated in serious games could provide appropriate feedback to the learner as well as enable an individually adaptive learning environment for learners with individual needs (Authors, 2020; Jamshidifarsani, Garbaya, Lim, Blazevic, & Ritchie, 2019), which seems to benefit especially those with lower initial skills (Hooshyar, Yousefi, & Lim, 2018). As the serious game platform, GraphoLearn, used here is already widely used in many orthographies, the results of this study may provide a basis for the use of SGA also in other language versions at least in regard to identifying reading fluency problems, a character that seems to be a universal feature for dyslexia (Ziegler, Perry, Ma-Wyatt, Ladner, & Schulte-Körne, 2003).
Recent advances show that dynamic assessment principles can be successfully implemented in digital and game-based formats (Foldnes, Uppstad, Grønneberg, & Thomson, 2024; Glatz et al., 2023; Maassen, Glatz, Borleffs, Martínez, & de Groot, 2025). Such approaches provide a scalable way to evaluate learning potential and responsiveness, complementing earlier face-to-face models (Petersen, Allen, & Spencer, 2016; Cho et al., 2014). Building on these results, the aim of our work is to integrate early identification with dynamic assessment and support in a digital environment that benefits both children at risk and their educators.

ENDNOTES

1. The GraphoLearn is a serious game developed at the University of Jyväskylä and Niilo Mäki Institute (NMI; a practice-orientated research and development non-governmental, non-profit organization focusing on child and youth learning disabilities and support) since 2004. Prior 2017 the game was called GraphoGame. In 2017 the IP's of the game including the name GraphoGame were transferred to a private company Grapho Group Ltd, therefore now GraphoGame is an application solely owned by Grapho Group Ltd that distributes GraphoGame applications, including their sales, marketing and

advertising. Independent to the private company, JYU and NMI continue autonomous, open and ethically sound research and development of the serious game calling the game GraphoLearn. In Finland, GraphoLearn (for the Finnish language called “Ekapeli”, and the Finnish-Swedish language called “Spell-Ett”) is available for everyone for free. However, outside Finland, GraphoLearn is used for research purposes only and it is not a commercially available product.

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Authors' Note

The authors thank Katja Korhonen for working as a research coordinator in the project, the numerous research assistants taking part of the data gathering at schools, and the teachers and children taking part in our study. We also thank Eva Malessa for her valuable comments on the manuscript. We would also like to thank the funders of this project. This research was funded by the Academy of Finland's Future Knowledge and Skills funding program for the project "Technology-enhanced environment for supporting reading development in all learners (ReadAll)" with grants 274050 and 274190 for the years 2014–2017. In addition, this research has been funded by Foundation Botnar, and working of J. H. for years 2018–2023 was supported by the grant 319911 from Academy of Finland; working of R. H. for years 2016–2018 was supported by the grant 277340 from Academy of Finland.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 21(3), December 2025, 576–595

STUDENT SATISFACTION AS A MEDIATOR BETWEEN ADMINISTRATIVE E-SYSTEM QUALITY AND UNIVERSITY REPUTATION: AN EMPIRICAL ANALYSIS FROM POLAND

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Abstract: *This study examines how administrative e-system quality influences student satisfaction and university reputation, addressing a research gap: most studies analyse the reverse relationship, where reputation drives satisfaction, and rarely consider administrative e-systems. Drawing on survey data from nearly 7,500 students at Polish universities collected in 2019 and 2020, eight features were evaluated - functionality, implementation, intuitiveness, interface layout, responsiveness/speed, reliability and availability, security and data protection, and mobile accessibility - using regression and Structural Equation Modelling. In 2019, satisfaction mediated the relationship between e-system quality and reputation. In 2020, during the COVID-19 pandemic, this mediation weakened, while direct effects of functionality and reliability on reputation strengthened, reflecting a shift from satisfaction-based to performance-based evaluations. Security also influenced reputation more strongly than satisfaction. Factor analysis grouped the eight indicators into three latent dimensions. Findings demonstrate that administrative e-systems, often overlooked, play a strategic role in shaping both satisfaction and reputation.*

Keywords: *e-system, satisfaction, reputation, universities, digitalization, higher education*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.5

INTRODUCTION

Although several years have passed since the outbreak of the COVID-19 pandemic, the changes it caused still require careful analysis of the challenges that emerged or intensified during that time. One of the key challenges was the rapid digitization of services in various sectors, including higher education. Universities had to implement both technological and organizational changes almost overnight to continue educational and administrative operations remotely (Pokhrel, Chhetri 2021; Webb et al. 2021; Jackson & Konczos, 2022).

The enforced shift to online education and remote administrative services significantly altered the dynamics of student-university interactions. Platforms such as Teams, Zoom, and Webex became the norm, demanding a rapid improvement in digital competencies among students, lecturers, and administrative staff (Strielkowski, 2020; Larbie, 2024). In particular, the student experience was redefined - not only in the learning process but also in the handling of administrative tasks, such as submitting documentation or receiving grades, which now relied heavily on institutional e-systems (Hudrea, 2023; Webb et al. 2021).

One way to assess how well universities were prepared for this sudden transition is to evaluate the quality of their administrative e-systems and their impact on students. While the pandemic served as a catalyst, the long-term implications of digitized administration merit thorough investigation. A Web of Science query for articles containing the terms "digital education" or "online learning" and "higher education" revealed 6,605 publications between 1998 and 2024, with a notable spike during the pandemic years (4,387 articles published from 2019–2024). However, when narrowing the search with the term "satisfaction," only 828 articles appeared, and when further adding "reputation," this number dropped to just 5, with only one based on empirical research (Bouranta et al., 2025). These results point to a significant research gap regarding the empirical analysis of the relationship between administrative e-system quality, student satisfaction, and university reputation.

This gap in literature leads to the core research problem of this study: Does the quality of a university’s administrative e-system influence students’ satisfaction, and does this satisfaction, in turn, affect the university’s reputation? To answer this question, the study aims to (1) assess students' satisfaction with university e-systems, (2) identify the features of e-systems that most significantly impact satisfaction, and (3) evaluate the relationship between satisfaction and the university's reputation. The analysis spans two academic years - 2018/2019 (pre-pandemic) and 2019/2020 (onset of the pandemic) - to provide a comparative perspective and explore how the role of e-systems evolved in response to external pressures. By doing so, the study not only addresses an empirical research gap but also offers insights into how universities can better align digital administrative services with students’ expectations.

THEORETICAL FRAMEWORK

Student Satisfaction and University Reputation

In the context of higher education, student satisfaction is widely recognized as a key determinant of institutional success. It influences student loyalty (Helgesen & Nesset, 2007), alumni engagement (Sung & Yang, 2009), and postgraduate decisions (Priporas & Kamenidou, 2011). Satisfaction stems from the perceived value of services offered in relation to expectations and costs (Coulter & Coulter, 2003; Staniec et al., 2023) and reflects the overall student experience, including both academic and organizational dimensions (Kireyeva et al., 2024).

University reputation, in turn, is shaped by stakeholder perceptions (Aras et al., 2017; Lacmanović & Škare, 2024; Maama, 2024) and has been found to influence students' initial university choice (Crispell, 1993; Dennis et al., 2016; Samoliuk et al., 2024), brand attachment (Dennis et al., 2016), and competitive positioning (Brown & Mazzarol, 2009; Kichurchak et al., 2024). Several studies demonstrate a bidirectional relationship, where satisfaction can reinforce reputation and vice versa (Gruber et al., 2010; Qazi et al., 2021). Despite this, the role of non-academic factors - particularly digital administrative services - in shaping both satisfaction and reputation has received limited attention.

Role of Administrative E-Systems in Higher Education: Quality Indicators

The digitalization of academic administration has become an integral part of the student experience, especially following the COVID-19 pandemic, which forced universities to accelerate the adoption of remote services (Bánhidi & Lacza, 2020; Hudrea et al., 2023; Pokhrel & Chhetri, 2021; Sułkowski et al., 2024). Administrative e-systems - responsible for processes such as enrolment, grade reporting, and formal documentation - support the academic journey alongside teaching platforms. However, while teaching-related systems have been thoroughly explored in literature, digital administration tools remain underexamined.

This oversight may be due to the traditional view of administrative systems as background infrastructure. However, as students increasingly interact with universities through digital channels, including non-academic tasks, these systems become more visible and impactful. As noted by Sofroniou et al. (2020), the quality-of-service organization and administrative support significantly influence overall student satisfaction. Similarly, Ramirez (2025) and Chandra et al. (2019) indicate that service quality across all university operations - educational and administrative - contributes to university reputation.

In the absence of a rich body of literature focused specifically on university administrative e-systems, this study draws upon well-established frameworks from research on university e-learning platforms. It is reasonable to hypothesize that the quality dimensions critical to educational technologies - such as ease of use, responsiveness, and data security - are also relevant in evaluating administrative tools. Students may not distinguish sharply between systems used for learning and those used for managing their academic status; rather, they expect both to meet high standards of usability and accessibility.

Based on this rationale, the study adapts eight quality dimensions from prior literature to assess administrative e-systems. These include:

1. Functionality: the extent to which a system enables students to complete key tasks (Harfoushi & Obiedat, 2011; Farid et al., 2018; Omona et al., 2011).
2. Intuitiveness: ease of navigation and clarity of system design (Garrett, 2010; Peltekova et al., 2015; Idkhan & Idris, 2023).

3. Interface layout: visual and structural organization (Hofer & Halman, 2005; Sharma et al., 2015).
4. Responsiveness/speed: system performance and efficiency (Kadry & El Hami, 2019).
5. Task integration: how comprehensively student affairs are managed within the system (Ibarrientos, 2015; Schuh et al., 2016).
6. Reliability and availability: system uptime and consistency (Immonen & Niemelä, 2008; Malkawi, 2013).
7. Security and data protection: legal and ethical safeguards, particularly considering GDPR (Phuoc et al., 2016; GDPR, 2016).
8. Mobile accessibility: adaptation to student use on mobile devices (Zhezhnych et al., 2020; Huang & Ma, 2020).

These indicators provide a comprehensive framework for evaluating how administrative systems affect students' perceptions and, by extension, their overall satisfaction and view of the institution.

Identified Research Gap

Despite their practical importance, administrative e-systems remain largely absent from theoretical models linking service quality to student satisfaction and university reputation. Most frameworks concentrate on teaching performance and branding (Gruber et al., 2010; Helgesen & Nesset, 2007; Davidavićiene et al., 2023; Potjanajaruwit, 2023), while back-office digital tools - despite their growing visibility - are overlooked. The limited empirical attention to administrative digital systems constitutes a significant research gap.

Moreover, much of the existing research predates the pandemic (e.g., Arbaugh, 2000; Hofer & Halman, 2005), failing to capture the expectations of digitally native student cohorts. The forced transition to remote administration has amplified the relevance of these systems, yet their evaluation remains under-theorized.

This study addresses this gap by investigating whether and how administrative e-system features influence student satisfaction and university reputation. It proposes a model integrating established quality dimensions and tests it empirically using data from Polish universities through correlation analysis and structural equation modelling (SEM).

METHODS

Research Methodology and Measurement Model

This study follows a quantitative design within a pragmatic mixed-method paradigm (Maarouf, 2019), combining empirical measurement with theoretical grounding. The conceptual model guiding the analysis was constructed prior to data collection and reflects the hypothesized relationships between system quality, student satisfaction, and perceived university reputation. Data was gathered through a structured online survey, which allowed for standardized assessment across a large and diverse student sample in Poland. The questionnaire included eight dimensions used to evaluate administrative e-systems, which were operationalized as independent variables. Students were asked to rate each dimension using a 10-point Likert scale (1 = very low, 10 = very high). The assessed features were:

1. Functionality
2. Implementation
3. Intuitiveness
4. Speed
5. Interface
6. Reliability and availability
7. Data security
8. Adaptation

Two additional variables were measured: general satisfaction with the e-system and the student’s perception of the university's reputation. These served respectively as a mediating and a dependent variable in the analytical model.

The data analysis was performed in several stages. Descriptive statistics were used to examine central tendencies and distributions. Nonparametric tests assessed differences across groups and periods. Correlation analyses and multiple regression models were applied to explore associations between variables. Finally, Structural Equation Modelling (SEM) was used to assess both direct and indirect effects within the conceptual model, particularly the mediating role of student satisfaction between system features and university reputation.

Demographics analysis

Data collection was conducted in two phases to capture both pre-pandemic and pandemic-era experiences:

- 2019: 2528 valid responses from 24 universities
- 2020: 4952 valid responses from 41 universities

The sample included students from a wide range of institutional profiles (table 1) (technical, humanities, economics, medical, arts, and others) and levels of study (table 2) (bachelor’s, master’s, long-cycle master’s, and doctoral programs) who participated in a variety of e-system device sessions (table 3). Purposeful sampling ensured the inclusion of universities with varied e-system maturity and administrative structures.

Table 1. Characteristic of the sample surveyed - University profile [Source: own developed]

	2019		2020	
Universities' profile	N=2528	%	N=4952	%
Technical Universities	676	26.74%	1356	27.38%
Universities of Humanities	628	24.84%	1826	36.87%
Universities of Economics	535	21.16%	520	10.50%
Nature Universities	376	14.87%	601	12.14%
Medical Universities	141	5.58%	101	2.04%
Art Universities	78	3.09%	100	2.02%
Others	63	2.49%	325	6.56%
Universities of Physical Education	31	1.23%	123	2.49%

Source: own developed

Table 2. Characteristics of the sample surveyed – number of years of studies [Source: own developed]

	2019 N=2522		2020 N=4952	
Number of years of studies	N	%	N	%
1 year (bachelor's degree or uniform master's studies)	1000	39.56%	1626	32.84%
2 years (bachelor's degree or uniform master's studies)	524	20.73%	1038	20.96%
3 years (bachelor's degree or uniform master's studies)	440	17.40%	885	17.87%
4 years (only in engineering bachelor's degree or uniform master's studies or 1st year of master's studies after bachelor's degree)	295	11.67%	831	16.78%
5 years (uniform master's studies or 2end year of master's studies after bachelor's degree)	239	9.45%	493	9.96%
6 years and more (phd)	30	1.19%	79	1.59%

Source: own developed

Table 3. Device used to work with e-system[1] [Source: own developed]

	2019 N=2528		2020 N=4952	
	N	%	N	%
Device used to work with the e-system - computer	2231	88,4%	3957	79,91%
Device used to work with the e-system - tablet	188	7,4%	285	5,75%
Device used to work with the e-system - smartphone	1957	77,5%	3940	79,56%

[1] Respondents could indicate more than one answer.

RESULTS

Regression Results – Comparative Analysis 2019 and 2020

Regression models assessed the direct effects of individual e-system features on students' satisfaction and the perceived reputation of the university. Tables 4 and 5 show the results of the regressions. In both 2019 and 2020, functionality was the most powerful predictor of satisfaction ($\beta = 0.49$ in 2019; $\beta = 0.50$ in 2020). This indicates that the range and usefulness of system features were fundamental for student approval. The degree of implementation of student affairs remained the second most relevant factor ($\beta = 0.14$ in 2019; $\beta = 0.17$ in 2020), highlighting the value of integrated and task-oriented services. Intuitiveness ($\beta = 0.09$ in 2019; $\beta = 0.10$ in 2020) consistently influenced satisfaction, supporting the role of user-friendly design. Speed of operation showed moderate importance for satisfaction ($\beta \approx 0.08$–0.10), but its impact on reputation diminished in 2020 ($p = 0.388$). Interface layout was statistically significant in 2019 but less relevant in 2020 ($p = 0.140$), indicating a shift in students' priorities toward pragmatic rather than aesthetic attributes. Variables like reliability and security marginally affect satisfaction but have statistically significant effects on reputation, particularly in 2020. Interestingly, adaptation to mobile devices, which was not significant in 2019, gained slight importance in 2020, possibly due to increased reliance on smartphones during the pandemic.

The adjusted R^2 for the satisfaction model was stable across both years (Table 4 for 2019; Table 5 for 2020), indicating a strong explanatory power. The reputation model showed lower R^2 values (2019: 0.438; 2020: 0.393), as shown in the same tables, suggesting that other factors beyond e-system quality may shape perceptions of university reputation. Table 6 synthesizes the predictors' evolution from 2019 to 2020.

Table 4. Impact of predictors on students' satisfaction and the university's reputation in 2019 [Source: own developed]

	Overall level of student satisfaction with the e-system			**The influence of predictors on reputation**		
Predictors	*Estimates*	*CI (confidence level)*	*p*	*Estimates*	*CI (confidence level)*	p
(Intercept)	0.64	0.44 – 0.84	<0.001	1.89	1.62 – 2.15	<0.001
Functionality	0.49	0.46 – 0.53	<0.001	0.35	0.30 – 0.40	<0.001
Implementation	0.14	0.11 – 0.17	<0.001	0.11	0.07 – 0.15	<0.001
Intuitiveness	0.09	0.05 – 0.12	<0.001	0.11	0.06 – 0.16	<0.001
Speed	0.08	0.05 – 0.12	<0.001	0.05	0.00 – 0.09	0.035
Interface	0.06	0.03 – 0.09	<0.001	0.09	0.05 – 0.13	<0.001
Reliability	0.03	0.00 – 0.06	0.044	0.04	0.01 – 0.08	0.026
Security	0.03	0.00 – 0.07	0.024	0.06	0.02 – 0.10	0.006
Adaptation	-0.00	-0.03 – 0.02	0.784	-0.03	-0.06 – 0.01	0.142
Observations	2528			2528		
R2 / R2 adjusted	0.674 / 0.673			0.440 / 0.438		

Table 5. Impact of predictors on students' satisfaction and the university's reputation in 2020 [Source: own developed]

	Overall level of student satisfaction with the e-system			**The influence of predictors on reputation**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.45	0.31 – 0.59	**<0.001**	1.98	1.80 – 2.16	**<0.001**
Functionality	0.50	0.47 – 0.52	**<0.001**	0.36	0.33 – 0.40	**<0.001**
Implementation	0.17	0.15 – 0.19	**<0.001**	0.12	0.10 – 0.15	**<0.001**
Intuitiveness	0.10	0.07 – 0.12	**<0.001**	0.07	0.04 – 0.11	**<0.001**
Speed	0.10	0.07 – 0.12	**<0.001**	0.01	-0.02 – 0.05	0.388
Interface	0.06	0.04 – 0.09	**<0.001**	0.02	-0.01 – 0.05	0.140
Reliability	0.00	-0.02 – 0.03	0.838	0.04	0.01 – 0.07	**0.006**
Security	0.00	-0.02 – 0.03	0.721	0.05	0.02 – 0.08	**0.001**
Adaptation	0.01	-0.01 – 0.03	0.231	0.02	-0.01 – 0.04	0.192
Observations	4952			4952		
R^2 / R^2 adjusted	0.680 / 0.679			0.394 / 0.393		

Table 6. Predictors' evolution from 2019 to 2020 [Source: own developed]

	Satisfaction		Reputation	
Predictor	2019	2020	2019	2020
Functionality	0.49	0.5	0.35	0.36
Implementation	0.14	0.17	0.11	0.12
Intuitiveness	0.09	0.1	0.11	0.07
Speed	0.08	0.1	0.05	0.01
Interface	0.06	0.06	0.09	0.02
Reliability	0.03	0	0.04	0.04
Security	0.03	0	0.06	0.05
Adaptation	0	0,01	-0.03	0.02

Shifts in Student Priorities and Evaluations

A notable shift occurred between 2019 and 2020 (see Figure 1). In 2019, students placed relatively equal emphasis on visual layout and intuitive features. However, in 2020, priorities clearly shifted toward system responsiveness, functionality, and task integration. Visual or aesthetic attributes such as interface layout became less influential.

Although reliability and security did not significantly influence satisfaction in either year, their impact on the university's reputation became more pronounced in 2020. This suggests that, in times of crisis, these features have more potential to contribute to perceptions of institutional trustworthiness than to direct user satisfaction.

Conversely, features such as mobile compatibility, although not statistically significant in either year, showed trends in students' expectations upward. The lowered impact of visual appeal and speed in 2020 further confirms a transition in users' evaluation criteria, where practical performance outweighed style and surface-level design.

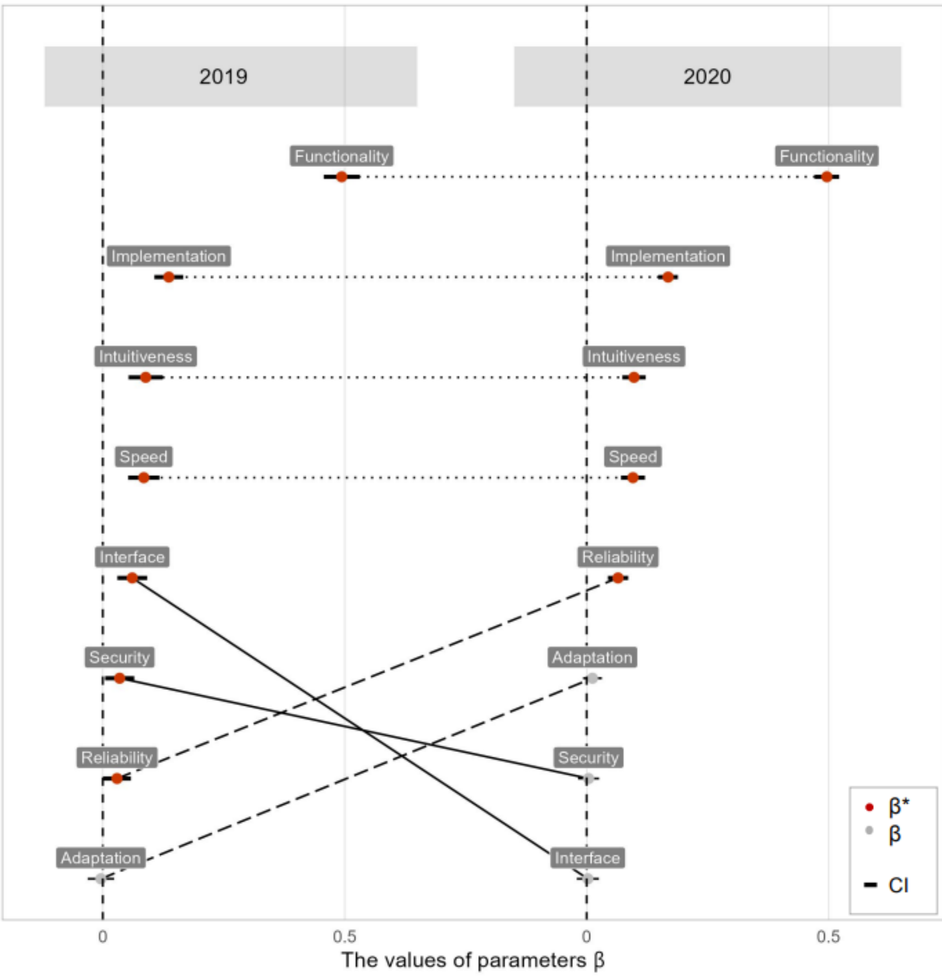

Figure 1. Changes in the assessment of the importance of selected E-system functions [Source: own developed]

Structural Equation Modelling (SEM) Findings

To provide a more nuanced understanding of how various e-system features affect perceived university reputation, Structural Equation Modelling (SEM) was applied for both the 2019 and 2020 datasets. The SEM allowed for testing both direct and indirect effects of e-system quality on reputation, with student satisfaction as a mediating variable.

Before proceeding, it is necessary to verify the adequacy of the sampled data using the KMO (Kaiser-Meyer-Olkin) and Bartlett's sphericity test. Table 7 shows the results performed by SPSS v. 27. All indicators are good, which means that the sampled data are adequate for both years. The limits are: (i) KMO > 0.9 for excellence; (ii) significance of the sphericity test < 0.05, which means that the sampled data differs from an identity matrix.

Table 7. Assessment of adequacy of the sampled data. [Source: own developed]

Test	2019	2020
KMO	0,910753	0,906676
Sphericity test Approx. Chi-Square	11205,04	21603,19
df	28	28
Sig.	0	0

In 2019, the model confirmed a strong mediating role of satisfaction. The influence of e-system features - such as functionality, implementation scope, and intuitiveness - was mostly indirect, operating through their impact on student satisfaction. The direct paths from these features to reputation were statistically weaker or non-significant. This suggests that in a pre-pandemic context, the way students felt about their administrative system largely shaped their perception of the university's reputation. Satisfaction served as a key transmission channel for reputational outcomes.

In contrast, the 2020 model revealed a shift in this dynamic. While satisfaction still played a role, the direct effects of e-system features on reputation became statistically significant and more substantial. Features like functionality and reliability began to affect students' perception of institutional reputation even when satisfaction was held constant. This shift indicates that in a crisis context - where digital infrastructure became a visible, essential element of the student experience - students began evaluating universities more directly on their technological responsiveness.

To validate the model fit and the reliability of conclusions, the following SEM quality indicators were assessed:

- Chi-square/df (χ^2/df): Values below 3.0 indicated acceptable model fit in both years.
- Comparative Fit Index (CFI): CFI was 0.932 in 2019 and 0.951 in 2020, both exceeding the 0.90 threshold for acceptable fit.
- Tucker–Lewis Index (TLI): TLI values of 0.921 (2019) and 0.944 (2020) confirmed a strong fit.
- Root Mean Square Error of Approximation (RMSEA): Values were 0.045 (2019) and 0.037 (2020), both below the commonly accepted cut-off of 0.06, indicating excellent approximation.
- Standardized Root Mean Square Residual (SRMR): Results below 0.08 in both years supported model validity.

These fit indices collectively indicate that both models adequately represent the empirical data, with slightly stronger performance in 2020. The standardized path coefficients for direct effects increased, while indirect coefficients via satisfaction slightly declined. The SEM thus captured a key behavioral shift: students transitioned from viewing digital systems as background utilities to treating them as frontline services that define institutional identity. The SEM findings reinforce the results of the regression analysis, but they also reveal more subtle dynamics. They show that context matters - in stable periods, satisfaction is a sufficient mediator; in uncertain times, system performance gains standalone reputational weight. This insight has important implications for digital strategy and student engagement in higher education.

Figures 2 to 5 show the measurement models considered for SEM analysis. Only loads greater than or very close to 0.707 were considered in the models. A loading of 0.707, when squared, results in 0.5, meaning that it explains 50% of the variance present in the sampled data. In practical terms, it reflects a moderate and positive relationship between two variables. A loading of this magnitude ensures the strength of a relationship, such as targeted in SEM applications or when a variable is associated or not with a particular construct, factor or component.

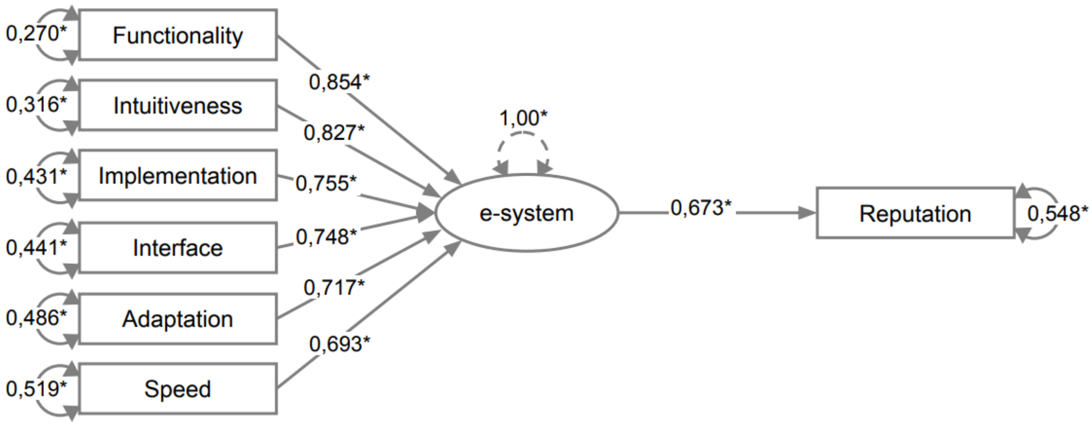

Figure 2. Direct impact of the hidden variable E-system on university reputation in 2019. [Source: own developed]

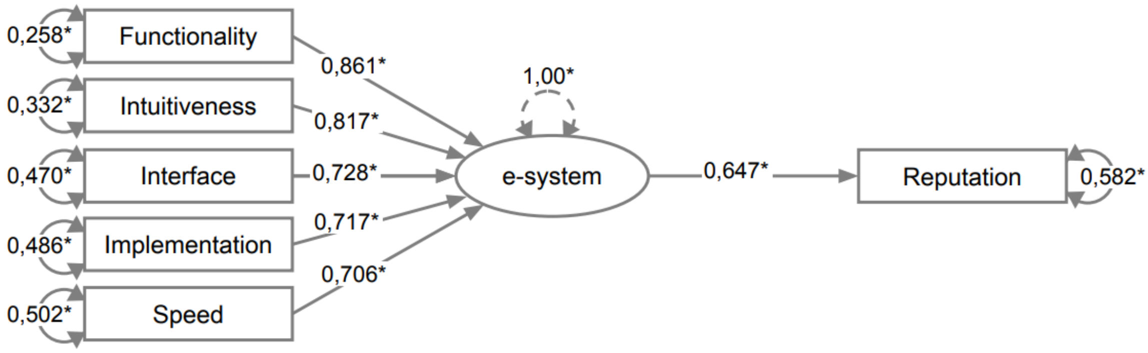

Figure 3. Direct impact of the hidden variable E-system on university reputation in 2020. [Source: own developed]

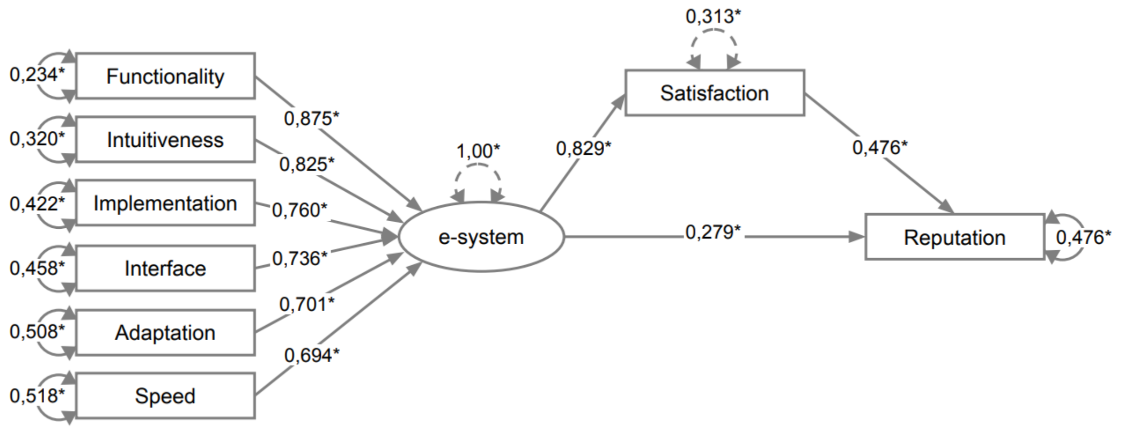

Figure 4. Indirect impact of the hidden variable E-system on university reputation in 2019. [Source: own developed]

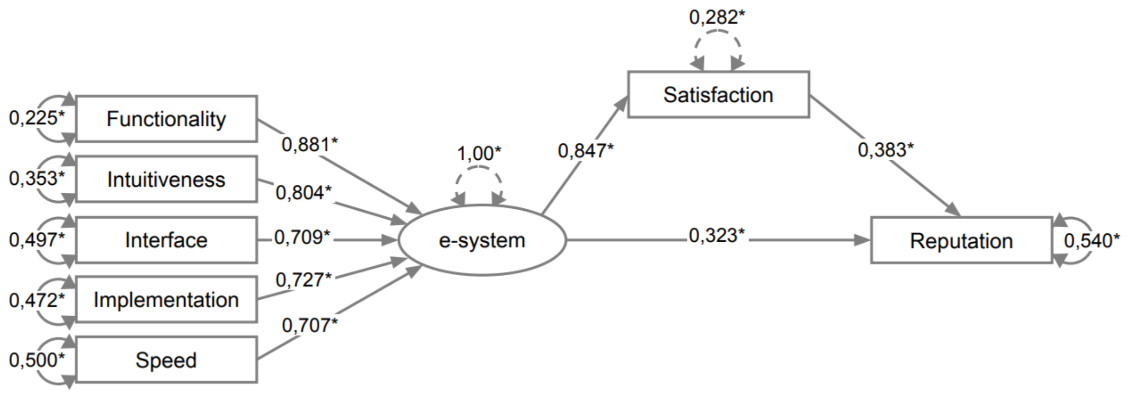

Figure 5. Indirect impact of the hidden variable E-system on university reputation in 2020. [Source: own developed]

KEY FINDINGS AND DISCUSSION

The study's findings address the role of digital administrative systems in higher education, specifically their influence on student satisfaction and institutional perception. Examination of these findings demonstrates several points for university operations.

Functionality, implementation, and intuitiveness represent factors driving student satisfaction with e-systems. Functionality, which encompasses the range and utility of system features, consistently showed the highest correlation with satisfaction in both 2019 and 2020. The degree of implementation, referring to the integration of student affairs processes within the system, also contributed to satisfaction. Intuitiveness, defined as the ease of navigation and clarity of system design, similarly relates to student approval. These three system attributes contribute to user experience and relate to student satisfaction.

Security and reliability exhibit a greater correlation with university reputation than with student satisfaction. In 2019, these features showed a statistical correlation with reputation. In 2020, their influence on the university's reputation increased. This observation indicates that system reliability and data security affect perceptions of institutional capability, particularly when reliance on digital services increases.

In 2019, student satisfaction mediated the relationship between e-system attributes and the university's reputation. In 2020, the direct impact of e-system features on reputation became more evident. This shift indicates a change in the evaluation process; e-system performance gained independent weight in reputation assessment, alongside the influence of satisfaction. This change occurred under conditions of increased digital dependency.

Mobile adaptation represents an emerging expectation. While its statistical correlation with satisfaction or reputation remained limited in both study periods, student expectations for mobile compatibility show an upward trend. This indicates a future demand for e-system accessibility and functionality across mobile devices.

University reputation correlates with student perception of system efficiency and broader institutional context. E-system attributes, including functionality and reliability, contribute to institutional perception. The R^2 values for the reputation model, lower than for the satisfaction model, indicate that other factors, such as academic programs, research output, faculty standing, facilities, and student life services, also affect a university's reputation. E-systems constitute a component of reputation development.

These key results confirm that e-system quality significantly contributes to students' overall academic experience and the public perception of institutional competence, especially during times of systemic disruption.

Regarding future implementations of the survey, the number of manifest variables may be reduced from eight to six without significant loss of content. This stage of the study aimed to simplify the complexity of the eight functional features of e-systems by identifying underlying structures. The best solution found involved grouping these eight manifest characteristics into three main latent (or non-manifest) factors, which represent broader dimensions of system quality.

A factor analysis can be a useful tool to perform such a reduction. With the extensive introduction of telematics devices and the diffusion of online activities, there is no meaning in focusing on the 2019 pattern. Therefore, this study focuses on the 2020 sampled data. Table 8 shows the factor analysis and the loading pattern of the manifested variables. The best solution found after a try-and-error approach was three factors, obtained by principal component analysis and after a varimax rotation with Kaiser normalization. The rotation converged in seven iterations. The extraction of the factors explained 76.4% of the total variance of the sample data. SPSS v. 27 was used.

Table 8. Factor analysis of the sampled data of 2020. [Source: own developed]

	Component		
Predictor	1	2	3
Functionality	**0,73**	0,29	0,38
Implementation	**0,78**	0,31	0,19
Intuitiveness	**0,71**	0,19	0,47
Speed	0,26	**0,70**	0,48
Interface	0,45	0,21	**0,71**
Reliability	0,15	**0,79**	0,38
Security	0,45	**0,73**	0,01
Adaptation	0,24	0,27	**0,81**

The first-factor groups functionality, implementation (of student affairs scope), and intuitiveness. This suggests that these three characteristics are perceived by students as intrinsically linked and, collectively, can be understood as application issues. The implication is that the core user experience with the e-system lies in its ability to perform tasks effectively and understandably. For university managers, the priority should be to ensure that systems are robust in their functionalities, comprehensive in their ability to integrate services, and simple to use, as these are the pillars of application-related satisfaction.

The second factor comprises speed, reliability, and security. These characteristics form a cohesive group that can be termed technical issues. This factor underscores the importance of the underlying technological infrastructure. The direct implication for university management is that investments in performance, stability, and data protection are crucial, as failures in any of these areas can undermine user trust and institutional reputation, regardless of functionality (Chiappetta, 2017). The perception that the system is technically sound is fundamental for its acceptance and continued use.

The third factor is composed of interface (layout) and adaptation (mobile accessibility). These two variables can be consolidated as user issues. This factor highlights the importance of design experience and flexibility of access. Although the study notes that interface layout became less relevant in 2020 compared to functionality, its combination with mobile adaptation indicates that ease of interaction and ubiquity of access are crucial aspects of the user experience. Universities' managers should, therefore, focus not only on aesthetics but also on usability and responsiveness across different devices to meet the expectations of a digitally native cohort.

By identifying these three latent factors, university managers can direct their improvement efforts more strategically. Instead of treating eight characteristics in isolation, they can focus on three broad areas of intervention: optimizing the application experience (tasks and usability), strengthening the technical foundation (performance and security), and enhancing the user interface and accessibility. This allows for more efficient resource allocation and more integrated project planning.

For example, an "application issues" problem suggests the need for process review, workflow design, and user training. In contrast, a "technical issues" problem would require interventions in IT infrastructure, servers, and security protocols.

It is possible to reduce the first and second factors by eliminating one of the manifested variables from both. One way to identify what indicator can, if deleted, produce less damage to the content is to measure Cronbach's alpha for the entire construct after removing one indicator at a time. The Cronbach's Alpha analysis for item deletion validates the integrity of the construct even with the exclusion of specific variables. This ensures that the representation of e-system quality remains valid and reliable but in a more concise manner. Maintaining a high Cronbach's Alpha after removing "Implementation" and "Security" confirms that the underlying constructs are still adequately measured by the remaining variables. Table 9 shows the result, which ensures that the best deletions are implementation and security.

Table 9. **Cronbach's alpha if item deleted. [Source: own developed]**

Predictor	Alpha if item deleted
Functionality	0.72
Implementation	0.83
Intuitiveness	0.77
Speed	0.67
Reliability	0.69
Security	0.82

The factor analysis also pointed to the possibility of reducing the number of manifest variables without significant loss of content. Specifically, the study suggests that Implementation and Security could be removed from future measurements, reducing the set from eight to six indicators. A reduced number of questions in future surveys would lessen the burden on respondents (students), potentially increasing response rates and data quality. Shorter questionnaires are less prone to causing respondent fatigue. For subsequent analyses (such as regression or SEM), variable reduction leads to more parsimonious models, which can facilitate the interpretation and replicability of results. By removing variables that are well-represented by others within the same factor or that have less impact on the explained variance, the measurement model becomes leaner and more robust.

In summary, the conclusions from the factor analysis and variable composition optimization offer a practical and conceptual roadmap for universities and researchers. They enable understanding of e-system quality not as a set of isolated elements but as interconnected dimensions. They also facilitate the development of more efficient and impactful evaluation tools that are aligned with student priorities in the digital age.

CONCLUSIONS AND LIMITATIONS

This study investigated the extent to which the perceived quality of administrative e-systems affects student satisfaction and the reputation of higher education institutions. The analysis responded to the core research problem: whether administrative e-system attributes contribute significantly to shaping institutional reputation and whether this relationship is mediated by student satisfaction.

The results clearly demonstrate that e-system functionality, degree of integration, and intuitiveness are consistently the most influential drivers of satisfaction. Furthermore, while in 2019, the effect of these features on reputation was mediated almost entirely through satisfaction, in 2020 - amid the COVID-19 pandemic - a significant direct relationship emerged. This shift signals that in times of heightened digital dependency, students form reputational judgments based more directly on their digital service experience.

However, several limitations must be acknowledged. First, the research is limited to Polish universities, and the findings may not be fully generalizable to other higher education systems. Second, the analysis relies on cross-sectional data from two distinct time points;

future longitudinal studies could capture more nuanced dynamics in student evaluations. Third, the study uses self-reported measures, which can be subject to perception bias.

IMPLICATIONS FOR RESEARCH

Our findings contribute to a growing body of literature by highlighting administrative digital services - not traditionally central in satisfaction-reputation frameworks - as meaningful determinants of student perception. They also illustrate how the structure of student evaluation evolves in response to external disruptions. In this regard, the study supports a more inclusive understanding of digital transformation in higher education, one that encompasses not only e-learning tools but also the usability and performance of administrative systems.

Despite its limitations, this research offers robust empirical support for integrating administrative e-system quality into broader models of student satisfaction and institutional reputation. The findings provide actionable insights for university management: improving digital service design and system responsiveness is not merely a matter of convenience - it is a strategic lever in shaping institutional standing in the eyes of digital-native students.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 21(3), December 2025, 596–619

HUMAN FACTORS IN PROPTECH ADOPTION: PROFESSIONAL READINESS AND ORGANISATIONAL CHALLENGES IN BALTIC REAL ESTATE

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Abstract: *This study examines the human and organisational factors influencing the adoption of property technology (PropTech) among real estate professionals in the Baltic States (Lithuania, Latvia and Estonia). Adopting a Human-Technology-Organisation (HTO) perspective, the research explores how professionals integrate digital tools into their daily work. Data collected via a questionnaire survey of 20 Baltic real estate executives was analysed using the Relative Importance Index (RII). The findings reveal that PropTech is primarily utilised for people-intensive functions, such as marketing, customer relations and contract administration. It serves to augment human interaction rather than replace it. The most significant barriers to adoption were found to be primarily human- and knowledge-based, including insufficient investment capital, legal ambiguity and, critically, low PropTech knowledge among employees. This knowledge deficit creates uncertainty among staff regarding the proper use of digital tools. Theoretically, the study emphasises that adoption of advanced technologies is strongly moderated by personnel availability, professional knowledge and learning processes rather than technology level itself. In practice, the results highlight the urgent need for real estate industry HR and training departments to address this knowledge gap through targeted training, knowledge transfer and dissemination of best practice. Furthermore, policy should prioritise aligning PropTech investment with human capital development.*

Keywords: *PropTech, human-technology interaction, technology adoption, professional competence, organisational change, real estate.*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.6

INTRODUCTION

The pervasive presence of technology permeates every facet of modern life, including the real estate sector, which is undergoing a profound transformation. Core activities such as property analysis, transactions (buying and renting) and facility management have been greatly improved by digital developments. Furthermore, these technologies effectively mitigate traditional barriers and neutralise challenges historically imposed by the physical location and distance of real assets. The digital transformation of the real estate sector has advanced significantly in recent decades as emerging technologies have continuously altered conventional methodologies (Le et al., 2019; Al-haimi et al., 2025). While technology has been used in real estate for many years, investment in innovative property technologies, or PropTech, has accelerated tremendously in recent years, driving rapid development in the sector (CRETI, 2024). This technological evolution is closely linked to changes in professional behaviour, cognitive demands, and organisational culture. Understanding how real estate professionals and consumers adapt to, and are affected by, these tools is essential for fostering a human-centred technological world. This research therefore provides vital empirical data on the social, organisational, and psychological challenges that accompany the adoption of sophisticated ICT in a professional setting.

PropTech is just one aspect of the real estate industry’s broader digital transformation. It encompasses technological and mental shifts within the industry, as well as client attitudes, movements, and transactions related to buildings and cities (El Jaouhari et al., 2025). PropTech encompasses a wide range of technological applications that serve as the foundation for digital transformation. It includes building technology, such as smart buildings and Internet of Things (IoT)-based sensors; smart city development; building information modelling (BIM); augmented reality; artificial intelligence; and data analytics. It also includes critical enabling technologies, such as digital twins, blockchain, and asset tokenisation; as well as specialised climate tech (ESG) solutions (El Jaouhari et al., 2025; Tagliaro et al., 2025a, 2025b). This ecosystem of PropTech solutions is essential for driving efficiency, automation, and value creation across the global real estate market.

The current phase of technological evolution, often referred to as PropTech 4.0, has already proven to be a transformative force in the real estate industry. By leveraging advanced technologies such as AI, digital twins and tokenisation, it improves efficiency, transparency and sustainability (ESCP Business School, 2024; Kassner et al., 2023; Starr et al., 2021). This shift redefines the role of real estate professionals, requiring them to master complex digital tools and collaborate more closely with automated systems. This redefines their core professional competencies. Building on this, the emerging concept of PropTech 5.0 will incorporate cutting-edge technologies, emphasising enhanced human–machine interaction, continued efficiency gains and a decisive focus on reducing the environmental impact of the real estate industry (Chen et al., 2025; Tagliaro et al., 2025b). This rapid evolution highlights the importance of continuous adoption and strategic investment to remain competitive in an increasingly digital global market.

