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Contents

Digital Transformation in Education and Human-Centred Governance in Africa

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Abstract

The adoption of digital technology in higher education has changed current forms of teaching and learning in Africa especially after the COVID-19 pandemic. Digital transformation has extended the academic space, made the tools of novel blended and online education available in wider circles and created cooperation among teachers and students beyond boundaries. The shift has also been notable in the existing imbalances of access, digital literacy and technological infrastructure. The paper will describe the extent and effect of digital transformation on higher education and its effect on human-centred values in a select group of African countries across the continent: South Africa, Nigeria, Rwanda, Kenya Ghana, Zambia and Egypt. The study involves the Technology Acceptance Model and the Human-Centred Digital Governance Theory to explore the effects of human-centred digital governance on the adoption of technology and inclusiveness in education. Qualitative review methodology was applied, and academic literature, policy papers and case studies were reviewed. The thematic content analysis of sources revealed the following: developments in digital transformation in Africa; the benefits of digital learning; limitations and equity issues; and the place of governance in the use of the digital technology. The results indicate that most rapid gains are attained in countries that have working capacity in digital policy and long-term investment in the Information and Communications Technology infrastructure, for example in Kenya and Rwanda. Though under-resourced contexts, the countries are also characterised by bottlenecks related to affordability, digital literacy, cybersecurity, inequality in internet access and institutional unpreparedness. The paper concludes by stating that digital transformation should not rely purely on the use of technologies but on an all-inclusive approach that include governance, capacity building, inclusivity, transparency, accountability and ethics. Equally important is fostering interinstitutional and intra-Africa collaboration and policy dialogue. This study caters for policy makers, scholars and institutions and provides insights for contributing to the development of ethically grounded digital transformation of the education sector in Africa and globally.

Keywords: digital transformation, higher education, human-centred governance, technologies

JEL Classification: 121,033,O15

Introduction

Digital transformation in higher education can refer to the use of digital technology in an attempt to improve teaching, learning, research, and administration processes. Digital transformation has gained traction over the past ten years in Africa and was further catalysed by the COVID-19 pandemic, which highlighted the weak institutional structures and made innovation faster. Education institutions in Africa have continued to gradually introduce the use

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of virtual learning environments, Artificial Intelligence (AI), cloud-based computing, data analysis, and the digital services to enhance performance and engagement (Sigfrids et al., 2023; Mhlanga et al., 2022)

Digital transformation offers opportunities including increased accessibility, resilience, innovation and creativity, fosters engagement and learning outcomes, collaboration, well-being and equity in education and offers administrative efficiency. However, the systemic issues, such as disparities in digital access, limited infrastructure, the high cost of high-technology products, lack of digital literacy, cybersecurity concerns and institutional unpreparedness, are also evident (Gbadebo, 2024). In this context, digital technology presents risks to the society. These challenges have necessitated the establishment of frameworks that balance the development of social responsibility, sustainable and inclusive educational outcomes with technology. Despite the challenges including the disruptive nature of the technologies on the education sector, digital transformation is increasingly becoming unavoidable (Mabotha & Ngcamu, 2026). This, therefore, calls for digital transformation to be managed cautiously considering issues such as privacy, civil liberties, cyberattacks and prevention of harmful aspects, and the unique circumstance of the institutions concerned (Wittmann & Meynhardt, 2025),

The African countries are, however, digitizing at varying speeds. South Africa has used digital learning to continue with its educational operations, though it has infrastructure gaps. Nigeria and Ghana have been prolific in the diffusion of internet-based learning through e-learning reforms, whereas, Rwanda and Kenya have become the digital learning leaders in the region following intensive government investments in technology (Mhlanga et al., 2022).

This study focuses on the development and impact of digital technology, the benefits and barriers on the education sector in Africa. The study questioned the influence of the digital transformation in African higher education on human-centred governance. The study is intended to contribute to the more informed understanding of the impact of digital transformation in Africa in line with the United Nations Sustainable Development Goal (SDG4) in inclusive and quality education and African Union Agenda 2063: Africa We Want - education for all, (*Agenda 2063*, 2015). The ethical questions in this case go beyond issues of access and include privacy and sustainability.

The aims of the study are:

i. To examine the level of digital penetration in select countries in Africa.
ii. To find out the influence of digital transformation in education on governance
iii. To remark on the benefits, as well as the opportunities that digital transformation has presented in higher education.

Research questions:

i. How digitized has the African higher learning become?
ii. How do we enhance digital transformation using governance, policy and innovations?
iii. What have been the opportunities and advantages behind this change?

Literature Review

The African higher education digital transformation has been developing at an extremely quick rate during the past five years with primary change drivers being the need to improve accessibility, to offer increased flexibility, and to improve the performance of the institutions involved. One of the events that caused higher education institutions to adopt online solutions in such a brief duration was the COVID-19 pandemic. Whereas the shift demonstrated the inadequacy of digital infrastructure, it also sped up institutional investments in learning management systems, as well as remote learning capabilities (Chrusciak et al., 2025).

Most of the activities that spurred the development of digital learning potential in Nigeria and South Africa were triggered particularly by the COVID-19 pandemic, while universities' use of e-learning platforms and Information and Communications Technology (ICT) infrastructure began to gain traction in supporting online learning activities (Baale, 2024); Mhalanga et al., 2022).

A review of Ghana's digital transformation demonstrates significant progress in its digital and AI integration with efforts aimed at bridging the gaps, and the International Monetary Fund (IMF) put Ghana as the regional leader in AI preparedness. However, the country is puzzled by similar challenges witnessed in other African countries including effective governance framework. In this respect, conscious efforts are being made at institutional levels and other sectors address capacity and other adoptions issues (Sarpong, 2023).

In the recent years Zambia has witnessed progressive integration of digital transformation in different sectors as part of addressing innovation, capacity development and economic growth. The higher education sector in Zambia is largely government controlled. The adoption of digital transformation and AI has been gradual, mainly stewarded by national policies, as well as institutional initiatives (O'Bryan, 2024).

The first ones in digital and AI preparedness are Rwanda and Kenya because the countries have already established such state investments in technology that can spur higher education innovation. Rwanda is no exception as universities have also implemented systems and adaptive learning and research with the use of AI to support students (Sebihi et al., 2025). Innovation in the higher education sector has also been enhanced by rapidly emerging African EdTech start-ups, low-bandwidth learning solutions, which can be deployed using infrastructural realities (Baale, 2024).

Egypt, like the other North African neighbours, has also witnessed exponential growth in advanced level broadband, mobile phone and internet usage. However, it is faced with disparities including affordability, gender equity and penetration. The AI capacity remains low across all major sectors, and there is poor integration of databases and human capacity. Despite the handicaps, the National AI strategy is intended to place Egypt among the tech-based economies (*Ministry of Communications and Information Technology*, n.d.).

Researchers have also established that digital transformation has a positive influence on inclusiveness, student engagement, and international cooperation given that it builds a hybrid learning environment (Kaliisa et al., 2022; Zhang, 2022). In addition, the application of online school reporting systems assists in the planning and decision-making of institutions, (Maluleke, 2024). It addresses issues of relevance and quality and prepares learners for the digital age (A. D. Gbadebo, 2024).

Nevertheless, studies also suggest several limitations to the digital learning ecosystem. The imbalance in the use of internet, devices and digital literacy shows the existence of digital divide in Africa. This phenomenon is disproportionately present among rural learners, low-income learners, and women (Baale, 2024; Šević et al., 2025; Zisengwe, 2024). The quick implementation of AI in some countries like Nigeria, Lesotho, and Rwanda, have met resistance from teachers who fear the risk of losing jobs, as well as raise ethical concerns (Mabotha & Ngcamu, 2026).

The other weaknesses are poor data governance and cybersecurity. Issues of cybercrimes and data hacking in the academic systems have remained a course source of worry. This has been exacerbated in institutional cyberspace security by weak policies (Mogaji & Nguyen, 2023). The fact that institutional platforms keep breaking down also limits their effectiveness as numerous systems cannot be interoperable with ministries and universities (*Artificial Intelligence in Education - AI | UNESCO*, 2025). These challenges have continued to erode confidence in the importance of digitalisation in the African public. Additionally, the implementation of the initiatives has tended to be top-down with minimal public participation. However, a comprehensive understanding of the adoption of technologies has been lacking among the institutions and other stakeholders. It is important, therefore, that technologies including underlying mechanisms for digitalisation of the education sector are clearly seen. Considering these challenges, a human-centred governance is necessary in ensuring linkages between the technology and public good. At the same time, in Africa countries like Kenya, Rwanda, Nigeria, South Africa have made commendable progress in digitalising education: the implementation of the programmes have not received attention (Goshtasbpour et al., 2023).

The literature thus explains that digital transformation is a dynamic process which ought to have coordinated activities including the following: infrastructure, policy, capacity of teachers, cybersecurity and inclusive access systems. However, the effect of digital transformation on human-centred governance in the education sector in Africa has not been precisely addressed, which necessitates a systematic literature review.

Theoretical Framework

To come up with the theoretical framework of explaining the dynamics of digital adoption and human-centred governance in higher education in Africa, this paper applied the Technology Acceptance Model (TAM) and the Human-Centred Design Theory.

Technology Acceptance Model (TAM)

The theory intends to forecast how new technologies will be accepted and used by the society by way of looking at behavioural aspects. Kamal et al. (2019) argues that TAM has become a significant framework in understanding technology, the internet of things and interactions involving technology. The model is premised on the Theory of Reasoned Action (TRA), which asserts that beliefs influence attitudes, which in turn generates intention and ultimately, behaviour. The Technology Acceptance Model (TAM), therefore, holds the view that acceptance and the continued use of technology is anchored on two psychological variables that include the perceived ease of use (PEOU) and perceived usefulness (PU). The theory postulates that the users find the digital technologies more acceptable because of the simplified ease of use, availability, and suitability within academic objectives. On the other hand, the rejection relates to situations where technology is complicated, unreliable and unsupported. TAM theory can be used to identify the variables influencing the adoption of new technologies in education.

The South Africans and the Nigerians have shown that the only way that major digital adoption gains can be realized is when higher education institutions are organized in a way that assists in meeting the needs of the users and when the institutions offer guides and training to learners among other digital resources (Mhlanga et al., 2022; Baale, 2024).

Human-Centred Design Theory

Human-Centred Design (HCD) Theory is a problem-solving methodology that has at the core the desires, perspectives and needs of people. It means developing solutions by involving human perspectives in the entirety of the process through an inclusive and collaborative process (Djatmiko et al., 2025). The theory emphasises the importance of synergy between all stakeholders (Garcia-Lopez et al., 2020). Human-centred design, therefore, focuses on the needs of the learners and on meeting them by leveraging on technology in a process that creates user-friendly learning experience. HCD, therefore, is meant to ensure that digital technologies and tools are tailored for learners in a way that increases productivity and efficiency.

Considering the fact that equity, access, privacy, and empowerment of the user are the most important features of the digital transformation of human-centred digital governance, prioritisation of the user – students, teacher, administrator or community – is essential. HCD increases the likelihood of all stakeholders benefiting from the digital learning solutions, as well as enhances educational outcomes in terms of addressing uniqueness, accessibility, the fostering of engagement, motivation and accessibility.

TAM and Human-Centred Design theory can be collectively discussed as complementary tools of analysis. Whereas TAM describes the micro-level factors of technology acceptance at a personal level, the Human-Centred Design Theory addresses the macro-level factors of equity and ethics of digital transformation. In other words, HCD is intended to reorient the mindsets and actions of the participants of the education sector towards people-centred, interactive approaches in addressing education challenges. At the centre of HCD is multidisciplinary collaboration, people's context, creativity and interaction, all of which challenges the often-rigid education delivery mechanisms, and address differing demands and perceptions.

All these perspectives collectively suggest that digital transformation is a fundamental shift in the educational systems particularly for the African countries, where the education sector is still characterised by inadequate technology that fails to address inclusiveness, learners' vulnerabilities, accessibility barriers associated with rural learners, low-income earners, and women. Further, epistemological concerns remain a major challenge. Digital platforms available in Africa tend to emphasise Western content and modes of knowledge, with minimal regard to local languages, cultures, customs and they appear to perpetuate global hierarchies and threaten sovereignty of local communities.

These theoretical perspectives provide a conceptual foundation for positioning digital transformation in ways that bring to the core human dignity, inclusivity and fairness. From the standpoint of human-centricity, digital transformation must ensure that the least advantaged members of society must benefit from technological development. This perspective underscores the need to ensure that technological progress remains grounded in compassion and contextual sensitivity in order to effectively and efficiently deliver the desired goals (Mauti & Nyambane, 2025).

These theoretical lenses are very much relevant in Africa, where the digital divide is of major concern morally and even politically. In that regard digital transformation must be addressed holistically from the point of view of infrastructure, digital literacy, inclusivity and participation in decision-making processes. The institutions including governments must ensure that policies and regulations address the principles of transparency and fairness as well as the impact of the transformation on social and environmental sustainability (Mhlanga et al., 2022).

Conceptual Framework

The conceptual framework describes the relationships among the study variables, i.e. digital transformation and human-centred governance. Digital transformation in this case is conceptualised as the independent variable, whereas human-centred governance is conceptualised as the dependent variable. Digital transformation and human centred governance affect higher education in Africa. Digital transformation of the higher education systems in Africa is an outcome of the interaction of several variables including digital infrastructure, affordability, digital competencies, policy governance, and accessibility.

Digital learning is supported by digital infrastructure that comprises broadband connectivity, access to devices and digital platforms. Rwanda and Kenya have moved more quickly towards the implementation of online learning system due to established infrastructure in the ICT sector (Nguyen & Mogaji, 2023). The second variable is affordability, i.e. the financial capacities of institutions and students to access the digital tools. One of the greatest obstacles to equalized learning in several African countries such as South Africa and Nigeria, which are still facing imbalances in their infrastructures, is high internet cost and the cost of technological devices (Nguyen & Mogaji, 2023; Zisengwe, 2024). The other variable relates to digital competences. The quality of education as well as the implementation of technologies can only succeed if all stakeholders adequately appreciate digitalisation. This involves enhancing the digital literacy of all players. In cases of ineffective capacity building, teachers have been witnessed to exhibit hostility to emerging technologies, whereas students have demonstrated difficulty in using online system of learning (Okoye et al., 2024). The other important element is policy governance. This involves, principles, rules and frameworks including institutional coordination and regulatory mechanisms used to control the use of technologies.

Digital transformation of the education sector therefore is intrinsically dependent on human-centricity as the mail pillar. Human centred governance in this context is centred around participation, accountability in the decision-making processes, human rights, trust and sustainability (Jin et al., 2024), operational structures and tools including methods and resources aimed at implementation and mainstreaming (Djatmiko et al., 2025). This involves balancing digitalization with security, inclusivity and ethical standards (Chrusciak et al., 2025).

Methodology

Qualitative, interpretive research design was used for this study. Literature synthesis method, which is suitable for studying the latest policy and technology trends, was applied. Secondary data were acquired through search using peer-reviewed journal articles, academic databases, institutional reports, and online education policy reports. Qualitative method was relevant considering its consistency with conceptual research and its relevance in developing an initial understanding from a second data set (Balkis et al., 2024).

The group of seven African countries (South Africa, Zambia, Nigeria, Ghana, Rwanda, Kenya and Egypt) was chosen as the sample size due to their extensive investment in ICT and technological infrastructure of digital policies. The sampling method used was purposive with West and Central, Southern and Eastern African regions being represented by two countries each, whereas one country represented the northern part of Africa. Literature discussing the digital transformation adoption, challenges, governance, and AI-enabled learning was chosen from the select countries. The analysis was done based on thematic coding, where the information was extracted and coded based on emerging themes in the research questions: developments in digital transformation, the benefits of digital learning, limitations and equity issues, and the place of governance in the use of digital technology.

Only the articles of reputable academic journals and international organizations containing evidence were used. Triangulation of the information across countries and cross-examination of similar or conflicting information across the sources were made to increase validity. The methodological drawbacks of the research are that secondary data was applied in the study, and therefore it was not possible to observe the experiences of the stakeholders directly. However, given the limitations of secondary data, particularly regarding lived experience, the extensive and diverse sources of data were meant to provide sufficient comparative understanding at the global level and they enable the establishment of structural patterns.

Findings

To begin with, all the reviewed countries are all moving towards digital transformation, albeit not in the same way. Rwanda and Kenya are the fastest-growing ones because of the significant rise in the level of government investment in ICT and the development of digital policy, AI-based academic systems, in particular (Sharawy, 2023). On the other hand, South Africa and Nigeria boast a very high growth rate but will still possess weak technological infrastructure that continues to slow down universal access (Mhlanga et al., 2022; Baale, 2024). Despite achieving significant progress regarding AI readiness, Egypt's AI capacity is still low in all sectors including governance, infrastructure, data technology and ecosystem. Other challenges are insufficient awareness and poor integration of databases, as well as improper AI use in higher education institutions (Sharawy, 2023; Government of Egypt, 2025).

From the reviewed literature, it is evident that the ethical and responsible use of AI in all the African countries is still couple with continental, country and institutional digital transformation (A. Gbadebo, 2024). According to the African Union Digital Transformation Strategy for Africa, digital transformation is critical to Africa's innovativeness and sustainable growth (*The Digital Transformation Strategy for Africa (2020-2030), African Union*, n.d.). In this context, several countries have established structures to manage digital transformation and AI integration: for example the Ghana Artificial Intelligence Association, the Egyptian National Council of AI, the South African Artificial Intelligence Institute and Centre for Artificial Intelligence Research (Sarpong, 2023).

Second, concerning enhanced teaching, learning and student engagement, online education has brought about flexibility, education and institutional personalization and hardiness as evidenced in Kenya, Zambia, Egypt and South Africa. The online learning management systems and AI-based applications have assisted the universities to introduce continuity in academic programmes besides enhanced monitoring of student performance (Sebihi et al., 2025). It is through virtual interaction that international cooperation in academics has been achieved. AI technologies also support learner-centred education and tailored feedback mechanism. According to Lewis et al. (2024), AI enhances attentiveness and can be leveraged for both theoretical knowledge and practical skills. AI, therefore, has the potential to enhance learning experiences and engagements. Funda et al. (2024) posit that AI tools enabled the transition to remote learning during emergency situations like the COVID-19 pandemic (Funda & Mbangeleli, 2024).