The widespread adoption of the Internet of Things (IoT) has significantly increased the global carbon footprint, making energy-efficient solutions and Green IoT (G-IoT) necessary. However, implementing G-IoT poses technological challenges relating to software, hardware, architecture and communication networks that require further analysis (Alsharif et al., 2023).

This is particularly important since smart buildings rely heavily on Information and Communication Technologies (ICT) to automate processes and control operations in an allegedly sustainable manner (Liu & Mishra, 2022). This reliance coincides with the growing demand for smart buildings in the real estate market. These buildings have interactive features that respond dynamically to users' needs and changing conditions, whether external (e.g., climate and grid prices) or internal (e.g., occupants' requirements) (Al Dakheel et al., 2020). Furthermore, smart technology, particularly digital twin modelling, can significantly improve occupant comfort and productivity while using less energy than conventional buildings (Liu et al., 2025; Plohl & Čuš Babič, 2024). Crucially, these systems enhance the human experience within the built environment by providing a better quality of life for users through the creation of personalised and adaptive indoor climates. The Internet of Things (IoT) is fundamentally changing how environments, cities, and buildings are managed. The potential impact of IoT applications extends beyond the systems and devices with which users interact (Le et al., 2019). These applications can also track and improve employee and occupant health and well-being (Semeraro et al., 2025; Venkateswarlu & Sathiyamoorthy, 2025). Despite the exponential growth of Internet of Things (IoT) deployment, developing smart, user-oriented applications requires integrating IoT technology with data from the built environment. This necessitates the convergence of diverse building disciplines and systems. This complex technological requirement demonstrates that a thorough evaluation of PropTech adoption must consider economic efficiency and environmental sustainability.

Big data is fundamentally revolutionising consumer and real estate analysis. Artificial Intelligence (AI) applications are critical for enabling this transformation, helping companies sift through large amounts of data to gain valuable insights about consumers, risk, profit, and performance (Jamaludin & Mustafa, 2025). AI's primary application in the real estate industry extends beyond passive information management; it serves as the core engine for prescriptive big data analytics. AI tools continuously collect, aggregate, and analyse extensive property, market, and portfolio data. This includes structured data as well as unstructured sources such as social sentiment and online reviews. Processing this vast and diverse dataset enables the behavioural modelling and automated analysis required to convert raw data into actionable real estate strategies (DeLisle et al., 2020). Consequently, AI technology reduces the cognitive load associated with data processing, enabling real estate professionals to dedicate their expertise to complex negotiations and client relationship management. However, AI technology is shifting the industry's focus from tracking past events to proactively managing future outcomes and adding value throughout the entire property lifecycle. This advanced intelligence, powered by deep learning and vast datasets, is driving significant change. AI enables superior prescriptive analytics, which directly enhances market trend forecasting by significantly improving accuracy compared to traditional methods (Kandi Pati, 2025). This is particularly important given that traditional transaction-based data can lag behind actual market developments by several quarters, potentially distorting price indices and market assessments (Hill et al., 2024; Kapingura et al., 2024). This increased precision allows real estate professionals to anticipate market changes and make informed decisions proactively.

Compared to traditional methods, AI methodologies, including machine learning, significantly improve the accuracy of market trend forecasting. These models improve prediction accuracy by efficiently processing large amounts of data and identifying patterns that humans might overlook (Fourkiotis & Tsadiras, 2023). Advanced statistical techniques such as Bayesian Model Averaging further enhance the identification of key determinants driving housing market dynamics (Trojanek et al., 2023; Mukayev et al., 2022). AI also improves operational management through automation. Furthermore, integrating AI (deep learning) with BIM-enabled AR is essential for improving model registration, which is crucial for utilising AR in maintenance operations and optimizing building management. This proactive management uses real-time data from IoT sensors to predict equipment failures, optimize maintenance schedules, and increase equipment lifespan, transitioning to a predictive maintenance model (Ashour & Yan, 2020; Das et al., 2025). This approach drives operational efficiency and cost reduction while ensuring higher reliability and performance. Proactive management also extends to energy efficiency and sustainable operations. In smart buildings, AI systems continuously adjust consumption to meet sustainability goals (Emedo et al., 2025). Finally, AI is restructuring client interfaces and transactional governance. AI optimizes client interaction through personalised, continuous responsiveness. Its integration into smart contracts ensures greater accuracy and transparency in real estate transactions (Zhao et al., 2024). Ultimately, AI provides real estate professionals and investors with valuable insights to guide strategic decisions and optimize investment strategies (Seagraves, 2024). The synergy between the Internet of Things (IoT), big data, and AI is radically reshaping the strategic landscape of real estate. This integrated framework, fuelled by real-time data from smart buildings and refined by advanced AI algorithms, improves operational efficiency, automates decision-making processes, and creates powerful predictive models. These models significantly impact and optimize marketing, sales, customer service, and consumer behaviour across all portfolios, establishing data as a strategic asset for gaining a competitive edge.

Despite the significant benefits of integrating AI into the real estate sector, three primary concerns arise. Firstly, data privacy is paramount because AI systems require large amounts of personal and proprietary data in order to learn. This necessitates the implementation of robust security measures (Rojek et al., 2025; Seagraves, 2024; Szumilo & Wiegelmann, 2024). Secondly, the integration of AI technology raises ethical concerns about the potential for algorithmic bias. AI models that are trained using historical data which reflects existing disparities can perpetuate those biases in their predictions. This can lead to unfair outcomes and necessitate the implementation of robust ethical frameworks (Kalogiannidis et al., 2024; Perry et al., 2023). These issues undermine human trust in the technology directly and challenge the principles of fairness and equity in market access and professional opportunities. Thirdly, automation has the potential to displace jobs, particularly those involving routine paperwork and compliance. Businesses must therefore develop strategies to upskill their existing workforce and navigate this complex technological transition effectively (Seagraves, 2024; Siderska et al., 2023; Wach et al., 2023). Addressing these challenges requires stringent governance models and a commitment to the responsible and ethical deployment of AI across the industry.

Building Information Modelling (BIM) is a vital tool in the real estate sector, improving construction project management, enhancing performance, and providing consistent data for strategic asset management throughout a building’s lifecycle (Dixit et al., 2019; Sarvari et al., 2020). Due to high demands for quality, efficiency, and sustainability, BIM has become essential for designing and assessing green buildings (Fonseca Arenas & Shafique, 2023; Tran et al., 2024; Waqar et al., 2023). In this context, BIM has become essential for improving efficiency and ensuring high-quality construction (Sarvari et al., 2020; Tran et al., 2024). It provides significant benefits in designing and assessing the sustainability of buildings. Furthermore, BIM is used to create comprehensive digital repositories of building components that facilitate the management of buildings and facilities throughout their lifecycle (Dixit et al., 2019). As BIM technology continues to evolve and transform the construction and real estate industries, it is primarily integrating with immersive visualisation technologies to unlock new levels of access and collaboration.

Specifically, the integration of BIM with technologies like augmented reality (AR) creates new functions by overlaying digital models onto real-world environments. AR technology overlays digital models onto real-world environments, offering a realistic and immersive view of proposed designs. The ability to transfer virtual building designs into the physical environment significantly improves the architectural design process by enhancing perception, communication, and collaboration among stakeholders (Khan & Panuwatwanich, 2021). Moreover, the integrated BIM and mobile augmented reality (MAR) environment provides facility managers with real-time, on-site access to essential BIM data. This access is crucial for tasks such as structure assembly and facility management (Khan & Panuwatwanich, 2021; Liao & Luo, 2025), and it helps managers make informed decisions quickly and efficiently. Systems that integrate BIM data into mobile augmented reality (AR) environments provide facility managers with interactive tools for maintenance and operations. Real-world applications have demonstrated the feasibility and significant advantages of this integration, enhancing the effectiveness, efficiency and precision of construction and facility management tasks (Dahbi et al., 2022; Khan et al., 2024). This integration transforms the cognitive work of facility managers by providing real-time data visualisation and reducing human error, thereby improving professional decision-making on-site.

However, the BIM-driven transformation extends beyond AR, encompassing the broader integration of AR and VR. This combination provides stakeholders with powerful, immersive digital tools throughout the property lifecycle. Notably, it allows customers to virtually explore properties for sale or rent, saving them significant time and money (Anderies et al., 2023; Deep et al., 2025; Pralhad et al., 2021). Thus, the sophisticated integration of BIM, AR, and VR demonstrates PropTech’s vast potential to transform traditional industry workflows and increase stakeholder value.

Blockchain technology is poised to revolutionise the real estate sector by establishing a foundation of efficiency, transparency, and trust. As a digitized, distributed ledger that immutably records and shares information, blockchain enables profound effects across the industry, transforming core operations such as property transactions, due diligence, and secure title management (Veuger, 2018). This foundational technology empowers the commercial real estate (CRE) industry to improve the transparency and efficiency of information sharing (Deloitte Center for Financial Services, 2017), possessing the potential for the creation of new business models and services. Noteworthy use-cases include smart contracts that can execute conditional transaction clauses and asset tokenisation, whereby property is broken down into digital shares. This significantly improves market liquidity and accessibility for smaller investors (Saari et al., 2022; Paavo et al., 2025). Consequently, blockchain acts as vital infrastructure within PropTech, ensuring that the data used by AI and IoT applications is verifiable and thereby bolstering the overall reliability of the system. This holistic ecosystem, which encompasses BIM/AR/VR visualisation, AI-driven analytics and blockchain-secured transactions, enables all stakeholders, including owners, investors and service providers, to collaborate and derive greater value, thus demonstrating the full transformative potential of PropTech.

PropTech is driving widespread changes across the real estate market, fundamentally altering how owners, investors and developers perceive real estate as an asset class (Brown, 2018). This transformation is intrinsically linked to financial technology (FinTech), given that the real estate sector is one of those most profoundly impacted by FinTech innovations. FinTech companies are developing new solutions that are advancing financial services and the real estate industries, thereby fundamentally altering real estate transactions. This synergy is primarily evident in crowdfunding, mortgages, lending, leasing, and sophisticated data and analytics platforms (Mattarocci & Scimone, 2022; Saiz, 2020). Overall, the integration of financial technology and real estate innovation is restructuring traditional capital allocation and transactional workflows.

Real estate entities must adopt a proactive strategy to manage the ongoing digital transformation of their financial and operational workflows. To ensure sustainable growth and long-term profitability, contemporary companies should prioritize the key areas identified in recent research (Ciaramella & Dall'Orso, 2021; Clayton et al., 2019; Kassner et al., 2023; Phan & Boge, 2023; Saull et al., 2020; Souza et al., 2021). These priorities include: (1) cultivating agility and innovation for a competitive advantage; (2) strategically integrating emerging technologies; (3) securing digital infrastructure and enhancing market transparency; (4) optimizing operational and financial management; and (5) developing customer-centric solutions delivered through digital interfaces.

Although technological innovations present challenges to the real estate sector, they also give companies that adopt them a competitive advantage. Nevertheless, some companies will fail to cope with the competition, particularly since the real estate sector lags behind technological advances by several years (Ullah et al., 2021). However, innovation and technology will not succeed unless real estate companies meet customer needs, since smart real estate must be user-centric (Ullah et al., 2018). Real estate companies must carefully monitor their clients' needs and decide which technologies to invest in (Ocampo, 2024). The slow pace of change is often rooted in the psychological resistance of key decision makers and the absence of adequate training to foster digital confidence throughout the organisation. Traditional managerial mindsets have hindered progress, but the sector must adopt advanced digital technologies to transform into smart real estate in line with Industry 4.0 requirements.

The successful adoption of PropTech is greatly influenced by regional organisational bodies that foster innovation and collaboration. PropTech Lithuania is a network of innovators and market leaders. Its core mission is to cultivate the domestic PropTech ecosystem and drive innovation by connecting stakeholders of all levels, from start-ups to established market leaders. PropTech Lithuania plays a crucial role in facilitating international growth by building global networks and actively attracting foreign PropTech companies to Lithuania. PropTech Lithuania is leveraging this robust network and progressive structure to partner with other organisations and extend its strategic analysis across the broader Baltic region (PropTech Lithuania, 2025).

The literature review consistently emphasised the critical importance of PropTech for the future viability of the real estate sector and its professional roles. However, effective adoption requires crucial alignment between favourable human-designed policy environments and robust technical standards. Financial commitment is limited due to the absence of standardised productivity data, which makes it difficult to anticipate future investment returns reliably and affects investor confidence. Due to these complex dependencies, where technological success relies heavily on external human factors such as policy and verifiable financial metrics, academic discourse currently lacks a unified, cross-regional, empirical comparison of adoption factors and the specific human and organisational risks in Baltic markets. The necessity of empirical research to assess the viability of current adoption and the quantifiable organisational and human barriers facing PropTech solutions in nascent markets such as the Baltic region is underscored by this reliance on verifiable financial metrics and supportive regulatory structures.

Technology adoption is primarily a human process involving cognitive, organisational and social elements (Xu & Lu, 2022). This study uses the Human-Technology-Organisation (HTO) framework to suggest that successful adoption requires alignment across individual, technological, and organisational factors (Olofsson Hallén et al., 2023). The framework emphasises that adoption is a sociotechnical process with significant implications for professional identity, work processes, and occupational well-being. The Technology Acceptance Model (TAM) and its successor, the Unified Theory of Acceptance and Use of Technology (UTAUT), have both identified perceived usefulness and perceived ease of use as the primary psychological predictors of technology adoption, regardless of the technology's actual performance (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

Incorporating new technology like PropTech into real estate work entails cognitive shifts in professional roles. Automating routine tasks changes the nature of cognitive work from procedural to oversight, requiring new competencies in data analysis, system management, and human-AI interaction (Siderska et al., 2023). This shift can create professional anxiety if not accompanied by adequate training and support, leading to potential resistance, underuse, or even rejection of the technology (Wang, 2022).

This study operationalises this framework by surveying: (1) perceived applicability of PropTech in various professional functions, as a measure of alignment with work processes; (2) barriers to adoption with an emphasis on human capital limitations; and (3) attitudes towards AI as a proxy for technology acceptance and psychological readiness.

The research in this paper aimed to:

- Elicit the views of professionals on how PropTech technologies align with professional work functions, and identify where PropTech enhances or hinders human core competencies in Baltic States' real estate markets.
- Explore and analyse the human and organisational factors influencing the adoption of PropTech, particularly with regard to knowledge and skill gaps and awareness.
- Identify professionals' opinions on artificial intelligence and automation to understand their potential impact on workforce adjustment and professional identity in PropTech-driven real estate organisations.
- Offer a data-informed discussion to inform a more human-centred approach to PropTech investment and human capital development.

The paper's main aim is to conduct a comprehensive comparative analysis of the Baltic region to determine the current landscape of PropTech technology needs and development. It will also assess the risks impacting the technology's long-term viability and the sustainability of human expertise within the evolving industry.

Success Factors for PropTech in the Real Estate Market

The deployment of PropTech technology in real estate is a relatively new field, and comprehensive research is still emerging. While its potential is transformative, the industry's fragmentation and the limited coverage of diffusion theory pose significant challenges to its efficient implementation and adoption (Shirowzhan et al., 2020). Success hinges on fully understanding the factors that govern adoption, which goes beyond technological capability to include institutional and human readiness (Qiu et al., 2023).

The viability of PropTech begins with aligning with macro-level imperatives, such as transitioning to high-quality development and achieving strategic modernisation goals. Institutional commitment is demonstrated through a focus on environmental, social, and governance (ESG)/sustainability; proactive research and development (R&D) investment; and fostering a co-creation model between established enterprises and start-ups (Ladha & Ladha, 2025; Petrescu et al., 2025; Tan & Miller, 2023). These external factors establish the essential strategic mandate and necessary resource foundation.

Industry-wide digitalisation and intelligence depend heavily on the strategic deployment of core digital technologies. This pillar requires integrating big data, artificial intelligence (AI), cloud computing, and blockchain technology to create new productive forces (Jacob & Asha, 2023; Oza et al., 2024; Zhang et al., 2025). The primary technical challenge is to ensure interoperability, enabling systems like BIM to efficiently exchange data with other PropTech platforms and facilitating seamless data flow (Pham Van et al., 2025).

To succeed in PropTech, it must be treated as a comprehensive human-technology-organisation (HTO) social system, considering all three elements together. Organisational leadership must actively promote cross-functional collaboration, implement technical standards and foster positive employee-technology interactions. These efforts can transform investments into systemic, holistic change across the organisation (Olofsson Hallén et al., 2023). Ultimately, however, adoption depends on the individual user. To facilitate this, it is necessary to assess user characteristics, develop team competencies and address technology acceptance (Olugboyega et al., 2024). Acceptance can be gauged through satisfaction and perceived usefulness in order to pre-empt resistance. The final essential measure of successful implementation and realising value is ensuring the project team embraces and utilises the technology effectively (Wang, 2022).

Therefore, the success of PropTech is determined by an interdependent microenvironment that spans institutional strategy, technology integration, organisational systems, and individual readiness. Effective adoption requires holistic alignment across four core pillars:

- External and institutional factors.
- Factors related to PropTech technology.
- Factors related to the project team and organisation.
- Factors related to individual user readiness.

PropTech technology is a transformative force. However, the industry's fragmentation poses significant challenges to efficient implementation and adoption (Shirowzhan et al., 2020). Although many applications for advanced construction and real estate technologies have been recommended in scholarly literature, comprehensive coverage of the process of their widespread integration remains limited. Success hinges on predicting the behaviours of adopters and identifying which components require additional effort for the successful integration of BIM and other advanced construction and real estate technologies (Khan et al., 2024). Predicting these behaviours depends on understanding compatibility – the degree to which technology aligns with users' experiences, needs, and values (Kim et al., 2022; Kim & Kim, 2021). As these technologies are designed for people, the primary objective is to accurately assess user characteristics and current task performance. This user-centric approach is vital for minimising professional disruption and maximising employee acceptance and satisfaction when introducing new tools. Developing tools that genuinely enhance and simplify the user's workflow ultimately elevates professional fulfilment and drives long-term organisational value through improved human performance.

Analysing the potential success of PropTech reveals a complex microenvironment influenced by multiple factors. Regardless of technological sophistication, the human factor is the most critical consideration for successful adoption (Olofsson Hallén et al., 2023). Since PropTech innovations are designed for people, a core goal of adoption research is to determine the characteristics, interactions, and competencies of individual users in order to develop tools and organisational support that facilitate technology use (Ata et al., 2025; Durdyev et al., 2021). Adopting a human-technology-organisation (HTO) perspective, PropTech is treated as a holistic social system. This acknowledges that technology alone is insufficient for efficient implementation (Tan & Miller, 2023; Xu & Lu, 2022). Consequently, neglecting the individual user in implementation strategies can hinder successful outcomes. As strategic viability now depends on managing these human and organisational complexities, real estate entities must proactively incorporate these insights into their core corporate strategies to ensure both technological adoption and the psychological well-being of their workforce.

Analysis of the scientific literature confirms that the successful deployment of PropTech extends beyond technology. Rather, it is determined by an organisation's strategic commitment and its ability to holistically manage change within key pillars: institutional strategy, organisational systems, and personnel readiness.

RESEARCH METHODS

The study commenced with a review of existing academic literature on the adoption of property technology (PropTech). To collect empirical data, a structured questionnaire was distributed to management executives of companies affiliated with the PropTech Baltics network in January 2024.

The study's sample comprised 20 real estate organisations operating in the PropTech sector across the Baltic States: 10 in Lithuania, 5 in Latvia and 5 in Estonia. To maximise the response rate and ensure adequate representation of the sample, 25 questionnaires were distributed via a combination of email and personal delivery. Twenty of these were returned fully completed and deemed valid responses, resulting in an 80% response rate.

The questionnaire was developed based on an initial literature review to address the study's objectives. Respondents assessed the importance of various factors related to PropTech adoption, challenges, and benefits using a five-point Likert scale. This scale was defined as follows: 1 = Not important, 2 = Less than important, 3 = Important, 4 = More than important, and 5 = Very important.

Analysis of the collected data aimed to determine the ranking of factors according to their relative importance in terms of the applicability and challenges of PropTech. For this purpose, the relative importance index (*RII*) was employed.

The Relative Importance Index (*RII*) is a non-parametric statistical technique used to quantify and rank the relative significance of different factors or variables. This makes it particularly useful for prioritising variables based on their perceived importance in surveys and questionnaires (Binoy et al., 2020; Holt, 2014; Siew et al., 2010). This methodology is well-suited to the present study, as it is commonly employed in research concerning construction (Altuwaim et al., 2023; Fernandes et al., 2024), real estate (Marasinghe & Amarawickrama, 2024; Owusu-Manu et al., 2015) and technology adoption (Alshibani et al., 2024; Desai et al., 2025). In these fields, data is typically gathered from structured questionnaires to determine consensus on the drivers of a given outcome.

Ranging from 0 to 1, the *RII* identifies and ranks the most influential factors within the given set. A higher *RII* value indicates a factor that is more critical in terms of PropTech's applicability, and vice versa.

Based on the experts' opinions collected via the survey, the *RII* was computed for each factor using Equation (1):

$$RII = \frac{\sum W}{A \times N} \ (0 \leq RII \leq 1) \qquad (1)$$

where $\sum W$ is the sum of the weightings given to each factor by the respondents (ranging from 1 to 5, where 1 is "not important" and 5 is "very important"); A is the highest weight on the scale (i.e., 5); and N is the total number of respondents.

The results of the questionnaire survey are shown in Tables 1–2.

RESULTS AND DISCUSSION

The survey targeted 20 executives and managers who are actively involved in PropTech within the Baltic real estate market. The demographic and professional characteristics of this leadership sample are summarized below.

The expert panel was highly experienced and concentrated in the prime working age bracket, with most executives falling between 30 and 49 years old. The vast majority of respondents possessed substantial industry experience (at least five years), and educational attainment was high, with the majority holding a university degree. The sample consisted primarily of male executives, a gender distribution reflecting patterns often observed in global real estate leadership. Importantly, the organisations represented a diverse market structure, ranging from micro-enterprises to small and medium-sized enterprises (SMEs). This combination of deep professional experience, high education, and varied organisational background ensures the experts possess the necessary knowledge and market context to effectively evaluate the applicability and challenges of PropTech in the Baltic real estate market.

The survey results from Baltic real estate companies reveal a dual-device strategy influenced by hybrid working. Managers in both Lithuania and Estonia primarily use laptops and smartphones, reflecting the priority placed on workplace flexibility and mobility. Desktop computers are used less frequently, indicating their diminished status as the default tool due to this shift towards flexibility. However, when employees need to carry out tasks that require advanced digital technologies, such as intensive data processing, detailed financial modelling or specialised reporting, the desktop computer is overwhelmingly identified as the preferred high-powered solution. Tablet usage consistently ranks last.

Real estate professionals across the Baltic States overwhelmingly rely on digital information in their daily work, yet the specific formats used vary by country. In both Latvia and Estonia, virtually all professionals utilise general digital documents (such as standard office files), confirming a fully digitised workflow for core document management. These countries also demonstrate a strong and consistent commitment to utilising specialised technical data, such as 2D/3D/CAD files. Latvia and Estonia are also largely paperless. Conversely, Lithuania exhibits a distinct pattern: although professionals frequently utilise general digital documents and cloud-based data, they exhibit a much lower reliance on specialised technical files (2D/3D/CAD). Lithuania is also the only country where a significant proportion of professionals still use paper documents and specific mobile apps in their daily work.

The rapid advances in artificial intelligence (AI) and machine learning (ML), particularly the emergence of generative AI, have transformed our perception of digital capabilities. These technologies allow organisations to analyse large volumes of data and produce highly accurate and dependable outcomes (Fourkiotis & Tsadiras, 2023; Kandipati, 2025; Zhao et al., 2024). As FinTech, ConTech and PropTech are expected to transform their respective industries with these new technologies within the next decade (Perera et al., 2025; Tiwari & Miao, 2022), it is essential to evaluate the attitudes of executives.

Professionals engaged with the latest PropTech solutions show a proactive and positive attitude towards artificial intelligence (AI), viewing it primarily as a means of augmentation and efficiency gains, rather than as an existential threat to their role. This positive disposition is substantiated by the finding that the vast majority of respondents indicated that they are not afraid of AI's potential impact. This attitude is consistent with the global trend of real estate professionals rapidly adopting technologies such as ChatGPT to enhance customer service and automate daily tasks. A similar trend can be seen in the construction sector, where professionals began using this technology for their daily tasks soon after ChatGPT's release (Sonkor & García De Soto, 2025). This widespread adoption highlights AI's role as a critical tool for boosting productivity and maintaining competitiveness in the digital economy, rather than as a competitor.

Factors Affecting PropTech Applicability

Utilising the robust knowledge base established by the expert respondents, a formal assessment was conducted to determine the perceived significance of digital transformation. Respondents provided their opinions on the applicability of PropTech across diverse real estate functions. The data was then subjected to the relative importance index (*RII*) analysis to establish an objective ranking of the factors. Table 1 details these findings, representing the collective view of executives and their authorized representatives in Lithuania, Latvia, and Estonia.

Based on the average *RII* across all three Baltic countries, as detailed in Table 1 and visualised in Figure 1, PropTech is perceived as being most applicable in areas that enhance efficiency and data intelligence. Marketing, contract management and interactive billing are definitively the most critical applications (*RII* = 0.973), reflecting a strong consensus among executives on PropTech's core value of automating customer-facing and sales processes. This is closely followed by data, valuation and analytics (*RII* = 0.927), which validates the industry's shift towards data-driven decision-making.

Table 1. *RII* of PropTech applicability in real estate companies across the Baltic States.

PropTech applicability	Lithuania		Latvia		Estonia		Average *RII*	Rank
	RII	Rank	*RII*	Rank	*RII*	Rank		
Property registry and search services	0.94	2	0.92	3-4	0.76	6-7	0.873	4
Real estate investment and financing	0.8	7	0.92	3-4	0.84	4	0.853	5-6
Marketing, contract management, and interactive billing	0.96	1	1	1	0.96	1	0.973	1
Market analysis and research	0.86	5	0.72	9	0.72	8-9	0.767	8
Alternative business models and events	0.74	9	0.76	8	0.76	6-7	0.753	9
Mortgage lending and loan services	0.92	3	0.84	7	0.8	5	0.853	5-6
Data, valuation, and analytics	0.9	4	0.96	2	0.92	2-3	0.927	2
Energy management and efficiency	0.78	8	0.88	5-6	0.72	8-9	0.793	7
Facility management	0.84	6	0.88	5-6	0.92	2-3	0.880	3

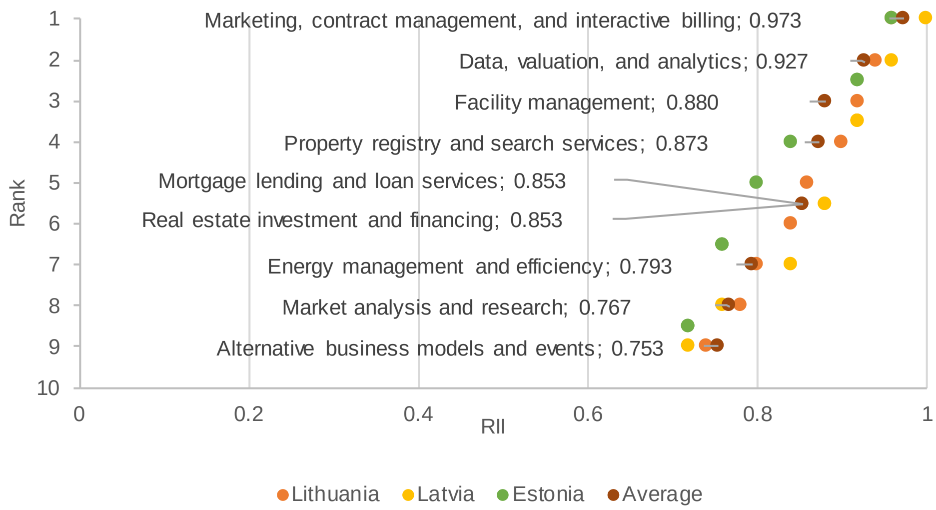

Figure 1. Relative importance (*RII*) and ranking of PropTech application goals in real estate companies across the Baltic States.

Accurate property valuation remains methodologically demanding, as the choice of index construction method significantly affects outcomes (Hill & Trojanek, 2022), reinforcing the need for PropTech tools that ensure analytical rigour. Facility management (*RII* = 0.880), which secures the third-highest rank. This indicates a strong regional commitment to leveraging IoT and smart technologies for reducing operational costs. Conversely, the categories perceived as the least applicable are alternative business models and events (*RII* = 0.753) and market analysis and research (*RII* = 0.767), suggesting that these are viewed as the least pressing areas for current technological investment.

Significant and instructive variations emerge when the data is analysed at country level. Latvia exhibits the highest consensus on the utility of PropTech in marketing, contract management and interactive billing (*RII* = 1), indicating a universal agreement among its executives to prioritise client-facing digitisation. In contrast, while Lithuania also prioritises marketing, real estate investment and financing receives its lowest score (*RII* = 0.800, rank 7) of all three countries, despite receiving high scores in both Latvia (*RII* = 0.920) and Estonia (*RII* = 0.840). Furthermore, property registry and search services reveal a paradox in Estonia, receiving a low *RII* of 0.760 (rank 6-7), which is notably below the score given by Lithuania (*RII* = 0.940). This likely reflects Estonia's mature e-government market, where the essential property registry function is already highly digitised by the state, limiting the perceived need for further private PropTech innovation in this area.

The top three applicability ratings for marketing, contract management and interactive billing (*RII* = 0.973) provide preliminary insights into the human elements of the equation. PropTech solutions are rated as being most applicable to supporting, rather than replacing, professional activity. More specifically, in client-facing roles that require strong relationships and effective communication, technology is most likely to be seen as a tool that can enhance human capabilities. At the other end of the scale, market analysis and research functions were rated the lowest (*RII* = 0.767), which may indicate an element of cognitive dissonance: while dispassionate data analytics certainly have an objective efficiency case, professionals may also intuitively see them as closely related to their expertise. As such, they may view technology as a more psychologically contentious prospect for mediation. As for country-level differences, Estonia's low score for property registry and related services (*RII* = 0.76) seems to indicate more of a psychological and economic threshold than a technological one. This is a function and market segment that has already experienced mainstream adoption of digitisation through Estonia's advanced e-government framework.

Challenges of PropTech Technology

It is crucial to identify the obstacles to technological integration in order to inform future investment in the region. To this end, survey respondents in the Baltic States were asked to evaluate the relative importance (*RII*) of various difficulties encountered when attempting to implement PropTech solutions in the real estate industry (see Table 2).

Based on the average *RII* across all three Baltic countries, as visualised in Figure 2, it is clear that the implementation of PropTech is overwhelmingly constrained by financial and regulatory hurdles. Insufficient investment capital is undoubtedly the most significant challenge (*RII* = 1.000), reflecting the general view that the environment of high interest rates is the primary financial barrier preventing firms from adopting solutions. This is closely followed by uncertainty regarding legal and regulatory obligations (*RII* = 0.960), which highlights the urgent need to manage the costs of complying with new EU mandates (e.g., ESG reporting). Third place goes to limited internal PropTech knowledge (*RII* = 0.927), highlighting the urgent need to address the human capital and skills gap within real estate firms. Conversely, the categories perceived as posing the least overall constraint are system interoperability challenges (*RII* = 0.673) and data and information security concerns (*RII* = 0.627), suggesting that while these are technical hurdles, they are currently overshadowed by financial and regulatory pressures.

Table 2. *RII* of PropTech implementation challenges in real estate companies across the Baltic States.

Challenges and difficulties using PropTech	Lithuania		Latvia		Estonia		Average *RII*	Rank
	RII	Rank	*RII*	Rank	*RII*	Rank		
Lack of initiative/proactivity	0.86	7	0.72	9	0.76	8	0.780	8
Insufficient investment capital	1	1	1	1	1	1	1.000	1
Administrative costs	0.74	9	0.76	8	0.72	9	0.740	9
Training and upskilling costs	0.78	8	0.8	7	0.88	4-5	0.820	7
Limited internal PropTech knowledge	0.94	3	0.92	3	0.92	3	0.927	3
Shortage of PropTech-skilled staff	0.92	4	0.88	4-5	0.88	4-5	0.893	4
System interoperability challenges	0.7	10	0.68	10	0.64	10	0.673	10
Data and information security concerns	0.68	11	0.6	11	0.6	11	0.627	11
Uncertainty regarding legal/regulatory obligations	0.96	2	0.96	2	0.96	2	0.960	2
Lack of external collaboration/partnerships	0.88	6	0.88	4-5	0.8	7	0.853	6
Absence of required hardware/infrastructure	0.9	5	0.84	6	0.84	6	0.860	5

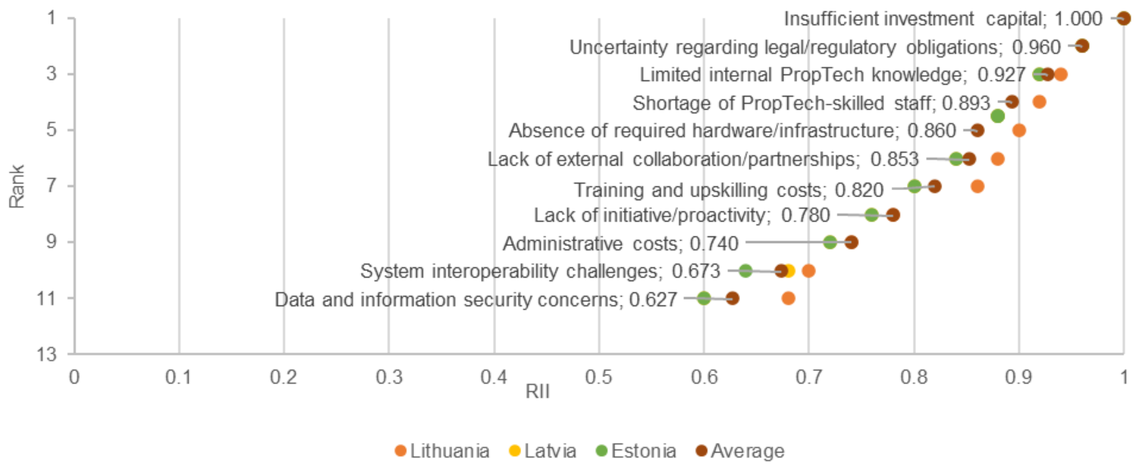

Figure 2. Relative importance (*RII*) and ranking of PropTech application goals in real estate companies across the Baltic States.

The cross-country comparison reveals that, while the top three constraints are universally shared, significant variations emerge in technical and human-factor priorities. Executives from all three countries unanimously agree that insufficient investment capital (*RII* = 1.000) and uncertainty regarding legal and regulatory obligations (*RII* = 0.960) occupy the top two ranks, highlighting the significant pressure exerted by the current economic and regulatory environment. However, training and upskilling costs are perceived as significantly more difficult in Estonia than in Lithuania and Latvia. Estonia ranks this challenge highly at *RII* = 0.88 (rank 4-5), prioritising it significantly more than Lithuania (*RII* = 0.78, rank 8) and Latvia (*RII* = 0.80, rank 7). Conversely, data and information security concerns and system interoperability challenges are unanimously deemed the least important barriers, occupying the bottom two ranks (rank 10 and 11) across all nations. Lack of initiative/proactivity is considered a minor obstacle in Lithuania (*RII* = 0.86, rank 7), but is ranked lower in both Latvia (*RII* = 0.72, rank 9) and Estonia (*RII* = 0.76, rank 8). These findings suggest that, while technical issues are not considered the main obstacle, the low ranking of lack of initiative may indicate an underlying behavioural or cultural issue within organisations. This could imply psychological resistance to change or a need for stronger management support for innovation. Furthermore, limited PropTech knowledge among staff creates a significant cognitive gap, which can lead to professional uncertainty and increased human error in complex system interactions. Therefore, overcoming these soft challenges associated with human capital, organisational motivation and training confidence is crucial for the successful implementation of PropTech.

The most interesting insights come from the barrier analysis. In all countries, human issues are the main obstacle to PropTech adoption. Although a lack of capital ranks top (*RII* = 1.000), the next three barriers are all human-related issues concerning cognition, skills, and organisational learning: regulatory uncertainty (*RII* = 0.960), limited internal knowledge (*RII* = 0.927), and staff skill shortages (*RII* = 0.893). These human barriers significantly outrank technical barriers such as system interoperability (*RII* = 0.673) and data security (*RII* = 0.627).

This implies that PropTech adoption is constrained by professional readiness rather than technology readiness. The gap between new digital tools and existing professional knowledge can result in information overload for staff using unfamiliar technologies, leading to errors, frustration, and the eventual rejection of new technologies. Training costs are ranked higher in Estonia (*RII* = 0.88) than in Lithuania (*RII* = 0.78), which could reflect a more realistic understanding of the costs and labour involved in upgrading staff skills. Paradoxically, the more digitally mature the market, the more aware it is of the significant training costs required to keep up with fast-developing, high-tech solutions.

The low overall ranking for a lack of initiative in all countries (with rankings ranging from 7 to 9) challenges the idea of professional resistance to change. Rather than negative attitudes being a barrier, the data suggests that the more pressing constraints to PropTech adoption are structural and relate to capital, knowledge or skills. With the right support, professionals are willing to adopt PropTech, which is consistent with the HTO model's focus on organisational enablers.

Prospects for the Adoption of the PropTech Technology

Despite existing challenges and difficulties associated with implementing PropTech innovations in Baltic real estate companies, industry experts generally accept the viability and applicability of this technology within Lithuania's real estate sector. This strong professional consensus indicates a positive long-term outlook for digital transformation in the region.

The adoption of PropTech in future real estate operations is expected to prioritise intelligence, automation and efficiency, and follow several key developmental paths. These paths focus on improving the sector's analytical and operational capabilities.

Intensifying the focus on intelligence and valuation will involve implementing sophisticated data control and analytics to optimise operations and property valuations. Furthermore, advances in augmented reality (AR) will play a pivotal role in enhancing the visualisation and design of properties, bridging the gap between digital models and physical structures. Another key growth area is operational automation, where smart buildings and the deeper integration of building robotics and mechanisation are set to increase significantly. Technologies focusing on automated construction, repair, and building management – such as predictive maintenance systems – are expected to reduce the need for manual labour significantly, bringing about substantial efficiencies and positive changes.

CONCLUSIONS

The field study yielded several critical insights into the readiness and challenges of the Baltic real estate sector regarding PropTech adoption:

- According to executives from the real estate industry, PropTech has the greatest immediate applicability in three high-value functional areas that define the sector's priorities for transactional efficiency and intelligence. Marketing, contract management and interactive billing are the top priority, highly valued for their direct business impact, which is achieved by automating customer-facing processes, accelerating sales cycles and significantly improving cash flow. The second key area is data and valuation analytics. This is crucial for reducing financial risk, generating predictive market insights, and ensuring accurate property valuations, all of which are essential for lending and investment decisions. Finally, facilities management translates directly into tangible benefits by reducing operational expenditure, maximising asset lifespan and supporting sustainability goals through energy optimisation and predictive maintenance.
- The most significant obstacle identified by all real estate professionals is the lack of investment funds, which hinders the initial implementation and subsequent improvement of PropTech solutions. This financial obstacle is immediately followed by three structural barriers that complete the executive risk matrix: uncertainty regarding legal and regulatory obligations (driven by EU ESG mandates); limited internal PropTech knowledge; and a shortage of PropTech-skilled staff.

Successfully activating and scaling PropTech technology across the region requires a concerted focus on several strategic areas. These include increased education and training, leveraging knowledge and experience from abroad through partnerships and study tours, initiating in-service training programs, hosting conferences, launching focused pilot projects, facilitating networking, and fostering collaboration among various project participants.

The speed at which PropTech is implemented in the real estate sector of the Baltic States depends on several critical factors, as revealed by the field study. These factors are unique to the current market context:

- Sustained capital commitment and strategic allocation of resources towards innovation, particularly in real estate start-ups;

- Visionary leadership coupled with deep technical expertise within the implementation team;
- Customer-centric agility for rapid adaptation to market volatility and evolving customer demands.
- Robust project governance and quality assurance mechanisms for innovative solutions.
- Organisational commitment to ensuring extensive application across many work spheres.

Overall, the findings confirm a very high underlying demand and significant potential for the expansion of PropTech technology within the Baltic region, despite the noted challenges.

IMPLICATIONS

The findings of this study provide a valuable blueprint for the future theoretical development, practical application and policy formulation relating to the adoption of PropTech. Specifically, the insights derived from the Baltic market's unique experience – characterized by high digital readiness and acute capital constraints – provide a directly applicable model for other emerging PropTech markets navigating the initial stages of technological implementation.

Future research should focus on developing longitudinal models that can accurately track PropTech maturity in the Baltics while addressing the difficulty of predicting successful scaling scenarios. While the *RII* method effectively ranks quantitative perceptions, future research could greatly benefit from the addition of qualitative methods, such as in-depth interviews, to explore the reasons behind these executive rankings and capture the human, social and psychological factors that influence adoption (Gimbel & Newsome, 2015). Nevertheless, the *RII* technique was suitable for this analysis, as its robust capacity for prioritising and achieving consensus on key factors provided the necessary quantitative basis for evidence-based policymaking and subsequent, more in-depth qualitative research. Scholars must also investigate the measurable impact of AI applications on real estate valuation and efficiency, linking professional acceptance with quantifiable productivity gains, given the high internal demand. The Baltic region's specific challenges, particularly regarding funding and skills shortages, necessitate comparative studies with more established PropTech markets. These comparisons are vital for providing a robust blueprint that will help other emerging economies to identify the most effective strategies for overcoming limited access to capital and specialised personnel during the initial stages of adoption.

Practitioners should use the identified strategic areas as a direct roadmap for acceleration. In order to bridge the skills gap, education, training and knowledge transfer from abroad must be prioritised. Scaling PropTech requires prioritising critical factors, such as allocating resources to real estate start-ups and ensuring that the team and leadership possess first-rate technical skills. This approach yields direct human benefits:

- Professionals benefit from reduced administrative tasks, enabling them to focus on strategic activities and personalised client relationships, thereby boosting job satisfaction and overall productivity.
- Automating repetitive tasks enables skilled staff to engage in high-value problem solving, leading to greater professional fulfilment and higher employee retention rates.

- Access to immediate, accurate data and predictive analytics empowers managers and sales agents to make more informed decisions, reducing errors and improving transactional reliability.
- High-applicability areas increase market transparency, lower investment barriers and provide clients and users with more flexible, cost-effective services.

This practical roadmap is valuable not only for the Baltic States but serves as a directly applicable blueprint for any other developing real estate market that is actively transitioning toward a data-driven, client-centric service model.

Policymakers in the Baltic States should prioritise designing targeted incentives to address the critical lack of investment funds. This can be achieved by establishing specific funding mechanisms or grants for start-ups innovating in the real estate sector. At the same time, the authorities must support the development of specialised educational programmes and certification schemes in PropTech to address recognised knowledge and skills gaps. Collaborating with industry associations is also essential for facilitating the transfer of expert knowledge. Addressing these deficits in investment and skills through targeted policy interventions will create a highly efficient market, yielding significant societal benefits such as more accessible housing, transparent transaction processes, and a higher-quality built environment for all citizens.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 21(3), December 2025, 620–639

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON TASK PERFORMANCE AND DECISION-MAKING: EMPIRICAL EVIDENCE ON GENERATION Z

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Abstract: *This study examines how generative artificial intelligence (AI) reshapes task performance, decision-making, and evaluative judgement in higher education assessments, with a focus on emerging human-AI assemblages among Generation Z university students. A controlled three-stage scenario-based experiment was conducted with the same cohort of students of business and economics, comparing a baseline session (no AI), independent reasoning (no AI), and identical AI-assisted conditions. Participants completed tasks involving situational judgment, quantitative reasoning, and short written responses. Results reveal that AI access increased average performance but markedly compressed score variance and reduced internal reliability, undermining the assessment's diagnostic capacity to differentiate independent abilities. Qualitative findings indicate that students perceived non-AI conditions as more cognitively effortful and educationally valuable, with AI shifting agency toward tool management and oversight. Together, these results highlight how AI redistributes agency in assessment, raising questions about responsibility and validity in sociotechnical contexts. Based on these insights, the study recommends hybrid assessment designs that separately evaluate independent reasoning and AI-augmented performance, incorporating reflective components to render distributed agency visible and preserve evaluative judgement.*

Keywords: *Artificial Intelligence; AI; Higher Education; Task Performance; Decision-Making; Experimental Study.*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.7

INTRODUCTION

Generative artificial intelligence (AI) is becoming an integral part of modern problem solving processes in academic and professional contexts (Kliestik et al., 2024; Andronie et al., 2024; Balcerzak & Valaskova, 2024; Lazaroiu & Rogalska, 2024; Moravec et al., 2024; Durica et al., 2023). In higher education, it challenges traditional assessment models that emphasise memorisation, recall, and individual performance (Barlybayev et al., 2025; Melisa et al., 2025; Ibieta et al., 2024; Kozova et al., 2024). Generative AI tools form human-AI assemblages in which cognitive agency is distributed between student and technology raising fundamental questions about responsibility, authorship, and what constitutes achievement in assessment (O'Dea, 2024; Southworth et al., 2023; Rensfeldt & Rahm, 2023; Durica et al., 2023; Zafari et al., 2022; Huang, 2021).