Third, the greatest constraint for African higher education institutions remains to be the digital divide. Rural students, families with low income and female students are overrepresented because they do not have access to uninterrupted internet and digital devices across the digital literacy levels (Sharawy, 2023). This shows both domestic and international inequality. The disparities in access and skills levels, the impact of poor digital connectivity and shortage of resources are evident in all the countries. The digital gap in Africa has been attributed to factors including shortage of digital infrastructure, technical skills, and costs. Application of AI therefore has the potential to improve access and inclusion by broadening learning opportunities through remote learning particularly, where traditional delivery methods are not the most appropriate. Therefore, AI interventions should be supported with investment in infrastructure, through mainstreaming AI literacy and readiness of institutions and training to bridge both the access and skills gaps in all sectors.

The fourth issue is related to digital literacy and lack of capacity building opportunities. All the countries reported the need for capacity and expertise including appropriate digital skills. Teachers are supposed to undergo methodical professional growth to fulfil the requirements of digital and AI-based study tasks. Based on the survey of the teaching staff in different regions, the teachers are worried about vague policy schemes, the absence of training and possible loss of jobs due to AI usage (Alshahrani et al., 2025; Sharmin et al., 2026). These uncertainties stem from the envisaged adjustments to new technology and have resulted in resistance to change. This call for provision of guidance and the right perspective on technology, which is closely connected to deficiencies in institutional leadership.

The fifth issue is digital governance including policy and framework. Many institutions lack well-defined policies to inform the implementation of diversity, equity and inclusion among other human-centred elements when driving digital policy. Many countries exhibit ineffective cybersecurity models, ineffective IT and policy regulations as well as trust and sustainability challenges. Whereas all the reviewed countries indicated the existence of several strategies, frameworks and policies, they also showed the existence of fragmentation of policy implementation and weak coordination among the various stakeholders and sometimes lack of consensus among the various government bodies. Most institutions cannot guarantee the privacy of the data, therefore, students and other stakeholders become targets of cyber-attacks and identity thefts. Teacher perceptions of AI-supported pedagogy and automation risks in African higher education are visible (Sharmin et al., 2026).

Discussion

The results of the literature review show the collaboration of a number of interdependent dimensions, such as government investment, digital skills, affordability, and governance affected digital transformation in African higher education. Due to the proactive digital investment nature of Rwanda and Kenya, these two countries have evolved at a better pace and thus offer a high impact of the capacity of the public digital policies on innovation in higher education. South Africa and Nigeria, on the other hand, are not in the same situation as the infrastructure distribution is uneven and the infrastructure is not affordable (Mhlanga et al., 2022).

The review supports the fact that the TAM is correct, because perceived usefulness and perceived ease of use influence the learner and teacher acceptance of digital platforms. Adoption becomes higher among the stakeholders when learning systems are easy to use, supportable, and available. Nevertheless, adoption is not even because of TAM conditions when there are affordability and access barriers even though the conditions are met. This is in line with the Human-Centred Design Theory, which states that technology should be relevant to human needs, values and social realities to become transformative (Zisengwe, 2024; Mauti & Nyambane, 2025).

The empirical data point to the fact that the most critical barrier to equal participation is the digital divide as opposed to technology availability. Populations living in rural areas and those with low income have lower access to devices and some form of internet connectivity, which perpetuates social inequalities in online education. In the meantime, educator capacity building can be defined as one of the key products of the adoption of AI since anxiety about new technologies and the absence of training limit their use (Alshahrani et al., 2025).

Also, the experience of cybersecurity is a new threat that may jeopardize trust and sustainability, in particular, when there are weak data privacy frameworks (Lebbie et al., 2026). Therefore, it can be observed that digital transformation can be best achieved when human-centred governance, affordability, infrastructure, and capacity development of developing countries progress in whole as opposed to separately. Any university that can invest in infrastructure but without training and governance reforms they are likely to be met with resistance, inequality and lack of sustainability.

Conclusion

In view of the opportunities and contextual challenges facing emerging economies, as well as the developed world, a blend of education and technology has the potential to spur growth and development. This study therefore aimed to investigate the implications of digital transformation in education on human-centred governance in Africa. This review was based on three research questions: How digitized has the African higher learning become; how to enhance digital transformation using governance, policy and innovations; and what have been the opportunities and advantages behind this digital transformation? In response to the questions, the study reveals that digital transformation has been a major route to the modernization of higher education in Africa and many other contexts globally. The study revealed that the integration of digital and artificial intelligence in education is a critical element in the realization of quality education as well as in nurturing and driving innovation in the whole world not only in Africa.

To attain the benefits of digital transformation including flexibility, improved learning analytics and innovation, there is need for increased access, a human-centred policy, clear ethical guidelines, government commitments, investments and regulatory environments. Other necessary prerequisites include technology, capacity building, governance, inclusive infrastructure and ethical protection.

The study underscored the need for context-sensitive approaches, particularly with regard to the establishment of more equitable and inclusive educational environments by connecting digital transformation with issues of inclusion, diversity and equity. Additionally, a need for a collaborative and inclusive participation was identified in the navigation of the complexities of digital transformation of education, while ensuring that it is aligned with the institutional values and educational objectives.

It emerged from the study that, unless digital transformation is implemented appropriately, it has the potential to perpetuate inequality due to infrastructural shortfall, affordability, internet penetration, cybersecurity and lack of access. The examples of effective digital strategies and long-term investment in countries such as Rwanda and Kenya are a clear indication of the fact that it is possible to modify the situation as long as the process of governance is adjusted to technology.

This study offers insights for policymakers, institutions and educators wishing to contribute to sustainable digital transformation and AI integration in education.

Recommendations

Based on the analysis and the evidence presented, the following recommendations could form the basis of future research.

1. Increase the national ICT infrastructure investment rate in order to minimize the urban-rural and gender digital divide. Inter-country and regional collaboration and partnerships should be adopted to benefit from the interconnectedness of the African countries as part of addressing the affordances and sharing among the communities.
2. Instead of funding digital education as an emergency on a short-term basis, develop long-term models. In addition, support collaboration, exchange of expertise and skills as well as sharing of resources among institutions and countries.
3. Energize the digital governance frameworks on cybersecurity system, student data ethics system, and accountability system. Establish legislation and oversight frameworks in order to ensure that protection of human rights remains at the centre of digital transformation initiatives. Institutions should establish robust AI governance frameworks with well-defined ethical standards.
4. Go more digital and AI-sensitive to gain confidence and competency in teachers' professional development. Expand the literature on social effects of online education, especially when dealing with at-risk learners.
5. Apply strategies of inclusive access such as subsidised devices, low bandwidth-based learning system and community Wi-Fi hotspots.
6. Encourage local collaboration to boost EdTech solutions and disseminate lessons of implementation. Governments and institutions should encourage collaboration, while ensuring the interests of Africans including data when negotiating with national and international partners.

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Participative Leadership as a Micro-level Governance Mechanism for Ethical Digital Transformation: A Conceptual Framework

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Abstract

Digital transformation is fundamentally reshaping how organisations enact accountability, transparency, and ethical responsibility. Yet much of the corporate governance literature continues to privilege macro-level mechanisms such as boards, regulations, and audits while paying limited attention to the behavioural processes through which ethical principles are enacted in everyday organisational practice. This conceptual paper develops a framework that positions participative leadership as a micro-level governance mechanism capable of embedding ethical values within digitally transforming organisations. Drawing on an integrative review of corporate governance, leadership scholarship and digital ethics, the framework explains how inclusion, transparency and human oversight translate normative ideals into organisational action, thereby narrowing the persistent gap between technological innovation and moral accountability. Governance is reconceptualised as a relational and participatory system in which leadership behaviour mediates the interaction between digital challenges and sustainable governance outcomes including trust, ethical technology adoption, and responsible innovation. The argument is particularly salient for emerging economies, where institutional fragility and low levels of civic trust amplify the ethical risks associated with digitalisation. By reframing leadership as a behavioural infrastructure of governance, this study extends existing theory beyond compliance-oriented architectures and offers a human-centred pathway for aligning digital transformation with social legitimacy and organisational moral purpose.

Keywords: Participative Leadership, Corporate Governance, Digital Transformation, Digital Ethics, Trust, Emerging economies

JEL Classification: D23, D83, O32, Z13

Introduction

Digital transformation is redefining how organisations make decisions, coordinate work, and uphold accountability. Artificial intelligence (AI), automation, and data-driven systems have become integral to governance processes, and offer unprecedented efficiency and analytical precision. Yet they also introduce complex ethical and managerial dilemmas surrounding transparency, fairness, and moral responsibility. These challenges underscore the need to revisit how governance frameworks adapt to technological complexity. The task today is not merely to design technological safeguards but to ensure that digital transformation remains human-centred, inclusive, and ethically sustainable (Floridi & Cowls, 2019; Stahl, 2013).