A growing body of research examines AI's transformative potential in education, highlighting benefits such as enhanced efficiency and personalisation alongside risks including overreliance, reduced critical engagement, and homogenisation of outputs (Gavira Durón & Jiménez-Preciado, 2025; Mishchuk et al., 2025; Wang et al., 2024; Chiu, 2024; Adiguzel et al., 2023; Wojciechowski et al., 2023; Chen et al., 2020). Particular attention has been paid to evaluative judgement – the learner's capacity to appraise the quality of work (Bearman et al., 2024) – which must now adapt to AI-rich environments where students evaluate AI outputs, reflect on AI-use processes, and risk undermining independent appraisal through uncritical dependence. Despite these conceptual advances, empirical evidence remains limited on AI's direct effects on assessment validity.

This study addresses this gap by quantifying a core tension: AI augments performance but simultaneously degrades the diagnostic power of assessments, shifting the focus of agency from individual cognition to sociotechnical assemblages. More specifically, we attempt to address these challenges and investigate how AI-assisted tools influence task performance and decision-making of a sample of educted generation Z representatives, namly speaking university students in economics-related problem-solving. We examine whether AI access improves their time efficiency and accuracy and how it affects cognitive engagement. The guiding intent is not to assess specific knowledge, but in particular to observe how participants reason, decide, and adapt to changing cognitive conditions.

A controlled three-stage experimental design was employed: a baseline diagnostic session (no AI), an independent reasoning session (no AI) and an identical AI-assisted session. This parallel comparison isolates the impact on task outcomes, decision-making quality, and perceptions of effort and learning.

The study is guided by the following research questions:

RQ1: *To what extent does access to generative AI affect task performance (accuracy and efficiency) in scenario-based economics assessments?*

The RQ1 draws on cognitive offloading and distributed cognition theories (Kirsh, 2013; Salomon et al., 1991). Research shows that external cognitive tools can reallocate mental resources, boosting efficiency but not necessarily deep understanding (Barr et al., 2015). In education, technology-enhanced problem-solving often improves surface performance while obscuring true competence (Baker & Siemens, 2014). Scenario-based assessments, grounded in situated cognition, highlight that performance depends on contextual supports rather than isolated skills (Mislevy et al., 2003).

RQ2: *How does AI access influence the psychometric properties (variance and internal reliability) of the assessment?*

This question draws on classical test theory and construct representation theory, which posit that score variance reflects differences in the latent construct rather than shared access to external resources (Embretson, 1983; Cronbach, 1951). Reliability and variance thus indicate an assessment's discriminatory power. Empirical studies on calculator use, open-book testing, and computer-assisted assessments show that external aids can compress score distributions, reduce item discrimination, and alter internal consistency by introducing construct-irrelevant or suppressing construct-relevant variance (Wainer & Thissen, 1993). These findings question whether AI access fundamentally changes score meaning.

RQ3: *What are students' perceptions of cognitive effort, learning value, and agency in AI-assisted versus independent conditions?*

This research question draws on Cognitive Load Theory (CLT), which distinguishes intrinsic, extraneous, and germane load and predicts that instructional supports may either aid learning or replace learning-relevant processes (Paas & van Merrienboer, 2020). Perceptions of learning value and agency are informed by self-regulated learning and self-determination theories, emphasizing autonomy and ownership (Deci & Ryan, 2000). Studies on automation bias and human-AI interaction suggest that reliance on intelligent systems can diminish perceived agency and critical engagement, especially when AI outputs are treated as authoritative (Dzindolet et al., 2003).

RQ4: *What implications arise for designing hybrid human–AI assessments that preserve evaluative judgement and diagnostic validity?*

This question draws on assessment validity theory, particularly Messick's unified framework, which views validity as an argument about score interpretation, use, and consequences (Messick, 1995), and argument-based approaches emphasizing evidentiary reasoning (Kane, 2013). Evidence-Centered Design (ECD) underscores modeling how tasks, tools, and scoring generate interpretable evidence of competence (Mislevy et al., 2003). Emerging AI-era scholarship advocates shifting focus from unaided performance to evaluative judgment, justification, and epistemic responsibility in AI-rich contexts (Luckin & Holmes, 2016).

The rest of this paper is structured as follows. The next section reviews the relevant literature on AI in education and assessment. This is followed by the research methodology, including the experimental design, data col-lection, and analytical approach. The subsequent sections present the re-sults, discuss their implications in relation to existing research, and con-clude with recommendations for integrating AI into higher education as-sessment.

LITERATURE REVIEW

The question of how best to integrate artificial intelligence into higher education has attracted increasing scholarly attention in recent years. Scholars have explored its applications in learning environments, the po-tential to personalise education, and the associated risks of over-reliance on technology (Gavira Durón & Jiménez-Preciado, 2025; Chiu, 2024; Adiguzel et al., 2023; Chen et al., 2020; Temerbulatova et al., 2025). AI is recognised not only as a technological innovation but also as a driver of pedagogical change, challenging traditional models based on memorisation and recall (Barlybayev et al., 2025; Melisa et al., 2025; Ibieta et al., 2024; Lazaroiu et al., 2024; Sarker, 2022). From a distributed cognition perspective, such technologies function as external cognitive resources that reshape how thinking and problem-solving are enacted, rather than simply supporting existing cognitive processes (Salomon et al., 1991; Kirsh, 2013).

Technological and social shifts pose new challenges for higher education, requiring students to master decision-making and problem-solving, as disciplinary knowledge alone is no longer sufficient (van Berkum et al., 2023). Traditional assessments often measure knowledge recall, yet research suggests that scenario-based and project-based approaches can better evaluate applied reasoning and strategic thinking (Gratchev, 2023; Ghosh et al., 2020; Koh, 2017; Clark, 2009; Haynes et al., 2009; Iverson & Colky, 2004). However, research on technology-enhanced problem solving cautions that improvements in observable performance may reflect surface-level efficiency gains rather than deeper conceptual understanding, particularly when external tools assume cognitively demanding processes (Barr et al., 2015; Baker & Siemens, 2014).

A growing body of scholarly literature underscores the transformative potential of education, examining its practical applications, emerging opportunities, and associated risks. Wang et al. (2024) conducted a bibliometric analysis of 2,223 research articles, complemented by a content review of 125 selected papers, which revealed a comprehensive conceptual framework within the existing literature. The findings highlight that, while AI tools in higher education offer notable benefits such as enhanced personalisation, efficiency, and feedback mechanisms, they also raise concerns regarding ethical implications, data privacy, algorithmic bias, and an overreliance on automation. Earlier scholarly contributions, including those by Bond et al. (2024), Castillo-Martínez et al. (2024), and Batista et al. (2024), also examine how artificial intelligence is reshaping higher education, with particular attention to its advantages and associated challenges. A key concern is the potential homogenisation of outputs and erosion of human judgement when AI is permitted, with scholars advocating blended approaches that preserve critical engagement while leveraging AI for efficiency (Lee et al., 2025; Frankford et al., 2024; Xia et al., 2024; Rensfeldt & Rahm, 2023).

A growing strand of scholarly inquiry advocates for increased emphasis on cultivating university students' evaluative judgement – that is, their capacity to appraise the quality of their own work and that of others – in response to the evolving educational landscape. Bearman et al. (2024) present a conceptual analysis of how evaluative judgement, a learner's ability to assess the quality of work, must evolve in response to generative AI. The authors identify three key intersections: evaluating AI-generated out-puts, assessing the processes of using AI, and using AI to appraise students' evaluative judgement. The paper highlights that while generative AI can support learning, it also risks undermining critical appraisal if students rely uncritically on its outputs. To address this, the authors propose adapting established assessment strategies – such as self-assessment, peer review, feedback, rubrics, and exemplars – to foster deliberate and contextualised evaluative judgement. These arguments align with assessment validity frameworks that emphasise the interpretation, use, and consequences of scores, rather than performance alone (Messick, 1995; Kane, 2013).

Although the body of literature is expanding, there remains a paucity of empirical studies that directly compare student performance and per-ceptions under AI-assisted versus non-AI assessment conditions. Han et al. (2025) calls for further empirical research to gain insights in areas such as surveillance during data collection, algorithmic bias, standardisation, and uniform design, and excessive reliance on AI for support.

Elshall & Badir (2025) addresses the pedagogical challenge of integrating AI tools into university-level education while preserving rigorous academic standards. The empirical data were gained under involvement of upper-level undergraduate and graduate students from disciplines of civil and environmental engineering and Earth sciences. The FACT framework comprising four components was applied: (F) Fundamental skills assessed through non-AI coding assignments; (A) Applied projects using AI tools to simulate real-world tasks; (C) Conceptual understanding evaluated via traditional paper-based exams; and (T) Critical thinking measured through complex, multi-step case studies involving AI. Research findings indicates that both AI tools and guided AI support enhanced performance and ena-bled learners to engage with complex tasks and authentic applications more effectively than AI tools used in isolation. Survey data revealed that while many students regarded AI tools as advantageous for problem-solving, some voiced apprehensions about potential over-reliance. By incorporating both AI-supported and traditional assessment formats, the FACT framework fosters AI-assisted learning whilst upholding rigorous academic standards, thereby equipping students for professional practice in an increasingly AI-driven landscape. Furthermore, using a student-centred approach, Han et al. (2025) employed the Story Completion Method to explore perceptions of AI-driven educational tools. Qualitative analysis of 71 university students revealed that AI may influence learner autonomy, pedagogical roles, and educational relationships, with impacts often interlinked. The study introduces a novel speculative design ap-proach and offers design recommendations to support ethically responsive AI development. Lee et al. (2025) conducted a large-scale study involving 319 knowledge workers to examine how generative AI influences critical thinking in professional contexts. Drawing on 936 real-world task exam-ples, the authors found that higher confidence in AI correlates with re-duced critical engagement, while greater self-confidence promotes more critical thinking, albeit with increased perceived effort. The study revealed that AI shifts cognitive effort from execution to oversight, particularly in tasks involving analysis, synthesis, and evaluation. The survey design in-corporated quantitative regression models and qualitative coding to ex-plore motivators and inhibitors of critical thinking, highlighting the need for AI tools to support user awareness, motivation, and the ability in fos-tering reflective practices.

Despite progress, empirical research quantifying AI's impact on psychometric properties – such as variance and internal reliability – in assessment remains scarce. This study fills this gap with controlled evidence of AI's dual effects: augmenting performance while degrading diagnostic validity and redistributing agency in human-AI assemblages.

METHODS

This study employed a controlled, sequential experimental design within an International Economics course at Brno University of Technology (Spring 2025), involving the same cohort of students across three thematically aligned assessment sessions. Each of the three sessions introduced a distinct context developed on the basis of a text book *International Economics* (Krugman et al., 2015).

Session 1 (diagnostic baseline, no AI) used situational judgement tests (SJTs) requiring selection of best/worst responses in economic scenarios, establishing independent judgement reference (Bardach et al., 2021; Whetzel & McDaniel, 2009). In session 2, expanded assessment was conducted that included SJT tasks, evaluative reasoning, numerical problem-solving, fill-in-the-blank and a short essay. Again, the use of AI or other digital tools was not per-mitted. This session foregrounded independent cognitive effort, sustained attention, and unaided problem-solving. Session 3 was identical to Session 2 in structure, order of questions, and scoring. However, an AI-assisted framework was introduced, where students were permitted to use tools such as GPT models, AI-driven cal-culators, or language models to support their responses. While time con-straints remained, students were encouraged to critically think about when and how to rely on AI, reflecting the kind of decision-making in-creasingly expected in digital policy and consulting environments. For details, see Table 1.

Data was collected across the three sessions, including (a) quantitative performance metrics, (b) post-session qualitative reflections, and (c) comparative survey responses that evaluated students' perceptions of AI and non-AI versions. Scenario-based methodology was applied (Ghosh & Francia, 2021; Clark, 2009; Haynes et al., 2009; Iverson & Colky, 2004). Each session was time-limited (40 minutes for Session 1, 20 minutes for Sessions 2 and 3). Assessments were administered via the Moodle e-learning platform (Athaya et al., 2021), which also facilitated data collec-tion.

Participants were 31 students in Session 1, decreasing slightly to 28 in Session 3 (attrition typical for longitudinal designs). Participation was voluntary; data were anonymised and handled in compliance with GDPR and ethical protocols.

The parallel design of Sessions 2 and 3 (differing only in AI permission) enabled rigorous isolation of AI's effects on performance, reliability, and agency.

After each session, the students completed a post-assessment ques-tionnaire designed to capture (a) perceived clarity of instructions, (b) cognitive difficulty and time pressure, and (c) overall satisfaction with the quiz format. Furthermore, following Session 3, students completed an additional comparative reflection survey where they evaluated their experiences across both non-AI (Session 2) and AI-assisted (Session 3) conditions. These included: categorical responses (e.g., "Which version was more challenging?"), Likert-scale items (e.g., satisfaction, perceived fairness, learning value) and open-ended questions (e.g., "What advice would you give a future student using AI?").

Quantitative analysis included descriptive statistics and Cronbach's α for internal reliability; qualitative data underwent inductive thematic analysis (themes: cognitive load, learning value, AI strategies, agency).

Researchers used generative AI ethically for data organisation, summarisation, and writing support only - mirroring student AI access but not influencing participant responses.

Table 1. Structure of the Assessment Sessions [Source: own processing]

Session	Objective	Format	Conditions	Duration	No of Questions	Scoring
Session 1: Diagnostic assessment	Establish a baseline for students' judgment, decision-making, and economic knowledge	Situational judgment test (SJT), using a dual-response structure (choose the “Best” and “Worst” option)	No AI tools or digital assistance permitted	40 minutes	20	Each question scored up to 1 point (0.5 for each correct BEST/WORST pair), maximum 20 points
Session 2: Independent reasoning (No-AI support)	Assess performance under increased complexity and diverse question types, without external assistance	Included SJT-style items, “Best + Neither Best Nor Worst” formats, numerical calculations, fill-in-the-blank, and a short written essay	No AI, calculators, or digital tools permitted	20 minutes	15	Mixed scoring (0.5–1 point per item), maximum 15 points
Session 3: AI-Assisted assessment	Evaluate how students interact with complex economic problems when supported by AI tools, reflecting digitally augmented decision-making contexts	Identical in structure to Session 2—same task types, sequence, and scoring—allowing direct comparison	AI tools were permitted (e.g., GPT models, online calculators), but students were advised to manage time and think critically	20 minutes	15	Same as Session 2, maximum 15 points

RESULTS

Session 1: Diagnostic Assessment

Session 1 served as a diagnostic baseline to establish students’ independent applied economic reasoning and decision-making performance under closed-book conditions, without AI or digital support. The assessment used a Situational Judgment Test (SJT) dual-response format (BEST and WORST option), intended to elicit evaluative judgement and prioritisation in realistic economic scenarios.

The diagnostic quiz was a closed-book, independent assessment with no AI or digital tools, consisting of 20 items completed within 40 minutes to simulate high-pressure conditions.

A total of 31 students participated in the Session 1 diagnostic assess-ment. For descriptive statistics, see Table 2.

Table 2. Diagnostic Assessment – Descriptive Statistics [Source: own processing]

Metric	Average score	Median score	Standard deviation	Skewness	Kurtosis	Internal consistency (α)	Standard error
Value	72.42%	72.50%	10.83%	-0.7866	1.1617	68.80%	6.05%

In terms of performance overview, 31 students participated in Session 1, achieving a mean score of 72.42% (median = 72.50%, SD = 10.83%). Scores clustered in the upper-middle range, with mild negative skewness (−0.79) and moderate kurtosis (1.16), indicating that most students performed well with relatively few low-scoring outliers. The majority of participants scored between 14 and 19 out of 20, suggesting strong engagement with the assessment logic and accessibility of the task despite the unfamiliar dual-response format.

Regarding the psychometric quality of the baseline instrument, internal consistency was α = 0.688, reflecting moderate reliability appropriate for a formative diagnostic assessment. This level of reliability supports the interpretability of students' independent judgement in the situational judgement test (SJT) format and provides a stable baseline for interpreting performance and measurement changes in later AI-assisted sessions.

With respect to student experience and baseline perceptions, post-assessment feedback was largely positive. Instructional clarity was rated as "very clear" by 77% of students, and most reported low time pressure, indicating that the 40-minute allocation was sufficient. More than 70% of students expressed satisfaction with the assessment. Qualitative comments described the task as realistic, cognitively engaging, and distinct from traditional quizzes, with students highlighting the value of the dual-response format in encouraging judgement from multiple perspectives.

In terms of alignment with the research questions, Session 1 establishes essential baseline evidence for RQ2 by documenting psychometric properties under no-AI conditions and contributes to RQ3 by demonstrating active evaluative judgement and learner agency in the absence of AI. While it does not directly address RQ1, it provides the necessary reference point for interpreting AI-related performance effects. Indirectly, the findings also inform RQ4 by supporting the use of scenario-based judgement tasks as a human-only component within hybrid assessment designs.

Session 2: Independent Reasoning (Non-AI Condition)

Session 2 extended the diagnostic baseline by increasing task diversity, cognitive demands, and time pressure under strictly non-AI conditions, thereby functioning as the human-only reference point for later AI comparisons. The assessment comprised 15 items across five task formats (Table 3), including scenario-based judgement, numerical reasoning, verbal logic, and a short written response, completed within a 20-minute time limit without access to AI tools, calculators, or digital resources. A total of 29 students completed the session.

Table 3. Assessment Format and Structure [Source: own processing]

Task type	Description	Quantity
Situational judgment (SJT)	Dual response: Best and worst option from four	5
Evaluative reasoning	Choose "Best" and "Neither Best nor Worst"	5
Quantitative Reasoning (ABCD)	Choose a correct numerical answer	2
Fill-in-the-Blank (Verbal Logic)	One question with three missing words	1
Short Essay	Write a response explaining a core economic concept	1
Conditions: No access to AI, calculators, search engines, or external support.		
Duration: 20 min.		
Scoring: Max score = 15 points		

Table 4. Session 2 – Descriptive Statistics [Source: own processing]

Metric	Average score	Median score	Standard deviation	Skewness	Kurtosis	Internal consistency (α)	Standard error
Value	56.44%	60.00%	22.64%	-0.1717	-0.7205	86.59%	8.29%

In terms of performance overview, the mean score was 56.44% (median = 60.00%), representing a substantial decline relative to Session 1 (72.42%). Score dispersion increased markedly (SD = 22.64%), indicating wide variation in students' ability to manage the mixed-format, time-constrained assessment. Most students scored between 7 and 12 out of 15, fewer reached the upper performance range (13–15), and no participant achieved a perfect score, suggesting that the assessment was calibrated to stretch cognitive limits rather than reward surface familiarity. This pattern indicates that while students were able to engage with individual task types, maintaining accuracy and pace across heterogeneous demands proved challenging.

Regarding the psychometric quality of the baseline instrument, internal consistency was high (Cronbach's $\alpha = 0.866$), despite the diversity of task formats. The combination of strong reliability and increased score variance suggests that the assessment coherently measured a single underlying construct - applied economic reasoning - while providing greater discriminatory power than Session 1. From a classical test theory perspective, the broader score distribution reflects meaningful differences in the latent construct rather than random error, establishing Session 2 as a psychometrically robust human-only benchmark.

With respect to student experience and baseline perceptions, post-session reflections indicated that Session 2 was perceived as substantially more demanding than the earlier diagnostic session. Students reported heightened time pressure, sustained concentration requirements, and difficulty switching rapidly between judgement-based, numerical, and verbal reasoning modes. Many described engaging in strategic triage, prioritising certain questions while responding heuristically to others. The short written response emerged as a key source of differentiation, with some students producing concise, well-structured arguments under pressure, while others struggled to articulate reasoning or left responses incomplete.

Numerical items also posed challenges, primarily due to calculation fluency and confidence under time constraints rather than conceptual misunderstanding. Despite these difficulties, many students characterised the experience as realistic and educationally valuable, noting increased awareness of their own reasoning strategies, time management, and cognitive limits – evidence of strong learner agency under independent conditions.

In terms of alignment with the research questions, the results demonstrate that, under non-AI conditions, the assessment exhibits both high internal reliability and substantial variance, supporting its diagnostic validity (RQ2). It also contributes to RQ3 by documenting high perceived cognitive effort, strategic self-regulation, and ownership of decision-making in the absence of external cognitive support, consistent with predictions from Cognitive Load Theory and self-regulated learning frameworks. While Session 2 does not address RQ1 directly, it establishes the essential control condition against which changes in performance, efficiency, and strategic behaviour observed under AI access can be meaningfully interpreted. Indirectly, the coherence between task demands, performance patterns, and student perceptions also informs RQ4 by illustrating how scenario-based, judgement-oriented assessments can preserve evaluative reasoning and diagnostic value in human-only conditions, providing a principled foundation for hybrid human–AI assessment design.

Session 3: AI-Assisted Assessment

Session 3 introduced AI access into the assessment environment while maintaining identical task structure, sequencing, scoring, and time constraints as in Session 2. Students were permitted to use AI-based tools, including GPT models, calculators, and other digital assistants, to support their responses. The purpose of this session was to observe how access to AI alters performance outcomes, score distributions, and student perceptions when solving the same scenario-based economics tasks under digitally augmented conditions. This session provides direct empirical evidence for RQ1, RQ2, and RQ3. The assessment format and conditions are summarised in Table 5. A total of 28 students participated. Self-reports indicate that most students used AI selectively – most frequently for the short essay, conceptual clarification, and numerical verification – while patterns of use varied from confirmatory checking to partial or full substitution of reasoning.

Table 5. Assessment Format and Conditions [Source: own processing]

Task type	Identical to Session 2 (SJT, Best+Neither, numerical, fill-in-the-blank, essay)	
Number of Questions	15	
Maximum Score	15	
Duration	20 minutes	
AI Policy	Students were allowed to use AI to support their responses, but were reminded to think critically and manage time effectively	
Key Control Factors	**Session 2**	**Session 3**
Task types	✔	✔
Question order	✔	✔
Scoring method	✔	✔
AI permitted	✗	✔

Table 6 shows descriptive statistics.

Table 6. Session 3 – Descriptive Statistics [Source: own processing]

Metric	Average score	Median score	Standard deviation	Skewness	Kurtosis	Internal consistency (α)	Standard error
Value	86.90%	86.67%	7.14%	-0.2945	-0.7329	31.02%	5.93%

In terms of performance overview, descriptive statistics (Table 6) show a substantial increase in performance relative to the non-AI condition. The mean score rose to 86.90% (median = 86.67%), representing a gain of more than 30 percentage points compared to Session 2. At the same time, score dispersion decreased markedly (SD = 7.14%), indicating strong convergence toward the upper performance range. The distribution exhibited slight negative skewness and reduced kurtosis, reflecting a flattened, top-heavy score pattern under AI-assisted conditions. Although task completion time was not directly measured, efficiency gains can be inferred from the combination of higher accuracy under identical time constraints and student reports of faster response formulation and verification.

Regarding the psychometric quality of the baseline instrument, Session 3 showed pronounced changes relative to the human-only control condition. Internal consistency declined sharply, with Cronbach's α dropping to 0.31 compared to 0.87 in Session 2, alongside a substantial compression of score variance. These shifts indicate a loss of discriminatory power under AI access, suggesting that observed scores no longer consistently reflected differences in applied economic reasoning. Instead, performance appears to have been influenced by heterogeneous AI-use strategies, including tool management, verification behaviour, and output editing, introducing construct-irrelevant variance into the measurement process.

With respect to student experience and baseline perceptions, post-session reflections indicated significantly lower perceived cognitive effort in Session 3 than in the non-AI condition. When asked which version was more challenging, 20 of 25 respondents identified Session 2 as more difficult, indicating that AI access reduced perceived difficulty despite higher scores. Qualitative comments revealed a shift in perceived agency: while many students appreciated the increased confidence and support provided by AI, several described reduced engagement in independent reasoning and greater focus on supervising or managing the tool, particularly for the essay and numerical items. At the same time, students reported selective trust in AI outputs, expressing reluctance to rely on AI for judgement-based SJT items involving ethical or evaluative considerations.

In terms of alignment with the research questions, Session 3 provides direct evidence for RQ1 by demonstrating that AI access substantially increases observable task performance and perceived efficiency under identical assessment conditions. It addresses RQ2 by showing that AI access compresses score distributions and sharply reduces internal reliability, thereby diminishing diagnostic validity. It also informs RQ3 by documenting reduced perceived cognitive effort and a shift in learner agency from independent reasoning toward tool-mediated oversight. Overall, Session 3 illustrates how AI access transforms both the product and process of assessment, improving output while weakening the assessment's capacity to function as a reliable diagnostic measure of independent applied reasoning.

Comparative Reflections – AI vs. Non-AI

Following the completion of both Session 2 (independent reasoning) and Session 3 (AI-assisted problem solving), students participated in a comparative reflection exercise designed to capture perceived differences in cognitive effort, learning value, and agency across the two assessment conditions. This phase provides direct descriptive evidence addressing RQ3, complementing performance-based findings with student-reported experiences that are not directly observable through score data.

The reflection instrument combined multiple-choice comparisons, short semantic descriptors, and open-ended questions. A total of 25 students completed the post-Session 3 survey. Responses to the question "Which version of the quiz was more challenging?" are reported in Table 7

Table 7. Research results when asked "Which version of the quiz was more challenging?" [Source: own processing]

Perceived challenge	Number of students	In per cent
Non-AI version	20	80
AI-assisted version	2	8
Both equally	1	4
Not sure	2	8

The results indicate a strong consensus that the non-AI version (Session 2) was more challenging, with 80% of respondents identifying it as such. Only 8% perceived the AI-assisted version as more challenging. Students frequently attributed the greater difficulty of the non-AI condition to higher mental workload, sustained concentration, time pressure, and the need to generate answers without external scaffolding ("I had to rely entirely on myself"; "The non-AI one felt like problem-solving").

Inductive thematic analysis of the open-ended student reflections revealed five recurring themes relevant to perceived cognitive effort, learning value, and agency (RQ3). Theme 1 (effort versus outcome) captured a commonly reported trade-off between ease of performance and depth of engagement. Students described the AI-assisted condition as more comfortable and confidence-enhancing, yet also as requiring less effort and offering weaker cognitive challenge, with several noting diminished ownership of their answers despite higher scores. Theme 2 (strategic adaptation and AI use) reflected heterogeneous patterns of tool deployment: some students used AI selectively to restructure essays, verify calculations, or explore alternative formulations, while others relied more extensively on AI in response to time pressure, indicating meaningful variation in how AI was integrated into individual reasoning processes. Theme 3 (selective trust in AI outputs) highlighted task-dependent reliance, with students expressing greater willingness to use AI for calculations and factual clarification than for judgement-based or ethically sensitive SJT items, suggesting the use of task-specific heuristics rather than uniform dependence on automation. Theme 4 (perceived learning value) revealed that many students reported learning more during the non-AI assessment despite lower performance, associating independent reasoning with deeper engagement, improved knowledge retrieval, and prioritisation under pressure. Finally, Theme 5 (metacognitive awareness) captured increased self-reflection on cognitive habits, including tendencies to overthink, underthink, or allocate time inefficiently, with several students explicitly contrasting their reasoning strategies across AI-assisted and non-AI conditions. A summary of student perceptions across both assessment conditions is presented in Table 8. Taken together, these themes indicate that AI assistance reduced perceived cognitive effort and altered students' sense of agency, whereas independent conditions promoted deeper engagement and metacognitive reflection, providing qualitative evidence directly addressing RQ3.

Table 8. Student Perceptions Across Sessions [Source: own processing]

Dimension	Non-AI (Session 2)	AI-Assisted (Session 3)
Cognitive effort	High	Low to moderate
Score performance	Lower average, higher range	Higher average, compressed
Authenticity	Strong (realism emphasized)	Mixed
Learning experience	Deep, effortful	Fast, surface-level
Tool use	N/A	Mixed: thoughtful to passive
Emotional impact	Stressful but rewarding	Comfortable but detached
Self-reflection	High	Moderate

DISCUSSION

This study examined how access to generative artificial intelligence reshapes task performance, assessment validity, and students' perceived cognitive effort and agency in scenario-based economics assessments. Using a controlled three-stage design comprising a diagnostic baseline, an independent reasoning condition, and an identical AI-assisted condition, the study provides a robust empirical basis for addressing RQ1-RQ4 and situating the findings within established theoretical frameworks.

With respect to RQ1, the results demonstrate that access to generative AI substantially improves observable task performance. Under identical task structures and time constraints, students achieved markedly higher scores when AI was permitted, indicating increased accuracy and inferred efficiency. These findings align with theories of cognitive offloading and distributed cognition, which posit that external tools reduce execution-related cognitive demands and enable faster problem resolution (Angammana & Jayawardena, 2022; Kirsh, 2013; Salomon et al., 1991). However, consistent with prior research, these performance gains should not be interpreted as evidence of deeper understanding (Barr et al., 2015; Baker & Siemens, 2014). Instead, they indicate that AI alters the cognitive conditions under which performance is produced. In scenario-based assessments grounded in situated cognition, performance is inherently dependent on contextual supports, and AI therefore transforms performance into an outcome of a human-AI assemblage rather than a measure of individual reasoning alone (Mislevy et al., 2003).

Findings related to RQ2 reveal a pronounced contrast between AI-assisted and non-AI conditions in terms of psychometric behavior. Under independent reasoning conditions, including both the diagnostic baseline and Session 2, the assessment exhibited meaningful score variance and strong internal reliability, indicating coherent measurement of applied economic reasoning. When AI access was introduced, however, score distributions compressed sharply and internal consistency declined substantially. From the perspective of classical test theory and construct representation theory, this pattern reflects a loss of discriminatory power and a disruption in construct measurement, such that the assessment no longer differentiated reliably between students with differing levels of independent reasoning ability (Embretson, 1983; Cronbach, 1951). These results are consistent with prior research on open-book and calculator-assisted assessments, which has shown that external aids can suppress construct-relevant variance and introduce construct-irrelevant influences (Wainer & Thissen, 1993). The present findings extend this literature by demonstrating that generative AI can fundamentally alter score meaning, thereby challenging the validity of traditional interpretations of assessment outcomes in AI-rich contexts.

With respect to RQ3, the results indicate substantial differences in students' subjective experience across assessment conditions. Independent, non-AI assessments were consistently perceived as more cognitively demanding and more educationally valuable, despite lower average scores, a pattern that was evident in the diagnostic baseline and intensified under the increased time pressure and task diversity of Session 2. This aligns with Cognitive Load Theory, as AI appears to reduce extraneous and execution-related cognitive load, enabling faster and more accurate responses (Paas & van Merrienboer, 2020). However, student reflections suggest that this reduction may also displace germane cognitive processing, particularly when AI outputs are accepted without critical evaluation. Perceptions of agency further reflect insights from self-determination and self-regulated learning theories: students reported stronger ownership over decisions and outcomes in non-AI conditions, whereas AI-assisted performance often shifted agency toward tool management and oversight (Deci & Ryan, 2000). At the same time, selective skepticism toward AI – especially in judgment-based or ethically sensitive tasks – indicates that students are not uniformly dependent on automation, but instead develop task-specific heuristics for trust, consistent with research on automation bias and human–automation interaction (Dzindolet et al., 2003).

Taken together, these findings provide a clear response to RQ4 concerning assessment design. Allowing AI into assessment environments without redesigning assessment logic risks undermining both evaluative judgment and diagnostic validity. From the perspective of Messick's unified validity framework and argument-based validity theory, validity depends on the interpretability and consequences of scores, and when AI mediates cognitive processes, correctness alone is insufficient evidence of competence (Messick, 1995; Kane, 2013). Drawing on Evidence-Centered Design principles, the results suggest that future assessments must explicitly model the role of tools in performance (Mislevy et al., 2003). Hybrid designs that distinguish between independent reasoning and AI-augmented performance, and that require students to justify, critique, and reflect on AI use, offer a viable pathway for preserving evaluative judgment in AI-rich contexts and align with emerging calls to foreground epistemic responsibility over unaided output (Luckin & Holmes, 2016).

CONCLUSIONS

This study examined the impact of access to AI-based models on university students' performance, decision-making quality, and learning perceptions within a scenario-based economic evaluation context. Students completed three sequential assessment sessions – baseline (no AI), independent reasoning (no AI), and AI-assisted – allowing for controlled comparison across conditions. The findings indicate that AI access substantially increased average performance (by 30.46 percentage points) and reduced variability in outcomes. While this performance amplification demonstrates AI's potential to enhance accuracy and efficiency, it was accompanied by a marked reduction in diagnostic value, evidenced by compressed score distributions and weakened internal reliability.

Student reflections reinforced this central trade-off. Most participants perceived the non-AI assessment as more challenging yet more educationally beneficial, citing higher cognitive effort, sustained concentration, time management demands, and deeper critical engagement. In contrast, AI assistance was valued for speed, convenience, and confidence support but was frequently described as reducing the need for deep reasoning. Notably, patterns of selective AI use – particularly reluctance to rely on AI for value-based or judgment-oriented SJT tasks – suggest emerging AI literacy among students, reflecting an ability to judge when AI support is appropriate and when human reasoning should take precedence.

Several limitations should be acknowledged. The study was conducted with a modest sample size within a single institutional context, and novelty effects may have influenced how students engaged with AI tools. Future research should replicate this design with larger and more diverse cohorts, incorporate inferential statistical analyses, and examine longitudinal effects of AI integration on reasoning skill development. Comparative studies across disciplines would also help determine whether the observed tension between performance gains and diagnostic validity is domain-specific or generalizable across educational contexts.

Overall, the results underscore the dual nature of AI-based models in higher education assessment: they function as powerful accelerators of performance while simultaneously posing challenges to assessment validity and interpretability. The key challenge for educators and policymakers is not whether AI should be used, but how assessment systems can be designed to harness AI's strengths while safeguarding the irreplaceable role of human reasoning, evaluative judgment, and accountability in academic and professional practice.

IMPLICATIONS FOR RESEARCH AND APPLICATION

From a research perspective, this study opens several important avenues for future inquiry. Replication studies with larger and more diverse samples are needed to assess the generalisability of the observed effects across disciplines, institutions, and cultural contexts. In particular, comparative research across fields with different epistemic traditions – such as economics, engineering, humanities, and professional education – could reveal whether the trade-off between performance amplification and diagnostic loss is domain-specific or universal.

Longitudinal research designs are also essential. While the present study captures immediate performance and perception effects, future research should examine how sustained exposure to AI-assisted assessment influences the development of reasoning skills, metacognitive awareness, and evaluative judgement over time. Such studies could clarify whether reliance on AI stabilises, intensifies, or diminishes as students gain experience, and whether hybrid assessment models can mitigate potential long-term erosion of independent reasoning capacity.

Methodologically, further work is needed to develop and test alternative psychometric and validity frameworks capable of capturing competence in human-AI assemblages, rather than in isolated individuals. Traditional indicators such as variance and internal consistency may be insufficient in AI-mediated contexts. Future research could explore process-oriented measures, trace data, or justification-based scoring models that better reflect distributed agency and epistemic responsibility.

From a pedagogical perspective, the findings suggest that AI should not be treated as a simple add-on to existing assessment formats. Instead, educators are encouraged to adopt hybrid assessment models that intentionally combine human-only tasks, AI-permitted tasks, and reflective components. Human-only components remain essential for diagnosing independent reasoning, while AI-assisted components can reflect authentic professional practice. Reflective tasks – such as requiring students to explain when, why, and how AI was used, or to critique AI-generated outputs – can help make cognitive processes visible and preserve evaluative judgement.

In terms of practical application, higher education institutions should develop transparent and pedagogically grounded AI policies that go beyond prohibition or unrestricted allowance. Integrating critical AI literacy into curricula is essential. Students must be supported not only in learning how to use AI tools effectively, but also in understanding their cognitive trade-offs, limitations, and ethical implications. Explicitly acknowledging the role of AI in assessment design can help align evaluation practices with real-world professional environments while safeguarding the central role of human judgement, reflection, and responsibility in learning and evaluation.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

HUMAN TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 21(3), December 2025, 640–667

CONDITIONS FOR THE ACCEPTANCE OF ADVERTISING CONTENT GENERATED BY GENERATIVE ARTIFICIAL INTELLIGENCE

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The dynamic development of GenAI tools and their growing availability suggest that this technology will play an increasingly important role in marketing, particularly in advertising. It redefines not only the way advertising materials are created, but also their visual, linguistic and narrative form, which is important for how they are perceived, evaluated and accepted by consumers. Furthermore, despite its numerous benefits, it is associated with a number of challenges that may be of significant importance to consumers. This article aims to identify the factors that determine the level of social acceptance of advertising materials generated using GenAI tools. The research process utilised the meta-UTAUT model, expanded with additional variables: hedonistic motivation, trust and habit, which in the context of advertising materials may play a significant role in the process of forming attitudes and behavioural intentions towards the use of generative AI. The results obtained are important both in the context of further research on the acceptance of this technology and the effects of its work, including in the advertising sector, as well as for practitioners operating in this market.

Keywords: *generative artificial intelligence (GenAI), advertising materials, acceptance, consumer*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.8

INTRODUCTION

Digital technologies, especially general purpose technologies, are changing consumer behaviour, expectations and attitudes. The future of marketing will undoubtedly be linked to artificial intelligence (AI), especially generative AI (GenAI), which will allow brands to respond to these changes in real time. The use of GenAI brings measurable benefits (e.g., increased effectiveness of actions taken, unlimited possibilities for creating engaging content, product arrangement in any style, reduced costs) and is one of the fastest-growing trends in marketing (Nguyen et al., 2021; Huderek-Glapska, 2023). Digital technologies are also reshaping consumer emotions and purchasing decisions in digital environments (Biercewicz et al., 2024; Victor et al., 2023).

Generative artificial intelligence (GenAI) is an advanced technology that, based on huge data sets, can almost instantly generate new texts, images, audio recordings, programming codes and synthetic data (Bommasani et al., 2021), with a quality and style similar to the work of humans. Its ability to imitate human creativity and expression opens up completely new possibilities for creative sectors, including the advertising industry. Unlike earlier digital technologies, which mainly supported data analysis, process automation and message personalisation, generative AI enters directly into the realm of creation. It enables the creation of unique concepts, visualisations and narratives on a scale previously unavailable, while reducing costs and production time. As a result, it significantly enhances the creative and strategic potential of marketing teams, allowing them to test different communication variants more quickly, tailor messages to micro-segments of audiences and optimise campaign effectiveness in real time.

There are already many generative artificial intelligence tools available on the market, covering various types of media and forms of creativity. Text tools include ChatGPT, Gemini, Claude, Perplexity and Copilot, which can be used to generate advertising content, advertising spot scripts and promotional slogans, including for social media. In the field of graphics, tools such as Midjourney, DALL-E, Stable Diffusion, NanoBana and Leonardo AI dominate, allowing the creation of illustrations, advertising photos, graphic concepts and broadly understood promotional materials in styles tailored to the expectations of the audience. Video generation tools such as Runway AI and Sora are also gaining popularity, allowing the creation of advertising spots, animations and video content without the need for actors or production crews. In turn, tools such as Suno, Udio and Soundful allow you to generate any soundtrack, from simple jingles to complex musical compositions, which can be tailored to the content of the advertising message, the emotions of the audience and the visual context.

The dynamic development of generative artificial intelligence tools means that they not only offer increasingly high quality and realistic content, but also enable the creation of more immersive and interactive user experiences. As a result, marketing communication is becoming more engaging, based on the emotional reception of the message and a deeper connection with the consumer. From the perspective of the advertising industry, this means that GenAI opens up enormous opportunities both in terms of the creativity of the content created and the effectiveness and efficiency of the campaigns based on it. In addition, it allows for partial or full automation of routine tasks, which increases the speed and efficiency of marketing teams (DeCremer et al., 2023). What is more, GenAI allows for the streamlining of processes, including the creation of advertising concepts and their actual creation (Cillo & Rubera, 2025), while increasing their level of personalisation. Generating advertisements using generative artificial intelligence tools is fast and produces reliable results thanks to the interaction between humans and technology, whereas previously, obtaining reliable images, for example, required knowledge of digital design and editing (Campbell et al., 2022). As a result, generative artificial intelligence not only redefines the way advertising materials are created, but also transforms the very model of work, shifting the emphasis to the area of human-technology interaction and synergy.

However, despite its many benefits, the growing availability and power of GenAI tools brings new challenges. These include hallucinations, such as references to fictional sources (Haluza & Jungwirth, 2023), content containing conceptual errors, and content that could be used unethically or deliberately with malicious intent (Weng et al., 2023). In particular, there is a risk of manipulating the emotions of recipients or violating their consumer rights and privacy. Inept use of GenAI tools in advertising can also lead to the perpetuation of cultural biases (Abdelhalim et al., 2024), intellectual property issues, and questions about human autonomy (Zohny et al., 2023). Such actions may undermine the credibility of advertising messages and weaken trust in the materials developed in this way and the brands they concern. Moreover, given the dynamic development of GenAI and consumers' limited knowledge, their awareness of the possibilities of using generative artificial intelligence in the process of, for example, creating advertising materials is relatively shallow and limited. This is because AI is a discreet technology, which means that consumers are generally unaware that they have interacted with this technology (Kumar et al., 2019) and are unable to distinguish between advertising materials created using generative AI tools and those created in the traditional way.

The way consumers perceive GenAI is undoubtedly a result of both the opportunities offered by this technology, including in advertising, and the risks it entails (Bozkurt & Gursoy, 2025; Chikosha & Potwana, 2021). The acceptance of artificial intelligence, as well as the level of its conscious use, therefore reflects consumer attitudes towards this technology. This is important for both declared and actual interactions with this technology and the resulting behaviours (e.g., reactions to AI-generated content or purchasing decisions made on this basis) (Venketesch, 2000; Venkatesh & Davis, 2000). Consumer demographics such as age, gender, level of education, and subjective assessment of one's financial situation play a key role in this process (Kaya et al., 2022; Zhan et al., 2023), but also psychographic factors, including technological sophistication and interest in science fiction pop culture (Hick & Ziefle, 2022).

It is crucial to determine the level of consumer acceptance of advertising materials created using generative artificial intelligence tools and to identify the factors that shape trust in this content. On the one hand, this contributes to a better understanding of how society perceives and accepts AI and its specific applications, and on the other hand, it supports the process of its implementation in the context of practical market applications. The aim of this article is to identify the factors determining the level of social acceptance of advertising materials generated using generative artificial intelligence tools. To achieve this goal, the authors posed the following research questions (RQ):

RQ1. What factors determine consumer attitudes towards marketing materials generated using GenAI tools?

RQ2. Are consumers willing to trust advertising materials created using generative AI tools?

RQ3. How do consumer demographics and selected behavioural characteristics influence the level of acceptance of advertising materials generated using GenAI tools?

To answer our research questions, we used the meta-UTAUT model, which includes four basic exogenous variables (*Performance Expectancy*, *Effort Expectancy*, *Social Influence*, *Facilitating Conditions*) and two endogenous variables (*Attitude*, *Behavioural Intention*) from the original UTAUT model (Dwivedi et al., 2000). For the purposes of the study, the model was expanded to include trust, consumer habits and hedonistic motivation, which are considered by many authors to be important variables in the context of the acceptance of digital technologies, including AI.

The research conducted may contribute to a better understanding of how consumers perceive generative AI and its specific applications in advertising, as well as what influences their level of acceptance. This is also important for the process of implementing this technology in the context of practical market applications in marketing departments, including advertising, as well as media houses and advertising agencies. The growing importance of digital commerce environments also shapes consumer expectations and behaviors (Oláh et al., 2023).

LITERATURE REVIEW

The use of generative artificial intelligence in advertising

Artificial intelligence (AI) is currently recognised as one of the key technologies with a significant impact on various industries and sectors of the economy. Defined by John McCarthy as ‘the science and engineering of making intelligent machines, especially intelligent computer programmes, involves using computers to understand human intelligence’ (McCarthy, 2007), embedded in a machine, enables learning based on hundreds of experiences (Davenport et al., 2020) and mimics elements of human intelligence and behaviour (e.g. perception, reasoning, learning or decision-making) (Syam&Sharma, 2018). This gives the impression that AI can think, analyse, react and act in a manner similar to humans (Kumar et al., 2019; Davenport et al., 2020).

The foundation of its operation is the effective analysis of huge databases, processing them into knowledge that is then used to create behaviours based on it (Jarrahi, 2018). Traditional artificial intelligence focuses on the intelligent execution of specific tasks and refers to systems designed to respond to a specific set of input data, while generative AI (GenAI) represents a qualitatively new stage in the development of this technology. It is a form of AI that can create something seemingly new, such as text, images, music, and even code in the programming process. What distinguishes it from ‘traditional’ AI systems is primarily its unlimited context and scale of potential use, as well as its unlimited possibilities for democratisation (Helberger & Diakopoulos, 2023). Generative artificial intelligence can therefore be defined as an artificial intelligence (AI) system that uses large data sets to create content that did not previously exist (Chiu, 2024), and is therefore innovative and creative in a certain way (Mannuru et al., 2023). This means that it is increasingly being compared to human artistic expression and creativity (Anantrasirichai & Bull, 2022). Based on large language models (LLM), it allows users to interact in a conversational mode, similar to a dialogue between humans. Trained on large data sets, it can generate coherent, logical and highly realistic content (Sætra, 2023), but its final form depends on the training data and the way humans interact with GenAI (Brown et al., 2024).

Generative AI technology is crucial to the content creation process. It allows for increased relevance through the selection of appropriate language, tone and style, and in the case of image generators, through visualisation tailored to the emotional and aesthetic context. What is more, GenAI has the unique ability not only to analyse data and provide typical responses based on it, but also to generate more complex content that goes beyond typical human-machine interactions (Liam et al., 2022), simulate alternative scenarios, and even deepen human creative processes (Dwivedi et al., 2023).

It is therefore not surprising that there is growing interest in this technology in the creative sector, including advertising. Marketing agencies are increasingly experimenting with AI-generated content, which, according to experts, may soon prove to be more effective than content prepared exclusively by humans (without the support of GenAI tools). The scope of such cooperation may be based on complementarity, interdependence, competition, but also full cooperation (Sowa et al., 2021). In this context, research indicates that 'co-creation' with generative systems can lead to significantly higher efficiency if users begin to perceive GenAI not as a neutral, passive tool, but as an individualised cognitive partner with whom they can engage in dialogue, exchange ideas and jointly develop concepts (Sebastian et al., 2025; Lyu et al. 2024).

Benefits and limitations of using generative artificial intelligence in advertising

GenAI has potential that could prove very useful for the advertising industry, particularly in the area of ad creation (Cillo & Rubera, 2025). The main advantage of this technology is its ability to process vast amounts of data, identify patterns and generate results that would be difficult for humans to obtain manually (Y. Liu et al., 2023). According to research by the World Federation of Advertisers, generative artificial intelligence is currently most commonly used in the areas of content creation (79%), content ideation (67%) and task automation (54%) (https://wfanet.org/knowledge/item/2024/09/17/eighty-percent-of-brands-have-concerns-about-agency-use-of-genai). It can therefore streamline entire processes or individual phases thereof, as well as assist people in performing their existing tasks, increasing the speed and efficiency of their work (DeCremer et al., 2023), including those related to customer service. It is useful in consumer behaviour analysis processes (Tang et al., 2024; Ford et al., 2023), media planning and purchasing, the development of increasingly personalised and responsive advertising campaigns (Qin&Jiang, 2019), the evaluation of their effectiveness, and the evaluation of specific advertising materials. It can not only speed up the process of creating advertisements, but also support dynamic experimentation with their form, style and how they reach the audience. The potential of this technology to quickly test, modify and improve individual elements of an advertising campaign creates space for data-driven creativity, especially in terms of Experimental studies have shown the potential of digital environments for testing advertising message effectiveness (Borawska et al., 2023).maximising consumer engagement and influencing their decisions. However, it seems that the advertising industry is still not fully exploiting the potential of generative AI in the creation and development of creative concepts (Demsar et al., 2025).

Perhaps this is due to the fact that generative AI entails significant social, cultural and ethical risks. This applies, among other things, to the issue of human autonomy – that of the marketer (Zohny et al., 2023). On the one hand, AI is becoming a tool that supports human decisions, but on the other hand, it is increasingly beginning to shape them, which may lead to a gradual change in the role of humans from creators to participants in a process shaped by algorithms. Another challenge for marketers is undoubtedly GenAI's tendency to hallucinate, i.e. to present credible-sounding content that is in fact untrue, including photos, graphics, videos or information containing factual errors (Dwivedi et al., 2023; Alkaissi&McFarlane, 2023). GenAI can also contribute to the perpetuation of stereotypes and cultural biases (Abdelhalim et al., 2024) or the reproduction of harmful or inappropriate content (e.g., violence, use of offensive language), which can have a negative impact on the reputation of brands using such tools. Models trained on historical or biased data often unconsciously reproduce patterns present in culture or the media. Furthermore, in the case of people who have difficulty using generative AI tools (e.g., children, the elderly, people who are less tech-savvy or have limited access to advanced digital tools), it will be much easier to manipulate their decisions through appropriately generated, unethical or deliberately misleading advertising messages. Another key issue is data security and confidentiality (Nah et al., 2023; Osadchaya et al., 2024). The use of personal or company data to train models carries the risk of unauthorised disclosure, improper processing or loss of control over the data.

Furthermore, according to the World Federation of Advertisers, other problems include: potential loss of control over brand intellectual property, generation of content that unintentionally infringes on the intellectual property rights of third parties, and lack of ownership or exclusive copyright to advertising materials generated using GenAI tools (https://www.media-marketing.com/en/news/use-of-generative-artificial-intelligence). Experts also point out that the use of GenAI may cause the problem of content duplication and gradual homogenisation of messages, as well as a decline in the originality and effectiveness of advertising campaigns. Consequently, it seems that GenAI technology will only be accepted in the advertising sector if the benefits are perceived as significant and the risks as potential but avoidable, minimisable or at least insurable (Floridi et al., 2018), both from the perspective of brands and consumers.

Trust in content generated by GenAI

Trust is considered a catalyst for interaction between consumers and technology, which can influence the formation of expectations towards it (Marriott & Williams, 2018). At the same time, however, trust depends on the attributes of AI (e.g., ease of use, intuitiveness of AI-based solutions, security, including data security) as well as subjective consumer expectations (McKnight et al., 2011). It is also reinforced by social influence (e.g., opinions of family, friends, acquaintances, influencers) (Johnson et al., 2008; Hsu & Lin, 2015), which constitutes the context in which the consumer operates (Venkatesh et al., 2012). In digital contexts, trust is also influenced by cybersecurity concerns and the perceived safety of online interactions (Kuzior et al., 2024).

The issue of transparency in advertising materials created using generative artificial intelligence is becoming increasingly important. The lack of clear information about the use of GenAI at any stage of the process may lead to a decline in consumer confidence or its loss if consumers feel misled about the authorship, authenticity or intent of the message. On the one hand, there are calls for content generated using GenAI to be labelled as such, pointing to this as a desirable practice from an ethical point of view. On the other hand, it is pointed out that disclosing the involvement of artificial intelligence may paradoxically lead to a decline in trust in the brand and content creator, as AI-generated advertisements are often perceived as less credible and less authentic (Schilke & Reimann, 2025). It would seem that disclosing the use of artificial intelligence would increase consumer trust, but paradoxically, it often leads to an erosion of that trust. Such reactions may stem from an aversion to AI-based solutions and avoidance of them (Erlei et al., 2022), especially in situations where the scope of use of this technology concerns areas considered typically 'human' (Longoni et al., 2019). Research also shows that consumer trust declines when consumers do not know to what extent GenAI was involved in the creation process (the entire text or part of it) (Jakesch et al., 2019), and mistrust stems from the fact that the use of this technology was considered laziness on the part of the creator. The resulting materials were considered unreliable and lacking in authenticity. Interestingly, human disclosure of AI involvement may lead to a reduction in legitimacy resulting from the unclear division of roles between humans (marketers) and GenAI (Can˜as, 2022), as a result of which the marketer will be perceived as less trustworthy, especially if the consumer considers such cooperation to be unjustified (Schilke&Reimann, 2025). On the other hand, other studies indicate that work generated entirely by AI has gained greater trust than content created by humans assisted by this technology. People also tend to underestimate the capabilities of artificial intelligence, which may be due to their failure to recognise the exponential pace of development of this technology (Yarza, 2025). As a result, consumers will interpret information about the use of GenAI in advertising in a way that is consistent with their own desires or beliefs, including those regarding artificial intelligence as a technology.

METHODS

Developing hypotheses

In order to identify the generative role of AI in advertising, a systematic literature review (SLR) was conducted, which minimises bias and allows for the collection of reliable results (Moher et al., 2009), forming the basis for the preparation and implementation of our own empirical research. The literature review was conducted based on two international and interdisciplinary databases, recognised as the databases with the widest access to literature in the social sciences: Web of Science and Scopus. The keywords were defined as: 'generative artificial intelligence', 'generative AI', 'GenAI' and "advertising", 'advertising materials', and the search period covered the years 2022-2025, with the start date of the search based on the activation date of the first GenAI tool (ChatGPT - November 2022). The identification process took into account articles published in English in the fields of Business, Management and Accounting. To increase methodological rigour, the literature search focused exclusively on articles published in peer-reviewed journals. At the analysis stage, the records obtained were subjected to established inclusion and exclusion criteria in order to narrow down the selection of relevant articles to those directly related to the analysed subject areas, and then an in-depth analysis of the content of these articles was carried out, taking into account their number of citations. This allowed us to identify key themes related to the use of GenAI in the creation of advertising materials.

The bibliometric analysis indicates a high degree of dispersion in the issues surrounding GenAI and its role in advertising, which is typical for new concepts and related areas of research. Previous research indicates that consumers' attitudes towards GenAI as a technology, as in the case of AI, are influenced by a number of factors, including the purpose for which the technology is used (Bozkurt & Gursoy, 2025; Guszcza et al., 2017) and the context of its application (Zehnle, 2025). Perceived usefulness, perceived ease of use, and the risks associated with its use (Liang et al., 2020) and the resulting level of consumer trust are also identified as key determinants of attitudes. Research on consumer reactions to the use of GenAI in the creation of advertising materials has only just begun and focuses primarily on the technical possibilities of generating specific materials and content and the ethical aspects associated with this. To a lesser extent, however, the issue of the level of social acceptance of advertising materials created using GenAI tools and the key factors determining the level of this acceptance and the level of consumer confidence in such materials is addressed. Research on AI integration in professional contexts reveals diverse perspectives on acceptance and adoption (Woźniak-Jęchorek et al., 2023).

In our study, we decided to use the meta-UTAUT model, which is a modified version of the UTAUT model. It was developed by adding attitude as an intermediary construct, which significantly increased the explanatory power in terms of behavioural intentions from 38% to 45% (Dwivedi et al., 2019). This model is currently considered an alternative to the UTAUT model in understanding acceptance, use, and Similar approaches have been applied to study digital entrepreneurship intention and technology acceptance in various contexts (Alkhalaileh et al., 2023; Malaquias et al., 2023).behaviour towards digital technologies (Dwivedi et al., 2020). Some authors believe that this model provides an opportunity for a holistic approach to research modelling, although in general, the model is only used in different contexts, and authors do not attempt to extend it with additional variables (Alkhowaiter, 2022). Similar to the UTAUT model, meta-UTAUT consists of four important variables: *Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions*). These have both a direct and indirect (through the *Attitude* construct) impact on *Behavioural Intention*. For the purposes of this study, the variables in the model have been expanded to include trust, hedonic motivation and consumer habits, which have a significant impact on the individual level of acceptance of digital technologies.

Performance Expectancy (PE) refers to the level of individual belief that using a given technology can help consumers achieve greater effectiveness in performing specific activities (Venkatesh et al., 2012). The authors defined it as the degree to which a consumer believes that using advertising materials generated with GenAI tools can increase their effectiveness in achieving specific goals (e.g., purchasing). This is because the content provided to them in this way is more personalised and tailored to their needs and expectations, which allows them to be more effective in the decision-making and purchasing process. PE may also have a positive impact on behavioural intention related to the use of advertising materials generated using GenAI tools (Alkhowaiter, 2022). This allowed us to formulate the following hypotheses:

H1. Performance expectations positively influence attitudes towards advertising materials generated using GenAI.

H2. Performance expectations positively influence behavioural intentions regarding the acceptance of advertising materials generated using GenAI.

Effort Expectancy (EE) is the level of comfort and convenience expected when using an application or system (Venkatesh et al., 2012). Consumers expect that using them will be easy, intuitive and not require much cognitive effort. In the context of advertising materials generated using GenAI tools, this concept refers to the consumer's belief that interacting with such materials does not require specialist technological knowledge and is intuitive. It is also assumed that EE has a significant impact on attitudes and behavioural intentions (Hermanto et al., 2022; Rana et al., 2023), which has led to the following hypotheses:

H3. Effort Expectancy positively influence attitudes towards advertising materials generated using GenAI.

H4. Effort Expectancy positively influence behavioural intentions regarding the acceptance of advertising materials generated using GenAI.

Social Influence (SI) is defined as the degree to which a consumer is convinced that people who are important in their life, such as family or friends, believe that they should use a given technology and solutions based on it (Venkatesh et al., 2003) and accept it. This is particularly important in the initial period of implementation of such solutions on the market (Alalwan et al., 2017). People tend to seek advice from others, and awareness of their opinions can influence BI in terms of acceptance of a given technology (Celedonio & Picaso, 2023). In the context of advertising materials generated using GenAI tools, this concept refers to the consumer's belief that the acceptance and use of such tools, e.g. in the decision-making process, are socially approved. Social influence can not only affect consumer attitudes, but also build behavioural intentions related to the acceptance of advertising materials generated using GenAI tools (Singh et al., 2020), which allowed the following research hypotheses to be formulated:

H5. Social Influence positively influence attitudes towards advertising materials generated using GenAI.

H6. Social Influence positively influence behavioural intentions regarding the acceptance of advertising materials generated using GenAI.

Facilitating Conditions (FC) refer to the degree to which a person believes that resources are available to support them in performing a specific action (Venkatesh et al., 2012). FC relate to the consumer's perception of the level of support, e.g. organisational and technological, in using a given technology. In the context of advertising materials generated using generative artificial intelligence tools, FC will refer to the consumer's perception of the extent to which a particular technological, legal or information environment supports their interaction with such materials.

H7. Facilitating Conditions positively influence attitudes towards advertising materials generated using GenAI.

H8. Facilitating Conditions positively influence behavioural intentions regarding the acceptance of advertising materials generated using GenAI.

Trust (TRST) is an important element in the relationship between consumers and a given technology, influencing the way in which their expectations of it are formed (Marriott & Williams, 2018). It leads to greater consumer engagement in specific activities (Alshboul,

2024) and reinforces behavioural intentions towards technology (Alkhowaiter, 2022) and the effects of its use. With regard to advertising materials generated using GenAI tools, trust will influence the assessment of the credibility and authenticity of such materials and their content, which will influence the consumer's willingness to accept them. As a result, trust will act as a mechanism to reduce consumer uncertainty and cognitive risk, increasing their behavioural intention to use such materials in the decision-making and purchasing process.

H9. Trust positively influence attitudes towards advertising materials generated using GenAI.

H10. Trust positively influence behavioural intentions regarding the acceptance of advertising materials generated using GenAI.

Hedonic Motivation (HM) is related to deriving pleasure from using a given technology (Venkatesh et al., 2012). As a result, consumers will be more likely to choose solutions that they find fun and enjoyable to use. In the context of AI-generated advertising, this concept means that consumers will derive pleasure from interacting with advertising materials generated using GenAI tools, e.g. due to their visual appeal or innovative creative approach. This influences both consumers' attitudes and their behavioural intention to use such advertising materials.

H11. Hedonic Motivation positively influence attitudes towards advertising materials generated using GenAI.

H12. Hedonic Motivation positively influence behavioural intentions regarding the acceptance of advertising materials generated using GenAI.

Habit (HT) is most often defined as the extent to which people tend to perform behaviours automatically (Venkatesh et al., 2012), which leads to repeatable consumer behaviour and is the result of their previous experiences. It reduces the need to make conscious decisions about, for example, purchasing specific products or products of a particular brand. In the context of the acceptance of advertising materials generated using generative artificial intelligence tools, Habit has been defined as the degree to which consumers automatically respond to this type of content, guided by existing cognitive and behavioural patterns shaped by previous encounters with similar forms of communication.

H13. Habit positively influence attitudes towards advertising materials generated using GenAI.

H14. Habit positively influence behavioural intentions regarding the acceptance of advertising materials generated using GenAI.

Attitudes (ATT) are related to individual consumer behaviour and are defined as individual characteristics that influence behaviour related to the adoption of a given system (Chatterjee et al., 2023), technology or solutions based on it. Attitude is a tendency that formulates positive or negative beliefs that can lead to behavioural change (Alkhowaiter, 2022). Furthermore, it is assumed that attitudes have both an indirect and direct impact on user behaviour (Dwivedi et al.), which means that the extent to which a given technology is used will depend on the user's individual attitude towards it. It is also noted that attitudes are significantly related to users' intentions to use a given technology or solutions based on it

(Chatterjee et al., 2023). Therefore, a positive attitude of consumers towards advertising materials generated using GenAI tools may positively influence their behavioural intentions to use them.

Behavioural Intention (BI) is most often defined as an indication of a consumer's readiness to engage in a specific behaviour and to accept and adopt a given technology (Chatterjee et al., 2023). It refers to the extent to which a given technology proves to be useful to the consumer and consistent with their expectations, which influences their attitude and leads to the formation of behavioural intention (Jeyaraj et al., 2019).

H15. Attitudes towards advertising materials generated using GenAI have a positive impact on consumers' behavioural intentions towards these materials.

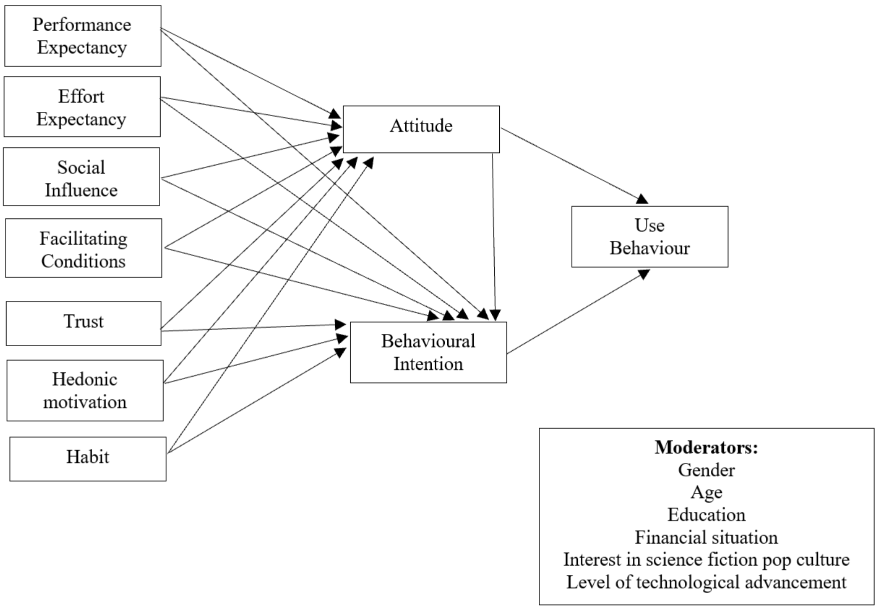

Figure 1. Research model

Consumers' attitudes towards AI and its effects are also related to their demographic and psychographic profiles, including, for example, their level of technological sophistication (Yang et al., 2016), cultural norms and beliefs they represent/adhere to (Jeon et al., 2018), previous experience with technology (McKechnie et al., 2006) or interests (Laakasuo et al., 2018), as well as the needs reported by consumers that technology allows them to satisfy, (Wang et al., 2011). These factors shape both the level of consumer acceptance and their behavioural intention.

The influence of gender on the perception of artificial intelligence, despite being the subject of repeated research, remains unclear. On the one hand, we have studies that show a significant impact of gender, emphasising the fact that men are more positive towards artificial intelligence technology and have greater knowledge about it than women (Hick & Ziefle, 2022). On the other hand, we have studies indicating that the differences between women and men are gradually blurring (Zhan et al., 2023). This suggests the complexity of the influence of this factor, especially when taking into account the socio-cultural context of consumers. However, the influence of age on consumers' attitudes towards AI is clear. Research shows that it changes with age (Zhan et al., 2023) and that the older people are, the less favourable their attitude towards artificial intelligence may be compared to younger people (O'Shaughnessy et al., 2023). Income level is also significant. Research indicates that people with low incomes may be more sceptical about artificial intelligence. It has been observed that people with low socio-economic status have a lower level of trust in artificial intelligence and are less likely to support its development (Bullock et al., 2022). On the other hand, people with higher incomes are usually more aware of the possibilities, potential applications and risks associated with artificial intelligence, and also demonstrate a higher level of technological competence and knowledge in this area.

Data collection

Survey methods were chosen because they allow for the effective collection of data from a large sample, providing a broad picture of users' experiences and perceptions (Dillman, 2011). The research was conducted in September 2024 using an online survey. The survey was addressed to adults who declared that they had encountered the concept of generative artificial intelligence (GenAI). The full characteristics of the population are presented in Table 1. The data collection process was anonymous, which was communicated to respondents before the study began. The authors did not impose a time limit on the completion of the research questionnaire.

The full research questionnaire consisted of 29 questions. For the purposes of this study, 9 items measured using the Likert scale were taken from it and supplemented with 7 demographic questions. Since the original measurement scale for the meta-UTAUT model was taken from English-language literature, it required adaptation. This process was carried out in accordance with the typical procedure used in such situations and focused primarily on the translation and transcription stage.

The questionnaire included typical control variables most commonly used in studies on the acceptance of digital technologies and solutions based on them (gender, age, level of education, place of residence, subjective assessment of one's financial situation). Other control variables we adopted included subjective assessment of one's own level of technological advancement and interest in science fiction pop culture. The study was preceded by a pilot phase, which allowed us to verify the correctness of the methodological assumptions and eliminate any ambiguities in the wording of the research questionnaire, as well as to assess its initial reliability and validity. After this validation process, the questionnaire was used in the actual study.

Sample

A total of 1,045 respondents took part in the survey. Women predominated (50.6%), with a similar percentage of men (49.3%), while the proportion of people who did not want to disclose their gender was marginal (0.1%). The average age of respondents was M = 49.86 years with a standard deviation SD = 17.13, which indicates a diversity in the age of the respondents. In terms of education, people with secondary (38.6%) and higher (32.2%) education predominate, while 29.3% of respondents have primary or vocational education. The assessment of the financial situation indicates that the majority of participants in the study declare an average level of wealth (60.8%), with 23.5% assessing their situation as good and only 13.2% as bad or very bad. Most respondents live in rural areas (36.6%) and small and medium-sized towns with up to 100,000 inhabitants (33.6% in total). The share of residents of large urban centres with more than 200,000 inhabitants was 21.8%, of which 12.5% were people from cities with more than 500,000 inhabitants. The level of technological advancement of the respondents is unevenly distributed – the largest group (42.6%) indicated level 3, corresponding to moderate advancement, while 17.6% of respondents rated themselves at level 2 or 4, and 6.5% at the highest level 5. In addition, 43% of respondents declare an interest in science fiction pop culture, while 57% do not show such interest.

Table 1. Characteristics of the respondents (n=1045)

Feature	Structure in %
Gender	
Woman	50.6
Man	49.3
I don't want to disclose	0.1
Age	
up to 24 years old	6.8
25–34 years old	17.2
35–44 years old	16.2
45–54 years old	17.6
55–64 years old	17.0
65 years and older	25.2
Education	
Basic	29.3
Medium	38.6
Higher	32.2
Financial situation	
Very bad	3.5
Bad	9.7
Average	60.8
Good	23.5
Very good	2.5
Place of residence	
Village	36.6
Town with up to 10,000 inhabitants	5.8
Town with a population of 10,001 to 50,000	16.9
Town with a population of between 50,001 and 100,000	10.9
Town with a population of between 100,001 and 200,000	7.9
Town with a population of between 200,001 and 500,000	9.3
City with a population of over 500,000	12.5
Level of technological advanced	
1	15.7
2	17.6
3	42.6
4	17.6
5	6.5
Interest in science fiction pop culture	
No	57.0
Yes	43.0

RESULTS

In order to empirically verify the research hypotheses, the full structural model was estimated using the maximum likelihood (ML) estimation method. The full SEM model showed a very good fit. The chi-square statistic was significant (χ^2=1682.748; $p<0.001$), which is typical for a large sample size and does not constitute an independent basis for rejecting the model. The relative index χ^2/df=3.67 falls within the range of values considered acceptable ≤5. The comparative fit indices take very good values: CFI=0.967, TLI=0.962, NFI=0.955, IFI=0.967 – all exceed the threshold of 0.95, which indicates a high fit of the theoretical model to the data (Hu&Bentler, 1999). The parsimony indices (PNFI=0.830, PCFI=0.840) confirm that despite the complex structure, the number of estimated parameters remains theoretically and statistically justified. The RMSEA approximation error index=0.051 (90% CI: 0.048–0.053; PCLOSE=0.362) indicates a good approximate fit of the model to the data, meeting the recommended criteria (RMSEA<0.06 – Hu & Bentler, 1999). The very good SRMR=0.0402 value confirms minimal differences between the observed and predicted covariance matrix, which further strengthens the global fit assessment. Hoelter's N values of 317 ($p<0.05$) and 331 ($p<0.01$) suggest that the model remains stable even with a sample size of over 300 observations, which is a sign of good identifiability and reliability of estimation. The results obtained confirm the good fit of the structural model.

In the next step, the reliability of the constructs under study and the F-L criterion (Fornell & Larcker, 1981) were analysed (Table 2).

Table 2. Measures of reliability of the examined constructs

Scale	Item	Factor loading	CR	AVE
PE	PE1	0,887	0,944	0,808
	PE2	0,896		
	PE3	0,915		
	PE4	0,898		
EE	EE1	0,91	0,936	0,784
	EE2	0,866		
	EE3	0,886		
	EE4	0,88		
SI	SI1	0,926	0,935	0,828
	SI2	0,893		
	SI3	0,91		
FC	FC1	0,876	0,867	0,622
	FC2	0,863		
	FC3	0,711		
	FC4	0,686		
HM	HM1	0,826	0,910	0,771
	HM2	0,909		
	HM3	0,897		
HT	HT1	0,903	0,913	0,723
	HT2	0,825		
	HT3	0,816		
	HT4	0,855		
BI	BI1	0,882	0,968	0,789
	BI2	0,895		

	BI3	0,915		
ATT	ATT1	0,866	0,947	0,780
	ATT2	0,899		
	ATT3	0,891		
	ATT4	0,883		
	ATT5	0,876		
TRST	TRST1	0,891	0,977	0,793
	TRST2	0,886		
	TRST3	0,909		

PE – expected performance, EE - expected effort, SI - social influence, FC - facilitating conditions, HM - hedonic motivation, HT - habit, BI - behavioural intention, ATT-– attitude, TRST – trust

All factor loadings took on high and significant values, exceeding the recommended threshold of 0.70, which confirms the strong correlation between the observed indicators and the corresponding latent variables. The Composite Reliability (CR) values for all constructs exceeded the threshold of 0.70, ranging from 0.867 (FC) to 0.977 (TRST), which indicates high internal consistency of the measurement. At the same time, all Average Variance Extracted (AVE) values exceeded the recommended level of 0.50 (Fornell & Larcker, 1981), reaching values from 0.622 (FC) to 0.828 (SI), which confirms the satisfactory convergent validity of the analysed constructs. High factor loadings (≥0.68 for FC and ≥0.82 for the other constructs) indicate that each element of the scale clearly reflects a conceptually defined theoretical construct. Particularly high coefficients were recorded for the variables PE (0.887–0.915), EE (0.866–0.910), SI (0.893–0.926) and BI (0.882–0.915) variables, which confirms the stability and precision of the measurement. The obtained values of reliability (CR) and convergent validity (AVE) meet the criteria accepted in the literature on the subject, indicating that the adopted measurement model is characterised by high consistency and theoretical validity, enabling further structural analysis. The results of the model testing are presented in the table below.

Table 3. Path coefficients

Hypothesis	Path	Standarised estimate	Unstandarised Estimate	S.E.	C.R.	p	Comments
H1.	PE → ATT	0,071	0,098	0,045	2,164	0,030	Supported
H2.	PE → BI	0,290	0,278	0,036	7,738	<0,001	Supported
H3.	EE → ATT	0,086	0,130	0,053	2,453	0,014	Supported
H4.	EE → BI	0,085	0,089	0,042	2,115	0,034	Supported
H5.	SI → ATT	–0,102	–0,156	0,037	–4,210	<0,001	Supported
H6.	SI → BI	0,128	0,135	0,031	4,400	<0,001	Supported
H7.	FC → ATT	–0,024	–0,046	0,073	–0,636	0,525	Not supported
H8.	FC → BI	0,040	0,053	0,057	0,932	0,351	Not supported
H9.	TRST → ATT	0,607	0,638	0,030	21,022	<0,001	Supported
H10.	TRST → BI	0,131	0,095	0,044	2,162	0,031	Supported
H11.	HM → ATT	0,436	0,618	0,045	13,811	<0,001	Supported
H12.	HM → BI	0,164	0,160	0,050	3,203	0,001	Supported
H13.	HT → ATT	–0,097	–0,147	0,042	–3,516	<0,001	Supported
H14.	HT → BI	0,242	0,252	0,034	7,363	<0,001	Supported
H15.	ATT → BI	–0,014	–0,010	0,056	–0,172	0,864	Not supported

Attitudes (ATT) towards advertising materials generated using GenAI tools were most strongly influenced by perceived threat (TRST) (β=0.607; p<0.001) and hedonistic motivation (HM) (β=0.436; p<0.001). A positive, albeit weaker, effect was observed for expected performance (PE) (β=0.071; p=0.030) and expected effort (EE) (β=0.086; p=0.014). On the other hand, social influence (SI) (β=–0.102; p<0.001) and habit (HT) (β=–0.097; p<0.001) had a negative effect on attitudes. The effect of facilitating conditions (FC) proved to be insignificant (β=–0.024; p=0.525). In the case of behavioural intention (BI), a significant and strongest effect was found for perceived efficacy (PE) (β=0.290; p<0.001) and habit (HT) (β=0.242; p<0.001). Hedonic motivation (HM) (β=0.164; p=0.001), perceived threat (TRST) (β=0.131; p=0.031), social influence (SI) (β=0.128; p<0.001) and, to a lesser extent, expected effort (EE) (β=0.085; p=0.034) also played a significant role. Paths from attitude (ATT) (β=–0.014; p=0.864) and facilitating conditions (FC) (β=0.040; p=0.351) to behavioural intention were statistically insignificant. The observed lack of a significant relationship between attitudes and behavioural intention suggests that the mechanism of shaping consumers' behavioural intentions towards advertising materials generated using GenAI tools is more direct and does not require mediation by attitudes**.**

Next, indirect, direct and total effects were analysed.

Table 4. Indirect, direct and total effects

Path	Indirect Effects	Direct Effects	Total Effects
PE → BI	0,008	0,290***	0,298***
EE → BI	0,010	0,085*	0,095*
SI → BI	0,011	0,128***	0,139***
FC → BI	0,006	0,040	0,046
HM → BI	0,044	0,164**	0,208***
HT → BI	0,010	0,242***	0,252***
TRST → BI	0,061	0,131*	0,192***
ATT → BI	–	–0,014	–0,014

* p<0,05; **p<0,01; ***p<0,001

The bootstrapping procedure (2000 replicates) revealed that the indirect effects of all independent variables are statistically insignificant, which means that there is no mediation by attitude (ATT). The ATT → BI path remains insignificant (β = –0.014; p = 0.864), therefore none of the predictors indirectly influence behavioural intention (BI). The strongest total effects were obtained for expected performance (PE, β=0.298***), habit (HT, β=0.252***), hedonic motivation (HM, β=0.208***), and perceived threat (TRST, β=0.192***).

The PROCESS macro (ver. 4.1, model 1) was used to verify the moderating effects, and the results are presented in the table below.

Table 5. Moderating effects

Path	Moderator						
	Gender	**Age**	**Education**	**Financial situation**	**Interest in science fiction pop culture**	**Financial situation**	**Level of technological advancement**
PE → ATT	0,2641	0,1979	0,1944	0,5816	0,3427	0,5816	0,1839
EE → ATT	0,4996	0,1879	0,0104*	0,2309	0,4775	0,2309	0,0700
SI → ATT	0,2502	0,0768	0,0889	0,5737	0,0358*	0,5737	0,2872
FC → ATT	0,9406	0,0474*	0,0232*	0,4279	0,0511	0,4279	0,0170*
HM → ATT	0,6516	0,2729	0,2930	0,7232	0,7952	0,7232	0,0412*
HT → ATT	0,1170	0,0755	0,6759	0,9194	0,1331	0,9194	0,9009
TRST → ATT	0,1578	0,5466	0,1010	0,3534	<0,001*	0,3534	0,1493

*p<0,05

The analysis shows that the relationship between EE and ATT is moderated by education (beta=–0.105; SE=0.041; t=–2.57; p=0.0104; F(3, 1041)=324.09; p<0.001, R2=0.48). An increase in the value of the moderator weakens the positive effect of EE on ATT — the higher the level of education, the weaker the relationship between expected effort and attitude becomes. In the case of the relationship between SI and ATT, moderation was demonstrated in relation to interest in fantasy (beta=0.161; SE=0.077; t=2.10; p=0.0358; F(3, 1041)=148.90; p < 0.001, R2=0.30). An increase in the value of the MX2 moderator therefore increases the strength of the positive social influence on the attitude towards technology. The relationship between FC and ATT is moderated by the level of education (beta=–0.102; SE=0.045; t=–2.27; p=0.0232; F(3, 1041=274.88, p<0.001, R2=0.44), indicating that the strength of the influence of favourable conditions on attitude decreases with increasing education. This relationship is also moderated by age (beta=–0.004; SE=0.002; t=–1.99; p=0.0474; F(3,1041) =274.34; p<0.001; R=0.44), a negative moderating effect was observed, as well as the level of technological advancement (beta=0.072; SE=0.030; t=2.39; p=0.017; F(3,1041) = 280.38; p<0.001, R2=0.45) – as the level of technological advancement increases, the strength of this relationship increases. In the case of the relationship between HM and ATT, moderation was observed in relation to the level of technological advancement (beta=0.044; SE=0.022; t=2.04; p=0.0412; F(3,1041)=694.28; p<0.001, R2=0.67) – analysis of simple effects showed that the impact of HM on ATT is positive and significant at all levels of the moderator, and the strength of this relationship increases with its growth. Moderation was also observed in the relationship between TRST and ATT in relation to interest in science fiction pop culture (beta=0.144; SE=0.034; t=4.28; p<0.001; F(3,1041) = 899.34; p<0.001, R^2 = 0.72). A stronger relationship was observed among people who are not interested in science fiction pop culture than among those who declared such an interest.

DISCUSSION

The article analyses factors influencing the level of acceptance of advertising materials generated using generative AI, including, in particular, the impact of trust, habit and hedonistic motivation. In addition, it examines whether consumers' attitudes towards advertising materials generated using GenAI influence their behavioural intention.

Research has shown that consumer attitudes towards materials generated using GenAI were most influenced by trust in such materials. This may include issues such as the credibility and authenticity of these materials, as well as the belief that they do not deliberately mislead consumers, manipulate their emotions, present a false reality, or violate their fundamental rights. Consumers who trust that the materials are credible and ethical are more likely to form positive attitudes towards them, which is consistent with previous research on trust (Siau & Wang, 2018; Taherdoost, 2018). The positive impact of hedonistic motivation on consumer attitudes towards advertising materials generated using GenAI is also not surprising. Such materials allow for the creation of highly attractive texts, photos or videos used in advertising campaigns (e.g., humour, engaging narrative, surprise effect, etc.), which provide aesthetic pleasure and, often, entertainment value. The pleasure experienced by consumers who encounter them will influence their positive attitudes towards them. These results are consistent with most of the existing research on the impact of trust and hedonistic motivation on the level of acceptance of digital technologies, new solutions based on these technologies, and expectations towards them.

Research has shown the negative impact of AI on consumer attitudes towards materials generated using GenAI (the impact of AI on attitudes is evident, for example, in studies by Johnson et al, 2008; Hsu&Lin, 2015). The negative impact of AI observed in this case may be the result of the prevailing scepticism towards this technology in the public sphere and the narrative focusing on the risks and challenges associated with it. It may also be due to the fact that these materials are very often not labelled, which leads to a lack of transparency towards consumers. As a result, consumers may perceive such materials as less credible or socially unacceptable when they observe, for example, negative reactions from their immediate environment towards this technology or its implementation in creative sectors, including advertising.

Assuming that habit is understood as the degree to which consumers automatically respond to advertising content by referring to previously developed cognitive and behavioural patterns, its negative impact on consumer attitudes towards advertising materials generated using GenAI tools does not seem surprising. Consumers, having established patterns of receiving advertising materials and consuming advertising content, may reject those that deviate from their existing, familiar standards, regardless of their attractiveness or quality (substantive, visual, aesthetic). Interestingly, however, our research shows that habit also has a positive impact on Behavioural Intention, suggesting that it functions as a mechanism that facilitates quick decision-making, regardless of initial uncertainty or scepticism towards such advertising materials. This correlation was also evident in other studies by the authors concerning the level of acceptance of AI wearables (Sułkowski&Kaczorowska-Spychalska, 2021). As a result, consumers may display a negative attitude towards materials generated using GenAI tools, but at the same time, despite this, automatically respond to them (positive behavioural intention). Moreover, the consumer's inability to identify which advertising materials were generated using GenAI tools can often exacerbate the observed relationship.

The behavioural intention of consumers was most influenced by expected performance, which may be due to the fact that consumers are more likely to take actions that they perceive as useful in achieving their goals and specific results. In the context of advertising materials generated using GenAI tools, it can be assumed that consumers who believe that such materials will provide them with valuable information that will facilitate their decision-making or purchasing process, as well as improve their experience of that process, will be more inclined to accept such materials. The observed correlation may be similar to that indicated by the authors in their earlier studies on payment implants. Negative opinions, often verbalised in the social sphere, influenced consumer attitudes, but at the same time, individual assessment of such implants depended on the level of perception of the pragmatic aspects they provided (Sułkowski&Kaczorowska-Spychalska, 2023).

The influence of favourable conditions (FC) proved to be insignificant, both in terms of shaping attitudes and behavioural intentions of consumers towards advertising materials generated using GenAI tools, which means that the technological, legal or information environment does not have to be a factor supporting their interaction with this type of material.

Interestingly, the study found no significant relationship between consumer attitudes towards advertising materials generated using GenAI tools and behavioural intention. This contradicts a significant portion of the research on the relationship between these variables. This indicates that the process of behavioural intention formation in this case is direct and does not require mediation by attitudes. Perhaps this is due to the fact that consumers will be guided primarily by the benefits that such materials provide them (e.g., personalisation of content or attractive visual form), marginalising their attitudes (positive or negative) towards the fact that they were generated with the support of generative AI tools. This may then indicate ambivalence in consumer attitudes and/or behaviour, as previously indicated by van Harreveld (van Harreveld et al., 2015).

Research has confirmed the influence of certain moderating factors: age (which is consistent with, among others, the research of Zhan et al., 2023), education, technological sophistication (subjective consumer assessment) (confirmed, among others, by the research of Yang et al., 2016; Gao et al., 2022) and interests (Hick & Ziefle, 2022). And although it is accepted that moderating factors are important, it is also noted that in some situations, some of them may be of little or no significance (Jeyaraj et al., 2019), which is evident in the study.

IMPLICATIONS FOR RESEARCH AND APPLICATION

Our research expands the existing knowledge on the factors determining the level of acceptance of GenAI tools in the advertising sector, contributing to the development of research on the conditions of perception and acceptance of advertising materials generated using generative artificial intelligence. We have thus responded to Alkhowaiter's suggestion that further research based on the meta-UTAUT model should include additional variables that allow for the modification of existing research constructs. In this way, our research expands on existing empirical results. The results obtained are also relevant to market practice from the point of view of the use of this technology in marketing departments, including advertising, as well as in media houses and advertising agencies.

We pay particular attention to the key importance of trust and hedonistic motivation in shaping consumer attitudes towards such materials. Research shows that, on the one hand, it is important to build consumer trust in this type of advertising material by ensuring transparency, e.g. in terms of authorship, credibility and ethical aspects. On the other hand, it is important that these materials are visually appealing and engaging so that consumers enjoy interacting with them. It would be advisable to expand this research to include constructs related to the perceived credibility and authenticity of such materials, as well as the aesthetic pleasure and satisfaction experienced by consumers when interacting with them.

Research has also shown that consumers will be more likely to engage with AI-generated messages when they see specific, objective benefits in them (e.g., the ability to make optimal purchasing decisions). Their habits also proved to be significant. Established consumer patterns regarding the perception of advertising materials may limit their openness to the effects of human and GenAI work in advertising. Therefore, it seems reasonable to design such materials in a way that ensures a balance between innovation and consumer habits, which may alleviate their distrust.

Finally, research indicates that the process of shaping consumers' behavioural intentions is largely direct and does not require the mediation of attitudes. However, this topic should be further analysed, especially considering the diversity of advertising materials created using GenAI tools. The results obtained mean that consumers may engage with GenAI materials primarily based on their usefulness or suitability to their own needs and expectations, regardless of their emotional evaluation. Therefore, the use of generative artificial intelligence in advertising should not be seen merely as a ‘trendy’ technological innovation, but as a well-thought-out, well-planned element that allows for more precise targeting of consumers. This can have a positive impact not only on the effectiveness and efficiency of future campaigns, but also on the long-term engagement of consumers with brands that use GenAI tools to create their advertising materials.

LIMITATIONS

As with most studies, the results of this article should be interpreted with its limitations in mind. Firstly, the study was conducted among consumers in a single country, which limits the generalisability of the results. The level of acceptance of advertising materials generated using GenAI tools may be strongly influenced by socio-cultural factors, the level of digitisation of society, and regulations governing the use of GenAI tools, including in advertising, from the point of view of the potential risk of consumer rights violations. It is therefore advisable to extend the research to other countries. This will allow for a comparative analysis in an intercultural context, which will result in the identification of potential similarities and differences in the level of acceptance of advertising materials generated using GenAI, as well as the identification of factors and patterns determining this process.

The study was based on consumers' declarative opinions, which may not fully reflect their actual behaviour when interacting with advertising materials generated using GenAI. It would therefore be worthwhile to supplement the research with an analysis of consumers' actual reactions to such materials, including experimental studies.

Furthermore, the high average age of respondents indicates the need for more in-depth analysis in an intergenerational dimension. Younger users, who are more familiar with digital technologies, may have different attitudes towards advertising materials generated using GenAI, which will be important for both their behavioural intentions and their actual decision-making or purchasing behaviour.

Finally, it should be noted that GenAI is developing rapidly. What is more, on the one hand, its democratisation is increasing, which affects consumers' knowledge and skills, and on the other hand, its market absorption, including in advertising, will gradually increase, which means that consumer attitudes and behaviours may change quickly. This means that research in this area should be systematically reviewed to identify trends in the acceptance of advertising materials created using GenAI.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Appendix

Please rate the following statements on a scale of 1 to 5, based on your own experience, where 1 means “strongly disagree” and 5 means “strongly agree”.