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Existing research on corporate governance has predominantly adopted a macro-level focus emphasising institutional structures such as boards of directors, regulatory frameworks, and audit systems (Aguilera et al., 2018; OECD, 2023). However, governance is also enacted at the micro-level through everyday leadership behaviours and interpersonal interactions that shape organisational culture. Within this behavioural domain, leadership serves as the conduit through which governance principles such as transparency, fairness, and accountability are internalised and operationalised. Despite this, the connection between leadership and ethical digital governance remains underexplored. Current debates on AI governance tend to prioritise technical design or policy compliance, and overlook how leadership practices translate ethical values into organisational conduct (Camilleri, 2024; Batool et al., 2025).

This paper addresses this gap by proposing a conceptual framework that positions participative leadership as a micro-level corporate governance mechanism. Grounded in inclusion, transparency, and shared decision-making, participative leadership ensures that technological innovation aligns with human values and reinforces stakeholder trust in digital governance systems (Wang et al., 2022; Lythreatis et al., 2024). By integrating insights from leadership theory, corporate governance, and AI ethics, the study advances a behavioural model of ethical digital transformation in which governance is not imposed from above but co-created through participation and trust.

Against this backdrop, the paper makes three interrelated contributions. First, it integrates fragmented literatures on governance, leadership, and digital ethics to propose a human centred framework for responsible digitalisation. Second, it reconceptualises governance as a relational and participatory process rather than a hierarchical system of control. Third, it offers contextual relevance for emerging economies such as Algeria, where institutional centralisation and low civic trust heighten the need for leadership that embeds ethical accountability into the fabric of digital transformation.

Methodological Approach

This conceptual study adopts an integrative literature review approach. Peer reviewed journal articles published between 2018 and 2025 in the Scopus and Web of Science databases were examined. The synthesis focuses on Q1 and Q2 publications in corporate governance, leadership studies, and digital ethics with the objective of developing a cohesive theoretical model linking participative leadership to ethical digital transformation.

The integrative literature review was selected because it facilitates the identification of cross-disciplinary linkages where leadership and governance literatures converge on issues of ethical digitalisation. Unlike traditional narrative or systematic reviews, this approach prioritises conceptual integration rather than exhaustive coverage, thus enabling diverse theoretical perspectives to be synthesised into a unified analytical framework. This approach is particularly appropriate for emerging domains such as AI governance and participative leadership, where conceptual boundaries are fluid and empirical evidence remains limited.

Guided by the principles of conceptual synthesis, the review identifies recurring mechanisms, constructs, and theoretical relationships across these literary sources. The resulting integration provides the foundation for a coherent conceptual model that not only advances theory but also offers a structured basis for subsequent empirical research.

To enhance methodological transparency, this review applied clearly defined inclusion criteria: (1) peer-reviewed journal articles; (2) published between 2018 and 2025; (3) indexed in Scopus or Web of Science; and (4) originating from journals belonging to Q1 or Q2 journal quartiles in the fields of corporate governance, leadership studies, digital transformation, or AI ethics. The initial search identified approximately 60–70 articles across these domains. Following a relevance screening focused on governance, participative leadership, digital transformation, and AI ethics, 21 studies were retained for final conceptual synthesis (matching the references used in this paper). This selective approach ensured conceptual depth and theoretical coherence while maintaining an analytically focused corpus suitable for developing a cross-disciplinary conceptual model.

Theoretical Background

Corporate governance provides the ethical and structural foundation through which organisations are directed, controlled, and held accountable, which ensures that strategic choices uphold transparency, fairness, and responsibility towards stakeholders (OECD, 2023). Traditional scholarship has concentrated on macro-level governance mechanisms boards of directors, regulatory frameworks, and external audits but recent works emphasise the growing importance of micro-level governance, where managerial behaviour and interpersonal relationships determine how ethical principles are enacted in practice (Aguilera et al., 2018).

This behavioural perspective has become increasingly salient in the era of digital transformation. Advances in artificial intelligence (AI) and data-driven decision-making often outpace formal regulation, and produce new tensions around ethical consistency, accountability, and moral oversight (Camilleri, 2024; Zaidan & Ibrahim, 2024). Within this environment, participative leadership emerges as a human-centred governance style built on inclusion, shared decision-making, and mutual respect. In contrast to hierarchical or authoritarian models, participative leaders cultivate dialogue, empowerment, and collective problem-solving thereby fostering innovation, engagement, and ethical awareness (Likert, 1967; Vroom & Jago, 1988; Bass & Riggio, 2006; Wang et al., 2022; Ahn et al., 2022).

From a governance standpoint, participative leadership complements macro-level mechanisms such as board oversight and regulatory frameworks by translating normative expectations into everyday organisational practices. While formal structures codify accountability, participative leaders internalise these values through dialogue, reflection, and trust building. In this sense, leadership provides the behavioural infrastructure that connects institutional design with lived organisational culture, shifting governance from a compliance-oriented architecture towards a participatory and value-driven process (Gil Cordero et al., 2023; Toufighi et al., 2024).

Digital transformation intensifies the relevance of this micro governance role. While emerging technologies enhance efficiency and transparency, they also create ethical vulnerabilities including privacy breaches, algorithmic bias, and the erosion of human oversight (Floridi & Cowls, 2019; Batool et al., 2025). To address these challenges, governance must integrate fairness, inclusivity, and accountability into both technological design and organisational implementation (Stahl, 2013; Cao & Moreno, 2025). In emerging economy contexts, where digital literacy remains limited and decision-making highly centralised, participative leadership offers a pragmatic mechanism for cultivating ethical awareness and stakeholder engagement (Budhwar, Chowdhury, & Saini, 2022). Recent evidence from *Prosperitas* reinforces this view showing that successful digitalisation in emerging industrial regions depends not only on technological capability but also on leadership practices that strengthen trust, collaboration, and adaptive governance (Wu & Tóth, 2025). By promoting dialogue, transparency, and shared responsibility, participative leaders align digital innovation with societal expectations and moral standards (Bokhari et al., 2025).

Taken together, these insights position participative leadership as a micro-level corporate governance mechanism that operationalises transparency, accountability, and inclusion within digitally transforming organisations. It bridges the divide between macro institutional structures and the behavioural realities of everyday decision-making. This theoretical synthesis provides the foundation for the conceptual framework developed in the following section, which explicates how participative leadership mediates the relationship between digital ethical challenges and sustainable governance outcomes.

Through this synthesis, participative leadership emerges as a micro-level corporate governance mechanism that bridges the structural and behavioural dimensions of ethical digital transformation. By embedding the principles of transparency, accountability, and inclusion into everyday managerial practice, participative leadership connects the normative intent of macro-level governance boards, regulation, and audit with the lived realities of organisational decision-making. This behavioural translation ensures that governance values are not merely prescribed but enacted thereby transforming compliance into collective moral responsibility.

The theoretical contribution of this model is threefold. First, it integrates fragmented literatures on corporate governance, leadership, and AI ethics into a unified explanation of how ethical digital transformation can be achieved through *human-centred leadership*. Second, it reconceptualises governance as a *relational and participatory system* grounded in dialogue and mutual accountability rather than hierarchical control. Third, it provides contextual relevance for *emerging economies*, where participative leadership can offset institutional weaknesses, foster ethical resilience, and strengthen public trust in digital reforms (Bokhari et al., 2025). Collectively, these insights demonstrate that participative leadership is not merely a management style but a governance mechanism capable of embedding ethical consciousness within the fabric of organisational decision-making.

Conceptual Framework

This section introduces the conceptual framework that synthesises the theoretical arguments developed in the preceding sections. As shown in Figure 1, participative leadership is theorised as a micro-level governance mechanism that mediates the relationship between digital ethical challenges and sustainable governance outcomes. The framework integrates insights from corporate governance, leadership theory, and digital ethics to illustrate how leadership behaviour operationalises inclusion, transparency, and human oversight within digitally transforming organisations.