		1	2	3	4	5
Performance Expectancy PE	PE1. I find generative AI tools useful in my daily life					
	PE2. Using generative AI tools increases my chances of achieving things that are important to me					
	PE3. Using generative AI tools helps me achieve my goal faster					
	PE4. Using generative AI tools increases my productivity					
Effort Expectancy EE	EE1. Learning how to use generative AI tools is easy for me					
	EE2. My interaction with generative AI tools is clear and understandable					
	EE3. I believe that generative AI tools are easy to use					
	EE4. It is easy for me to become proficient in using generative AI tools					
Social Influence SI	SI1. People who are important to me think that I should use generative AI tools					
	SI2. People who influence my behaviour think that I should use generative AI tools					
	SI3. People whose opinions I value prefer me to use generative AI tools					
Facilitating Conditions FC	FC1. I have the resources necessary to use generative AI tools					
	FC2. I have the knowledge necessary to use generative AI tools					
	FC3. Generative AI tools do not cause problems when using other technologies that I work with					
	FC4. I can get help from others when I have problems using generative AI tools					
Hedonic Motivation HM	HM1. Using generative AI tools is fun					
	HM2. Using generative AI tools is enjoyable					
	HM3. Using generative AI tools is very interesting					
Habit HT	HT1. Using generative AI tools has become a habit for me					
	HT2. I am addicted to using generative AI tools					
	HT3. I need to use generative AI tools					
	HT4. Using generative AI tools has become natural for me					
Trust (TRST)	TRST1. I trust GenAI systems and tools					
	TRST2. I consider GenAI systems and tools to be secure					
	TRST 3. I consider GenAI systems and tools to be trustworthy					
Behavioural Intention BI	BI1. I intend to continue using generative AI tools in the future					
	BI2. I will always try to use generative AI tools in my daily life					
	BI3. I plan to use generative AI tools frequently					
Attitudes (ATT)	ATT1. Using generative AI is a wise idea					
	ATT2. I enjoy using generative AI					
	ATT3. Using generative AI is fun					
	ATT4. Using generative AI is beneficial					
	ATT5. Using generative AI is interesting					

Gender

☐ Woman ☐ Man ☐ I don't want to disclose

Age

☐ up to 24 years old ☐ 25–34 years old ☐ 35–44 years old
☐ 45–54 years old ☐ 55–64 years old ☐ 65 years and older

Education

☐ Basic ☐ Medium ☐ Higher

Financial situation

 Very bad Bad Average Good Very good

Place of residence

 Village Town with up to 10,000 inhabitants
 Town with a population of 10,001 to 50,000
 Town with a population of between 50,001 and 100,000
 Town with a population of between 100,001 and 200,000
 Town with a population of between 200,001 and 500,000
 City with a population of over 500,000

I rate my level of technological advancement on a scale of 1 to 5, where: 1 means a low level of technological advancement or a lack thereof, and 5 means a very high level of technological advancement:

 1 2 3 4 5

Interest in science fiction pop culture

 Yes No

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 21(3), December 2025, 668–693

THE ROLE OF GOVERNMENT AI READINESS IN SHAPING RENEWABLE ELECTRICITY CAPACITY AND OUTPUT

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Abstract: *The accelerating energy transition increasingly depends on human–AI interaction in government, how public agencies, regulators, and system operators use AI to plan, permit, and manage renewable integration while maintaining reliability. This study examines whether Government AI Readiness is associated with renewable electricity development, distinguishing between installed capacity and total generation. An unbalanced panel of 179–183 countries (2020–2024) combines Government AI Readiness Index scores with renewable capacity and generation data and GDP per capita (IRENA/World Bank), analysed using transformed variables, diagnostics, and fixed/random effects panel models in R. Government AI Readiness is positively and significantly linked to total installed renewable capacity; in the FE model, a one-point increase in AI readiness is associated with ~0.017 higher log installed capacity (p < 0.001). No significant association is found for total renewable generation, implying that AI-ready governance may accelerate infrastructure rollout without automatically increasing output due to operational, infrastructural, or climatic constraints.*

Keywords: *artificial intelligence, government AI readiness, energy transition, renewable electricity capacity, renewable electricity generation, panel data analysis.*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.9

INTRODUCTION

Governments worldwide are rapidly expanding investments in renewable energy to meet ambitious climate goals. According to the International Energy Agency, global renewable energy installations broke records in 2024 – adding around 700 GW, with renewables accounting for 38% of global energy supply growth (IRENA, 2025). However, IRENA (2025) underscores that this pace falls short of what is needed; to triple global renewable capacity by 2030 in alignment with the 1.5 °C pathway, renewables must grow at an annual rate of 16.6 %, far exceeding current trends. At the same time, the IEA's flagship Energy and AI report reveals that AI not only increases electricity demand, particularly via energy-intensive data centres, but also holds strong potential to optimise energy systems, enhance grid capacity, and improve cost-efficiency via data-driven deployment and operations.

AI has emerged as a strategic enabler for renewable energy deployment and integration. The IRENA (2019) identifies AI and big data among the six principal categories of innovation needed to integrate variable renewable energy into power systems. These technologies improve forecasting accuracy, enable real-time grid optimisation, and support predictive maintenance, ultimately enhancing system flexibility, reducing operational disruptions, and improving the efficiency of renewable energy installations.

Moreover, the World Bank (2025) underscores how digital transformation, including AI, can modernise energy infrastructure and help scale up renewable energy deployment. Their energy overview highlights that AI-powered digital tools, such as those for grid management and demand forecasting, are critical for increasing system efficiency and reducing energy losses, supporting the broader adoption of clean energy sources. By combining technological readiness with structural energy transition strategies, these developments position AI as a linchpin in overcoming key operational and infrastructural challenges in the shift to clean electricity.

In this context, understanding the *role of government AI readiness* in facilitating renewable energy development is more relevant than ever. AI readiness reflects a government's capacity to harness digital infrastructure, governance frameworks, and human capital to support innovation in the energy sector. While agencies like the IEA spotlight the AI–energy nexus, and policy memos such as those by the U.S. Department of Energy outline AI's deployment opportunities in planning and grid management (UNESCO, n.d.), systematic empirical evidence on how government AI capabilities translate into renewable energy installation and generation remains sparse. This gap underscores the urgency of exploring whether AI preparedness is a meaningful enabler of renewable energy transitions, which is precisely the focus of this study.

Renewable electricity capacity expansion and output growth increasingly depend not only on resource endowments and market incentives, but also on a country's ability to plan, regulate, finance, and digitally operate complex energy systems. This shifts attention towards "government AI readiness" as a public-sector capability that can accelerate renewable deployment through better forecasting, permitting, grid management, risk oversight, and the quality of public services supporting the energy transition (Androniceanu, 2024; Murko et al., 2024). Government AI readiness is also intertwined with broader governance quality and integrity, because the benefits of digital decision-support tools depend on transparency, accountability, and bias control in public administration (Pollifroni et al., 2025; Yefimenko et al., 2025a). At the macro level, readiness can affect economic confidence and investment conditions by strengthening state capacity to manage shocks and coordinate infrastructure programmes, which is relevant in turbulent periods when energy markets and inflation pressures co-move (Senci & Afful, 2025; Wołowiec et al., 2022).

The research landscape therefore suggests a plausible “public capability channel”: higher government AI readiness supports faster renewable electricity capacity growth and more stable renewable output by improving policy execution, market coordination, and operational efficiency across the electricity value chain. This channel is consistent with the expansion of digital governance models and AI-enabled public management, where administrative performance and socio-economic welfare outcomes increasingly reflect digital maturity and institutional design (Androniceanu, 2024; Murko et al., 2024). At the same time, this landscape also highlights constraints, ethical safeguards, skills, organisational adoption, and the political economy of reforms, without which AI readiness may remain symbolic rather than productive for the energy transition (Mujtaba, 2025; Mura & Stehlíková, 2025).

Defining the capability base: governance, ethics, skills, and adoption as prerequisites

A first cluster of studies frames AI readiness as a governance and institutional capacity issue rather than a purely technological one. Public administration perspectives emphasise that generative AI and automation reshape public-sector processes, but the realised value depends on how governments design rules, oversight, and service delivery models (Androniceanu, 2024; Murko et al., 2024). Because electricity transitions rely on long-horizon planning and high-trust regulation, ethical governance becomes directly relevant: AI systems can amplify opacity, bias, and unequal access if safeguards are weak, which may undermine public acceptance of energy reforms and infrastructure decisions (Haley, 2025; Mujtaba, 2025). The literature further stresses the need to protect human dignity and social justice while also considering environmental stability when scaling AI in governance and the economy, implying that “readiness” should include normative and regulatory maturity, not only technical infrastructure (Mura & Stehlíková, 2025).

A second enabling dimension is human capital and organisational adoption. Evidence on intention to use AI and the competence structure of effective AI use indicates that readiness is shaped by skills, perceived usefulness, and organisational conditions, factors that matter in public utilities, regulators, and state-owned network operators as much as in private firms (Alhammadi, 2025; Popa et al., 2024). Related work shows that technological competence can moderate sustainability-oriented HRM effectiveness when AI is embedded into management systems, suggesting that capability complements (skills, processes, and culture) condition the transition benefits of digital tools (Abid et al., 2024). This adoption lens is reinforced by research on AI in project management, where bibliometric mapping implies a growing emphasis on how AI changes planning, coordination, and delivery, precisely the domains critical for renewable energy programmes and grid investments (Ibadildin et al., 2025).

A third prerequisite concerns integrity and trust. Awareness of unethical AI and mitigation measures points to the practical need for risk identification, standards, and training to prevent harmful or unreliable AI use (Höller et al., 2023). Broader societal attitudes (ranging from fear to hope) also shape how technology-led reforms are received, which can indirectly influence the political feasibility of renewable energy expansion and the acceptance of operational digitalisation (Yarovenko et al., 2024). In education and research systems, the relationship between AI, integrity, and capability building is likewise highlighted as a condition for sustainable skill pipelines and trustworthy innovation ecosystems (Artyukhov et al., 2024b).

Linking AI readiness to the macro investment environment and sustainable finance for renewables

Renewable electricity capacity is capital intensive, so the literature on digitalisation, sustainable finance, and ESG performance provides an important bridge between AI readiness and renewables. International evidence indicates that ICT development is associated with improved ESG performance, which can strengthen the investment narrative and disclosure environment relevant to green power finance (Zheng et al., 2024, Azizov et al., 2023). Complementary work stresses ICT investment as a strategic imperative for organisational change, consistent with the view that digital infrastructure and institutional learning are necessary conditions for large-scale transition investments (Sahnouni & Kadri, 2025; Jabijev et al., 2022). AI-enabled financial analytics is also entering sustainable markets, with evidence on applying advanced AI to green bond market prediction illustrating how digital tools can support pricing, risk management, and market depth for transition instruments (Sembiyeva et al., 2024). Broader linkages between sustainable-ethical assets and dynamic relationships in financial markets suggest that digital maturity can influence how investors allocate capital across “green” and “ethical” segments, potentially affecting renewable project financing conditions (Nuzula Agustin et al., 2025).

Macroeconomic cycles and structural conditions remain crucial. Evidence from EU countries links the business cycle to renewable energy consumption and sustainable development, indicating that expansion conditions can amplify or dampen renewable uptake (Bușu et al., 2024). In parallel, research on balancing growth and environmental management shows the importance of CO_2 efficiency and renewables within EU development pathways, underscoring that digital governance and AI readiness could matter most where the state can align growth, climate targets, and energy investment planning (Dilanchiev et al., 2024). Because inflation and unemployment dynamics still condition policy space, fiscal support, and household welfare, macro-stability remains a background constraint in which AI-enabled state capacity may improve targeting and efficiency of transition policies (Senci & Afful, 2025; Naumenkova et al., 2025).

Energy-system determinants: capacity deployment, renewable output, and energy security as interacting outcomes

A second major stream maps determinants of renewable electricity penetration and the broader energy-security context. Evidence on renewable penetration in Nordic and Baltic EU countries highlights that renewable development is uneven even in advanced regions, implying that institutional capacity and system management quality can be differentiators beyond resource availability (Štreimikienė, 2024). Systematic review evidence for Greece reinforces that renewable and non-renewable consumption co-evolves with economic structure and policy design, implying that the “capacity-to-output” relationship is mediated by system integration constraints and demand-side conditions (Triantafyllidou et al., 2024). Cross-country causality and cointegration analyses across Nordic and South-Eastern European states further indicate that macroeconomic factors and energy variables are jointly determined over time, strengthening the rationale for governance capabilities that can coordinate interdependent policy levers (Georgescu et al., 2024).

The literature also emphasises that renewables are linked to energy security and resilience, especially under geopolitical risk. Evidence that renewable energy can enhance energy security (under certain dynamics and contexts) implies that accelerating renewables has strategic value, and that AI readiness may shape how effectively countries convert renewable investment into security outcomes (Havrylenko & Myroshnychenko, 2025). Composite approaches to evaluating economic, environmental, and energy security, as well as analyses of sustainable governance in turbulent times, underscore that energy outcomes depend on multidimensional institutional performance, an environment where AI-enabled monitoring and decision support could improve coherence and responsiveness (Mentel et al., 2020; Wołowiec et al., 2022). At the service-delivery level, determinants of consumer satisfaction with energy services highlight that reliability, affordability, and responsiveness are crucial for social acceptance, suggesting a role for data-driven governance in managing distributional trade-offs during renewable energy scaling (Ghimire et al., 2025; Naumenkova et al., 2025).

Operational digitalisation on the demand side also affects the integration of renewable output. Adoption scenarios for home energy management systems illustrate how household-level digital technologies can shape load profiles, flexibility, and the effective utilisation of intermittent renewables (Gualandri & Kuzior, 2023). Because these demand-side tools typically require supportive regulation, standards, and consumer trust, the public-sector readiness component becomes relevant to turning digital adoption into system-level renewable output gains (Murko et al., 2024; Yarovenko et al., 2024).

Innovation ecosystems and entrepreneurship: how readiness shapes the pipeline of renewable projects

Capacity growth is constrained not only by grid and finance, but also by the project pipeline, start-ups, innovators, and investable ventures. Evidence on barriers to clean and digital energy start-ups suggests that access to credit and investor rights protection are key conditions, implying that state capacity and regulatory quality (potentially enhanced by AI-ready governance) influence renewable innovation and project creation (Artyukhov et al., 2024a). This is reinforced by studies of renewable energy entrepreneurship that highlight investment risks and the need for supportive institutional arrangements to mobilise capital and reduce uncertainty (Dobrovolska et al., 2024). Regulatory barriers and bibliometric mapping of entrepreneurship constraints suggest that policy complexity and administrative frictions can hinder renewable deployment, highlighting a concrete pathway where AI-enabled public administration could reduce transaction costs and enhance policy targeting (Myroshnychenko et al., 2024).

A related perspective emphasises decentralisation of energy sources and renewability as a co-evolving research and policy theme, implying that local governance capacity and digital coordination tools are increasingly important for integrating distributed renewable assets into national systems (Belgibayeva et al., 2025). This decentralised landscape also connects to waste and circular economy domains, where AI-enabled industrial automation and municipal waste management can contribute to sustainability performance and potentially to energy-from-waste strategies within broader low-carbon transitions (Kajda & Karwot, 2025; Matvieieva et al., 2023). Technological efficiency in production and consumption within a circular economy framing likewise suggests that country-level technological maturity shapes sustainability outcomes, consistent with the proposition that AI readiness strengthens the efficiency frontier for transition pathways (Gedvilaite & Ginevicius, 2024).

Sectoral digital transformation: supply chains, digital twins, and infrastructure coordination for renewables

Renewable electricity capacity and output depend on equipment supply chains, construction delivery, and operational analytics. Evidence that digital technologies and AI improve supply-chain efficiency supports a mechanism where higher AI readiness can reduce delays, improve procurement transparency, and stabilise renewable build-out (Golubtsov et al., 2025). This aligns with evidence linking AI technology to energy security through global supply-chain channels, suggesting that AI-enabled logistics and risk sensing can influence both the pace of capacity additions and the reliability of renewable output (Wang et al., 2025). The emerging literature on digital twin and industrial metaverse systems also signals a shift towards simulation, predictive maintenance, and complex system modelling, which are directly relevant for grid integration, renewable asset performance, and planning of flexible capacity (Kliestik et al., 2024).

Applied innovation evidence in power generation, such as project-level technological developments, illustrates the ongoing role of engineering innovation in shaping capacity and output trajectories, again implying that public-sector capability (permitting, standards, public procurement) affects diffusion (Ziaja & Lichota, 2024). Studies on AI use in energy and climate security reinforce the expectation that AI readiness can influence strategic planning and risk management around climate-energy objectives, strengthening the readiness-to-renewables link in security-relevant contexts (Mammadov et al., 2025). These mechanisms become especially salient in countries facing heightened geopolitical risks and large infrastructure modernisation needs, including EU–Ukraine integration and reconstruction contexts (Makarenko & Vorontsova, 2024; Vakulenko & Rekunenko, 2025).

The distributional and public health dimension: why output gains must align with welfare outcomes

Renewable electricity expansion is often justified by environmental and health benefits, and this welfare framing shapes political support. Evidence connecting pollution reduction strategies to renewable transition highlights health improvement pathways, implying that capable governments can use data and AI to target interventions and strengthen the credibility of transition policies (Badreddine & Larbi Cherif, 2024). Related work on public health impacts of waste incineration and energy recovery underlines that technology choices require careful governance, monitoring, and communication—areas where AI-ready institutions may better manage externalities and compliance (Matvieieva et al., 2023). Broader AI ethics discussions in public health and automated enforcement remind that technology-led governance must address equity and social justice, suggesting that AI readiness should include safeguards to prevent new forms of exclusion during transition implementation (Haley, 2025; Mura & Stehlíková, 2025).

Distributional concerns are particularly evident in energy poverty. Evidence on government support mechanisms for addressing energy poverty in low-carbon transitions indicates that policy design and administrative capacity matter for protecting vulnerable households while scaling renewables (Naumenkova et al., 2025). This links to consumer behaviour and acceptance dynamics in digital contexts, where AI-driven change can alter trust, habits, and willingness to adopt new services, relevant for demand response, smart metering, and tariff reforms that affect renewable output utilisation (Dias et al., 2023; Gualandri & Kuzior, 2023).

Spatial talent dynamics and institutional spillovers: readiness, brain drain, and capacity to deliver transition

Government AI readiness also has spatial and labour-market implications that can feed back into renewable deployment capacity. Evidence on the relationship between government AI readiness and brain drain in the EU implies that readiness is embedded in broader socio-economic attractiveness and institutional performance; weaker readiness may accelerate talent outflows, undermining the technical and administrative capacity needed for renewable project pipelines (Iuga & Socol, 2024). Organisational leadership and resilience research similarly suggests that AI can enhance sustainable leadership and adaptability, implying that readiness may strengthen institutions' ability to deliver complex transition agendas under uncertainty (Koldovskyi et al., 2025). Governance innovations in e-recruitment and bias-free decision-making further show that AI can improve transparency and administrative quality when used responsibly, an enabling condition for large-scale infrastructure programmes and trust-based regulation (Pollifroni et al., 2025; Yefimenko et al., 2025a).

Broadening the behavioural and societal context: technology acceptance, emotions, and legitimacy

Even when state capacity is strong, renewable outcomes depend on public legitimacy and behavioural responses. Research on consumer eco-emotions in novel sustainability markets signals that emotional and value-based responses can influence acceptance of environmentally framed innovations, suggesting that governments need communication and engagement capacity alongside technical readiness (Kouarfaté et al., 2024). Evidence on AI-driven customer feedback management and content analysis highlights how AI can support responsive governance and service improvement by processing large-scale citizen input—potentially relevant for siting decisions, community acceptance, and continuous improvement in renewable programmes (Kildei et al., 2025; Murko et al., 2024). Studies on the creative economy and expert perceptions of AI adoption underscore that opportunities and barriers are context-specific, reinforcing the argument that readiness includes institutional learning and adaptation rather than simply technology acquisition (Schinello, 2025; Yarovenko et al., 2024).

Technology acceptance evidence from adjacent domains, such as digital insurance adoption among older adults and smart financial strategies for ageing populations, illustrates that demographic factors, trust, and perceived value shape uptake of digital services, implying parallels for smart energy services and the household-facing components of renewable integration (Batizani, 2024; Chandran & Ittimani Tholath, 2025). In parallel, occupational safety applications of AI-based image analysis highlight that AI readiness can improve compliance and risk management in construction-like environments, offering an additional pathway for safer, more efficient renewable infrastructure delivery (Zaryczańska & Karwot, 2025).

Ukraine–EU transition context: reconstruction, integration, and the strategic role of readiness

In transition and reconstruction settings, the linkage between AI readiness and renewable electricity outcomes becomes particularly policy-relevant. Evidence on green energy in Ukraine highlights the state of development, public demand, and trends, implying that readiness and governance quality may shape how quickly renewable capacity can scale and how effectively output is integrated into a resilient system (Kuzior et al., 2021). EU–Ukraine benchmarking work and clean energy cooperation initiatives reinforce that harmonisation, institutional capacity, and project governance are central to transition success, suggesting that government AI readiness can support the administrative and analytical demands of integration and rebuilding (Makarenko & Vorontsova, 2024; Vakulenko & Rekunenko, 2025). Environmental tax reform and carbon tax research mapping further position fiscal instruments as complements to capability-driven implementation, implying that AI-ready institutions may better design, monitor, and enforce market-based transition policies while limiting unintended effects (Kusumawati et al., 2025; Samusevych et al., 2024).

Evidence linking the share of renewables to CO_2 emissions over long horizons supports the basic motivation for capacity and output expansion, but it also implies the need for consistent governance to maintain policy credibility and investment continuity across cycles (Tutar & Bilan, 2025; Dilanchiev et al., 2024). Finally, sectoral evidence on climate mitigation performance in tourism destinations indicates that transition performance varies across sectors and regions, again pointing to the value of state capability and digital governance tools to coordinate cross-sector decarbonisation efforts (Streimikiene & Kyriakopoulos, 2024).

Overall, the existing literature implies that government AI readiness can shape renewable electricity capacity and output through multiple, mutually reinforcing pathways: (i) higher-quality public governance and ethical safeguards that enable trustworthy digital decision-making; (ii) stronger human capital and organisational adoption capacity; (iii) better mobilisation of sustainable finance and improved ESG environments; (iv) more efficient supply chains and project delivery; and (v) improved distributional targeting and legitimacy that stabilise transition policy over time (Androniceanu, 2024; Zheng et al., 2024; Golubtsov et al., 2025; Naumenkova et al., 2025; Wołowiec et al., 2022). However, the same landscape suggests that these effects are conditional on complementary institutions and social acceptance, meaning readiness is unlikely to translate into renewable outcomes uniformly across countries and phases of transition (Mujtaba, 2025; Höller et al., 2023; Iuga & Socol, 2024). This motivates empirical analysis that explicitly connects government AI readiness to renewable electricity capacity and output while accounting for institutional quality, macroeconomic conditions, and energy-system constraints, especially in turbulent geopolitical environments where the payoff to state capability may be highest (Havrylenko & Myroshnychenko, 2025; Mammadov et al., 2025; Mentel et al., 2020).

This research aims to empirically examine the extent to which Government AI Readiness influences the development of renewable energy systems by assessing its relationship with (i) Total Renewable Electricity Installed Capacity and (ii) Total Renewable Electricity Generation across a global panel of countries.

This study formulates two core hypotheses based on the theoretical link between technological readiness, institutional capacity, and the transition to sustainable energy systems. The first hypothesis (H1) posits that higher Government AI Readiness is positively associated with greater Total Renewable Electricity Installed Capacity. This assumption reflects that AI readiness enhances a country's ability to plan, finance, and deploy renewable energy projects by improving decision-making, optimising resource allocation, and streamlining project implementation. The second hypothesis (H2) proposes that higher Government AI Readiness is positively associated with greater Total Renewable Electricity Generation. This relationship is expected because AI-driven tools can optimise system operations, improve grid integration of intermittent renewables, and enhance efficiency in energy production. These hypotheses aim to capture both the infrastructural and operational dimensions of the renewable energy sector that could be influenced by a country's preparedness to adopt and utilise artificial intelligence technologies.

METHODS

Data and variables

The analysis employs an unbalanced panel dataset covering 179–183 countries (the samples of countries for analysis are presented in Appendix A) over the period 2020–2024. The primary independent variable is the Government AI Readiness Index (*x1*), compiled annually by the Oxford Insights AI Readiness Index database (Oxford Insights, n.d.). This index measures a nation's preparedness to implement and leverage artificial intelligence across governance, infrastructure, and human capital dimensions.

Two dependent variables are examined:

1. Total Renewable Electricity Installed Capacity (*y1*, MW), and
2. Total Renewable Electricity Generation (*y2*, GWh),

sourced from the International Renewable Energy Agency Statistics Database (IRENA, n.d.).

The primary control variable is GDP per capita (constant 2015 US$) (*x3*), obtained from the World Bank's World Development Indicators (World Bank, n.d.), serving as a proxy for economic development and financial capacity to invest in renewable energy.

Data transformation and normalisation

Descriptive statistics revealed that *y1*, *y2*, and *x3* exhibited substantial positive skewness and leptokurtosis, indicating non-normal distributions and the presence of extreme values. The Box–Cox procedure was applied to each variable using intercept-only models to determine the optimal transformation. These transformations reduce skewness, mitigate the influence of outliers, stabilise variance, and align with standard econometric practice in energy economics, where proportional changes are often of primary interest.

Econometric specification

The empirical analysis estimates Fixed Effects (FE) and Random Effects (RE) panel regression models using the plm package in R. The general model specification is:

$$y_{it}=\beta_0+\beta_1 x1_{it}+\beta_2 x3_{it}+\mu_i+\epsilon_{it}$$

Where y_{it} represents either $ln(y1)$ or $ln(y2)$ for country *i* in year *t*, $x1_{it}$ is the Government AI Readiness Index, $x3_{it}$ is *ln(GDP per capita)*, μ_i denotes unobserved country-specific effects, and ϵ_{it} is the idiosyncratic error term.

The FE model controls for time-invariant unobserved heterogeneity, while the RE model assumes these effects are uncorrelated with the regressors. Model selection between FE and RE was guided by the Hausman test, where a statistically significant result favours the FE specification.

Diagnostic testing

Diagnostic tests were performed on the FE models to check for heteroskedasticity and serial correlation, ensuring robust inference.

- Heteroskedasticity was tested using the studentised Breusch–Pagan test.
- Serial correlation was examined using both the Breusch–Godfrey/Wooldridge test for panel models and Wooldridge's test for autocorrelation in FE panels.

For both *y1_log* and *y2_log* models, the null hypotheses of homoskedasticity and no serial correlation were rejected, indicating violations of classical OLS assumptions.

Robust standard errors

Given heteroskedasticity and autocorrelation, all FE models were re-estimated using cluster-robust standard errors to produce consistent estimates. Two clustering strategies were applied:

1. One-way clustering by entity (country), and
2. Two-way clustering by both entity and year.

In all cases, results were robust to the choice of clustering dimension, and statistical significance levels remained consistent across specifications.

All statistical calculations, data transformations, model estimations, and diagnostic tests were conducted in RStudio (version 4.4.0), ensuring the reproducibility and transparency of the analytical process.

RESULTS

AI readiness and total renewable electricity installed capacity

Table B1, Appendix B, presents the descriptive statistics for the panel dataset, which comprises 901 country–year observations from 2020 to 2024. The dataset covers 183 countries, with the panel balanced in terms of temporal coverage.

The Government AI Readiness Index (x1) has a mean score of 46.08 (SD = 16.71), ranging from 13.46 to 88.16. The moderate skewness (0.46) and slight platykurtosis (–0.89) indicate a distribution that is close to symmetric, with no severe deviations from normality.

The dependent variable Total Renewable Electricity Installed Capacity (MW) (y1) exhibits substantial dispersion (mean = 19,292.18; SD = 103,500.04) and an extensive range (0.43 to 1,817,956.01). The extreme positive skewness (12.18) and very high kurtosis (171.46) indicate a highly non-normal distribution with strong right-tail outliers.

Similarly, GDP per capita (constant 2015 US$) (x3) is positively skewed (2.21) and leptokurtic (5.16), indicating a heavy-tailed distribution and substantial cross-country variation.

In contrast, Total Renewable Electricity Generation (GWh) (y2, not displayed in this excerpt) exhibits comparable distributional patterns to y1, with high variability and right skewness, reflecting the concentration of renewable energy generation in a subset of high-capacity countries.

Given the extreme skewness and kurtosis in y1and x3, statistical transformations – such as logarithmic or Box–Cox – are necessary to normalise distributions, reduce the impact of extreme values, and satisfy econometric model assumptions.

A Box–Cox transformation was applied using an intercept-only model for each variable to identify the most appropriate functional form for the highly skewed variables. For Total Renewable Electricity Installed Capacity (MW) (y1), the estimated Box–Cox parameter λ was 0.0606, which lies very close to zero. This outcome indicates that a natural logarithm transformation is optimal, as it effectively reduces the extreme right skewness (12.18) and high kurtosis (171.46) observed in the descriptive statistics. The log transformation mitigates the disproportionate influence of a small number of high-capacity countries, resulting in a more symmetrical distribution suitable for regression analysis.

For GDP per capita (constant 2015 US$) (x3), the estimated λ was –0.0202, again essentially equivalent to zero in Box–Cox terms. This confirms that a natural logarithm transformation is the most appropriate choice. Applying the log form reduces the moderate right skewness (2.21) and elevated kurtosis (5.16), stabilises the variance, and aligns with standard econometric practice for income variables, where proportional differences are analytically more relevant than absolute differences.

Accordingly, y1 and x3 were transformed using the natural logarithm before further econometric modelling. This ensures that distributional assumptions are better satisfied and that extreme values do not unduly influence estimated relationships.

To account for the severe skewness and kurtosis identified in the descriptive analysis, Total Renewable Electricity Installed Capacity (MW) (y1) and GDP per capita (x3) were transformed using the natural logarithm prior to modelling. The FE model (Table 2) reveals that both the Government AI Readiness Index (x1) and log GDP per capita (x3_log) are positive and highly statistically significant predictors of y1_log. Specifically, a one-unit increase in x1 is associated with a 1.71% increase in installed renewable capacity, holding other factors constant. In comparison, a 1% increase in GDP per capita corresponds to an almost proportional 0.95% increase in capacity. The within R^2 is 0.091, indicating modest explanatory power for within-country variation.

The RE model (Table 1) also reports statistically significant coefficients for both x1 and x3_log, with slightly different magnitudes: a one-unit increase in x1 is linked to a 2.87% increase in installed capacity, and a 1% rise in GDP per capita corresponds to a 0.53% increase. The overall R^2 (0.088) is similar to the FE specification.

The Hausman test ($\chi^2(2) = 72.877$, $p < 0.001$) strongly rejects the null hypothesis that the RE estimator is consistent, indicating that the FE model should be preferred for inference.

Table 1. The outputs of FE and RE models for y1_log (Total Renewable Electricity Installed Capacity, log-transformed) [Source: authors' calculations in R Studio]

Variable/ model stat	One-way (individual) Fixed Effect Within Model	One-way (individual) effect Random Effect Model (Swamy-Arora's transformation)
N (obs)	867	
Entities	183	
Time	2–5 years	
(Intercept)	–	0.9395 (0.2810)
x1 (Government AI Readiness Index)	0.0171 (0.0000)***	0.0287 (0.0000)***
x3 (GDP per capita, constant 2015 US$)	0.9546 (0.0000)***	0.5270 (0.0000)***
Model stats		
Within R²	0.0908	–
Overall R²	–	0.0878
Adj. R²	–0.1545	0.0857
F-statistic	34.064 (0.0001)***	–
Chi²	–	124.822 (<0.0001)***
Hausman test result		
χ²(2)		72.877
p		<0.001

Note: '–' – not calculated for this type of model.
Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Diagnostic tests were conducted to assess the validity of the error structure in the Fixed Effects specification for y1_log. The Breusch–Pagan test (BP = 37.16, df = 2, $p < 0.001$) strongly rejects the null hypothesis of homoskedasticity, indicating the presence of heteroskedasticity in the residuals.

Tests for autocorrelation also provided consistent evidence of serial correlation in the idiosyncratic errors. The Breusch–Godfrey/Wooldridge test for serial correlation in panel models yielded a $\chi^2(2)$ statistic of 145.87 ($p < 0.001$), while Wooldridge's test for autocorrelation in FE panels reported an F-statistic of 71.90 ($p < 0.001$). Both results reject the null of no serial correlation.

The joint presence of heteroskedasticity and serial correlation violates the classical OLS assumptions, leading to biased standard errors. Therefore, subsequent inference for the Fixed Effects model was based on cluster-robust standard errors to ensure consistency and reliability of statistical inference.

Following the detection of heteroskedasticity (Breusch–Pagan test, $p < 0.001$) and serial correlation (Breusch–Godfrey/Wooldridge and Wooldridge FE tests, both $p < 0.001$) in the residuals of the Fixed Effects model, the standard error estimates were adjusted using cluster-robust methods. This adjustment ensures that statistical inference remains valid despite violations of the classical OLS assumptions, which, if ignored, can lead to underestimation of standard errors and inflation of t-statistics.

The re-estimation of the Fixed Effects model with one-way clustering by entity (Table 2) confirms the robustness of the results. The Government AI Readiness Index (x1) and log GDP per capita (x3_log) retain positive and statistically significant coefficients at the 1%. Substantively, a one-unit increase in x1 is associated with an estimated 1.71% increase in total renewable electricity installed capacity. In comparison, a 1% increase in GDP per capita corresponds to an almost proportional 0.95% increase, holding other factors constant.

Table 2. Fixed Effects model with cluster-robust SE (one-way, clustered by entity) [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0171	0.00568	3.017	0.0026 **
x3_log (GDP per capita, log)	0.9546	0.30631	3.116	0.0019 **
Model stats				
N (obs)	867			
Entities	183			
Time	2–5 years			
Within R^2	0.0908			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Applying two-way clustering by entity and time (Table 3) yields identical coefficient estimates and robust standard errors to the one-way clustered results. This indicates that the significance and magnitude of the estimated effects are not sensitive to the clustering dimension, further strengthening confidence in the findings.

The consistent statistical significance of x1 and x3_log across both clustering approaches suggests a stable and economically meaningful relationship between government AI readiness, economic development, and the deployment of renewable electricity capacity in the sampled countries.

Table 3. Fixed Effects model with cluster-robust SE (two-way, clustered by entity and time) [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0171	0.00568	3.017	0.0026 **
x3_log (GDP per capita, log)	0.9546	0.30631	3.116	0.0019 **
Model stats				
N (obs)	867			
Entities	183			
Time	2–5 years			
Within R^2	0.0908			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

AI readiness and total renewable electricity generation

Table B2 (Appendix B) presents the descriptive statistics for the panel dataset, which comprises 687 country–year observations from 2020 to 2023, covering 179 countries. The Government AI Readiness Index (x1) shows a mean score of 45.62 (SD = 16.63) and a range from 13.46 to 88.16, with moderate positive skewness (0.49) and mild platykurtosis (–0.86), indicating an approximately symmetric distribution without extreme tails.

In contrast, Total Renewable Electricity Generation (GWh) (y2) exhibits very high dispersion (mean = 47,093.31; SD = 212,454.99) and an extensive range from 0.14 to 2,842,825.71. The extreme right skewness (9.84) and high kurtosis (110.06) reveal a highly non-normal distribution with substantial outliers concentrated in a small subset of high-generation countries.

GDP per capita (constant 2015 US$) (x3) also displays considerable variability (mean = 14,304.92; SD = 19,575.53) with values ranging from 253.45 to 110,873.19. The positive skewness (2.18) and leptokurtosis (5.00) indicate a heavy right tail, with a few high-income countries significantly above the median.

These results suggest that both y2 and x3 deviate significantly from normality, warranting logarithmic or Box–Cox transformations prior to econometric modelling to reduce skewness, mitigate the influence of extreme values, and improve compliance with model assumptions.

To address the severe skewness and kurtosis observed in the descriptive statistics, the Box–Cox transformation was applied to Total Renewable Electricity Generation (y2) and GDP per capita (x3) using an intercept-only model. For y2, the estimated Box–Cox parameter was λ = 0.0606, effectively zero in practical terms, indicating that a natural logarithm transformation is optimal. This transformation substantially reduces the extreme right skewness (9.84) and high kurtosis (110.06), mitigating the disproportionate influence of many high-generation countries.

For x3, the estimated λ was –0.0202, which is effectively zero, supporting the use of a natural logarithm transformation. This adjustment corrects for the variable's positive skewness (2.18) and leptokurtosis (5.00), which arise from a few high-income economies far exceeding the sample median.

Accordingly, both variables were log-transformed before econometric modelling to improve distributional properties, stabilise variance, and ensure that coefficient estimates reflect proportional rather than absolute changes.

To analyse the relationship between Total Renewable Electricity Generation (y2_log), the Government AI Readiness Index (x1), and log GDP per capita (x3_log), both Fixed Effects (FE) and Random Effects (RE) panel models were estimated.

The FE model (Table 4), estimated on an unbalanced panel of 179 countries over 2–4 years (N = 687), indicates that x3_log is positively and highly statistically significant ($\beta = 0.960$, $p < 0.001$), suggesting that a 1% increase in GDP per capita is associated with an almost proportional 0.96% increase in renewable electricity generation within countries over time. The coefficient for x1 is positive ($\beta = 0.0081$) but only marginally significant at the 10% level ($p = 0.086$), indicating a weaker within-country association between government AI readiness and renewable generation capacity. The within R^2 of 0.063 indicates modest explanatory power for within-country variation.

In the RE model (Table 4), both x1 ($\beta = 0.0200$, $p < 0.001$) and x3_log ($\beta = 0.5585$, $p < 0.001$) are positive and highly statistically significant. Here, the x1 effect is larger compared to the FE estimate, while the x3_log effect is more negligible, reflecting the inclusion of both within- and between-country variation in the RE estimation.

The Hausman test ($\chi^2(2) = 53.3$, $p < 0.0001$) rejects the null hypothesis of no systematic difference between FE and RE estimators, indicating that the RE model is inconsistent and that the FE model should be preferred for inference.

Table 4. FE and RE models for y2_log (Total Renewable Electricity Generation, log-transformed) [Source: authors' calculations in R Studio]

Variable	One-way (individual) effect Within Model	One-way (individual) effect Random Effect Model (Swamy-Arora's transformation)
N (obs)	687	
Entities	179	
Time	2–4 years	
(Intercept)	–	1.9815 (0.0456) *
x1 (Government AI Readiness Index)	0.0081 (0.0859) .	0.0200 (0.0001) ***
x3_log (GDP per capita, log)	0.9605 (0.0000) ***	0.5585 (0.0000) ***
Model stats		
Within R²	0.0627	–
Overall R²	–	0.0440
Adj. R²	–0.2707	0.0412
F-statistic	16.934 (p < 0.0001)	–
Chi²	–	65.747 (p < 0.0001)
Hausman test result		
χ²(2)		53.3
p		<0.0001

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Diagnostic tests were applied to the Fixed Effects model for y2_log to evaluate the validity of the error structure. The studentised Breusch–Pagan test (BP = 32.78, df = 2, $p < 0.001$) rejects the null hypothesis of homoskedasticity, indicating the presence of heteroskedasticity in the residuals.

Tests for autocorrelation also point to significant serial correlation. The Breusch–Godfrey/Wooldridge test for serial correlation in panel models reports a $\chi^2(2) = 79.20$ ($p < 0.001$), and Wooldridge's test for serial correlation in FE panels yields an F-statistic of 12.70 ($p < 0.001$). Both results confirm the rejection of the null hypothesis of no serial correlation.

The joint presence of heteroskedasticity and serial correlation violates the classical OLS assumptions for the error term, potentially biasing standard errors and leading to unreliable inference. To address this, subsequent model estimation for y2_log is conducted using cluster-robust standard errors, ensuring consistent and valid statistical inference.

Given the detection of heteroskedasticity and serial correlation in the error structure of the Fixed Effects model for y2_log, the model was re-estimated with cluster-robust standard errors, clustering by entity (country). As shown in Table 5, the Government AI Readiness Index (x1) coefficient remains positive ($\beta = 0.0081$). However, it is no longer statistically significant ($p = 0.155$), indicating that there is insufficient evidence to conclude a within-country effect of AI readiness on renewable electricity generation once robust inference is applied. In contrast, log GDP per capita (x3_log) retains a positive and highly significant relationship with y2_log ($\beta = 0.9605$, $p < 0.001$), suggesting that a 1% increase in GDP per capita is associated with an almost proportional 0.96% increase in renewable electricity generation.

Table 5. FE model with cluster-robust SE (one-way, clustered by entity) for y2_log [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0081	0.00571	1.424	0.1552
x3_log (GDP per capita, log)	0.9605	0.24083	3.988	0.0001 ***
Model stats				
N (obs)	687			
Entities	179			
Time	2–4 years			
Within R²	0.0627			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

Table 6. FE model with cluster-robust SE (two-way, clustered by entity and time) [Source: authors' calculations in R Studio]

Variable	Estimate	Robust Std. Error	t-value	p-value
x1 (Government AI Readiness Index)	0.0081	0.00571	1.424	0.1552
x3_log (GDP per capita, log)	0.9605	0.24083	3.988	0.0001 ***
Model stats				
N (obs)	687			
Entities	179			
Time	2–4 years			
Within R²	0.0627			

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

Applying two-way clustering by both entity and time produced identical coefficient estimates and robust standard errors, confirming the stability of the results across clustering specifications. This robustness suggests that the observed GDP per capita effect is consistent and not sensitive to alternative error correlation structures. In contrast, the effect of AI readiness remains weak when accounting for potential violations of classical OLS assumptions.

The observed difference in the influence of the Government AI Readiness Index between the two dependent variables suggests that AI readiness may primarily facilitate the planning, deployment, and installation of renewable energy capacity rather than directly translating into higher electricity generation within the short time frame of the panel. High AI readiness often reflects greater digital infrastructure, advanced data management capabilities, and institutional capacity to integrate emerging technologies into energy planning. These capabilities can streamline permitting processes, optimise site selection through AI-assisted geospatial analysis, and improve investment targeting – all factors that accelerate the installation of renewable assets.

However, translating installed capacity into actual electricity generation depends on additional factors not necessarily captured by AI readiness. These include variability in renewable resource availability (e.g., wind speeds, solar irradiation), operational efficiency, grid integration, storage capacity, and maintenance regimes. Countries with high AI readiness may therefore be able to expand capacity rapidly. However, suppose grid constraints, intermittent resource availability, or operational inefficiencies persist. In that case, this capacity may not be fully utilised, resulting in no statistically significant effect on total generation during the observed period. This distinction underscores the importance of complementary investments in grid infrastructure, storage solutions, and operational optimisation to ensure that capacity gains lead to proportional increases in renewable electricity output.

DISCUSSION

The empirical results indicate a statistically significant positive relationship between the Government AI Readiness Index and the total installed capacity of renewable electricity. In contrast, no significant effect was observed for total renewable electricity generation. This finding suggests that AI readiness at the governmental level may play a stronger role in enabling the development of renewable energy infrastructure than in directly influencing the operational output of these assets. The result aligns with studies highlighting AI's potential to improve planning, investment allocation, and capacity-building in the energy sector through enhanced forecasting, project management, and optimisation of infrastructure deployment (Ibadildin et al., 2025; Koldovskyi et al., 2025; Wang et al., 2025). These capabilities may expedite the installation of capacity. However, the absence of a significant effect on generation indicates that additional operational, technical, or market factors, such as intermittency, grid constraints, or policy incentives, continue to determine actual output levels (Triantafyllidou et al., 2024; Havrylenko & Myroshnychenko, 2025).

The stronger link with installed capacity can be further explained by AI readiness supporting strategic-level decisions and long-term infrastructure investment, as observed in public governance and clean energy transition research (Murko et al., 2024; Naumenkova et al., 2025). AI-enabled analytics help governments identify optimal sites for renewable installations, improve permitting processes, and coordinate financing mechanisms (Dobrovolska et al., 2024; Myroshnychenko et al., 2024). However, these benefits may not automatically translate into higher generation without parallel advances in grid integration, storage solutions, and demand-side management (Gualandri & Kuzior, 2023; Golubtsov et al., 2025).

The non-significant relationship with generation echoes the conclusions of previous studies, which emphasise the importance of operational AI applications (such as real-time energy dispatch, predictive maintenance, and supply-demand balancing) for achieving consistent output growth (Wang et al., 2025; Kildei et al., 2025). The absence of such operational integration at scale in many countries could explain why government-level AI readiness has yet to yield a measurable effect on generation. This finding is consistent with those from renewable energy resilience studies, which emphasise the need for targeted technological investments and adaptive policy frameworks to address challenges related to variability and intermittency (Ghimire et al., 2025; Vakulenko & Rekunenko, 2025).

Overall, the results suggest that while AI readiness can catalyse infrastructure expansion, its impact on energy output requires a more direct integration of AI into grid operations, market mechanisms, and renewable plant management. Future energy strategies should therefore combine AI-driven planning with targeted operational AI applications to bridge the gap between installed capacity and actual generation. Such integrated approaches are likely to yield higher returns in terms of capacity utilisation and system efficiency (Yefimenko et al., 2025a; Artyukhov et al., 2024b).