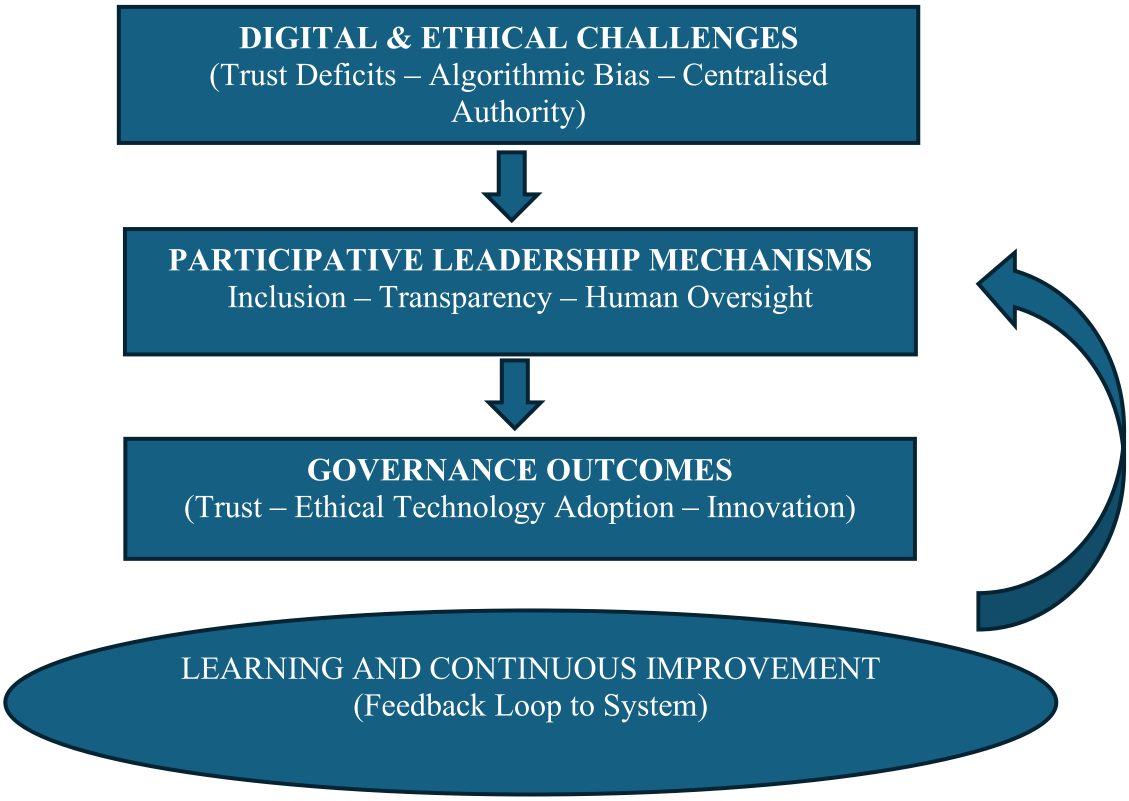

Figure 1: *Participative leadership as a micro-level governance mechanism for ethical digital transformation*

Source*: authors' own compilation*

The framework theorises participative leadership as the mediating process linking *digital and ethical challenges* to *sustainable governance outcomes*. Digital transformation creates technological and moral tensions: trust deficits, algorithmic bias, and concentrated authority that cannot be addressed through rule-based governance alone. Participative leaders resolve these tensions through three mutually reinforcing mechanisms: inclusion, transparency, and human oversight.

- **Inclusion** engages diverse stakeholders in ethical deliberation and shared ownership of digital decisions.
- **Transparency** ensures openness about technological objectives and risks, reinforcing legitimacy and accountability.
- **Human oversight** preserves moral judgment and critical reflection within algorithmic processes.

Institutionalised together, these mechanisms generate governance outcomes characterised by trust, ethical technology adoption, and a culture of responsible innovation. Conceptually, the model positions participative leadership as both a behavioural process and a governance infrastructure ensuring that digital transformation remains transparent, accountable, and human-centred. This integration provides a coherent foundation for the discussion and implications that follow.

Discussion and Implications

The proposed framework reconceptualises governance in the digital era as a multi-level and participatory process rather than a static hierarchy of control. By positioning participative leadership as a micro-level governance mechanism, the model demonstrates how leadership behaviour operationalises accountability, transparency, and inclusiveness within digitally transforming organisations. Digital transformation is not merely a technological shift but a reorganisation of the ethical and relational foundations of governance. While macro-level mechanisms codes of conduct, regulatory standards, and institutional oversight define *what* organisations should do, participative leadership determines *how* those principles are enacted in practice. Through dialogue, collaboration, and shared responsibility, participative leaders embed ethical values into organisational culture, transforming governance from a compliance-based framework into a living system of moral practice.

At the theoretical level, the framework contributes to the micro foundations of corporate governance (Aguilera et al., 2018) by identifying leadership as the behavioural mechanism through which governance ideals are internalised and enacted. It extends leadership theory into the domain of digital ethics (Wang et al., 2022; Lythreatis et al., 2024) and advances AI governance research by framing ethical digital transformation as a *co-governance system* in which human judgment and institutional design interact dynamically (Zaidan & Ibrahim, 2024; Batool et al., 2025). In doing so, it reconceptualises governance as a relational and participatory system that relies on shared values and human agency rather than hierarchical enforcement.

The model also carries clear implications for policy and organisational practice. From a policy perspective, it underscores that regulation alone cannot ensure ethical digitalisation. National digital strategies should therefore incorporate leadership development and ethics programmes that promote participatory decision-making, algorithmic transparency, and civic engagement. Such initiatives can democratise digital transformation by linking top-down governance with community-level participation. In emerging economies such as Algeria, where institutional capacity and civic trust remain limited, participative leadership can bridge the gap between centralised policy directives and organisational realities, cultivating legitimacy and societal trust through inclusive and transparent engagement. For organisations, the framework offers a roadmap for embedding ethical principles into digital projects by institutionalising participative structures, open communication, and human oversight mechanisms that preserve accountability in algorithmic processes. These practices create a culture of ethical resilience, i.e. an organisational capacity to manage digital risks collaboratively rather than coercively, while enhancing employee engagement and stakeholder confidence.

Beyond its conceptual and practical contributions, this study also lays the groundwork for future empirical research. The proposed relationships invite testing through mixed-methods designs including survey-based structural equation modelling and comparative case studies across industries and national contexts. Future research could explore how contextual variables such as institutional maturity, cultural norms, or technological intensity moderate the effects of participative leadership on governance outcomes. Such empirical inquiry would refine the model’s explanatory power and further illuminate how human-centred leadership sustains ethical digital transformation.

Ultimately, this study reaffirms that responsible digitalisation is not simply a technological or regulatory challenge but a human enterprise grounded in trust, inclusion, and reflective dialogue. Participative leadership embodies this human dimension by translating governance principles into lived organisational realities. In doing so, it redefines governance in the digital age not as control imposed from above but as collaboration built on shared ethical responsibility and collective moral purpose.

Limitations and Future Research

Although this study offers a novel behavioural perspective on ethical digital transformation, its contributions should be interpreted in the light of several limitations that also point to promising directions for future research. First, the paper is conceptual in nature and is based on an integrative review of the literature rather than on original empirical data. This design is well-suited for theory building and cross-disciplinary integration, yet it does not allow for direct empirical testing of the proposed relationships. Accordingly, the framework should be viewed as a theoretically grounded foundation intended to guide subsequent empirical inquiry.

Second, the integrative review emphasises conceptual relevance and theoretical coherence over comprehensive coverage. While the analysis draws primarily on high-quality Q1 and Q2 journal publications in corporate governance leadership and digital ethics, this focus may limit the representation of more critical or alternative perspectives. Future research could strengthen and challenge the framework by explicitly engaging with competing governance logics or leadership approaches, particularly those that prioritise formal control, technological determinism, or algorithmic autonomy over participatory processes.

Third, although the framework is presented as especially pertinent to emerging economies, contextual variation is not explicitly incorporated into the model. Institutional capacity, cultural norms, regulatory enforcement, and levels of digital maturity are likely to shape how participative leadership operates as a governance mechanism. Future studies could address this limitation through comparative research across countries, industries, or organisational settings thereby clarifying the conditions under which participative leadership most effectively supports ethical digital transformation.

Building on these limitations, several avenues for future research emerge. Quantitative studies employing survey-based designs and structural equation modelling could empirically examine the proposed relationships between participative leadership, ethical governance mechanisms, and digital transformation outcomes such as trust and responsible innovation. Qualitative approaches, including interviews and case studies, could further illuminate how leaders enact inclusion, transparency, and human oversight in practice, particularly in environments characterised by increasing algorithmic decision-making. Together, these research directions would enhance the explanatory depth of the framework and advance understanding of how micro-level leadership behaviours interact with broader governance structures in shaping ethical digital transformation.

Conclusion

Digital transformation represents not only a technological revolution but a moral reconfiguration of how organisations define responsibility and trust. This study has proposed a conceptual framework that positions participative leadership as the *human core* of this transformation in a micro-level governance mechanism that translates ethical principles into lived organisational practice. By operationalising inclusion, transparency, and human oversight, participative leaders mediate the tension between digital efficiency and moral accountability, which thus generate governance outcomes anchored in trust, ethical innovation, and social legitimacy.

The proposed framework contributes to corporate governance theory by bridging macro institutional design with micro behavioural enactment. It advances leadership studies by demonstrating that participative leadership is not a soft relational style but a structural governance function through which organisations internalise ethics and sustain moral agency in technology-driven environments. The study also expands the domain of digital ethics research, revealing leadership behaviour as the missing link between abstract regulatory ideals and the practical realisation of responsible AI and data governance.

Contextually, the model carries particular significance for emerging economies. Where institutional fragility and centralised decision-making constrain ethical innovation, participative leadership offers a flexible governance architecture that builds ethical resilience from the ground up. By democratising digital transformation and nurturing trust through deliberation and shared ownership, participative leadership transforms compliance-based governance into a participatory culture of responsibility rooted in human dialogue rather than technical design.

Although conceptual, the framework provides fertile ground for empirical validation and comparative inquiry. Future research should test its propositions through multi-method approaches combining survey-based structural equation modelling with qualitative and cross-country analyses to examine how institutional maturity and cultural context shape the effectiveness of participative leadership as an ethical governance mechanism. Such investigations would refine the model's explanatory precision and clarify how leaders operationalise governance ideals across diverse digital ecosystems.

Ultimately, this study reaffirms a simple but profound truth: ethical digital transformation begins with people and not with machines. Governance in the digital age is sustained not by algorithms or codes of conduct, but by the collective moral reasoning of those who lead, decide, and trust one another. Participative leadership embodies that reasoning. It transforms governance from an external apparatus of control into an internal ethic of care ensuring that progress in the digital era remains not only intelligent but just, inclusive, and deeply human.

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Next-Generation SAP Testing with Cloud ALM - Evidence from Four Company Cases

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Abstract

Enterprise resource planning implementation projects remain high-risk undertakings, and failures frequently arise from insufficient test depth, weak defect management, and limited readiness assessment. Nowadays, the cloud environment is the platform where Enterprise Resource Planning systems have transitioned. The importance of structured test processes is a primary focus in Enterprise Resource Planning projects, as they simulate the future system. This study compares four cloud-based implementations (two with Excel for testing and two with cloud-based application lifecycle management). The study analyses how testing tools affect testing quality, defect management, and post-go-live stability. The comparison was based on quantitative project data, including test case logs, defect records, testing duration, cycle counts, and hypercare incidents. Descriptive statistics and non-parametric comparative methods were used for analysing the data. The research results show that projects with integrated lifecycle management tool support conducted deeper test cycles and detected more defects before go-live, and, as a result, systems were more stable after deployment. Excel-based testing was adequate only for smaller, less complex rollouts and led to higher defect density post-go-live due to limited traceability and fragmented workflows. The study highlights the strategic relevance of testing depth and demonstrates the benefits of integrated lifecycle management tools for implementation quality. These results contribute to Enterprise Resource Planning research by providing empirical evidence that test management tools influence project outcomes and long-term system stability.

Keywords: Systems, Applications, and Products in Data Processing (SAP), implementation, Cloud Application Lifecycle Management (CALM), Enterprise Resource Planning (ERP), testing, defect management, testing quality, defect, go-live, cloud, project governance, hypercare

Introduction

Enterprise Resource Planning (ERP) systems such as Systems, Applications, and Products in Data Processing (SAP) are fundamental to company operations, as they integrate financial, logistics, purchasing, and operations departments. The primary goal of ERP systems is to make operations more efficient and safer; however, their implementation remains difficult, costly, and risky. A study states that only 64% of ERP projects are successful, while the remaining 36% encounter problems such as budget increases, schedule delays, or scope changes (Panorama Consulting Group, 2023).

The Standish Group's CHAOS Report lists IT project failure factors and names lack of user involvement, insufficient executive ownership, unclear requirements, and ineffective

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project planning and delivery. ERP failures also highlight these issues and are heavily influenced by factors such as cross-functional complexity, poor data quality, and insufficient testing.

Testing is still one of the most critical process steps, but it is not properly standardised as part of ERP implementation. Many organizations still use Excel spreadsheets to manage their test cases, execution status, and defects, simply because they find this solution easier and more flexible. Although Excel spreadsheets offer limited collaboration, prior experience is not included, and no integrated defect tracker is provided. Defect resolution and traceability are key to go-live success.

Systems, Applications, and Products in Data Processing (SAP) Cloud Application Lifecycle Management (CALM) is SAP's new cloud-based lifecycle management platform for the future and is expected to overcome current limitations. The platform offers comprehensive process traceability, live dashboards, integrated defect workflows, and alignment with SAP Activate. CALM can provide centralised test-case design, future-state simulation, and readiness analytics throughout project phases.

This research explores the impact of testing tools (Excel and SAP Cloud ALM) on the success of SAP implementation projects. By comparing the real-life situations of four companies (two using Excel and two using CALM), the study examines variables such as the thoroughness and frequency of testing, defect leakage, and system stability after going live.

This research has two main focuses:

- To establish whether the use of structured and tool-supported testing leads to higher quality in implementation.
- To provide empirical research to the existing literature on critical success factors and ERP testing management.

Literature review

Introduction to ERP Implementation Research

Enterprise Resource Planning (ERP) systems have been the subject of the most in-depth research on information systems for over 20 years. Key studies by Esteves and Pastor (2001) introduced the concept that ERP implementations must be understood and evaluated across multiple dimensions of technology, organisation, people, and strategy. In the two decades since, ERP research has continued to show that the success or failure of ERP implementation depends a lot on the organisation, industry, and approach. One of the main conclusions from past research on ERP is that technology alone cannot guarantee success. As ERP systems allow organisations to integrate complex business processes across departments, the success of implementations is closely related to management and leadership, governance, user readiness, and data quality (Gattiker & Goodhue, 2005; Bradford & Florin, 2003). The latest research has not changed this and has established quite the opposite: ERP technology moves from traditional on-premises environments to cloud-based, agile delivery models (Wynn et al., 2024).

With these changes, a core element of ERP implementation success that has often been overlooked in research is the scope of testing, test management, and the maturity of defect resolution, which this study focuses on.

Critical Success Factors in ERP Implementations

Critical success factors (CSFs) in ERP implementations have been the subject of extensive research. Al-Fawaz, Al-Salti, and Eldabi (2008) conducted a broad-based study that showed the most often mentioned CSFs to be top management support, a strong project management team, user involvement, well-defined project requirements, training, and communication. Maditinos et al. (2012) also found that organizational culture, project governance, and user readiness significantly impacted the success of ERP projects in Greek companies. Kouriati et al. (2022), who studied the implementation of ERP systems in companies in the food and agricultural processing sector, identified CSFs including change management, process clarity, and user engagement and provided quantitative data to support the view that these factors play a significant role in successful implementation. Other regional studies (Shafi et al., 2019 in Pakistan; Idilbi & Abu-Shanab, 2022 in Qatar) also support these findings and emphasize that employees' experiences with support, communication, and training directly affect whether ERP is accepted and successful.

As ERP projects move towards cloud-based solutions, the role of CSFs is likely to become stronger. According to Wynn et al. (2024), ERP implementations in the digital era follow different patterns: they occur in shorter, more frequent release cycles, are more complex, involve a greater number of systems and tools, and rely more heavily on lifecycle management tools for governance. These changes put testing under even more pressure.

ERP Value Realisation and Long-Term Performance

Beyond success in the project phase, some researchers have examined the positive impact of ERP systems on long-term organisational performance. Hitt, Wu, and Zhou (2002) showed that productivity improvements following ERP adoption largely depend on organisational readiness, process standardisation, and data governance. Their results point to the interplay between technology and managerial practices: when internal capabilities are lacking, firms struggle to translate ERP capabilities into measurable value. More recent evidence supports this view. Bradford and Florin (2003) found that innovation diffusion factors, such as user learning, communication, and perceived usefulness, strongly influence the benefits observed after implementation. Gattiker and Goodhue (2005) studied outcomes at the plant level and concluded that employee interdependence and process harmonisation have a significant impact on ERP success. Together, these studies make it clear that technology by itself does not generate value: it is the organisation's ability to implement, manage, and stabilise the system that drives long-term performance. This clearly links value realisation to testing governance: if test planning, defect management, and go-live readiness are not carried out meticulously, organisations will experience issues that not only affect the implementation but will also hinder the benefits of the ERP system in the future.

The Role of Testing Quality in ERP Implementations

Initially, in the ERP literature, testing was considered a project activity, but more recent research regards it as a strategic factor for successful implementation. Shatat and Dana (2016) showed that insufficient testing leads to operational instability, increased defects, and user dissatisfaction. Shafi et al. (2019) concluded that testing quality and user training were among the most significant factors for user satisfaction in ERP systems implemented in the manufacturing sector. Testing is now seen as a business readiness check. Immidi and Mane (2025), in their study of the confluence of Artificial Intelligence and SAP IBP, noted that strong, well-documented testing frameworks are indispensable for ensuring consistency across modules and reliable performance. Their research highlighted a key point: only by covering end-to-end scenarios can we be sure that the forecasting system will behave as expected in a real-world setting rather than merely testing individual components.

ERP implementations that do not allocate sufficient resources to testing often encounter many defects during go-live and hypercare. This, in its turn, delays the stabilisation process and erodes user confidence. Mahraz, Benabbou and Berrado (2019) mentioned the lack of testing depth as one of the main risk factors for ERP projects in their literature review. Moreover, research on implementation methodologies (Viljakainen, 2024) shows that SAP projects must undergo multiple well-structured test cycles, particularly when they are multi-country or multiphase. In such cases, business processes need to be checked and re-checked as they evolve from one release to the next.

Testing Tools and Lifecycle Management

Modern ERP systems have become sophisticated and valuable, but many companies still rely on Excel to manage test cases. If we are to believe Aires and Abrantes (2022), such reliance on spreadsheets for testing will become increasingly problematic as project size increases, because Excel cannot provide version control, team collaboration, and traceability up to the desired standards. The transition to cloud ERP systems has only accelerated the adoption of integrated Application Lifecycle Management (ALM) tools. According to Gupta (2025), who studied over 80 SAP implementations globally, the key to managing large-scale ERP deployments is maintaining consistency, visibility, and traceability across the project stages. Madathala and Yeturi (2025) also observed that a well-defined defect workflow and early issue identification were crucial to the success of SAP ERP projects in Indian companies.