Limitations. While the study provides robust evidence on the relationship between government AI readiness, economic development, and renewable energy deployment, several limitations should be acknowledged. First, the panel dataset covers a relatively short period (2020–2024), which restricts the ability to capture long-term dynamics and potential lagged effects of AI readiness on renewable energy outcomes. Second, while comprehensive, the Government AI Readiness Index may not fully reflect the actual AI implementation capacity or the effectiveness of AI-related policies in the energy sector, potentially leading to measurement bias. Third, although transformations and robust estimation techniques were applied to address skewness, heteroskedasticity, and serial correlation, unobserved time-varying factors, such as changes in national energy policies, geopolitical events, or technological breakthroughs, may still confound the estimated relationships. Fourth, the analysis is limited to macro-level country data; sectoral, regional, or plant-level variations in renewable energy deployment and generation could not be explored due to data unavailability. Finally, the study assumes data comparability across countries, but differences in statistical reporting practices, particularly for renewable electricity generation and capacity, may introduce cross-country measurement inconsistencies.

Future research could extend the temporal scope to include a longer time horizon, allowing for the assessment of long-term and lagged effects of AI readiness on renewable energy transitions. Incorporating sector-specific or regional-level data could provide deeper insights into how AI influences renewable energy outcomes. Additionally, future studies may benefit from integrating qualitative assessments of AI policy implementation, exploring the interaction between AI readiness and other enabling factors such as grid modernisation, energy storage, and market regulation. Comparative case studies between high- and low-AI-readiness countries could also shed light on best practices and contextual constraints in leveraging AI for renewable energy development.

CONCLUSIONS

The primary aim of this research was to investigate the extent to which Government AI Readiness influences renewable energy development, focusing on two key outcomes: Total Renewable Electricity Installed Capacity and Total Renewable Electricity Generation. By formulating and testing two hypotheses, the study sought to determine whether countries with higher AI readiness can expand renewable energy infrastructure and increase renewable electricity output.

The analysis was based on an unbalanced global panel dataset covering 183 countries from 2020 to 2024. The Government AI Readiness Index, the core explanatory variable, was obtained from the Oxford Insights database. At the same time, renewable energy indicators were sourced from IRENA, and GDP per capita from the World Bank. Severe skewness and kurtosis in *y1*, *y2*, and *x3* were addressed through natural logarithm transformations, supported by Box–Cox analysis. Econometric modelling employed both Fixed Effects and Random Effects specifications, with the Hausman test guiding model selection. Diagnostic tests identified heteroskedasticity and serial correlation, and all FE estimates were reported with cluster-robust standard errors to ensure valid inference.

The results reveal that both Government AI Readiness and GDP per capita are positive and statistically significant predictors of installed capacity. Specifically, a one-unit increase in AI readiness is associated with a 1.71% increase in installed renewable capacity, while a 1% increase in GDP per capita corresponds to a 0.95% increase in capacity. For electricity generation, GDP per capita remains a strong and significant predictor (0.96% increase in generation per 1% GDP per capita growth). In contrast, the effect of AI readiness is positive but statistically insignificant once robust errors are applied. This suggests that while AI readiness supports the deployment of renewable infrastructure, its impact on actual generation may depend on additional operational, technical, and resource factors.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

From a policy perspective, the findings highlight the potential of AI readiness as a facilitator of renewable energy capacity expansion. Governments aiming to accelerate the deployment of renewable energy sources should consider integrating AI-driven tools into project planning, resource mapping, permitting, and investment allocation processes. However, complementary investments are needed in grid modernisation, energy storage, and operational optimisation to translate installed capacity into tangible generation gains. Furthermore, enhancing AI readiness should go hand in hand with targeted policies that improve the efficiency, reliability, and utilisation rates of renewable energy assets. Such an integrated approach can maximise the benefits of both technological preparedness and clean energy transitions, ultimately contributing to global decarbonisation goals.

ACKNOWLEDGEMENT

This study was prepared as part of the project 101127491-EnergyS4UA-ERASMUS-JMO2023-HEI-TCH-RSCH. Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or European Education and Culture Executive Agency. Neither the European Union nor the granting authority can be held responsible for them. The authors are grateful to the Silesian University of Technology for providing financial support to conduct this research.

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Human Technology
ISSN 1795-6889
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Appendix A

The sample of countries in the analysis of the interaction of the AI readiness and total renewable electricity installed capacity

Afghanistan,
Albania,
Algeria,
Andorra,
Angola,
Antigua and Barbuda,
Argentina,
Armenia,
Australia,
Austria,
Azerbaijan,
Bahamas,
Bahrain,
Bangladesh,
Barbados,
Belarus,
Belgium,
Belize,
Benin,
Bhutan,
Bolivia (Plurinational State of),
Bosnia and Herzegovina,
Botswana,
Brazil,
Brunei Darussalam,
Bulgaria,
Burkina Faso,
Burundi,
Cabo Verde,
Cambodia,
Cameroon,
Canada,
Central African Republic,
Chad,
Chile,
China,
Colombia,
Comoros,
Congo,
Costa Rica,
Côte d'Ivoire,
Croatia,
Cuba,
Cyprus,
Czechia,
Democratic Republic of the Congo,
Denmark,
Djibouti,
Dominica,
Dominican Republic,
Ecuador,
Egypt,
El Salvador,
Equatorial Guinea,
Estonia,
Eswatini,
Ethiopia,
Fiji,
Finland,
France,
Gabon,
Gambia (Republic of the),
Georgia,
Germany,
Ghana,
Greece,
Grenada,
Guatemala,
Guinea,
Guinea-Bissau,
Guyana,
Haiti,
Honduras,
Hungary,
Iceland,
India,
Indonesia,
Iran (Islamic Republic of),
Iraq,
Ireland,
Israel,
Italy,
Jamaica,
Japan,
Jordan,
Kazakhstan,
Kenya,
Kiribati,
Kuwait,
Kyrgyzstan,
Lao People's Democratic Republic,
Latvia,
Lebanon,
Lesotho,
Liberia,
Libya,
Lithuania,
Luxembourg,
Madagascar,
Malawi,
Malaysia,
Maldives,
Mali,
Malta,
Marshall Islands,
Mauritania,
Mauritius,
Mexico,
Mongolia,
Montenegro,
Morocco,
Mozambique,
Myanmar,
Namibia,
Nepal,
Netherlands,
New Zealand,
Nicaragua,
Niger,
Nigeria,
North Macedonia,
Norway,
Oman,
Pakistan,
Panama,
Papua New Guinea,
Paraguay,
Peru,
Philippines,
Poland,
Portugal,
Qatar,
Republic of Moldova,
Republic of Korea,
Romania,
Russian Federation,
Rwanda,
Saint Kitts and Nevis,
Saint Lucia,
Saint Vincent and the Grenadines,
Samoa,
São Tomé and Príncipe,
Saudi Arabia,
Senegal,
Serbia,
Seychelles,

Sierra Leone,
Singapore,
Slovakia,
Slovenia,
Solomon Islands,
Somalia,
South Africa,
Spain,
Sri Lanka,
Sudan,
Suriname,
Sweden,
Switzerland,
Syrian Arab Republic,
Taiwan,
Tajikistan,
Thailand,
Timor-Leste,
Togo,
Tonga,
Trinidad and Tobago,
Tunisia,
Türkiye,
Turkmenistan,
Uganda,
Ukraine,
United Arab Emirates,
United Kingdom,
United Republic of Tanzania,
United States of America,
Uruguay,
Uzbekistan,
Vanuatu,
Viet Nam,
Yemen,
Zambia,
Zimbabwe.

The sample of countries in the analysis of the interaction of the AI readiness and total renewable electricity generation

Afghanistan
Albania
Algeria
Andorra
Angola
Antigua and Barbuda
Argentina
Armenia
Australia
Austria
Azerbaijan
Bahamas
Bahrain
Bangladesh
Barbados
Belarus
Belgium
Belize
Benin
Bhutan
Bolivia(Plurinational State of)
Bosnia and Herzegovina
Botswana
Brazil
Brunei Darussalam
Bulgaria
Burkina Faso
Burundi
Cabo Verde
Cambodia
Cameroon
Canada
Central African Republic
Chad
Chile
China
Colombia
Comoros
Congo
Costa Rica
Côte d'Ivoire
Croatia
Cuba
Cyprus
Czechia
Democratic Republic of the Congo
Denmark
Djibouti
Dominica
Dominican Republic
Ecuador
Egypt
El Salvador
Estonia
Eswatini
Ethiopia
Fiji
Finland
France
Gabon
Gambia(Republic of the)
Georgia
Germany
Ghana
Greece
Grenada
Guatemala
Guinea
Guinea-Bissau
Guyana
Haiti
Honduras
Hungary
Iceland
India
Indonesia
Iran(Islamic Republic of)
Iraq
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kazakhstan
Kenya
Kiribati
Kuwait
Kyrgyzstan
Lao People's Democratic Republic
Latvia
Lebanon
Lesotho
Liberia
Libya
Lithuania
Luxembourg
Madagascar
Malawi
Malaysia
Maldives
Mali
Malta
Mauritania
Mauritius
Mexico
Mongolia
Montenegro
Morocco
Mozambique
Myanmar

Namibia
Nepal
Netherlands
New Zealand
Nicaragua
Niger
Nigeria
North Macedonia
Norway
Oman
Pakistan
Panama
Papua New Guinea
Paraguay
Peru
Philippines
Poland
Portugal
Qatar
Republic of Korea
Republic of Moldova
Romania
Russian Federation
Rwanda
Saint Lucia
Saint Vincent and the Grenadines
Samoa
São Tomé and Príncipe
Saudi Arabia
Senegal
Serbia
Seychelles
SierraLeone
Singapore
Slovakia
Slovenia
Solomon Islands
South Africa
Spain
Sri Lanka
Sudan
Suriname
Sweden
Switzerland
Syrian Arab Republic
Taiwan
Tajikistan
Thailand
Timor-Leste
Togo
Tonga
Trinidad and Tobago
Tunisia
Türkiye
Turkmenistan
Uganda
Ukraine
United Arab Emirates
United Kingdom
United Republic of Tanzania
United States of America
Uruguay
Uzbekistan
Vanuatu
Viet Nam
Yemen
Zambia
Zimbabwe

Appendix B

Table B1. Descriptive statistics of key variables in the panel dataset for y1 analysis [Source: authors' calculations in R Studio]

Variable	Government AI Readiness Index (x1)	Total Renewable Electricity Installed Capacity (MW) (y1)	GDP per capita (constant 2015 US$) (x3)
N	867	867	867
Mean	46,08	19,292,18	14,134,40
SD	16,71	103,500,04	19,302,90
Median	41,83	1,660,14	5,828,07
Trimmed	45,15	3,915,39	9,899,10
MAD	17,17	2,408,31	6,974,67
Min	13,46	0,43	253,45
Max	88,16	1,817,956,01	110,873,19
Range	74,7	1,817,955,60	110,619,70
Skew	0,46	12,18	2,21
Kurtosis	–0,89	171,46	5,16
SE	0,57	3,448,09	643,43

Table B2. Descriptive statistics of key variables in the panel dataset for the y2 analysis [Source: authors' calculations in R Studio]

Variable	x1 (Government AI Readiness Index)	y2 (Total Renewable Electricity Generation, GWh)	x3 (GDP per capita, constant 2015 US$)
N	687	687	687
Mean	45,62	47,093,31	14,304,92
SD	16,63	212,454,99	19,575,53
Median	41,5	5,268,99	5,831,83
Trimmed	44,61	11,465,93	10,050,95
MAD	16,89	7,692,47	6,995,32
Min	13,46	0,14	253,45
Max	88,16	2,842,825,71	110,873,19
Range	74,7	2,842,825,57	110,619,74
Skew	0,49	9,84	2,18
Kurtosis	–0,86	110,06	5
SE	0,63	8,105,66	746,85

Human Technology

ISSN: 1795-6889

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Volume 21(3), December 2025, 694–730

DIGITAL TECHNOLOGIES SUPPORTING PREDICTIVE HEALTHCARE: REVIEW OF RESEARCH TRENDS

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Abstract: *This study examines research trends in digital technologies supporting predictive healthcare, with particular attention to the role of digital twins. A structured bibliometric analysis combined with qualitative thematic analysis was conducted using publications indexed in the Scopus and Web of Science databases from 2015 to 2025. The results indicate a clear shift towards integrated, data-driven healthcare solutions, in which digital twins function as central frameworks linking artificial intelligence, machine learning and Internet of Medical Things technologies. Three emerging thematic areas were identified: integrated patient data ecosystems, predictive and preventive digital twins, and digital twin–based treatment planning and patient response simulation. The findings highlight increasing interest in personalised, predictive and simulation-oriented healthcare models. At the same time, the analysis reveals a gap between technological development and routine clinical implementation. The study contributes to a clearer understanding of the evolving structure of this research field and outlines directions for future research and application in predictive healthcare.*

Keywords: *predictive healthcare, digital twin, artificial intelligence, machine learning, big clinical data, Internet of Things, Internet of Medical Things, patient monitoring, extended reality*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.10

INTRODUCTION

Over the past decade, healthcare systems have been undergoing an intensive process of digital transformation. One of its key directions is the development of solutions that support predictive healthcare. Increasing attention is being paid to digital technologies that enable continuous health monitoring, advanced analysis of clinical data and the forecasting of health risks and disease trajectories. In this context, wearable devices, Internet of Medical Things (IoMT) systems, artificial intelligence and healthcare digital twins have gained particular importance.

Contemporary digital healthcare solutions integrate data from multiple sources. These include physiological sensors, wearable and mobile devices, medical imaging systems and electronic health records. Such data are analysed using machine learning and deep learning methods. The aim is to support diagnosis, predict disease progression, simulate therapeutic effects and assist clinical decision-making. More recently, generative adversarial networks have been increasingly used to augment medical datasets. Such methods are particularly valuable in contexts characterised by limited availability of high-quality clinical data.

Healthcare digital twin systems represent another important development within predictive healthcare. These systems enable the modelling of patients, clinical processes or entire healthcare environments in real time. By integrating sensor data, healthcare information systems and artificial intelligence algorithms, digital twins make it possible to simulate patient health states and predict disease evolution. They also allow for the assessment of potential therapeutic interventions before their implementation. As a result, digital twins support personalised treatment, patient flow optimisation and faster clinical response, including in critical care settings such as intensive care units (Jameil & Al-Raweshidy, 2025; Rahim et al., 2024).

The expansion of predictive healthcare technologies is closely linked to issues of secure data processing and exchange. Blockchain solutions, when combined with IoMT infrastructures and digital twin systems, are increasingly analysed as tools for strengthening trust, ensuring data integrity and improving interoperability across distributed healthcare systems (Sadeghi & Mahmoudi, 2024; Addula et al., 2025). At the same time, edge computing and cloud computing architectures enable real-time data processing and scalable digital services. These technologies are particularly important for predictive applications and for health monitoring conducted outside traditional clinical environments (Jameil & Al-Raweshidy, 2024a).

The traditional reactive model is increasingly complemented by predictive, preventive and personalised approaches. Data collected from wearable devices, IoT sensors and digital twins support early detection of health disturbances, assessment of complication risks and planning of interventions tailored to individual patient characteristics. Despite the growing number of publications on predictive digital technologies in healthcare, the existing research remains thematically and methodologically fragmented. The literature covers technical, clinical, organisational and data security aspects. However, there is still a lack of a comprehensive synthesis that would organise this body of knowledge, identify dominant research streams and indicate directions for further development.

In response to this research gap, this article presents a structured review of the literature that combines bibliometric analysis with qualitative thematic exploration. The study aims to map the main research areas associated with digital technologies supporting predictive healthcare. It aims also to identify the main contributors who influence the development of this research area and to examine how its thematic focus has evolved over time. The study draws on publications indexed in the Scopus and Web of Science databases and covers the period from 2015 to 2025. Taken together, the applied approaches offer a structured and coherent picture of a research field that is expanding rapidly and spans multiple disciplinary perspectives.

The structure of the article reflects the adopted research objectives. Section 2 presents the research methodology, including the literature search strategy, publication selection criteria and applied bibliometric and qualitative methods. Section 3 reports the results of the quantitative analysis, covering publication dynamics, authorship structures, institutional and journal productivity, as well as collaboration and citation networks. Section 4 presents the results of the qualitative thematic analysis, focusing on the identification and structuring of emerging research areas in digital technologies supporting predictive healthcare. Section 5 places the findings in a broader conceptual perspective and discusses the main research directions shaping the future of the field. The article concludes with a synthesis of the key findings and a discussion of the study's limitations and directions for future research (Section 6). It also outlines implications for further research and practical application (Section 7).

METHODS

The research procedure was designed as a two-stage process: quantitative and qualitative analysis. The aim of the study was to organise and synthesise the existing body of scientific literature on predictive digital technologies in healthcare, as well as to identify the main research areas and directions for further development in this field. At the preliminary stage, three research questions were formulated: (1) Which authors, institutions, countries and journals are the most influential in research on predictive digital technologies in healthcare?; (2) Which thematic areas are most frequently addressed in publications related to predictive healthcare digital technologies?; (3) What directions for future research can be identified on the basis of the existing scientific output?

The quantitative stage was based on bibliometric analysis. The study was conducted using two international databases: Scopus and Web of Science. The identification and selection of publications followed the PRISMA guidelines, which ensured transparency and replicability of the research procedure (Figure 1). In the first step, a search strategy was defined based on the simultaneous occurrence of the keywords healthcare, predictive, digital and technology. Inclusion criteria were then specified. Publications published between 2015 and 2025 were included in the analysis. The adopted time frame made it possible to capture the evolution of research, from early and fragmented studies to the marked growth of interest in predictive healthcare digital technologies in recent years.

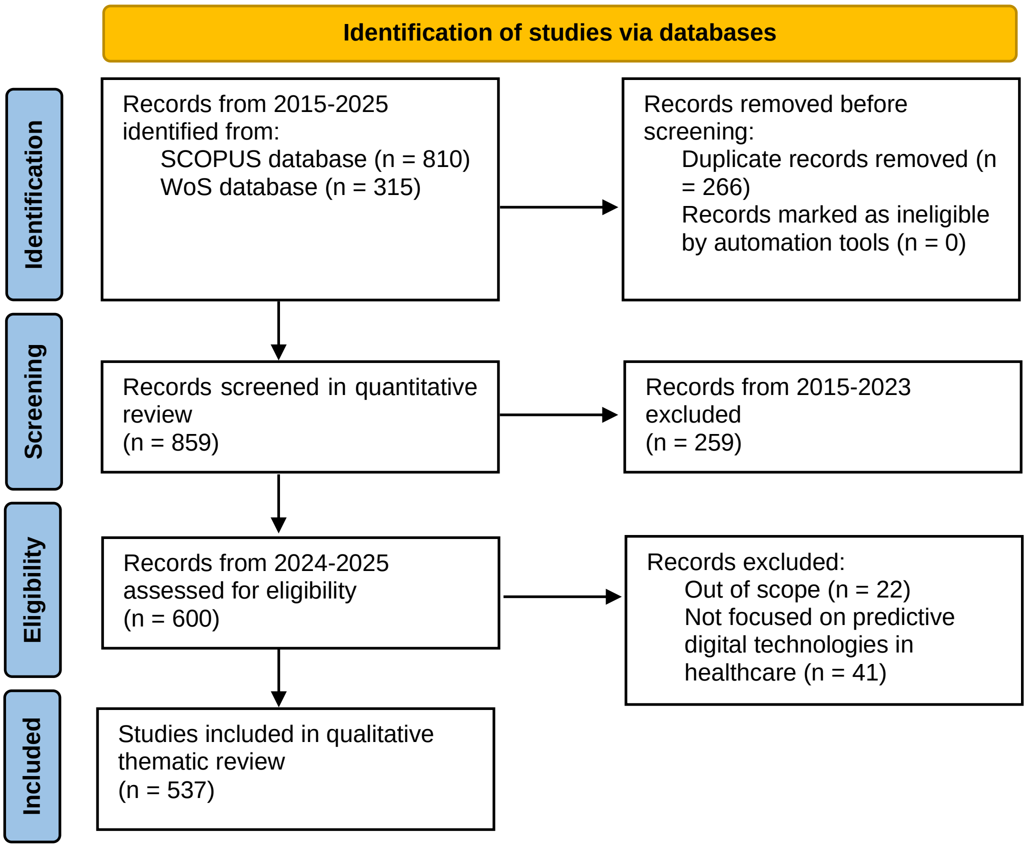

Figure 1. PRISMA flow diagram of the literature selection process.

The search strategy was designed in a stepwise manner in order to gradually narrow the set of publications and increase its thematic coherence (Table 1). In the first step, a very broad query was applied, covering the simultaneous occurrence of the terms healthcare, predictive and digital across the entire bibliographic record. This approach made it possible to identify a very large number of publications: 73,277 records in the Scopus database and 1,586 in the Web of Science database. Many of these publications were only indirectly related to the research focus.

In the second stage, the search was restricted to titles, abstracts and keywords. The application of the query TITLE-ABS-KEY (healthcare AND predictive AND digital) in Scopus and an analogous query in Web of Science significantly reduced the number of results to 1,573 publications in Scopus and 659 in Web of Science. Despite this refinement, the dataset still included studies with a diverse thematic profile, including publications in which the predictive or digital dimension played a secondary role.

The next step involved further refining the query by adding the term technology(-ies). This was intended to isolate publications in which digital technologies constitute a central element of predictive analyses in healthcare. As a result, 889 records were obtained from Scopus and 333 from Web of Science prior to the application of inclusion criteria.

Table 1. Search results.

Specification	Scopus	Web of Science
	Search 1	
Query	ALL (healthcare AND predictive AND digital)	ALL= (healthcare AND predictive AND digital)
Number of publications before inclusion criteria	73,277	1,586
	Search 2	
Query	TITLE-ABS-KEY (healthcare AND predictive AND digital)	TS = (healthcare AND predictive AND digital)
Number of publications before inclusion criteria	1,573	659
	Search 3	
Query	TITLE-ABS-KEY (healthcare AND predictive AND digital AND technolog*)	TS = (healthcare AND predictive AND digital AND technolog*)
Number of publications before inclusion criteria	889	333
Number of publications following inclusion criteria*	810	315
	Data extraction	
Removing duplicates based on titles and DOIs	859	

Note. * inclusion criteria – period: 2015-2025; document types: articles, proceedings papers, conference papers, books, book chapters, reviews, conference reviews, early access.

Subsequently, inclusion criteria were applied, covering the publication period from 2015 to 2025 and specific document types, such as journal articles, conference papers, book chapters, monographs, review articles, conference materials and early access publications. After applying these criteria, 810 publications from Scopus and 315 from Web of Science were retained for further analysis.

The final search was conducted on 30 May 2025, and the dataset was updated on 20 December 2025 as part of the review process. The update aimed to include the most recent publications and to enhance the timeliness and completeness of the analyses.

During the data extraction phase, duplicates across both databases were removed using publication titles and DOI numbers. The final research dataset consisted of 859 unique records and formed the basis for subsequent bibliometric and qualitative analyses.

Data retrieved from the Scopus and Web of Science databases were first subjected to descriptive processing using Microsoft Office Excel 25. At this stage, publication dynamics were analysed on an annual basis, and summary statistics were prepared for the most productive authors, institutions, countries and journals. Basic citation indicators were also calculated, including average citation counts and the H-index. More advanced bibliometric analyses were conducted in the RStudio environment (version 2024.12.1+563) using the Biblioshiny interface from the bibliometrix package. These tools were applied to identify the most influential publications, examine citation structures, and explore the thematic evolution and emerging research trends within the analysed field.

Network-based analyses, including co-authorship, journal co-citation and keyword co-occurrence, were performed using VOSviewer (version 1.6.20). This enabled the identification of collaboration patterns, thematic clusters and the main conceptual areas of research. The relationships between the research objectives, applied methods and analytical tools are summarised in Table 2.

Table 2. Overview of research objectives, methods and analytical tools. [Source: authors' own elaboration based on Korzeb et al., 2024; Raamkhumar & Swamy, 2024]

Objectives	Methods	Tools
Identification of publication dynamics by year and descriptive overview of the dataset	descriptive bibliometrics: annual production; most productive authors/institutions/countries/ journals; average citations; H-index	MS Office Excel 25; RStudio 2024.12.1+563 – Biblioshiny (bibliometrix) version 5.2.1
Identification of the most influential publications and citation structure	citation analysis; identification of top-cited documents; comparison of citations across Scopus and WoS	RStudio 2024.12.1+563 – Biblioshiny (bibliometrix) version 5.2.1; MS Office Excel 25
Identification of co-authorship networks (authors and countries)	co-authorship network analysis; collaboration mapping	VOSviewer version 1.6.20; RStudio 2024.12.1+563 – Biblioshiny (bibliometrix) version 5.2.1
Identification of co-citation networks (journals)	journal co-citation analysis; network visualisation and cluster detection	VOSviewer version 1.6.20; RStudio 2024.12.1+563 – Biblioshiny (bibliometrix) version 5.2.1
Identification of the conceptual structure and thematic clusters	co-occurrence analysis of author keywords; thesaurus-based keyword normalisation; network mapping; cluster identification	VOSviewer version 1.6.20; RStudio 2024.12.1+563 – Biblioshiny (bibliometrix) version 5.2.1
Identification of thematic map, thematic evolution and research trends	thematic mapping (centrality–density), thematic evolution (Sankey), trend topics analysis	RStudio 2024.12.1+563 – Biblioshiny (bibliometrix) version 5.2.1

The qualitative stage of the study was conducted after the completion of the quantitative analyses and aimed to provide a deeper interpretation of current research directions in predictive digital technologies in healthcare. Based on the selection procedure illustrated in the PRISMA flow diagram, publications published in the years 2024–2025 were selected for further analysis. This temporal focus allowed the analysis to concentrate on the most recent studies. These publications best reflect current research trends, dominant methodological approaches and emerging applications of predictive technologies in clinical practice.

In the first step, 600 publications from this period were assessed. The analysis was based primarily on abstracts, and, where further clarification was required, on full-text review. During the screening process, 63 records were excluded. These included studies falling outside the thematic scope of the research or publications not directly focused on predictive digital technologies in healthcare.

Ultimately, 537 publications were included in the qualitative thematic analysis. This stage aimed to capture the main lines of inquiry emerging in recent research. The analysis paid particular attention to the ways in which technological solutions are linked with concrete healthcare applications and to the directions in which the field appears to be evolving. Special emphasis was placed on research addressing the integration of predictive models into everyday clinical workflows, the increasing personalisation of healthcare, and the growing importance of data-driven and digital tools in medical decision-making.

RESULTS

During the analysed period from 2015 to 2025, 810 publications were identified in the Scopus database, while 317 publications were indexed in the Web of Science database. After the removal of duplicate records, a total of 859 unique papers from both databases were retained for further analysis (Figure 2).

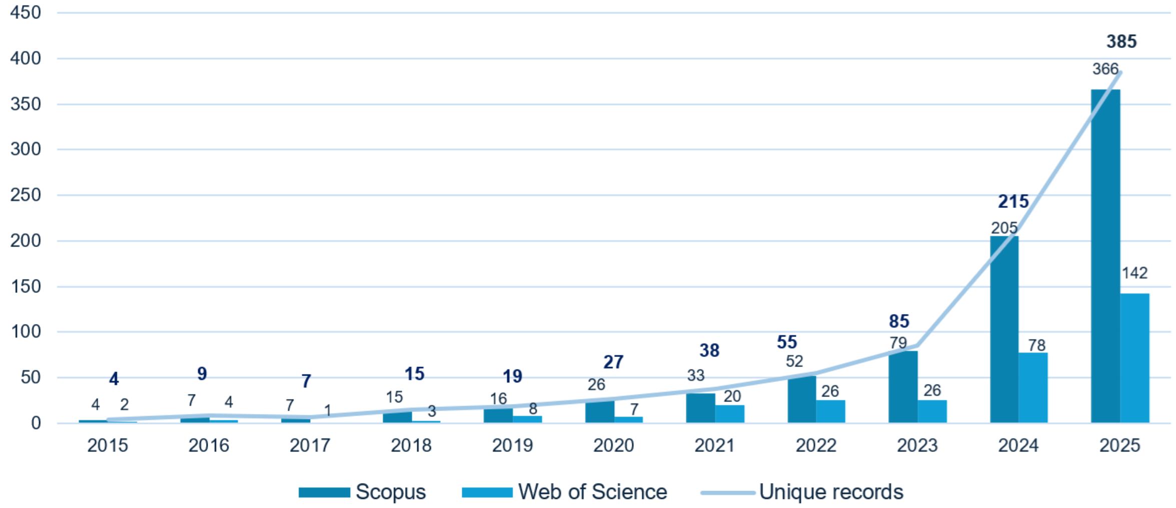

Figure 2. Number of publications in Scopus and WoS databases.

In the initial phase of the analysis, covering the years 2015–2017, research activity was limited. The annual number of unique publications did not exceed 10 items. In 2018–2019, a gradual increase was observed. The number of unique records reached 15 and 19, respectively. A more noticeable acceleration occurred in 2020. In that year, 27 unique publications were identified. The upward trend continued in 2021, when the number of records increased to 38. From 2022 onwards, the development of research became more dynamic. In 2022, 55 unique publications were recorded, followed by 85 in 2023. The strongest growth occurred in 2024 and 2025, with 215 and 385 records, respectively. The year 2025 represents the peak of the analysed period. The results indicate a steadily increasing scientific interest in digital technologies supporting predictive healthcare.

The analysis of authors' productivity in the field of digital technologies supporting predictive healthcare shows that only a small number of researchers have published at least four papers on this topic (Table 3). The highest number of publications is observed for A. K. Tyagi and J. K. Paik. Each of these authors has produced seven papers, accounting for 0.8% of the total number of analysed publications. Tyagi's work shows a low citation impact. In the Web of Science, the average number of citations is 0.6, and the H-index is 2. The publication record of J. K. Paik shows a slightly higher impact. The average number of citations is 4.2 in Scopus and 1.5 in the Web of Science. The topic-specific H-index equals 3 in Scopus and 1 in the Web of Science. B. Singh has published six papers. The average number of citations in Scopus is 2.3. The H-index for this author is 2. Both H. J. Kim and A. Khang have authored four publications each. Kim's papers received an average of 4.5 citations in Scopus and 4.7 in the Web of Science. The H-index is 2 in both databases. In the case of Khang, the average number of citations in Scopus is 6.3, with an H-index of 2.

Overall, the results indicate that even the most productive authors account for less than 1% of the total publication set. Their citation impact remains moderate. This confirms the early stage of development of the research field.

Table 3. Productivity of authors in the field of digital technologies supporting predictive healthcare.

No.	Item	Number of publication	Percent of total publications*	Average citations		H-index	
				Scopus	WoS	Scopus	WoS
1	Tyagi, A.K.	7	0.8	0.6	N/A	2	N/A
2	Paik, J.K.	7	0.8	4.2	1.5	3	1
3	Singh, B.	6	0.7	2.3	N/A	2	N/A
4	Kim, H.J.	4	0.5	4.5	4.7	2	2
5	Khang, A.	4	0.5	6.3	N/A	2	N/A

Note: * – percent of total 859 publications. N/A – data not available.
Source: authors' work.

The co-authorship map shows a clearly differentiated structure of collaboration among the authors of the analysed publications. A large and dense cluster is visible in the central part of the map. This cluster is marked in red and includes a substantial group of researchers linked by numerous co-authorship ties. On the right-hand side of the map, a smaller cluster appears in green. It is centred around P. Kartsidis and P. D. Bamidis, who act as key nodes within this group. They also connect this cluster to the main network. Links between the two clusters are present but less intensive. This indicates limited, yet meaningful, collaboration between the groups (Figure 3).

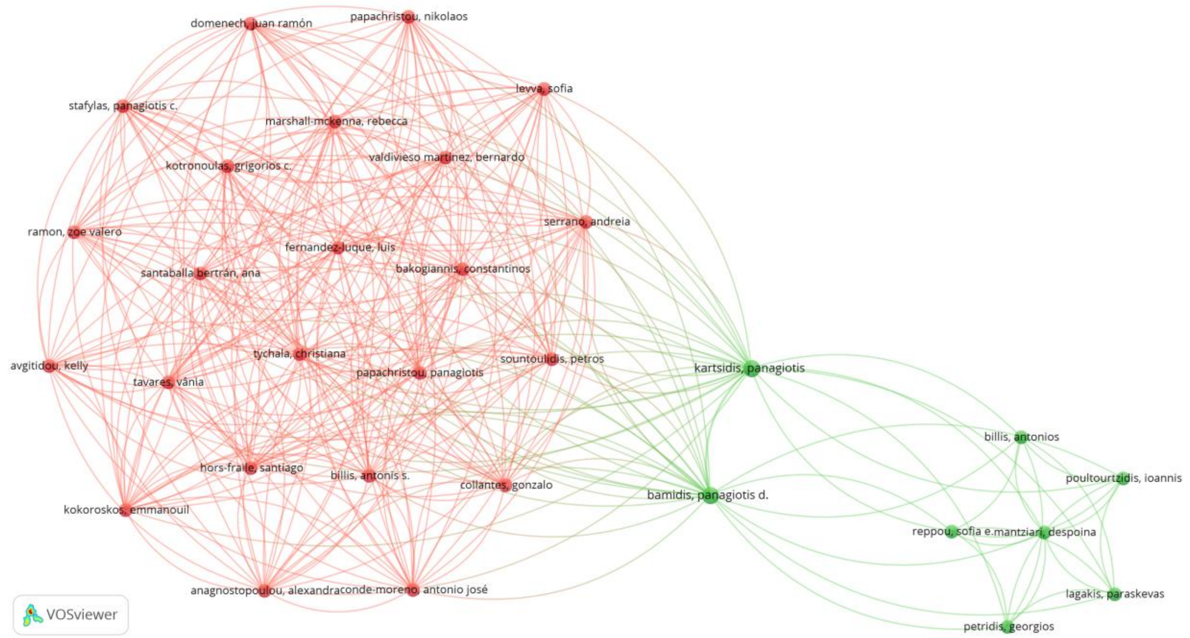

Figure 3. Author co-authorship network in research on digital technologies supporting predictive healthcare. [Source: authors' own elaboration using software VOSviewer 1.6.20]

The analysis of institutional productivity in the field of digital technologies supporting predictive healthcare indicates that even the most active research centres account for only a small share of the total publication output (Table 4). None of the institutions included in the table exceeds 1.5% of the overall number of analysed publications. The highest number of publications is recorded for Amity University (India), with 12 papers (1.4% of the total), accompanied by a moderate level of citations in both databases. A similar level of productivity is observed for SRM Institute of Science and Technology, Lovely Professional University, and Sharda University, each with 11 publications (1.3%). In the case of SRM Institute of Science and Technology, the high average number of citations in the Web of Science (38.0 citations per paper) results from a single highly cited publication, which limits broader conclusions regarding the overall impact of the institution's output. Institutions based in the United Kingdom generally show slightly lower publication volumes but a relatively higher citation impact. University College London has 10 publications (1.2%), with high average citation values in both Scopus and the Web of Science, as well as the highest H-index. University of London, despite the absence of citation data in Scopus, demonstrates visible impact in the Web of Science, with an average of 13.7 citations per paper and an H-index of 4. The remaining Indian institutions, including Symbiosis International (Deemed University), Chandigarh University, and Chitkara University, Punjab, each contributed nine publications (1.0%). Their citation impact varies from moderate to low, which further reflects the dispersed and still developing nature of research in the analysed field.

Table 4. Productivity of institutions in the field of digital technologies supporting predictive healthcare.

No.	Item	Number of publication	Percent of total publications*	Average citations		H-index	
				Scopus	WoS	Scopus	WoS
1	Amity University (India)	12	1.4	2.8	1.0	4	1
2	SRM Institute of Science and Technology (India)	11	1.3	7.7	38.0	3	1
3	Lovely Professional University (India)	11	1.3	2.1	2.3	2	2
4	Sharda University (India)	11	1.3	1.5	N/A	2	N/A
5	University College London (United Kingdom)	10	1.2	19.4	15.4	5	4
6	University of London (United Kingdom)	9	1.0	N/A	13.7	N/A	4
7	Symbiosis International (Deemed University) (India)	9	1.0	3.4	5.3	3	1
8	Chandigarh University (India)	9	1.0	5.1	15.0	3	1
9	Chitkara University, Punjab (India)	9	1.0	2.9	0	2	0

Note. * – percent of total 859 publications, N/A – data not available.

The analysis of journals publishing the largest number of articles on digital technologies supporting predictive healthcare reveals a clearly dispersed publication landscape. The most productive outlet is Lecture Notes in Networks and Systems, which published 19 papers, accounting for 2.2% of the total dataset. At the same time, this source shows very limited citation impact, with an average of fewer than one citation per article and low H-index values.

A much higher impact is observed in journals with a smaller number of publications. IEEE Access, with 14 articles, records the highest average citation rate in Scopus, exceeding 58 citations per paper, and relatively high H-index values. This indicates that studies with the strongest scientific influence tend to be published in less prolific but more visible outlets.

Journals such as Frontiers in Digital Health (14 publications) and Sensors (11 publications) combine moderate productivity with solid citation performance in both databases and comparable H-index values. This suggests their growing role as specialised publication platforms in this research area.

Conference-oriented and technical series, including Lecture Notes in Computer Science (10 publications) and Smart Innovation Systems and Technologies (12 publications), contribute a substantial number of papers, but their citation impact remains limited. This indicates that they mainly serve as dissemination channels rather than as core sources shaping the intellectual debate (Table 5).

The data indicate that despite the presence of several productive journals, scientific impact is concentrated in a small number of high-visibility outlets, while a large share of publications is dispersed across technical and conference-based sources. This pattern reflects the still evolving nature of research on digital technologies supporting predictive healthcare.

Table 5. Journals publishing the most articles on digital technologies supporting predictive healthcare.

No.	Item	Number of publication	Percent of total publications*	Average citations		H-index	
				Scopus	WoS	Scopus	WoS
1	Lecture Notes in Networks and Systems	19	2.2	0.8	0	2	0
2	Frontiers in Digital Health	14	1.6	17.1	13.7	6	5
3	IEEE Access	14	1.3	58.2	19.9	8	7
4	Smart Innovation Systems and Technologies	12	1.4	1.8	12	2	1
5	Sensors	11	1.3	10.4	8.7	5	5
6	Lecture Notes in Computer Science	10	1.2	1.3	0.5	2	1
7	Healthcare (Switzerland)	9	1.0	3.8	2.9	3	2
8	Studies in Health Technology and Informatics	7	0.8	0.4	0	1	0
9	Communications in Computer and Information Science	7	0.8	1.9	5	1	1
10	AI Powered Digital Twins for Predictive Healthcare Creating Virtual Replicas of Humans	6	0.7	0.7	N/A	1	N/A

Note. * – percent of total 859 publications, N/A – data not available.

The journal co-citation map shows that the literature in the analysed field is concentrated around 18 leading medical and interdisciplinary journals (Figure 4). One journal clearly dominates the centre of the network. This is the Journal of the American Medical Association (JAMA). It plays a key role in connecting different research streams. JAMA is frequently co-cited with the Journal of Medical Internet Research, the International Journal of Environmental Research and Public Health, and BMC Medical Education. This pattern reflects strong links between clinical research, public health, and digital health technologies. Another visible cluster consists of highly prestigious clinical journals. These include The Lancet, the New England Journal of Medicine, and the European Heart Journal. These journals are often co-cited with each other. This indicates that research on predictive healthcare technologies is firmly grounded in high-impact clinical literature. A separate but connected cluster relates to digital medicine and sensor-based research. It includes NPJ Digital Medicine, Sensors, IEEE Access, and Scientific Reports. This cluster highlights the growing role of technological and engineering approaches in predictive healthcare research. Overall, the map shows that the intellectual core of the field is shaped by the integration of clinical studies, public health research, and digital health solutions. These studies are mainly published in leading medical and interdisciplinary journals.

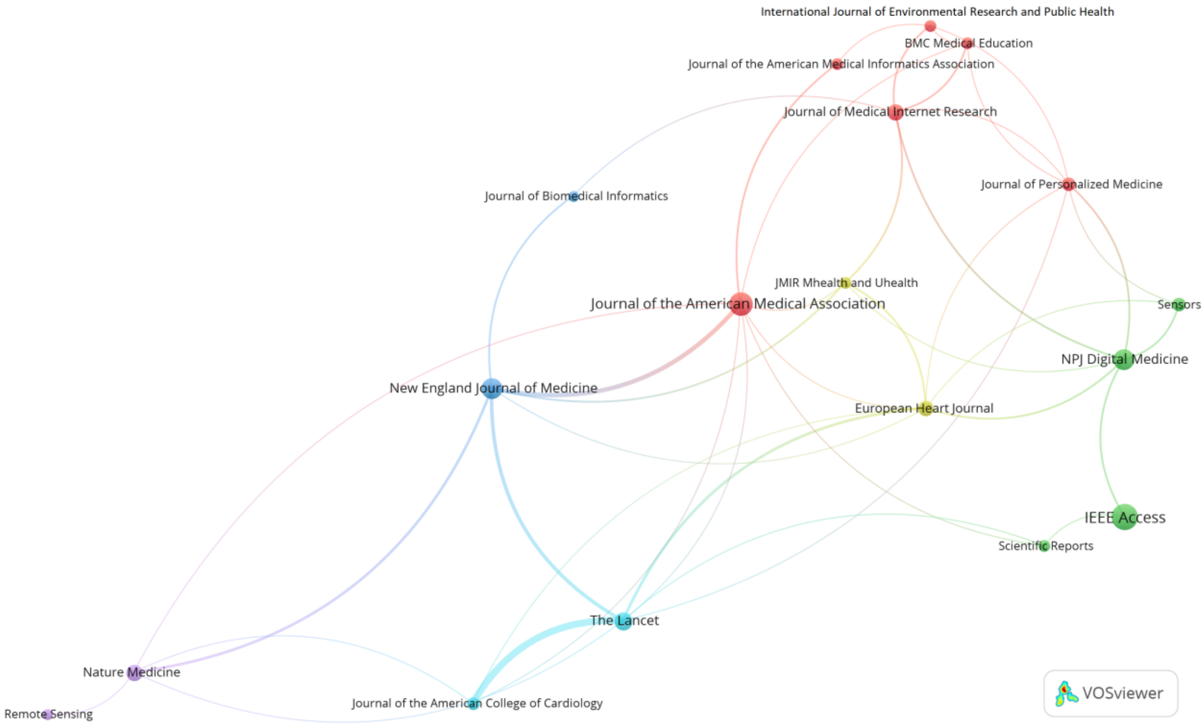

Figure 4. Journal co-citation network in research on digital technologies supporting predictive healthcare.
[Source: authors' own elaboration using software VOSviewer 1.6.20]

The country co-authorship map includes 47 countries involved in research on digital technologies supporting predictive healthcare (Figure 5). The level of international collaboration is clearly uneven. India occupies a very strong position in the network. It maintains numerous co-authorship links with other countries. Particularly strong connections are visible with the United States, the United Kingdom, and several Asian countries. The United States acts as an important connecting node. It links different collaboration clusters across regions. A clear cluster is formed by Western European countries, including the United Kingdom, Germany, France, and Italy. These countries are strongly connected with each other and with the United States. Their collaboration appears stable and well established. Another visible cluster includes countries from Asia and the Pacific region, such as China, South Korea, Singapore, and Malaysia. These countries show intensive collaboration, especially with India and the United States. Countries from Africa, South America, and the Middle East are located more peripherally. Their co-authorship links are weaker and usually limited to a small number of connections with the main research hubs.

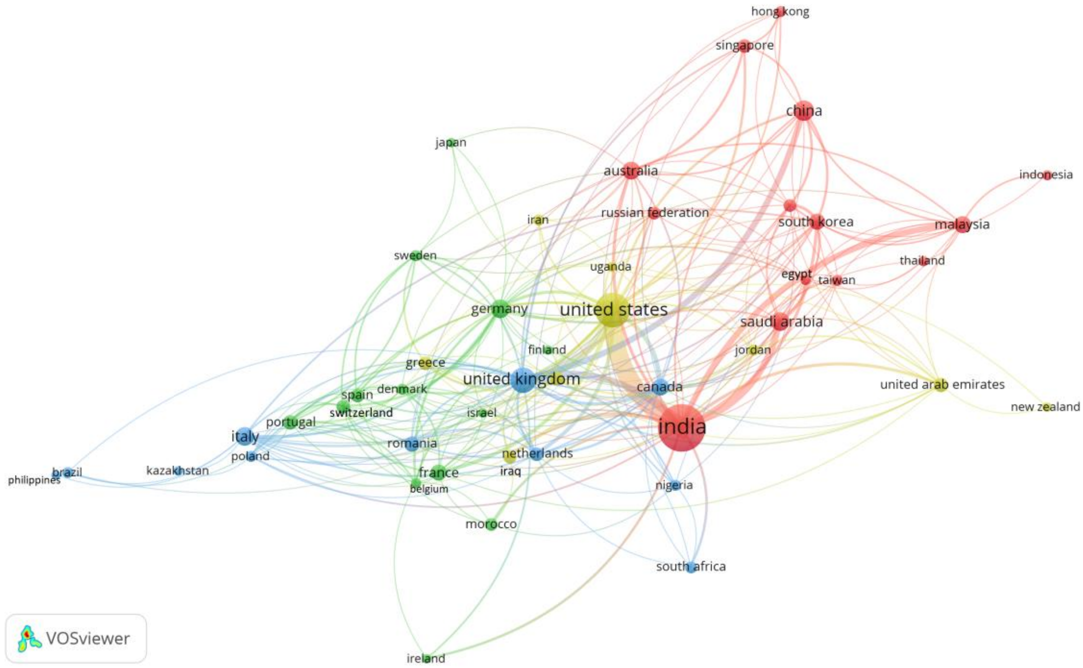

Figure 5. Country co-authorship network in research on digital technologies supporting predictive.
[Source: authors' own elaboration using software VOSviewer 1.6.20]

The geographical distribution of publications in digital technologies supporting predictive healthcare is clearly uneven. India is the most productive country, with 295 publications, accounting for 34.3% of the total output. The United States ranks second, with 134 publications (15.6%). It is followed by the United Kingdom, which produced 60 papers (7.0%). China contributes 38 publications, while Saudi Arabia and Italy each report 30 papers. Several other countries show a moderate level of research output. These include Germany (28 publications), Australia (24), Malaysia (22), and Canada (21). Together, these countries account for a smaller, yet still visible, share of the total publication volume. Citation indicators reveal a more differentiated pattern of impact. The United Kingdom records the highest average citation rates, with 26.7 citations per paper in Scopus and 23.6 in the Web of Science. Italy also demonstrates strong citation performance, with average values of 21.0 in Scopus and 18.8 in the Web of Science. The United States combines a high publication volume with a relatively strong citation impact and the highest H-index values in both databases. In contrast, some countries with high publication output, such as India and Malaysia, show lower average citation levels in Scopus, which suggests that a substantial share of their contributions is cited less frequently within the core literature of the field. In the case of China, citation impact appears more balanced across databases (Table 6).

Table 6. Countries producing the highest number of publications in digital technologies supporting predictive healthcare.

No.	Item	Number of publication	Percent of total publications*	Average citations		H-index	
				Scopus	WoS	Scopus	WoS
1	India	295	34.3	5.0	22.8	18	13
2	United States	134	15.6	18.0	20.3	25	17
3	United Kingdom	60	7.0	26.7	23.6	16	11
4	China	38	4.4	7.3	21.7	9	8
5	Saudi Arabia	30	3.5	9.0	10.1	7	6
6	Italy	30	3.5	21.0	18.8	8	6
7	Germany	28	3.3	13.8	6.2	9	7
8	Australia	24	2.8	7.6	17.7	8	7
9	Malaysia	22	2.6	13.9	4.8	7	3
10	Canada	21	2.4	11.5	3.8	6	3

Note. * – percent of total 859 publications.

The map of international co-authorships shows a clearly asymmetrical pattern of global collaboration in research on digital technologies supporting predictive healthcare (Figure 6). China and the United States act as the two main hubs of the network. They are connected by the strongest collaborative ties. China maintains particularly strong links with several Asian countries, including South Korea, Singapore, and Malaysia. Frequent cooperation is also visible with Australia. The United States occupies a central bridging position between Asia and Europe. It collaborates intensively with China, the United Kingdom, and a range of European countries.

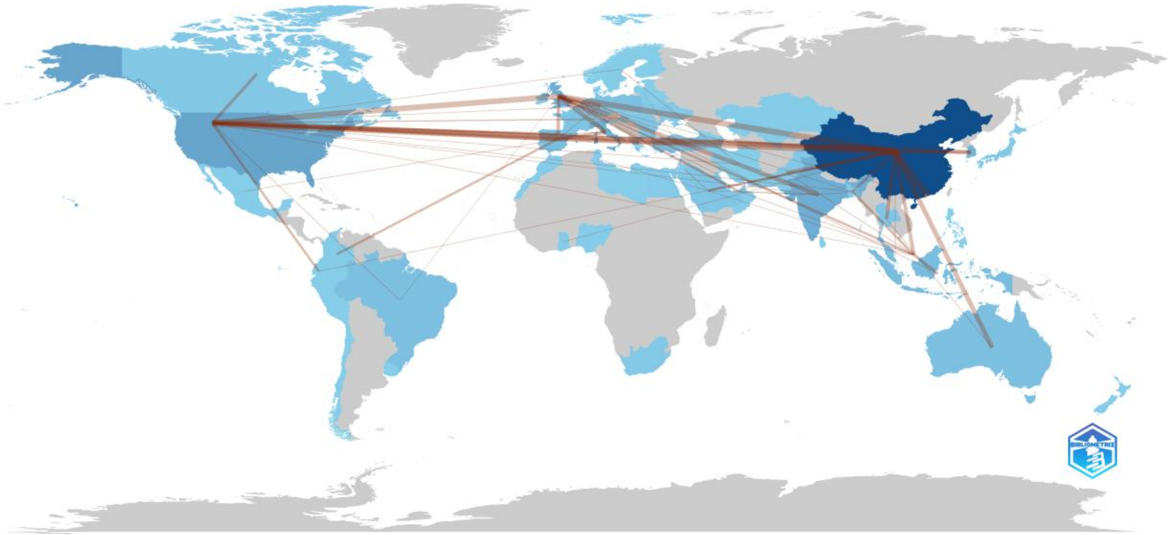

Figure 6. International collaboration network of countries in research on predictive healthcare digital technologies. [Source: authors' own elaboration using software RStudio – Biblioshiny 5.2.1]

The United Kingdom serves as the main European connector. It maintains close research ties with both China and the United States. Regular collaboration is also observed with countries such as Germany and Italy. Within Europe, collaboration is relatively dense and multi-directional. No single bilateral axis dominates the region. In contrast, countries from Africa, South America, and parts of the Middle East appear in more peripheral positions.

Their collaboration is often mediated through the main research hubs. Overall, the map indicates that the global collaboration network in this field is structured primarily around China, the United States, and the United Kingdom.

Citation data highlight a group of publications that clearly stand out in research on digital technologies supporting predictive healthcare (Table 7). The most highly cited articles are predominantly survey and review papers, indicating a strong demand for integrative and systematising studies in this field. The highest citation counts are recorded for two survey articles on digital twins. The paper by Wu et al. (2021) and the study by Mihai et al. (2022) both exceed 700 citations in Scopus and 490 citations in the Web of Science. These works serve as key reference points for research on digital twin architectures, applications, and future research directions. High citation impact is also observed for studies linking artificial intelligence and big data analytics with healthcare and sustainability outcomes. The article by Benzidia et al. (2021), which examines AI-driven green supply chain integration and hospital environmental performance, has attracted more than 500 citations in Scopus. Similarly, the study by Mamoshina et al. (2018) on blockchain and next-generation artificial intelligence technologies is frequently cited in Scopus, despite the absence of citation data in the WoS.

Several highly cited publications focus on machine learning and explainable artificial intelligence in clinical and healthcare settings. This group includes narrative and conceptual reviews, such as Peiffer-Smadja et al. (2020) and Saraswat et al. (2022), which address clinical decision support systems and the broader concept of Healthcare 5.0. Their citation levels indicate strong interest in both practical applications and ethical challenges related to AI adoption in healthcare. More recent contributions, including Giuffrè and Shung (2023) and Marques et al. (2024), concentrate on synthetic data, precision medicine, and in silico approaches. Although these studies were published recently, they already show notable citation activity, pointing to emerging research fronts within the field.

Table 7. Most cited articles in research on digital technologies supporting predictive healthcare.

No.	Authors	Article title	Journal title	Citations	
				Scopus	WoS
1	Wu Y.W., Zhang K., Zhang Y. (2021)	Digital Twin Networks: A Survey	IEEE Internet of Things Journal, 8(18)	721	523
2	Mihai S.,Yaqoob M., Hung D., Davis W., Towakel P., Raza M., Karamanoglu M., Barn B., Shetve D., Prasad R., Venkataraman H., Trestian R., Nguyen H. X. (2022)	Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects	IEEE Communications Surveys and Tutorials, 24(4)	753	492
3	Benzidia S., Makaoui N., Bentahar O. (2021)	The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance	Technological Forecasting and Social Change, 165, 120557	547	414
4	Mamoshina P., Ojomoko L., Yanovich Y., Ostrovski A., Botezatu A., Prikhodko P., Izumchenko E., Aliper A., Romantsov K., Zhebrak A., Ogu I. O., Zhavoronkov A.	Converging blockchain and next-generation artificial intelligence technologies to decentralize and accelerate biomedical research and healthcare	Oncotarget, 9(5)	414	N/A

	(2018)				
5	Peiffer-Smadja N., Rawson T.M., Ahmad R., Buchard A., Pantelis G., Lescure F.-X., Birgand G., Holmes A.H. (2020)	Machine learning for clinical decision support in infectious diseases: a narrative review of current applications	Clinical Microbiology and Infection, 26(5)	413	N/A
6	Saraswat D., Bhattacharya P., Verma A., Prasad V. K., Tanwar S., Sharma G., Bokoro P. N., Sharma R. (2022)	Explainable AI for Healthcare 5.0: Opportunities and Challenges	IEEE Access, 10	377	169
7	Giuffrè, M., Shung, D.L. (2023)	Harnessing the power of synthetic data in healthcare: innovation, application, and privacy	Npj Digital Medicine, 6(1), 186	222	179
8	Marques L., Costa B., Pereira M., Silva A., Santos J., Saldanha L., Silva I., Magalhães P., Schmidt S., Vale N. (2024)	Advancing Precision Medicine: A Review of Innovative In Silico Approaches for Drug Development, Clinical Pharmacology and Personalized Healthcare	Pharmaceutics, 16(3), 332	188	141
9	Rehman A., Abbas S., Khan M. A., Ghazal T. M., Adnan K.M., Mosavi A. (2022)	A secure healthcare 5.0 system based on blockchain technology entangled with federated learning technique	Computers in Biology and Medicine, 150, 106019	181	N/A
10	Fitzpatrick P.J. (2023)	Improving health literacy using the power of digital communications to achieve better health outcomes for patients and practitioners	Frontiers in Digital Health, 5, 1264780	177	N/A

Note. * – percent of total 859 publications, N/A – data not available.

Author keywords were analysed as part of the bibliometric study of research on digital technologies supporting predictive healthcare. The co-occurrence mapping was carried out using VOSviewer. Before the analysis, a dedicated thesaurus file was prepared. It was used to unify terminology and correct inconsistencies in keyword spelling and meaning. Closely related terms were merged. This step improved the overall coherence of the dataset. At the initial stage, 87 author keywords met the minimum threshold of at least five occurrences. General or redundant terms were then reviewed and removed. Expressions with similar meanings were harmonised. The aim was to focus on more specific and analytically relevant concepts. After the cleaning process, 64 distinct author keywords remained. These keywords were used to construct the co-occurrence map. The map illustrates the main thematic areas of the field and the relationships between them (Figure 7).

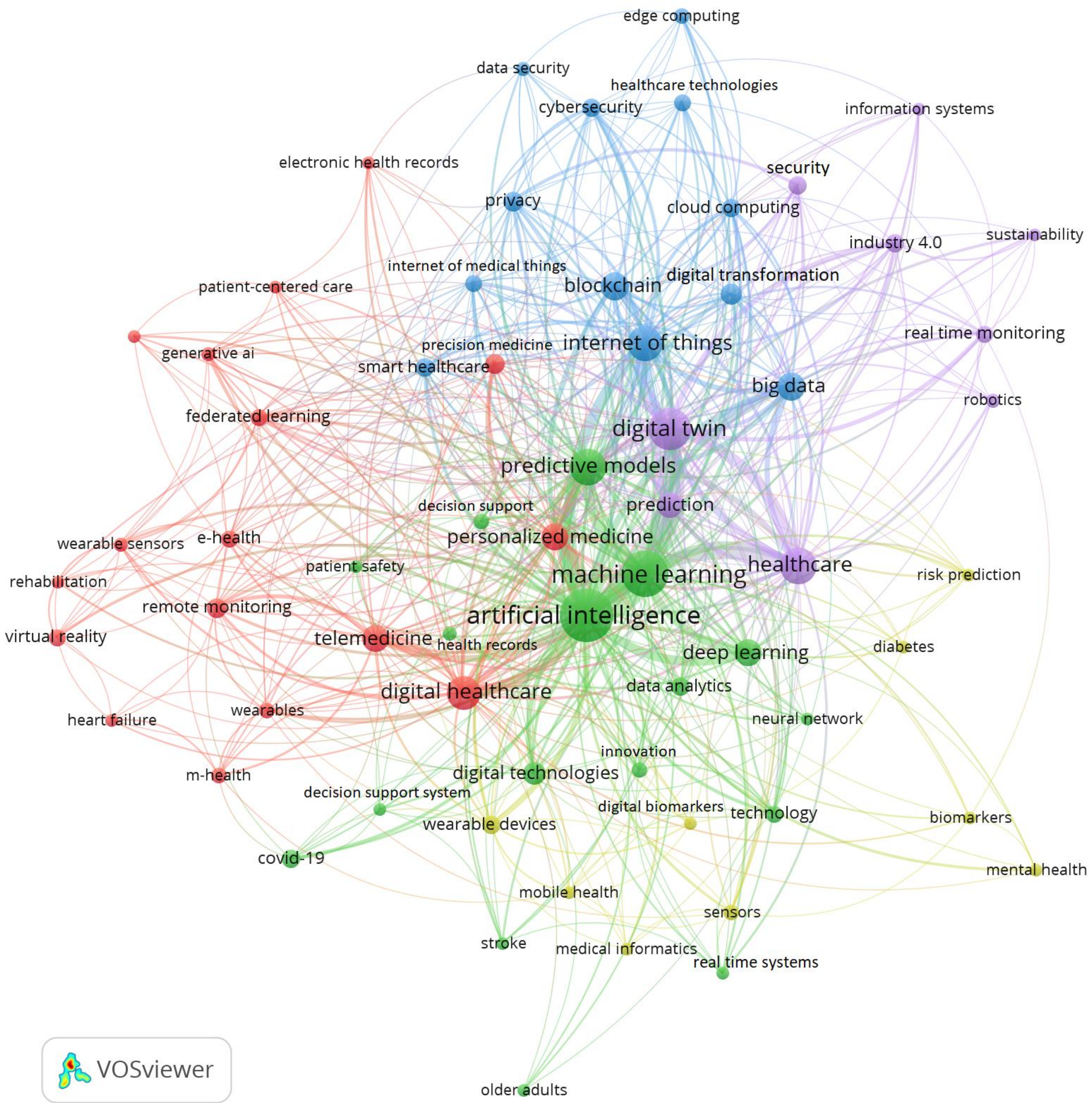

Figure 7. Co-occurrence network of author keywords in research on predictive healthcare digital technologies. [Source: authors' own elaboration using software VOSviewer 1.6.20]

A co-occurrence analysis of author keywords was conducted to identify the main research themes in studies on digital technologies supporting predictive healthcare. Only keywords that appeared in at least five publications were included in the analysis. This threshold helped to focus on the most established and recurrent topics in the literature. The analysis resulted in the identification of five major thematic clusters, which are summarised in Table 8. Each cluster represents a distinct but interrelated research sub-area within the field.

Table 8. Main research sub-areas in digital technologies supporting predictive healthcare.

No.	Research sub-areas	Keywords
1	Digital and personalised healthcare (red)	digital healthcare (65), telemedicine (36), personalized medicine (35), remote monitoring (17), precision medicine (16), federated learning (12), e-health (10), virtual reality (10), m-health (8), wearables (8), generative ai (7), wearable sensors (7), electronic health records (5), heart failure (5), oncology (5), patient-centered care (5), rehabilitation (5)
2	Artificial intelligence and predictive models in healthcare (green)	artificial intelligence (200), machine learning (140), predictive models (73), deep learning (33), digital technologies (22), COVID-19 (13), data analytics (13), technology (12), innovation (9), decision support (8), health records (7), decision support system (6), patient safety (6), neural network (5), older adults (5), real-time systems (5), stroke (5)
3	Digital infrastructure and data security in healthcare (blue)	internet of things (68), big data (39), blockchain (38), digital transformation (18), privacy (17), cloud computing (14), cybersecurity (14), smart healthcare (14), healthcare technologies (12), internet of medical things (12), edge computing (8), data security (7)
4	Wearable devices and digital biomarkers (yellow)	wearable devices (14), sensors (8), biomarkers (6), mobile health (6), diabetes (5), digital biomarkers (5), medical informatics (5), mental health (5), risk prediction (5)
5	Digital twin and predictive systems in healthcare (violet)	digital twin (111), healthcare (79), prediction (31), industry 4.0 (13), security (13), real-time monitoring (12), robotics (7), information systems (6), sustainability (5)

The first cluster, “Digital and personalised healthcare”, brings together studies that examine the ongoing digital transformation of healthcare systems. This transformation is discussed both from the perspective of patients and from the viewpoint of how care is organised and delivered. Much of the literature concentrates on digital healthcare and telemedicine as emerging modes of service provision. These concepts are used to describe new forms of medical care, including remote and hybrid models that extend beyond traditional clinical settings. Empirical findings suggest that such solutions improve access to healthcare services, support more continuous monitoring of patients’ health status and encourage greater patient involvement in the treatment process (Chen et al., 2025b; Wellmann et al., 2024). A well-defined line of research within this cluster relates to personalised and precision medicine. In this context, digital technologies are applied to adapt therapeutic interventions to individual patient characteristics. The analysed studies emphasise the importance of clinical data, patient-generated information and longitudinal health records in the design of personalised care pathways. These approaches are particularly visible in areas such as oncology, heart failure and the management of chronic diseases, where individual variability plays a critical role in treatment outcomes (Samathoti et al., 2025; Wattanachayakul et al., 2024). The cluster also encompasses work on remote monitoring solutions that enable the continuous observation of health parameters outside medical institutions. The literature indicates that these approaches allow for earlier identification of health deterioration and provide support for rehabilitation processes. At the same time, they reinforce patient-centred models of care, which are especially relevant in long-term treatment and during the post-hospitalisation phase (Wellmann et al., 2024; Ardelean et al., 2024). In addition, several studies focus on the use of wearable devices, wearable sensors and virtual reality technologies as tools that support therapy, rehabilitation and patient education. These technologies are discussed mainly in relation to improving patient experience and further advancing the personalisation of healthcare interventions (Smokovski et al., 2024; Baron & Haick, 2024).

The cluster "Artificial intelligence and predictive models in healthcare" encompasses research focused on the use of artificial intelligence, machine learning, and predictive models in the analysis of health data and in supporting clinical decision making. A central role is played by machine learning and deep learning algorithms, which are applied to disease trajectory prediction, risk identification, and early detection of health threatening conditions (Chen et al., 2025b; Pinto et al., 2025). An important research stream concerns the development of predictive models based on clinical data, electronic health records, and real time generated data. These models are used, among others, for predicting exacerbations of chronic diseases, detecting sepsis, forecasting stroke events, and assessing the risk of rehospitalisation (Pinto et al., 2025; Boussi Rahmouni et al., 2025). The cluster also strongly represents studies on decision support and decision support systems that integrate artificial intelligence algorithms into clinical practice. These studies emphasise the role of automated data analysis in improving patient safety, reducing the workload of medical staff, and supporting therapeutic decisions in time critical environments such as intensive care units (Boussi Rahmouni et al., 2025; Shankar et al., 2025). A clearly visible research theme relates to the application of artificial intelligence in the care of older adults and patients with chronic conditions. The findings indicate that predictive algorithms can support early infection detection, monitoring of health deterioration, and the personalisation of therapeutic interventions in older populations (Tana et al., 2025; Pinto et al., 2025). The COVID-19 pandemic provided an additional developmental impulse for this cluster. Predictive models and analytical tools were extensively used to forecast resource demand, analyse the spread of infection, and optimise decision making processes within healthcare systems (Nair et al., 2025). This cluster reflects a shift in research towards data driven healthcare, in which artificial intelligence plays a key analytical role.

The "Digital infrastructure and data security in healthcare" cluster covers work that examines the technical underpinnings of contemporary digital health systems. It describes, in a fairly practical way, how health data are acquired, transmitted, processed and protected as care becomes increasingly data-intensive and interconnected. A recurring theme is the role of Internet of Things and Internet of Medical Things solutions. These technologies enable continuous data collection and support the integration of information produced by multiple medical devices. In this way, data that were previously fragmented can be brought together and used within more coordinated clinical workflows. The literature underlines that this level of connectivity is a fundamental condition for the development of smart healthcare solutions and for systems that rely on real-time data processing (Sadeghi & Mahmoudi, 2024; Yigit et al., 2024). Alongside connectivity, the cluster gives substantial attention to data volume and computing capacity. Studies on big data and cloud computing show how cloud platforms enable healthcare organisations to scale digital services and combine sensor-derived data with electronic health records. This integration is presented as a key condition for analysing large datasets and delivering more advanced digital health solutions (Bellavista & Di Modica, 2024). The expansion of distributed digital infrastructures is accompanied by a new set of challenges. A key concern relates to the protection of sensitive health data. The literature increasingly points to risks associated with privacy breaches, cyberattacks and the loss of data integrity. As a result, a substantial body of research addresses security-related issues, particularly in settings characterised by a rapidly growing number of interconnected devices (Nankya et al., 2024; Otoom, 2025). Within this line of research, blockchain is discussed as a promising solution. It is most often presented as a tool that can strengthen trust and transparency in data management. The literature also highlights its potential to reduce the risk of data breaches and to improve interoperability between healthcare systems that are otherwise poorly integrated (Addula et al., 2025; Adeniyi et al., 2024). Edge computing appears in the same line of argument as a complementary solution. By relocating part of the processing closer to the data source, it can reduce latency and lessen reliance on cloud resources, which is particularly relevant for real-time monitoring scenarios (Jameil & Al-Raweshidy, 2024b).

The "Wearable devices and digital biomarkers" cluster comprises studies examining the use of wearable technologies and digital biomarkers in health monitoring. This body of research concentrates on technological solutions that allow for the continuous and non-invasive acquisition of physiological data. A key feature of these approaches is that data collection takes place in everyday settings, beyond conventional clinical environments. Central to this cluster are wearable devices and sensors, which provide real-time information on an individual's health status. A key line of inquiry within this body of work concerns digital biomarkers. These are defined as measurable indicators of health that are derived directly from data generated by digital technologies. These biomarkers are increasingly used to detect early changes in health condition and to monitor disease progression over time (Smokovski et al., 2024; Wasilewski et al., 2024). The literature consistently highlights their role in supporting a gradual shift from reactive healthcare towards more predictive and personalised models of care. Mobile health technologies emerge in the literature as a particularly important area of application within this cluster. This is most clearly reflected in studies focusing on diabetes and cardiovascular diseases. In these settings, information collected through wearable sensors is integrated with predictive modelling techniques. This combination supports clinical risk evaluation and enhances anticipatory decision-making. In particular, it allows clinicians to identify early warning signals, such as impending glycaemic events or the onset of clinical deterioration in patients with chronic diseases (Ying et al., 2025; Wattanachayakul et al., 2024). These approaches contribute to earlier clinical responses and improved disease management. Mental health applications are also clearly represented in this cluster. Analyses in this area often focus on physiological parameters such as sleep patterns and heart rate variability. These measures are used to derive digital indicators of stress and psychological burden (Rana et al., 2025; Pataca et al., 2025).

The "Digital twin and predictive systems in healthcare" cluster focuses on digital twins and predictive systems in healthcare. It covers models that represent a patient, a clinical process, or a hospital environment. These models are fed with sensor and information system data. They often operate in real time (Jameil & Al-Raweshidy, 2025; Rahim et al., 2024). The literature highlights continuous monitoring and early anomaly detection. It also stresses the integration of cloud, edge solutions, and AI. The aim is to shorten response time and improve predictive performance (Jameil & Al-Raweshidy, 2024b). Emergency management is an important strand. Digital twins are linked to operational decision-making and system load forecasting. Issues related to system resilience and the efficient flow of information emerge as important themes in this body of research (Zheng et al., 2025). Many studies also explicitly refer to the concepts of Industry 4.0 (Lăzăroiu et al., 2022a,b; Andronie et al., 2023a,b) and the Internet of Things, which frame digital twins as integral components of broader processes of digital transformation in healthcare systems. In this view, they support data integration and predictive decisions (Bongomin et al., 2025; Narigina et al., 2024). Security is also central. It concerns privacy, data integrity, and cyber risks. The literature addresses a range of security-related mechanisms, including encryption methods, authentication procedures and approaches to risk auditing. In this context, blockchain is frequently analysed as a potential means of enhancing trust and enabling secure data exchange across healthcare systems (Addula et al., 2025; Nankya et al., 2024; Otoom, 2025; Sadeghi & Mahmoudi, 2024). At the same time, applied studies extend these technological considerations to clinical domains, with particular attention given to areas such as cardiology and oncology. Authors point to personalised simulation and risk prediction. At the same time, they note the need for stronger validation and implementation readiness (Stefaniga et al., 2024; Thangaraj et al., 2024).

As part of the conducted analyses, a thematic map was also developed (Figure 8). Its purpose was to capture the structure and directions of research on digital technologies supporting predictive healthcare.

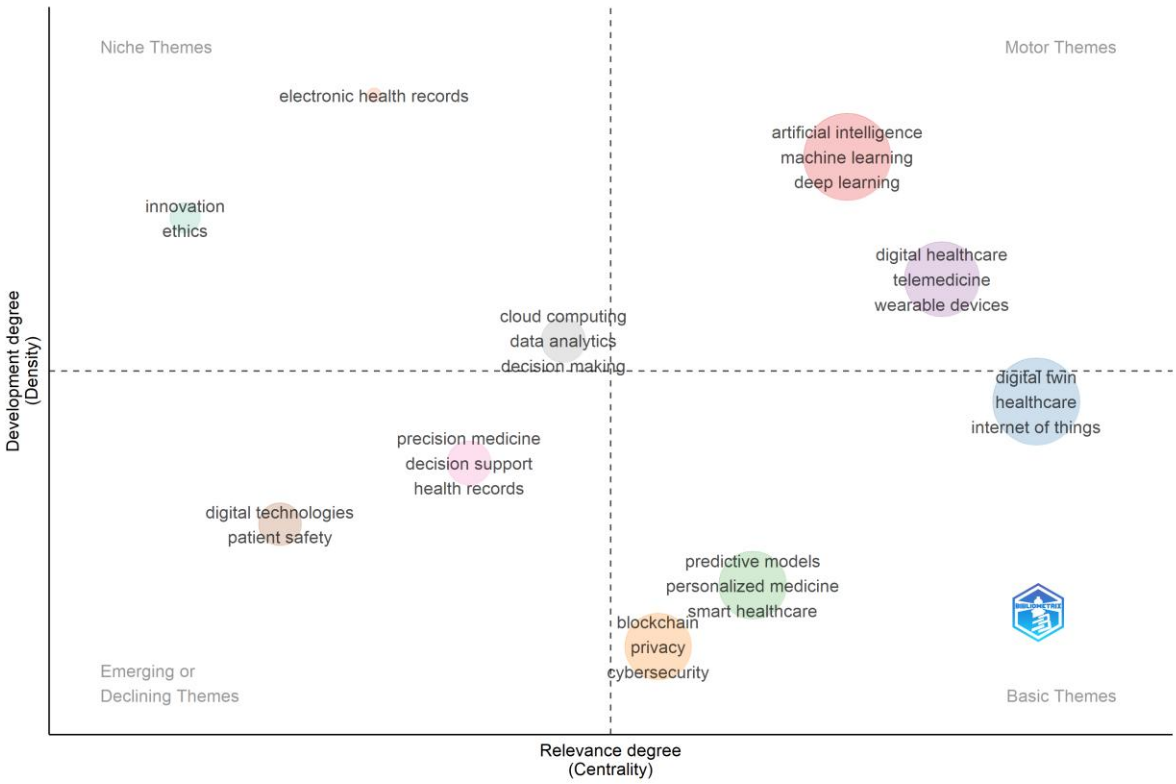

Figure 8. Thematic map of research on digital technologies supporting predictive healthcare.
[Source: authors' own elaboration using software RStudio – Biblioshiny 5.2.1]

The map makes it possible to identify both central research areas and more specialised themes, while taking into account their level of development and their connections with other topics. A central position on the map is occupied by themes related to artificial intelligence, including machine learning and deep learning (high centrality and high density). Their location confirms that AI-based approaches currently form the core of research on predictive healthcare. These themes are strongly integrated with other research streams and are intensively developed. Close to this core are themes such as digital healthcare, telemedicine, and wearable devices (high centrality and moderate density). Their placement indicates that digital care models and remote monitoring technologies have become a stable element of the dominant research discourse. An important position on the map is also held by topics related to data security and digital infrastructure. Themes such as blockchain, privacy, and cybersecurity are located among the basic themes (high centrality with moderate density). This suggests that they are strongly connected with other research areas but are still undergoing systematic development. Blockchain appears mainly in the context of data integrity protection, trust in predictive systems, and the secure exchange of medical information between healthcare stakeholders.

Themes such as predictive models and personalised medicine play a supporting role (high centrality, moderate density). They provide a conceptual foundation for the application of AI and secure data-processing systems, although their internal consolidation is still in progress. At the margins of the map, more specialised topics can be observed, including electronic health records, ethics, and innovation (lower centrality with relatively higher density). These themes often appear in regulatory, organisational, and ethical contexts, particularly in relation to data security and the responsible use of blockchain and AI technologies.

The previous static analyses are complemented by a thematic evolution map, which makes it possible to trace how the main research topics have changed over time. The Sankey diagram shown in Figure 9 illustrates both continuity and thematic shifts in research on digital technologies supporting predictive healthcare.

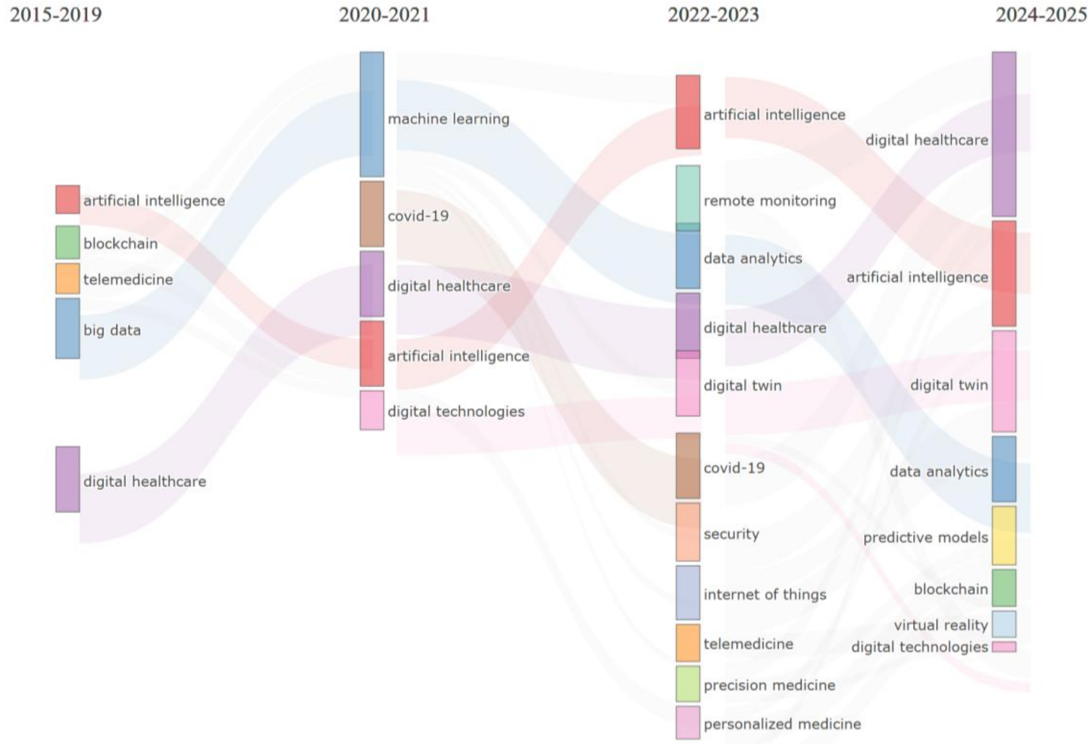

Figure 9. Thematic evolution of research on digital technologies supporting predictive healthcare.
[Source: authors' own elaboration using software RStudio – Biblioshiny 5.2.1]

In the first period (2015–2019), the thematic scope was relatively narrow. Research focused mainly on broad concepts such as artificial intelligence, blockchain, telemedicine, and big data. These terms functioned more as general technological frames than as components of mature analytical models. The early presence of digital healthcare already signalled the later development of this research stream. During 2020–2021, the thematic structure became more differentiated. Machine learning gained visibility, while COVID-19 emerged as an important, though temporary, topic. At the same time, research on digital healthcare and artificial intelligence expanded, indicating a shift towards more advanced analytical methods and clinical applications.

The period 2022–2023 was marked by further deepening and specialisation. Alongside artificial intelligence and digital healthcare, topics such as data analytics, remote monitoring, and digital twin became more prominent. At the same time, themes related to security and the internet of things developed more strongly, reflecting the growing importance of digital infrastructure and data protection in predictive systems. In the most recent period (2024–2025), the focus moves towards more integrated and application-oriented themes. Digital healthcare, artificial intelligence, and digital twin occupy central positions. Increasing attention is also given to predictive models and data analytics, as well as immersive and interactive technologies such as virtual reality. The reappearance of blockchain at this stage points to rising interest in trust, data integrity, and system security in healthcare environments.

Complementing the analyses of thematic structure and evolution, the trend chart offers a forward-looking perspective on research into digital technologies supporting predictive healthcare (Figure 10).

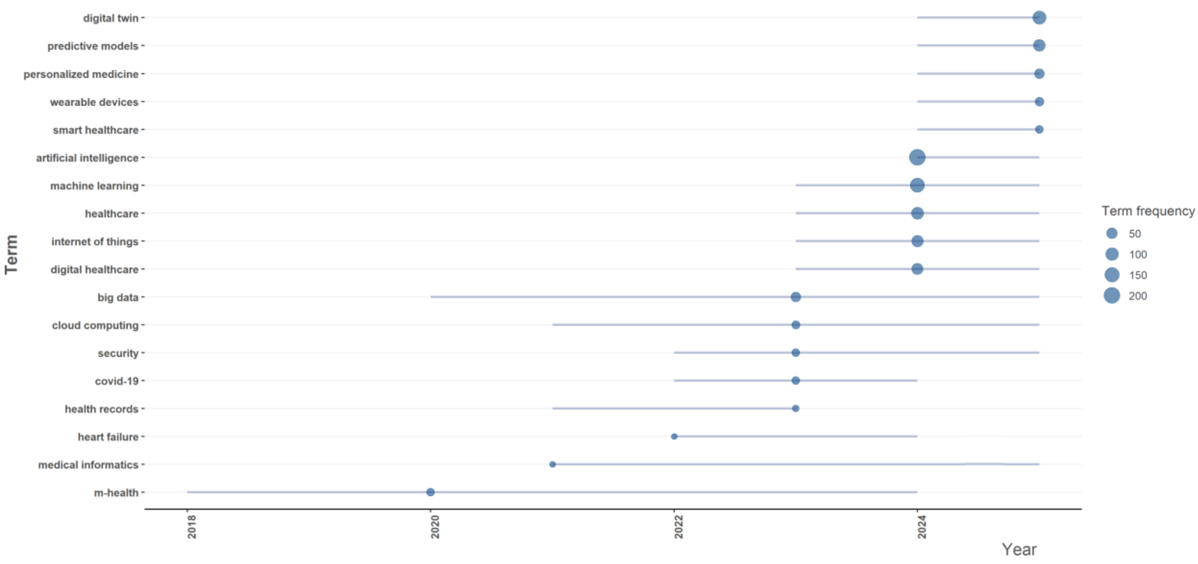

Figure 10. Research trends in predictive healthcare digital technologies.
[Source: authors' own elaboration using software RStudio – Biblioshiny 5.2.1]

It shows that in recent years topics related to artificial intelligence and machine learning have become increasingly dominant, closely linked with predictive models and digital healthcare. At the same time, the growing visibility of themes such as digital twin, personalised medicine, wearable devices, and smart healthcare points to a shift towards more integrated, personalised, and continuously monitored healthcare solutions. The stable presence of topics related to cloud computing, the internet of things, and data security further highlights that the future development of predictive systems relies strongly on robust digital infrastructure and trust in data processing.

EMERGING THEMATIC AREAS

The results of the bibliometric analysis clearly indicate that the concept of digital twins currently represents one of the most rapidly developing research trends within the field of digital technologies supporting predictive healthcare. The trend analysis presented in Figure 10 shows that interest in digital twin–related research has increased markedly in recent years. This development is closely linked to the growing role of artificial intelligence and machine learning methods, which form the foundation of contemporary predictive models. The increasing frequency of terms such as digital healthcare and predictive models further confirms a shift in the research paradigm towards solutions focused on forecasting health processes and adopting a more proactive approach to patient care.

At the same time, the trend analysis reveals a gradual shift in research interests towards healthcare models based on greater data integration and continuous monitoring. More frequent references to personalised medicine, wearable devices and smart healthcare systems suggest that digital twins are no longer viewed as isolated analytical tools. Instead, they are increasingly embedded within broader patient data ecosystems. These ecosystems enable the integration of information derived from multiple sources and its application in diagnostic and decision-making processes. The stable presence of themes related to cloud infrastructure, the Internet of Things and data security highlights the importance of robust and trustworthy technological foundations for the further development of predictive healthcare systems.

On the basis of the obtained results, three emerging thematic areas were identified that particularly reflect current and future directions of research into digital technologies for predictive healthcare. The first area focuses on digital twins and integrated patient data ecosystems, including interoperability, large-scale data analytics and clinical decision support. The second area concerns predictive and preventive digital twins aimed at care personalisation, disease prevention and the optimisation of health trajectories. The third area addresses treatment planning and patient response simulation using digital twins, with particular emphasis on clinical, surgical and rehabilitation applications. A detailed discussion of each of these thematic areas is provided in the following subsections.

Topic 1. Digital Twins and Integrated Patient Data Ecosystems

Digital twins that use artificial intelligence and wearable IoMT sensors are increasingly applied in healthcare. They enable the simulation of disease progression and the planning of therapeutic interventions. They also support predictive medical analytics, the analysis of large clinical datasets, and clinical decision support systems (Cappon & Facchinetti, 2024). This allows the delivery of virtual medical services and the precise adjustment of therapies to individual patient needs.

Models of treatment response based on physical principles and analysed across multiple scales strengthen clinical decision support systems. They improve the prediction of treatment response, clinical risk, and disease trajectories. They also facilitate the assessment of adverse event risk and the selection of therapeutic strategies (Trayanova & Prakosa, 2024). Predictive analytics based on IoMT digital twins support cloud-based and blockchain-enabled remote medical care and data-driven healthcare decision-making using large datasets (Jain et al., 2024).

Wearable IoMT sensors and blockchain technology are also used to simulate clinical procedures. They enable remote and personalised patient treatment. They also support care and recovery processes through cloud-based digital twins (Ghaempanah et al., 2024). Federated and swarm learning approaches enable the analysis of large, multimodal clinical datasets. These solutions support disease diagnosis and prognosis and the development of predictive patient digital twins (Chakshu & Nithiarasu, 2024). The analysis and interoperability of patient engagement data enable more personalised clinical decision-making in virtual environments (Samei, 2025).

Real-time analysis of large clinical datasets enables the simulation of clinical procedures, surgical interventions, and treatment responses. This supports the optimisation of patient care and recovery processes (de Oliveira El-Warrak & Miceli de Farias, 2025). Cyber-physical medical systems and extended reality technologies support treatment planning and disease progression forecasting. They facilitate diagnosis, prevention, and the evaluation of treatment effectiveness. They also enable continuous monitoring of patient vital signs (Nadeem et al., 2025).

Artificial intelligence and machine learning-based digital twins integrate different types of patient physiological data. This increases the accuracy of predicting severe disease conditions and improves diagnostic quality. These solutions also support real-time remote patient monitoring (Upadrista et al., 2025). Real-time patient data analysis enables the development of immersive healthcare delivery within the healthcare metaverse. It supports personalised treatment and disease diagnosis (Jeong & Lee, 2025).

Advanced digital twin models use deep learning and reinforcement learning to analyse patient health data. They enable the simulation of disease progression and treatment response. They also support the monitoring of medication adherence and therapy planning. They facilitate early disease detection and the adjustment of care to individual patient needs (Rizzo, 2025). Digital twins are also used in virtual simulations of surgical procedures. They support treatment, diagnosis, monitoring, and health status forecasting. As a result, they contribute to improved decision-making in healthcare systems (Xue et al., 2025).

Topic 2. Predictive and Preventive Digital Twins for Personalised Healthcare

Simulations of healthcare ecosystems based on cloud computing, blockchain technology, and IoT enable the creation of interoperable and immersive healthcare environments. These solutions support the modelling and prediction of healthcare service delivery in extended reality settings. They also facilitate diagnostic and therapeutic interventions and improve patient health status and treatment outcomes within the healthcare metaverse (Li et al., 2024b). Personalised virtual healthcare services integrate large volumes of patient medical data within extended reality environments. This enables more precise and individualised approaches to healthcare delivery (Ling & Butakov, 2024). Effective therapy planning and disease progression modelling require access to large-scale physiological and clinical data. They also involve predictive disease modelling, virtual clinical practice simulations, and continuous patient health monitoring and analysis (Bhagirath et al., 2024).

Predictive artificial intelligence-based digital twins enable the simulation of patient disease progression. They support treatment outcome prediction and preventive actions. They also facilitate clinical and healthcare decision-making, therapeutic target identification, and the optimisation of medication adherence (Li et al., 2025). Digital twins that integrate medical imaging and machine learning allow the monitoring of patient-specific pathological conditions. They support disease risk prediction, treatment planning, and clinical decision support systems. As a result, they contribute to improved treatment outcomes and greater accuracy in medical decision-making (Kimpton et al., 2025).

Connected healthcare digital twins that use explainable artificial intelligence and cyber-physical systems enable the analysis of multidimensional and multimodal patient health data. These solutions support real-time remote diagnosis, treatment, therapy, and rehabilitation. They rely on IoT sensors and actuators as well as blockchain technology to monitor and predict patient health status (Araghi et al., 2025).

Predictive digital twins based on deep learning and machine learning support the analysis and modelling of timely surgical interventions. They enable real-time monitoring of patient physiological signals. They support medical decision support systems based on support vector machines and k-nearest neighbour methods. They also facilitate early disease and abnormality detection using random forests and convolutional neural networks. These approaches contribute to improved treatment protocols and survival rates (Khan et al., 2025). The simulation and prediction of individual patient health trajectories support precise diagnosis and medical intervention planning. The use of multidimensional physiological and disease-related data enables the development of personalised treatment models. These solutions are applied within predictive digital twins based on explainable artificial intelligence. They support tailored health recommendations and the optimisation of clinical practice (Sel et al., 2025).

Digital twins that use reinforcement learning and machine learning support personalised preventive treatment and targeted therapies. They enable virtual patient diagnosis and prognosis prediction. They improve the accuracy of therapeutic decisions and surgical planning based on data from wearable IoT sensors. They also integrate the fusion and analysis of multimodal clinical and imaging data in real time. These solutions support treatment response modelling using generative adversarial and convolutional neural networks (Shen et al., 2025).

The healthcare metaverse and deep learning-based digital twins enable remote, immersive, and evidence-based rehabilitation. They allow real-time monitoring of patient health status, engagement, and responses to therapy. Wearable IoT sensors are used to support disease prevention and diagnosis (Chen et al., 2025a). Simulations of disease progression and patient responses, as well as the modelling of surgical and therapeutic interventions, enable more accurate treatment response prediction. They contribute to improved therapy effectiveness, clinical outcomes, and diagnostic and prognostic accuracy (Wu et al., 2025). Simulations of surgical procedures and predictive modelling of treatment pathways based on wearable IoT sensors support clinical decision-making. They also contribute to improved health outcomes and the monitoring of therapeutic intervention effects (Vaughan Robinson et al., 2025).