SAP Cloud ALM (CALM) is considered to be the future of SAP lifecycle management. Its main features are as follows:

- the ability to trace a business process all the way to the test case,
- a seamless integration with the defect management system,
- real-time dashboards and key performance indicators for readiness,
- an implementation that follows the SAP Activate methodology,
- support for distributed teams through shared workspaces.

There is not much research on CALM in academic circles, but it is worth noting that the characteristics of CALM identified so far are very much in line with general findings on ALM systems. Such systems are effective in ensuring thorough testing and fewer defects slip through, and they are also adequate for supporting project delivery in an auditable manner (Vaid, Reddy & Prabhagaran, 2024; Wynn et al., 2024). Apparently, testing is about managing risk and ensuring that the business is ready for change. In this context, a fully integrated ALM system offers capabilities that Excel cannot provide. In SAP projects that involve frequent releases and dependencies, and where multiple modules might interact, these properties are fundamental.

Defect Management and Post-Go-Live Stabilisation

Research consistently finds that the later defects are found in a project, the higher the cost of fixing them and the greater the disruption caused. Studying SAP MM/WMS implementations in manufacturing environments Banța (2020) identified a pattern of insufficient unit and integration testing, which ultimately led to a large number of defects being discovered after go-live and a significant hypercare period. Likewise, Salas (2023) contended that modern ERP implementations using agile methods must identify defects iteratively and maintain continuous feedback loops to achieve stability.

Idilbi and Abu-Shanab (2022) described how organisations with robust defect management processes and clear accountability structures achieved smooth go-lives and high user satisfaction. Their observations are supported by broader studies, which conclude that adopting a structured approach to logging defects, identifying them promptly, and being transparent about them reduces the risk of operational failure. One of the ways SAP Cloud ALM meets this need is by connecting defect workflows to test cases and business process models, so that anyone can follow the thread of a defect right through a project.

Summary of Gaps in the Existing Literature

Despite the large number of studies dealing with ERP CSFs, value realisation and testing principles, there are some open questions:

- Empirical research is largely lacking with respect to a comparison of Excel-based vs. CALM-based testing approaches in SAP environments.
- The literature rarely examines test depth and testing cadence as measurable predictors of go-live readiness and stabilisation speed.
- Testing is usually considered a technical activity rather than a strategic lever for value realisation.
- Empirical studies rarely examine defect leakage rate, scenario coverage metrics, and incident resolution outcomes across different testing tools.

This research is filling these gaps by directly comparing four SAP projects, empirically showing how testing tools influence project outcomes, defect patterns, and organisational readiness.

Research Methodology

Research Design

The present research uses a comparative multiple-case study to analyse how different test management tools (Excel spreadsheets and SAP Cloud ALM (CALM)) affect the depth of testing, defect discovery, and the project's post-go-live phase in SAP implementations. A multiple-case study method is suitable for ERP research, as implementation occurs in real-world organisations and involves a complex interplay among tools, processes, and project management. The study is explanatory and comparative in nature: it does not only aim to describe differences but also seeks to understand how and why the use of a structured ALM platform may lead to more thorough testing and more stable stabilisation phases than spreadsheet-based approaches.

Case Selection and Sampling

Four SAP projects were selected based on the availability of complete test datasets and the clarity of the testing approach. The cases were selected using theoretical purposive sampling to ensure they contrast and are comparable across key dimensions.

Sampling criteria:

- Two projects where test management was done using Excel
- Two projects where test management was done using CALM
- Availability of quantitative data (test-case logs, defect logs, completion rates, duration, hypercare data) without gaps
- Similar implementation scope (SAP Public/Private Cloud rollouts)

Regarding case characteristics, the four companies are the representative mix of:

- deployment types (2 Public Cloud, 2 Private Cloud),
- testing approaches (2 Excel, 2 CALM),
- sizes and complexities (ranging from a small template rollout to an extensive multi-country programme).

The sampling is based on the following replication logic:

- Excel projects are used as literal replications (expected similar low-depth testing behaviour),
- CALM projects are used as theoretical replications (expected to provide deeper and more structured testing due to the tool capabilities).

Data Sources

Quantitative Testing Artefacts Extracted from uploaded project files:

- Test-case logs (Excel sheets and CALM exports)
- Execution status (passed, failed)
- Testing duration (months)
- Number of test cycles (mixed in all types of phases and modules)
- Defect logs (closure rates)
- Hypercare defect tickets (first 90 days).

The study is entirely data-driven.

Key Variables and Measurement

Four main variable groups were operationalised.

1. Testing Depth Indicators: total number of executed test cases, end-to-end business process coverage, number of testing cycles performed, test cases per month (testing intensity)
2. Defect Behaviour Indicators: total defects detected per phase, defect leakage, rework volume
3. Stabilisation Performance Indicators: hypercare defects (0–90 days), recurring issues
4. Tool Capability (Excel vs CALM) features: test-case traceability, real-time dashboards, integrated defect lifecycle, collaboration model

Table 1 below shows the structured way of the Key variables and Measurement used as the scope of the research.

Table 1: *Key Variables Used in the Study and Their Measurement Indicators*

Key Variables and Measurement	**Indicators**
Testing Depth	Total number of executed test cases End-to-end business process coverage Test cases per month
Defect Behaviour	Total defects detected per phase Defect severity distribution Defect leakage Rework volume
Stabilisation performance	Hypercare defects Recurring issues
Tool Capability (Excel vs CALM)	Test case traceability Real-time dashboards Integrated defect lifecycle Collaboration model

These definitions correspond to SAP Activate's testing governance model and to CALM's default configuration.

The research employs a mixed quantitative analytical approach, combining statistical comparison.

1. Descriptive Statistical Analysis: mean, median, range of test-case volumes, summarised defect patterns, testing duration, frequency, and hypercare issue distributions.
2. Derived Metrics Analysis: two calculated indicators allow comparability.

- Testing intensity = total test cases ÷ testing months.
- Defect density = hypercare defects ÷ 100 test cases.

3. Group Comparison Methods: non-parametric tests were chosen; the Mann-Whitney U test, the calculated testing intensity and defect density were used As stated in the manuscript, these did not reach significance but showed apparent directional differences favouring CALM due to low statistical power.

Validity, Reliability, and Limitations

Data are from similar SAP projects with comparable testing structures. It depends on the project how much the given test case is broken down into steps. In CALM-based testing, the test cases are more fragmented. One of the samples with a large number of items is high because not only was the implementation complex (several modules at once), but all testing was included for every period, and the project duration itself was extended due to the company's size and the complexity of processes.

The research limitation is the small sample size. Differences in scope and complexity partly influence results. However, since the study focuses solely on data-based tool comparison, a quantitative design is suitable and methodologically sound.

Results and Analysis

Overview of the Analysed Cases

The four SAP implementation projects considered in the study are summarised in Table 2. The cases refer to a balanced mix of deployment models and testing approaches: two Public Cloud and two Private Cloud implementations; two Excel-based and two CALM-based testing projects. This allows for a meaningful comparison while maintaining a certain level of project diversity in terms of scope and complexity. The cases represent both smaller, template-driven, and larger, multi-module implementations, thus providing a basis for the results to be relevant to a wide range of testing workloads and quality requirements.

Table 2: *Key characteristics of the four implementation projects*

Company	Deployment Type	Testing Tool	Customisation Level	Region / Industry
Company 1	SAP Private Cloud	CALM	Medium–High	Hungary
Company 2	SAP Public Cloud	Excel	Low	Hungary
Company 3	SAP Public Cloud	CALM	Medium	Hungary
Company 4	SAP Private Cloud	Excel	Medium	Hungary

Descriptively, the distinction between the two groups of cases in terms of testing approach is quite pronounced: projects with CALM support were generally more customised and had a broader geographical or functional scope, whereas projects that used Excel for testing were usually less complex and only involved single-country rollouts. This issue should be considered when reviewing the more detailed quantitative indicators below.

Descriptive Comparison of Testing Activities

Table 3 shows the main testing KPIs for the four projects, along with their original descriptive values. The difference in testing volumes is striking. The two CALM projects executed 1,879 and 74 test cases in total, whereas the two Excel projects only managed 27 and 82, respectively. This large gap also explains the difference in testing duration: the two CALM projects typically ran their tests for 6–18 months, whereas the two Excel projects ran their tests for only 2–4 months.

The percentage of test cases closed at go-live is relatively similar across all projects (76–91%), which indicates that, regardless of methodology, teams completed test execution as planned. However, the scope of the testing differs greatly. The two Excel-based projects managed to close a high % of their test cases, mainly because the total number of test cases was very low to begin with. Again, the number of defects logged during Hypercare (0–90 days) follows a similar trend: the two CALM projects also have a higher absolute number of defects (208 and 6) than the two Excel projects (5 and 17). At face value, this could suggest quality issues; however, the subsequent KPIs show that the higher defect numbers are driven by thorough, deep defect discovery activities conducted before go-live.