Topic 3. Digital Twin–Based Treatment Planning and Patient Response Simulation

Personalised predictive digital twins in healthcare, based on IoMT sensors and blockchain technology, are increasingly used in disease diagnosis. These solutions enable the interoperability and analysis of large healthcare and physiological datasets. They also support computer-aided diagnostic systems and medical decision support (Sadeghi & Mahmoudi, 2024). Modelling physiological and diagnostic process data using artificial intelligence and generative adversarial networks, combined with medical imaging analysis based on deep learning, reinforcement learning, and machine learning, enables the simulation and prediction of personalised therapeutic decisions (Jean-Quartier et al., 2024). Artificial intelligence-based digital twins support treatment planning, the simulation of patient responses to interventions, and disease progression modelling. They also enable the analysis of dynamic, multivariate patient state data and support clinical decision-making (Wentzel et al., 2025).

Healthcare delivery simulations, real-time medical image analysis, and the study of disease trajectories and treatment responses support better tailoring of interventions for at-risk patients. These approaches also contribute to improved treatment outcomes, as well as disease prediction, prevention, prognosis, and therapy planning (Li et al., 2025). Artificial intelligence-based digital twins support medical decision-making and healthcare process modelling. Therapy simulations in the healthcare metaverse, using extended reality technologies, enable forecasting of patient treatment outcomes. Treatment recommendation analysis based on IoMT sensors and cloud computing supports real-time diagnostic prediction. These solutions improve clinical decision-making, patient care, and the development of healthcare services in the metaverse (Sharma et al., 2025). Patient treatment modelling and simulation using IoMT sensors, together with real-time health data from wearable IoT devices, enable continuous patient monitoring. They support early disease detection, shorter surgical and recovery times, and improved surgical performance and patient outcomes (Asciak et al., 2025).

Internet of Medical Things solutions, based on wearable sensors and cloud computing, enable the simulation of patient care and medical diagnosis. They play a key role in remote, real-time monitoring of vital signs and patient health status. They also support early detection and prediction of health problems (Mistry & Dafoulas, 2025). Medical extended reality metaverse environments and predictive healthcare digital twins based on artificial intelligence support disease diagnosis, therapeutic decision-making, and treatment monitoring. They also enable prognosis and the simulation of preventive and rehabilitative interventions. The interoperability of physiological data collected from IoMT sensors, supported by blockchain technology, enables more coherent clinical data analysis. These solutions support virtual medical procedures, immersive rehabilitation, and the optimisation of diagnosis and therapy. They also improve healthcare delivery, patient engagement, and clinical outcomes, while supporting recovery processes and personalised healthcare interventions (Morone et al., 2025). Immersive simulations of remote surgical procedures using digital twins, artificial intelligence, and virtual medical systems enable patient motion tracking through IoT sensors and actuators (Kumar Jagatheesaperumal et al., 2024).

Modelling patient physiological state and treatment outcome data supports post-surgical care and recovery simulations. It also enables long-term forecasting of physiological parameters and therapeutic responses (Halder et al., 2025). Remote monitoring of patient vital signs and health status using IoT sensors and actuators, together with clinical data interoperability, enables the simulation of precise surgical interventions. These solutions can be used for early disease prevention, detection, diagnosis, and progression monitoring (Kumar et al., 2025). They also enable treatment planning, optimisation of therapeutic outcomes using machine learning-based digital twins, disease diagnosis, disease progression monitoring, and medication adherence assessment (Fatouros et al., 2025).

DISCUSSION

Taken together, the obtained results suggest that research on digital technologies supporting predictive healthcare is centred on a rapidly developing ecosystem that combines large-scale medical data analytics, machine learning algorithms and simulation-based technologies. Both the bibliometric and qualitative analyses indicate that solutions based on digital twins and Internet of Medical Things systems play a dominant role in this area, forming the foundation of cyber–physical healthcare systems (Shoukat et al., 2024).

The findings show that a substantial proportion of the analysed literature focuses on the application of deep learning algorithms, particularly convolutional neural networks, for early and accurate disease prediction and diagnosis. These methods are applied to both clinical and medical imaging data, enabling earlier detection of pathological changes and supporting therapeutic decision-making processes (Kulkarni et al., 2024; Badjatia et al., 2025). The observed link between artificial intelligence algorithms and the digital twin concept confirms the growing role of simulation-based and immersive environments in predictive healthcare research (Li et al., 2024a; Wang et al., 2024).

One clearly identifiable research direction emerging from the analysis concerns the integration of digital twins with cloud-based architectures and multi-agent systems, which appears to support more continuous and adaptive healthcare workflows. The reviewed studies indicate that such integration enables continuous processing of biosensor data and contributes to the optimisation of healthcare workflows (Lakhan et al., 2024). In parallel, an expanding body of research links digital twin technologies with distributed ledger solutions, aiming to enhance data security, improve interoperability and strengthen trust within patient care and treatment processes (McCourt, 2024).

The thematic analysis also highlights the increasing importance of virtual patient modelling and the prediction of treatment outcomes. Numerous publications emphasise the role of big healthcare data analytics and synthetic data in simulating disease trajectories and patient responses to therapeutic interventions. These approaches are particularly relevant for treatment planning and for anticipating disease progression (Delerm & Pilottin, 2024; Zerrouk et al., 2024). Within research on virtual clinical environments, solutions employing interoperable data and feedback mechanisms, including haptic feedback, are also emerging, supporting diagnostic procedures and therapy planning (Li et al., 2024b).

The analysed publications further demonstrate that, alongside advanced deep learning methods, classical machine learning algorithms and optimisation techniques remain relevant for improving diagnostic accuracy and supporting personalised treatment planning (Sultanpure et al., 2024). At the same time, digital twins are increasingly applied in remote medical rehabilitation and long-term patient monitoring, indicating an expansion of their use beyond acute care contexts (Xie et al., 2025).

Another important theme identified in the results is the development of personalised health trajectories and preventive planning. Data-driven approaches based on large healthcare datasets enable the assessment of individual health risks, the simulation of preventive interventions and the optimisation of treatment outcomes over longer time horizons (Yurkovich et al., 2024; de Oliveira El-Warrak & Miceli de Farias, 2025). In this context, artificial intelligence-supported healthcare models gain prominence by enabling real-time diagnosis, personalised therapies and advanced forms of telepresence (Arastouei & Khan, 2025).

The analysis confirms the growing significance of integrating blockchain technologies with cloud computing, IoT systems and wearable devices to enable secure remote patient monitoring and data-driven clinical process simulation (Alhamam et al., 2025). Increasing attention is also given to advanced learning techniques, including reinforcement learning and generative adversarial networks, which enhance the predictive capabilities of digital healthcare systems (Böttcher et al., 2025; Rizzo, 2025).

The obtained results align with a broader stream of research addressing disease prevention, diagnosis and treatment through digital technologies (Núñez-Merino et al., 2024). In particular, publications focusing on blockchain- and cloud-based IoMT systems indicate improvements in diagnostic accuracy, prognostic performance and therapeutic effectiveness (Gana & Jamil, 2025). The use of digital twins for the analysis of clinical and medical imaging data is also increasingly applied to the early detection of clinical deterioration (Badjatia et al., 2025).

The findings further confirm that earlier studies concentrated primarily on patient digital twins and disease risk prediction within metaverse environments (Ma et al., 2024; Kulkarni et al., 2024). At the same time, research advanced solutions based on wearable sensor data and neural networks for smart healthcare systems (Liu et al., 2024), as well as cloud and edge computing architectures supporting the evaluation of medical procedures (Akbarialiabad et al., 2024).

The growing role of artificial intelligence in tailoring therapeutic interventions, managing chronic conditions and supporting virtual clinical practice is also clearly evident (Mosquera-Lopez & Jacobs, 2024; Hu & Zheng, 2024). Recent studies increasingly identify the automation of clinical processes as a fundamental pillar of future healthcare architectures. Within this context, decision-support systems based on multi-agent models are gaining prominence due to their capacity to incorporate patient-specific data and situational factors into clinical reasoning in a flexible manner (Qiu et al., 2024). These developments are further complemented by blockchain-based metaverse solutions, which extend clinical decision support by embedding diagnostic and therapeutic services within secure, transparent and trusted digital environments (Ling & Butakov, 2024).

Recent contributions further underline the role of digital twin-based simulation frameworks in enhancing treatment effectiveness, examining healthcare operational processes and supporting improvements in organisational performance across healthcare systems (Penverne et al., 2024). Cyber–physical healthcare systems increasingly integrate data from wearable sensors with deep learning algorithms. Such configurations enable the virtual support of therapeutic processes and allow for continuous monitoring of patient health status (Xing et al., 2024). In parallel, Internet of Things solutions enhanced with artificial intelligence are gaining importance in predictive healthcare. These systems facilitate the early identification of disease-related changes and support anticipatory models of healthcare delivery (Shehzad et al., 2024; Arunprasath & Annamalai, 2024).

Taken together, the results indicate that predictive healthcare is moving towards increasingly interconnected and analytically driven systems. Digital twins, artificial intelligence and IoT technologies are no longer developed in isolation, but function as mutually reinforcing components of broader computational infrastructures. The literature reviewed in this study points to an increasing focus on integrated solutions in predictive healthcare. These approaches aim to support more individualised care pathways and enable earlier identification of potential health risks. They also contribute to clinical decision-making that is more anticipatory rather than reactive. At the same time, the results consistently reveal a persistent gap between conceptual and technological developments and their routine application in everyday clinical practice. This observation highlights the need for further validation studies, research oriented towards implementation, and closer cooperation between technological innovation and clinical stakeholders.

CONCLUSIONS

The bibliometric and qualitative analyses conducted in this study provide a structured overview of current research directions in digital technologies supporting predictive healthcare. The results clearly indicate the central role of digital twins. These systems increasingly serve as integrative frameworks for artificial intelligence, machine learning and Internet of Medical Things solutions. The analysed literature shows a clear shift away from isolated technological applications towards complex and interoperable patient data ecosystems. Such ecosystems enable continuous health monitoring, disease trajectory modelling and real-time clinical decision support.

The distinction of three emerging thematic areas helps to clarify how this research field is organised and how it is evolving. The first area centres on digital twins and integrated patient data ecosystems, drawing attention to the role of data interoperability and the analysis of large-scale health data. The second area addresses predictive and preventive applications of digital twins, with an emphasis on care personalisation and early health risk identification. The third area concerns treatment planning and patient response simulation, particularly in clinical, surgical and rehabilitation contexts. Across all thematic areas, predictive modelling is becoming a central element of contemporary healthcare research. Simulation environments are playing a growing role in shaping new approaches to the organisation and delivery of healthcare services.

The results suggest that many technological innovations have not yet been fully embedded in everyday clinical practice. There remains a noticeable distance between conceptual advances and their practical application. This points to the need for further validation in real clinical settings. More implementation-oriented research is required. Organisational conditions also deserve greater attention. Ethical and regulatory issues should be addressed more explicitly. Future studies need to focus on how digital twin solutions fit into existing clinical workflows. Decision-making processes in practice should be a central reference point. Such an approach is necessary to achieve the full benefits of predictive healthcare.

Several limitations of this study should be acknowledged. The analysis was limited to publications indexed in the Scopus and Web of Science databases. As a result, some implementation-oriented studies and grey literature may not have been captured. The bibliometric and qualitative methods used in this study enable the examination of publication dynamics and the identification of dominant thematic patterns. They do not, however, provide direct evidence of the clinical effectiveness of the analysed solutions. The field of predictive healthcare technologies is developing rapidly. Consequently, the patterns identified in this study may evolve as new evidence becomes available. This does not call into question the overall robustness of the results. However, the findings should be interpreted with appropriate caution. The identified limitations are also relevant when outlining priorities for further research.

IMPLICATIONS FOR RESEARCH AND APPLICATION

The conducted analysis makes it possible to indicate several observations relevant for further research on digital technologies supporting predictive healthcare. From a research perspective, further investigation of digital twins in everyday clinical environments is needed. Existing studies provide limited insight into how these solutions operate in routine care. Future research could therefore examine their alignment with established diagnostic and therapeutic workflows. Empirical studies are also required to explore organisational and technological factors that shape the adoption of digital twin technologies in healthcare practice.

From an application perspective, the findings highlight the importance of coherent and interoperable patient data ecosystems. The effective use of digital twins depends on appropriate digital infrastructure and on solutions that enable the secure integration of data from multiple sources. At the same time, implementation processes should take into account the organisational realities of healthcare institutions and the readiness of medical staff to work with advanced analytical tools. Attention to these aspects may support a more gradual and realistic use of digital technologies in predictive healthcare.

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Authors' Note

This paper is funded in the framework of the work No. WZ/WIZ-INZ/3/2025 at the Bialystok University of Technology and financed from a research subsidy provided by the minister responsible for science.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 21(3), December 2025, 731–747

SOCIAL INFLUENCE AS A DETERMINANT OF MOBILE APPLICATION ACCEPTANCE ACROSS GENERATIONS: A POLISH PERSPECTIVE

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Abstract: *The widespread diffusion of mobile devices has made mobile applications an integral part of everyday life across age groups. Although prior research has consistently identified social influence (SI) as an important determinant of technology acceptance, its role across different generations remains insufficiently examined in the context of mobile applications. This study investigates the impact of social influence on behavioural intention to use mobile applications among four generational cohorts: Baby Boomers, Generation X, Generation Y, and Generation Z. The analysis is based on data from a nationwide CAWI survey conducted in Poland (N = 2,400; 600 respondents per generation). Reliability analysis, exploratory factor analysis, linear regression, and comparative statistical tests were applied. The results show that social influence is a significant predictor of behavioural intention in all generational groups. However, no statistically significant differences are observed in the strength of the SI–BI relationship across generations. At the same time, significant differences emerge in perceived levels of social influence, with Baby Boomers reporting higher mean values than younger cohorts. The findings highlight generational differences in the perceived relevance of social influence rather than in its behavioural impact, contributing to research on human–technology interaction.*

Keywords: *social influence, mobile application, technology acceptance; behavioural intention; generations; human–technology interaction*

DOI: https://doi.org/10.14254/1795-6889.2025.21-3.11

INTRODUCTION

Smartphones and mobile applications have evolved from communication tools into socio-technical environments that mediate everyday activities, shape user practices, and transform human-technology interaction patterns. Contemporary research emphasises that mobile applications operate not only as functional technologies but as socially embedded systems that influence cognition, behaviour, and mediated communication (Leonardi, 2021; Norman, 2013) This broader framing is essential for aligning the study with the scope of Human Technology, which prioritises conceptualisations of technology that extend beyond utilitarian adoption.

Although social influence (SI) is a well-established determinant of technology acceptance, prior findings on generational differences remain fragmented and theoretically inconsistent. Some studies report diminishing SI effects among younger, digitally autonomous users (Carter & Yeo, 2016), whereas others highlight the rising importance of digitally mediated SI such as peer-generated reviews, influencers, and algorithmic visibility,which may exert comparable influence across age groups (Sözer, 2020; Tran & Vu, 2024). This tension points to a broader theoretical gap concerning generational differences in socio-technical mechanisms of social influence and their implications for behavioural intention. Addressing this ambiguity positions the present study within current debates in human-technology interaction.

The past decade has witnessed a substantial increase in the use of mobile devices, particularly smartphones, which have become integral to everyday life (Huang & Kao, 2015). As of 2025, 5.78 billion people globally use a mobile phone, representing 70.5% of the world's total population. Over the past 12 months, the number of unique mobile subscribers has grown by 112 million, reflecting a year-on-year increase of 2.0%. Furthermore, smartphones now account for nearly 87% of all mobile handsets in use worldwide (DataReportal – Global Overview, 2025). In Poland, 96% of individuals aged 16 to 64 own a smartphone, and the number of active cellular mobile connections in early 2025 reached 53.7 million equivalent to 140% of the total population. This figure is influenced by individuals owning multiple devices (DataReportal – Digital 2025: Poland, 2025). Smartphones have evolved beyond their original purpose of voice communication, transforming into multifunctional mobile computing devices that facilitate a broad spectrum of activities. Today, they are widely used in professional settings, entertainment, communication, and healthcare (Ma et al., 2016).

Mobile applications, as one of the most rapidly evolving digital products, play a crucial role in shaping this transformation. In 2023, global spending on mobile applications rebounded, reaching 171 billion USD (Statista - Mobile Internet & Apps, 2024). In Poland, the mobile application market generated 753.37 million USD in revenue, reflecting a significant increase compared to previous years. The highest revenues were recorded in the categories of gaming (241.7 million USD) and social media (196 million USD), while shopping (65.99 million USD) and entertainment applications (57.75 million USD) also contributed substantially to market expansion (Sirant & Kucia, 2024). These figures highlight the continuous growth of the mobile app economy, driven by technological advancements that are reshaping interactions between businesses and consumers (Payne & Frow, 2017).

Designed for use on smartphones and tablets, mobile applications have increasingly become a pivotal element in business strategy, serving as a powerful marketing tool (San-Martín et al., 2016). Their widespread adoption has garnered considerable attention from enterprises (Nah et al., 2005), positioning these digital solutions as innovative platforms for communication and customer relationship management. The transformative impact of mobile applications is particularly evident in the evolving dynamics of business-consumer interactions (Viswanathan et al., 2017). However, fully leveraging the benefits of mobile applications requires a comprehensive understanding of user behavior and the factors influencing technology acceptance.

The growing prevalence and diversification of mobile applications have significantly altered user behaviors (Juaneda-Ayensa et al., 2016), emphasizing the necessity of systematic academic inquiry in this area. Existing literature highlights that the rapid development of digital communication technologies, including mobile applications, often surpasses the pace of rigorous scientific validation (Boudreaux et al., 2014; Vahdat et al., 2021). Consequently, empirical research aimed at understanding user motivations and behavioral patterns in adopting mobile technologies remains a critical endeavor.

Over years of research, multiple determinants have been identified as influential in technology acceptance theories. One of the key factors consistently linked to the intention to use digital information systems and mobile applications is social influence (SI) (Alam et al., 2018; Boontarig et al., 2012; Martins et al., 2021; Sun et al., 2013; Wills et al., 2008). Social influence is defined as the extent to which individuals perceive that significant people in their lives (e.g., family, friends) believe they should adopt a specific technology (H. Peng et al., 2019; Venkatesh et al., 2012). This factor has been highlighted in various technology acceptance models, including the Theory of Reasoned Action (TRA) (Taylor & Todd, 1995), the Technology Acceptance Model (TAM) (Venkatesh & Davis, 2000), the Extended Technology Acceptance Model (TAM2) (Lu et al., 2005), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012). Given the growing significance of public opinion in contemporary society, it is essential to examine its role in mobile application adoption.

Literature suggests that age-related differences play a crucial role in the acceptance of new communication technologies (ICT), including mobile applications. However, findings in this area remain inconclusive. Some studies indicate that social influence is more pronounced among younger individuals due to peer pressure dynamics (Carter & Yeo, 2016). In contrast, other studies highlight the increasing reliance on external opinions among individuals with lower technological competence, who often depend on the skills and recommendations of those around tchem (Muñoz-Leiva et al., 2017; Schierz et al., 2010).

Considering the identified research gap and the lack of comprehensive studies on this subject in the Polish market, this research aims to examine the impact of social influence on mobile application adoption. Specifically, the study will assess the strength of social influence among representatives of different generational cohorts: Baby Boomers, Generation X, Generation Y, and Generation Z. Understanding generational variations in technology acceptance is crucial for businesses and policymakers seeking to develop effective digital strategies tailored to different demographic groups.

LITERATURE REVIEW

The place of social influence in the theory of technology acceptance

Technology acceptance research has historically emphasized utilitarian determinants, primarily perceived usefulness and perceived ease of use as central predictors of technology adoption. However, behavioral science and psychology consistently demonstrate that adoption is also driven by non-utilitarian drivers such as social norms, identity signalling, interpersonal expectations, and social image (Ajzen & Fishbein, 2002; Triandis, 1971, 1980). These elements shape how individuals interpret and respond to technological innovations.

Social influence (SI), defined as the degree to which an individual perceives that significant others believe they should use a system, has been recognized across multiple decades of technology acceptance research (H. Peng et al., 2019; Venkatesh et al., 2003, 2012). Diffusion-of-innovation theory highlights that individuals turn to social cues to reduce uncertainty about novel technologies, relying on both informational and normative pressures (Peng et al., 2017; Rogers, 2003; Salancik & Pfeffer, 1978). As uncertainty declines, the role of SI typically shifts but does not disappear.

Across foundational frameworks: TRA, TPB, TAM2, IDT, MPCU, UTAUT, SI appears under varying conceptual labels (subjective norm, social factor, image) but consistently reflects the influence of external expectations on behavioral intention (Garavand et al., 2019; Karahanna et al., 1999; Lewis et al., 2003). In UTAUT, SI is a primary determinant of intention, moderated by age, gender, and experience. UTAUT2 further extends this recognition to voluntary contexts, demonstrating that SI remains a relevant factor even when users are free to adopt or reject a technology (Venkatesh et al., 2012).

Taken together, prior research clearly establishes SI as a positive predictor of behavioral intention. Thus, we propose:

H1: Social influence (SI) has a positive impact on behavioral intention (BI) to use mobile applications across all generations.

Generational dynamics in social influence: socio-technical mechanisms underlying age differences

Age-related differences play a crucial role in shaping technology-related behaviors, yet empirical findings remain mixed. Younger users (Millennials, Generation Z) have grown up in a digitally dense environment, where technology use is individualized, exploratory, and often detached from direct interpersonal pressure (Carter & Yeo, 2016). Their high digital literacy reduces reliance on external validation, and their adoption choices are frequently shaped by digitally mediated forms of SI, such as peer-generated reviews, influencers, and algorithmically curated trends (Sözer, 2020; Tran & Vu, 2024). For these groups, SI tends to be subtle, embedded in digital ecosystems, and intertwined with identity expression.

In contrast, older generations (Generation X, Baby Boomers) often rely more heavily on direct interpersonal SI in technology adoption (Blok et al., 2020; Hoque & Sorwar, 2017). Limited digital confidence, heightened perceived complexity, and lower technological autonomy result in a greater need for reassurance from trusted individuals (Muñoz-Leiva et al., 2017; Schierz et al., 2010). For this group, SI functions as both a facilitatorwhen encouragement is present and a barrier when social networks express skepticism (Soh et al., 2024). Older adults are also more likely to rely on face-to-face, trust-based social cues rather than digital forms of influence (Webster & Trevino, 1995).

This indicates that generational differences in SI stem not merely from demographic variation but from distinct socio-technical contexts, including:

- disparities in digital literacy and autonomy,
- reliance on interpersonal vs. digital social cues,
- differences in perceived technological risk,
- divergent expectations regarding technology's role in daily life.

Given these distinctions, SI may operate through qualitatively different mechanisms across generations. Therefore:

H2: The impact of social influence (SI) on behavioral intention (BI) to use mobile applications varies across generations.

Integrating Human-Technology Interaction Perspectives

In line with the expectations of Human Technology, SI must be conceptualized not only as interpersonal pressure but as a socio-technical process shaped by digital affordances, mediated communication, and contemporary hybrid interaction environments (Leonardi, 2021; Norman, 2013). Mobile applications increasingly function as socially embedded technologies, enabling visibility, comparison, recommendation, and social signalling within digitally mediated ecosystems (Boyd & Ellison, 2007; Faraj et al., 2018; Korjonen-Kuusipuro & Wojciechowski, 2022, 2023). As a result, SI emerges through layered mechanisms offline interpersonal cues and online platform-based cues rather than a single normative channel (Leonardi & Treem, 2020).

Existing technology acceptance models (TRA, TAM, UTAUT) capture only partial aspects of this complexity. These frameworks were developed in contexts characterized by more stable and less digitally mediated social structures, where social influence was primarily conceptualized as subjective norms or direct interpersonal pressure(Ajzen & Fishbein, 2002; Davis, 1989; Venkatesh et al., 2003). Contemporary digital ecosystems, however, introduce algorithmically curated influence, asynchronous communication, and decentralized online sociality, which are not explicitly addressed in traditional acceptance models (Kellogg et al., 2020; Leonardi, 2021). Therefore, a contemporary interpretation of SI should incorporate these socio-technical affordances rather than treat social influence as a purely interpersonal construct.

This broader framing suggests that Baby Boomers may rely more strongly on direct interpersonal mechanisms of social influence, such as family members, peers, or trusted professionals, while younger users navigate digitally embedded forms of SI, including platform visibility, online reviews, and peer activity cues (Cimperman et al., 2016; Muñoz-Leiva et al., 2017). Importantly, this distinction does not necessarily imply stronger statistical effects of SI on behavioural intention (BI) among older adults. Instead, it reflects differences in the mechanisms and channels through which social influence is experienced and enacted, rather than differences in effect magnitude (Leonardi & Vaast, 2017).

Building on this distinction between generational mechanisms of social influence, the following hypothesis focuses on differences in the nature and mode of influence, rather than its statistical strength:
H3: Baby Boomers may rely more heavily on interpersonal social influence mechanisms than younger generations; however, this does not necessarily imply a stronger SI → BI effect.

METHODS

The study on the impact of social influence on the acceptance of mobile applications was conducted using the CAWI method via the Manulo professional research panel. The research complied with Polish quality standards for public opinion and market research (PKJPA). Measurement items were adopted from established scales reported in prior studies. In total, 12 items were included in the analysis, seven measuring Social Influence (SI) and five measuring Behavioral Intention (BI). All items were assessed using a five-point Likert scale.

Data collection was carried out in August 2023. A control question regarding the use of mobile applications was applied, and only respondents who declared using mobile applications at least several times per year were allowed to participate in the survey. The study employed a quota-based sampling design. The final sample consisted of 2,400 respondents, with 600 individuals in each generational cohort: Baby Boomers, Generation X, Generation Y, and Generation Z (Table 1). The gender structure of the sample reflected the distribution of the Polish population (52% female and 48% male).

Table 1. Sample size [Source: own research, 2023]

Generations	Gender		N
	Female	**Male**	
Baby Boomers	312	288	600
Gen X	312	288	600
Gen Y	312	288	600
Gen Z	312	288	600
SUM	**1248**	**1152**	**2400**

To avoid regional bias, the survey was conducted across all Polish voivodeships. The sample included respondents from rural areas, small towns, and large cities with more than 500,000 inhabitants, representing diverse educational backgrounds and professional statuses.

Statistical analyses were conducted using the Statistical Package for the Social Sciences (SPSS). The analytical procedure consisted of three stages. First, data screening was performed to assess missing values and potential outliers. Second, scale reliability and validity were evaluated using Cronbach's alpha and exploratory factor analysis (EFA). Third, the relationship between the independent variable (SI) and the dependent variable (BI) was examined using regression analysis conducted separately for each generational group.

RESULTS

Test reliability using Cronbach's Alpha coefficient

Scale reliability was assessed using Cronbach's alpha coefficient. Following established guidelines, a Cronbach's alpha value of 0.70 or higher was considered indicative of acceptable internal consistency (Hair, 2010; Nunnally & Bernstein, 1994). Reliability was examined separately for the independent variable (Social Influence, SI) and the dependent variable (Behavioral Intention, BI), reflecting the conceptual distinction between the constructs.

In addition to Cronbach's alpha, corrected item–total correlations were analysed to evaluate the contribution of individual items to their respective scales. Values above 0.30 were regarded as satisfactory, indicating adequate item discrimination (Nunnally & Bernstein, 1994).

Table 2. Reliability statistics of SI and BI variables [Source: data analysis]

	Cronbach's Alpha	N of Items
SI	0.815	7
BI	0.843	5

As reported in Table 2, both scales demonstrate good internal consistency, with Cronbach's alpha values of 0.815 for SI and 0.843 for BI. Item–total statistics presented in Table 3 show that all items exceed the recommended threshold for corrected item–total correlation. These results confirm that the measurement scales for both SI and BI are reliable and suitable for further analysis.

Table 3. Item-Total Statistics of SI and BI variables [Source: data analysis]

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SI1	17.05	17.995	0.659	0.773
SI2	17.20	18.158	0.631	0.777
SI3	17.49	18.238	0.584	0.785
SI4	17.05	19.255	0.482	0.803
SI5	17.16	18.537	0.568	0.788
SI6	17.18	18.367	0.605	0.782
SI7	16.68	20.565	0.354	0.823
BI1	13.88	9.657	0.632	0.816
BI2	14.23	9.513	0.695	0.798
BI3	14.02	9.390	0.687	0.800
BI4	14.33	10.313	0.587	0.827
BI5	14.37	9.905	0.643	0.813

EFA analysis for independent and dependent variables

Exploratory factor analysis (EFA) was conducted to assess the construct validity of the measurement scales. The suitability of the data for factor analysis was evaluated using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. A KMO value above 0.70 and a statistically significant Bartlett's test ($p < 0.05$) were considered indicative of adequate factorability (Hair, 2010). In addition, factors with eigenvalues greater than 1 were retained, and factor loadings of 0.50 or higher were regarded as acceptable.

EFA was first performed for the independent variable, Social Influence (SI). The initial analysis included seven items; however, item SI7 exhibited an unsatisfactory factor loading and was therefore removed in line with established recommendations. The subsequent analysis, based on six items, met all evaluation criteria. The KMO value was 0.876, and Bartlett's test of sphericity was statistically significant ($p < 0.001$), confirming the adequacy of the data for factor analysis. The total variance explained reached 53.325%, exceeding the recommended threshold. All retained items loaded above 0.50 on a single factor, indicating satisfactory convergent validity.

A separate EFA was conducted for the dependent variable, Behavioral Intention (BI). The results also met all required criteria. The KMO value was 0.840, Bartlett's test of sphericity was significant ($p < 0.001$), and the total variance explained amounted to 61.483%. All BI items demonstrated factor loadings above 0.50, supporting the unidimensionality of the scale.

The final component matrix for both SI and BI variables is presented in Table 4. Overall, the EFA results confirm that the measurement scales exhibit adequate construct validity and are suitable for subsequent regression analysis.

Table 4. Component Matrix of SI and BI variables [Source: data analysis]

Variables	SI1	SI2	SI3	SI4	SI5	SI6	BI1	BI2	BI3	BI4	BI5
Component	0.787	0.774	0.741	0.609	0.712	0.744	0.771	0.820	0.813	0.734	0.780

Regression analysis of the relationship between SI and BI

To examine the relationship between social influence (SI) and behavioural intention (BI), simple linear regression analysis was conducted. Given that the model included one independent variable (SI) and one dependent variable (BI), separate regression models were estimated for each generational cohort: Baby Boomers, Generation X, Generation Y, and Generation Z. All analyses were performed using SPSS 22.

Model adequacy was assessed using the F-statistic derived from the ANOVA table. As shown in Table 5, the regression models are statistically significant across all generational groups ($p < 0.001$), indicating that the models provide an adequate fit to the data.

Table 5. ANOVA test of generation groups [Source: data analysis]

Generation		Model	Sum of Squares	Df	Mean Square	F	Sig.
Baby boomers	1	Regression	63.444	1	63.444	137.312	0.000
		Residual	276.301	598	0.462		
		Total	339.745	599			
Generation X	1	Regression	37.731	1	37.731	81.771	0.000
		Residual	275.931	598	0.461		
		Total	313.662	599			
Generation Y	1	Regression	47.236	1	47.236	96.902	0.000
		Residual	291.504	598	0.487		
		Total	338.741	599			
Generation Z	1	Regression	53.689	1	53.689	115.829	0.000
		Residual	277.183	598	0.464		
		Total	330.872	599			

Regression coefficients for each cohort are reported in Table 6. In all generational groups, the standardized regression coefficient for SI is positive and statistically significant ($p < 0.001$), indicating that higher levels of perceived social influence are associated with stronger behavioural intention to use mobile applications. The standardized beta coefficients range from 0.347 to 0.432, suggesting a moderate relationship between SI and BI across generations.

Table 6. Regression coefficient of generation group [Source: data analysis]

Generation	Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
			B	*Std. Error*	*Beta*			*Tolerance*	*VIF*
Baby boomers	1	(Constant)	2.754	0.099		27.863	**0.000**		
		SI	0.375	0.032	**0.432**	11.718	**0.000**	1.000	1.000
Generation X	1	(Constant)	2.468	0.111		22.203	**0.000**		
		SI	0.355	0.039	**0.347**	9.043	**0.000**	1.000	1.000
Generation Y	1	(Constant)	2.332	0.113		20.674	**0.000**		
		SI	0.396	0.040	**0.373**	9.844	**0.000**	1.000	1.000
Generation Z	1	(Constant)	2.292	0.111		20.573	**0.000**		
		SI	0.430	0.040	**0.403**	10.762	**0.000**	1.000	1.000

Collinearity diagnostics indicate no multicollinearity concerns, as variance inflation factor (VIF) values remain well below the commonly accepted threshold (Hair, 2010). Based on the estimated coefficients, standardized and unstandardized regression equations for each generational group are reported in Table 7.

Table 7. Regression coefficients for BI [Source: data analysis]

Generation	Unstandardized regression equations	Standardized regression equations
Baby boomers	BI = 2.754 + 0.375SI + ε	BI = 0.432SI + ε
Generation X	BI = 2.468 + 0.355SI + ε	BI = 0.347SI + ε
Generation Y	BI = 2.332 + 0.396SI + ε	BI = 0.373SI + ε
Generation Z	BI = 2.292 + 0.430SI + ε	BI = 0.403SI + ε

Overall, the regression results confirm that social influence is a significant predictor of behavioural intention to use mobile applications in all analysed generational cohorts.

Differences in the SI–BI relationship and perceived social influence across generations

To examine whether the impact of social influence (SI) on behavioural intention (BI) differs across generational groups, pairwise comparisons of regression coefficients were conducted using the procedure proposed by Paternoster et al. (1998). This approach allows for statistical testing of differences between regression slopes by accounting for both coefficient estimates and their standard errors.

The results of the Z-tests are reported in Table 8. Across all pairwise comparisons between Baby Boomers, Generation X, Generation Y, and Generation Z, the obtained p-values exceed the conventional significance threshold ($p > 0.05$). These findings indicate that there are no statistically significant differences in the strength of the SI–BI relationship across generational groups.

Table 8. Z test results between generations [Source: data analysis]

Generation		Z-test	p-value
Baby boomers	Generation X	0.396448	0.345887
	Generation Y	0.409956	0.340919
	Generation Z	1.073695	0.858520
Generation X	Baby boomers	0.396448	0.345887
	Generation Y	0.733900	0.231505
	Generation Z	1.342500	0.089717
Generation Y	Baby boomers	0.409956	0.340919
	Generation X	0.733900	0.231505
	Generation Z	1.342500	0.089717
Generation Z	Baby boomers	1.073695	0.858520
	Generation X	1.342500	0.089717
	Generation Y	0.601041	0.273906

In addition to slope comparisons, differences in the perceived level of social influence across generations were examined using one-way analysis of variance (ANOVA). As shown in Table 9, the ANOVA results reveal a statistically significant effect of generation on perceived social influence ($F = 16.880$, $p < 0.001$), indicating that mean SI scores differ across generational cohorts.

Table 9. ANOVA test of SI between generations [Source: data analysis]

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	28.366	3	9.455	16.880	0.000
Within Groups	1342.089	2396	0.560		
Total	1370.455	2399			

Post-hoc multiple comparison tests were conducted to identify the specific group differences (Table 10). The results show that Baby Boomers report significantly higher levels of perceived social influence compared to Generation X, Generation Y, and Generation Z ($p < 0.001$ for all comparisons). No statistically significant differences in perceived social influence were observed among Generations X, Y, and Z.

Table 10. Post-hoc comparisons of SI between generations [Source: data analysis]

(I) Generation	(J) Generation	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Baby boomers	Generation X	**0.223**	0.043	**0.000**	0.14	0.31
	Generation Y	**0.256**	0.043	**0.000**	0.17	0.34
	Generation Z	**0.266**	0.043	**0.000**	0.18	0.35
Generation X	Baby boomers	-0.223	0.043	**0.000**	-0.31	-0.14
	Generation Y	0.034	0.043	**0.437**	-0.05	0.12
	Generation Z	0.043	0.043	**0.319**	-0.04	0.13
Generation Y	Baby boomers	-0.256	0.043	**0.000**	-0.34	-0.17
	Generation X	-0.034	0.043	**0.437**	-0.12	0.05
	Generation Z	0.009	0.043	**0.827**	-0.08	0.09
Generation Z	Baby boomers	-0.266	0.043	**0.000**	-0.35	-0.18
	Generation X	-0.043	0.043	**0.319**	-0.13	0.04
	Generation Y	-0.009	0.043	**0.827**	-0.09	0.08

Figure 1 presents the mean levels of perceived social influence for each generational group. Consistent with the ANOVA results, Baby Boomers display the highest mean SI values, while the remaining generations show relatively similar levels of perceived social influence.

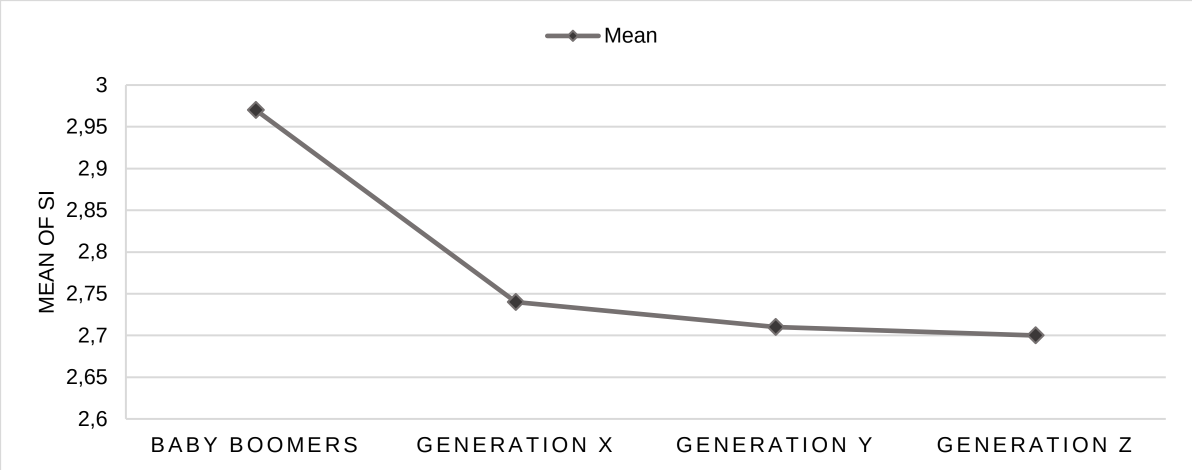

Figure 1. Mean levels of perceived social influence across generations. [Source: data analysis]

DISCUSSION

This study examined the role of social influence (SI) in shaping behavioural intention (BI) to use mobile applications across four generational cohorts in Poland. The results provide clear support for the central premise that SI is a significant and positive predictor of BI in all analysed generations, thereby supporting H1. Across Baby Boomers, Generation X, Generation Y, and Generation Z, SI consistently exhibited a statistically significant relationship with BI, with standardized coefficients ranging from moderate to moderately strong.

At the same time, the comparative analyses indicate that the strength of the SI-BI relationship does not differ significantly across generations. Although the standardized regression coefficients vary numerically between cohorts, the Z-tests reveal no statistically significant differences in slopes. Consequently, H2, which posited generational variation in the impact of SI on BI, is not supported in terms of effect size. This finding is theoretically important, as it suggests that social influence remains a robust determinant of mobile application acceptance regardless of generational affiliation, even in an era of widespread digital familiarity (Chaouali et al., 2016; Martins et al., 2021). At the same time, prior research indicates that the relative importance of social influence and other acceptance determinants may vary across national and cultural contexts, suggesting that these findings should be interpreted within the specific socio-cultural setting of Poland (Alkailani & Nusairat, 2022).

Importantly, the absence of significant differences in regression coefficients should not be interpreted as evidence that social influence operates identically across generations. The additional ANOVA and post-hoc analyses demonstrate significant differences in mean levels of perceived social influence, with Baby Boomers reporting higher SI than Generations X, Y, and Z. These results indicate that while SI exerts a comparable impact on behavioural intention across cohorts, its salience and experiential relevance differ by age group (Cimperman et al., 2016; Muñoz-Leiva et al., 2017). In other words, generational differences are more apparent in how strongly SI is perceived and valued, rather than in how effectively it translates into behavioural intention. Recent empirical evidence confirms that social influence continues to play a meaningful role in contemporary mobile application contexts, including mental health applications evaluated using the UTAUT2 framework (Malik & Mushquash, 2025).

From a human-technology interaction perspective, this distinction is critical (Leonardi, 2021; Norman, 2013). For older users, social influence appears to be more closely tied to interpersonal mechanisms, such as recommendations from family members, peers, or professionals, which help reduce uncertainty and compensate for lower digital confidence. For younger users, SI is more likely to be embedded in digitally mediated environments, including online reviews, platform visibility, and social media cues, even if these forms of influence are perceived as less salient at a conscious level. This interpretation aligns with prior research showing that younger generations often rely on platform-based and algorithmically mediated signals rather than direct interpersonal persuasion (Tran & Vu, 2024).

Taken together, the findings refine existing UTAUT-based research by demonstrating that generational differences in mobile application acceptance are not primarily a matter of stronger or weaker effects, but of differing socio-technical mechanisms through which social influence is experienced and enacted (Leonardi, 2021; Venkatesh et al., 2012). This contributes to the Human Technology literature by highlighting the importance of distinguishing between the presence, perceived relevance, and mode of operation of social influence in technology adoption processes.

Despite the contributions of this study, several limitations should be acknowledged. The analysis is based on cross-sectional survey data and simple linear regression models estimated separately for generational cohorts. While this approach enables transparent and interpretable comparisons, it does not capture more complex structural relationships or latent interactions that could be examined using advanced modelling techniques such as multi-group structural equation modelling. In addition, the model focuses on social influence in isolation from other UTAUT-related determinants, which constrains its explanatory scope. Finally, although the sample is large and nationally representative, the findings are embedded in the Polish socio-cultural context and should not be directly generalized to other settings without caution.

CONCLUSIONS

This study provides empirical evidence that social influence is a significant and positive determinant of behavioural intention to use mobile applications across generational cohorts in Poland. The results confirm that SI plays a meaningful role in mobile application acceptance for Baby Boomers, Generation X, Generation Y, and Generation Z alike. Contrary to some expectations in the literature, the strength of the SI–BI relationship does not differ significantly across generations, suggesting a stable role of social influence in contemporary mobile technology adoption (Chaouali et al., 2016; Martins et al., 2021).

At the same time, the study reveals clear generational differences in perceived levels of social influence. Baby Boomers report higher sensitivity to SI compared to younger cohorts, indicating that social context and interpersonal reassurance remain particularly salient for older users (Cimperman et al., 2016; Muñoz-Leiva et al., 2017). These findings underscore the importance of differentiating between statistical effect size and subjective relevance when interpreting generational patterns in technology acceptance.

By integrating large-scale empirical evidence with a human–technology interaction perspective, the study advances understanding of how social and technological factors jointly shape mobile application adoption (Leonardi, 2021; Norman, 2013). Rather than framing generational differences in terms of stronger or weaker effects, the results point to variations in the socio-technical forms through which social influence is encountered, interpreted, and acted upon.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

From a research perspective, the findings suggest that future studies should move beyond simple comparisons of effect sizes across demographic groups and focus more explicitly on the mechanisms through which social influence operates in digitally mediated environments. Incorporating constructs related to digital affordances, platform design, trust cues, and algorithmic visibility may provide a richer understanding of how SI is embedded in human–technology interaction. Longitudinal and mixed-method approaches could further clarify how reliance on different forms of social influence evolves with experience and technological change.

For practitioners and application developers, the results highlight the need to recognise generational differences in the form rather than the strength of social influence. For older users, facilitating interpersonal support and providing clear, trustworthy guidance may enhance adoption, particularly for applications related to essential services such as healthcare, banking, or public administration. For younger users, attention should be given to usability, transparency of platform cues, and the integration of socially mediated signals within digital ecosystems, rather than relying on direct interpersonal persuasion.

From a policy perspective, the findings support initiatives aimed at promoting digital inclusion and reducing age-related barriers to technology use. Policies that encourage accessible design, user support mechanisms, and digital literacy programmes may help ensure that mobile technologies are adopted equitably across age groups. At the same time, policymakers should remain attentive to how social influence is embedded in digital platforms, particularly with regard to transparency, data protection, and the potential vulnerabilities of older users in socially mediated digital environments.

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Co-financed by the Minister of Science under the "Regional Excellence Initiative

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