Table 3: *Key Testing KPIs of analysed implementation cases*

Company	Testing Duration (months)	Total Test Cases	Test Case Closure Rate (%)	Number of Test Cycles	Hypercare Defects	Deployment Type	Testing Tool
Company 1	18	1,879	76%	3 cycles	208	Private	CALM
Company 2	2	27	91%	1 cycle	5	Public	Excel
Company 3	6	74	85%	2 cycles	6	Public	CALM
Company 4	4	82	85%	1–2 cycles	17	Private	Excel

Derived Indicators: Testing Intensity and Defect Density

Table 4 shows two normalized indicators, testing intensity and defect density, to provide a more meaningful comparison across projects of different sizes.

Testing Intensity:

The testing intensity of the two CALM projects was more than double:

- CALM average: 58.35 test cases per month
- Excel average: 17.00 test cases per month

Table 4: *Testing Performance Metrics for the Four SAP Projects*

Company	Testing Tool	Testing Intensity (Test Cases / Month)	Hypercare Defect Density (Defects / 100 Test Cases)	Test Completion at Go-live (%)
Company 1	CALM	104.40	11.10	76%
Company 2	Excel	13.50	18.50	91%
Company 3	CALM	12.30	8.10	85%
Company 4	Excel	20.50	20.70	85%

The central part of the difference is attributed to a single country project (1,879 test cases). In contrast, the two CALM projects demonstrate more thorough and continuous testing, even when the large project is excluded. Testing in Excel was limited to brief periods in both projects, indicating not only the constraints of the methodology but also the projects' narrower testing scope.

Defect Density:

The results are reversed when we look at the number of defects found after the go-live. Lower values are to be expected in this case because they indicate better quality assurance before the release:

- Average defect density for CALM projects: 9.59 defects per 100 test cases
- Average defect density for Excel projects: 19.63 defects per 100 test cases

This supports one of the study's main conclusions: projects that use CALM for testing find a larger share of their defects before going live and therefore have fewer issues during Hypercare. In other words, testing supported by CALM moves defect detection earlier in the project timeline, making it cheaper and less disruptive to fix defects.

Statistical Comparison Between Excel and CALM Projects

Given the limited sample size (n=4), the statistical power of this analysis is restricted. However, Table 4 presents a formalised comparison with Mann–Whitney U tests to complement the descriptive analysis.

While none of the tests are statistically significant, all the effects are consistent with the advantages of CALM-based testing:

- Testing intensity: a strong effect in favour of CALM
- Defect density: an effect in favour of CALM (lower density)
- Closure rate: mixed effect, with a slight advantage for Excel due to a smaller scope

Based on the Table 4 data, we can calculate the Mann-Whitney test, although the sample sizes are small.

Table 5: *Mann–Whitney U Test Results for Key Testing Indicators*

Indicator	**CALM Mean**	**Excel Mean**	**p-value (Mann-Whitney)**	**Direction**
Testing intensity	58.36	17.00	1.000	CALM > Excel
Defect density	9.59	19.63	0.333	CALM < Excel
Closure rate	80.5%	88%	0.414	Mixed

These findings support the view that CALM's functionalities (traceability, workflow integration, analytics) contribute to more comprehensive test planning and deeper defect detection than spreadsheet-based testing.

The result of the Mann–Whitney U tests was from a minimal sample size (n = 4). Therefore, results should be considered exploratory rather than confirmatory. The p-values with these tests are not indicative of statistical significance. However, the descriptive trends suggest that projects with CALM had broader testing and lower post-go-live defect rates. The non-significant p-values indicate limited statistical power rather than the absence of substantial differences. Therefore, the statistical tests serve as a supplement to the descriptive and process-based interpretation of the results and they cannot be substituted.

Summary of findings

Looking across all five tables, the findings are consistent:

- CALM enables more comprehensive and structured testing than Excel.
- Projects that use CALM find more defects earlier, which thereby lowers the risk of production escapes.
- Excel testing may seem efficient only because the testing is shallow, not because of higher quality.
- The relative post-go-live defect density is significantly lower in CALM projects, which indicates better readiness.
- CALM's process traceability, dashboards, and workflows lead to measurable quality improvements.

Taken together, these findings suggest that testing tools matter and that organisations planning any mid- to large-scale SAP implementation should consider using SAP Cloud ALM or a similar lifecycle management platform.

Discussion / Conclusion

Discussion

Table 6 below combines qualitative observations and quantitative data to provide a broader perspective on how testing tools influence project behaviour and outcomes.

We have collected the outcomes of the research as follows:

- Traceability and Progress: Excel does not have automated traceability, and it is challenging to link defects to specific business processes. CALM's process mapping facilitated accountability, defect tracking, and readiness reporting throughout the project.
- Scalability for complex implementation: The two CALM-supported projects were able to significantly increase their testing volumes while at the same time maintaining coordination and visibility across the team. The two Excel-based projects, on the other hand, were not only limited in size but also in complexity. Test cases can be missed because CALM uses build scenarios based on previous standardized project experiences.
- Defect Management: Defect workflows in Excel were manual, and errors could be tracked manually. These ineffective ways result in delayed resolution or incomplete documentation. CALM's integrated defect management system streamlined the process, reduced duplicate efforts, improved defect closure cycles, and enabled earlier resolution.
- Hypercare stability: The combined effect of these efficiencies is most noticeable in hypercare. The two CALM projects had lower relative defect density and faster stabilisation. In comparison, the two Excel projects had fewer defects identified during testing, but more than expected after go-live.

Table 6: *Comparative Assessment of Testing Practices: Excel vs. CALM*

Aspect	Excel-Based Testing	CALM-Based Testing	Observed Impact
Traceability	Manual, fragmented	End-to-end automated	Earlier defect discovery in CALM projects
Test coverage	Limited scalability	High scalability	CALM projects executed 10–20× more test cases
Collaboration	Static sheets	Shared workspace	Better cross-team coordination in CALM
Defect management	Manual & error-prone	Integrated lifecycle	Faster closure cycles in CALM
Hypercare stability	Higher defect density	Lower defect density	Faster stabilisation in CALM projects

This aligns with broader theoretical arguments in the ERP literature that testing depth and governance are key factors in implementation success and long-term system stability.

Conclusion

This paper studied four SAP implementation projects to check if using different test management tools, Excel spreadsheets, or SAP Cloud ALM can affect testing efficiency and quality via thoroughness of testing, the number of defects, and stability after go-live. For all descriptive, derived, and comparative indicators, a clear pattern emerged: Testing supported by CALM is more thorough, organized, and transparent than testing with spreadsheets. Projects with CALM performed much more testing and maintained a much higher testing intensity throughout the project months. Implementations with CALM found more defects in absolute terms; however, this was due to more rigorous, thorough testing rather than lower quality. Once accounting for testing volume, CALM projects experienced a lower defect density after go-live, indicating better risk mitigation before cutover.

Testing in Excel was only adequate for smaller, less complex rollouts. The lack of traceability, fragmented defect management, and limited scalability prevented testing from being deep enough, which led to a higher relative number of defects during hypercare. These results are consistent with the general ERP literature, which argues that the success of an implementation depends not only on the quality of the process design but also on the rigor, cadence, and governance of testing activities.

In short, the paper shows that the test tool is not only a matter of administration but also a key success factor in SAP projects. By enabling end-to-end traceability, integrated defect lifecycle management, and real-time readiness analytics, SAP Cloud ALM can make SAP implementations more predictable, transparent, and stable.

Future Research and Practical Next Steps

The outcomes of this study are indicative but highlight several opportunities for subsequent research and practical application.

Potential Research in the Future

- Broader multi-sector sample: Subsequent research could investigate a wider range of SAP implementations with various industries and regions to confirm the applicability of the testing intensity and defect resolution trends.
- Longitudinal study: A Longitudinal study (covering all phases of the project) could identify changes in test coverage, defect leakage, and stabilisation speed more clearly than a retrospective study.
- Further development of the testing model: Some aspects can be added to the model, like risk-based testing weights or process criticality scores. The further development of this model would enable organisations to predict testing sufficiency and readiness with greater precision.
- The role of AI and predictive analytics: Currently, there is embedded AI in CALM. This can be used for automated test generation, defect prediction, and readiness scoring. This would link ERP quality assurance to advanced decision-support techniques.

Suggestions for Practice

- Moving from Excel-based test management to integrated ALM platforms: In the case of companies still using Excel for test management. If they implement a broader scope with many modules and test cases, CALM can be the right solution from a testing perspective.
- Readiness for the design phase: The Project team can invest earlier in traceability mapping, defect categorization, test data creation, and end-to-end design.
- Risk-based testing and test KPI dashboards: Test KPIs, including defect density, leakage, and testing intensity, should be tracked regularly. CALM dashboards lay a strong foundation for such tracking.
- Define governance roles: Although some of the implementation team have these project-related roles, there are still many who do not focus on the right capabilities. CALM requires a clear role for each: the test manager, the defect coordinator, and the process owner.

- Using the hypercare period to estimate quality: The number of defects in the hypercare period is a solid indicator of deep testing. Companies should use it to demonstrate the maturity of project testing during the execution phase.

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Bridging Technology and Humanity: The Impact of Digital and Emotional Intelligence on Hotel Management

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Abstract

This paper examines how Artificial Intelligence (AI) and Emotional Intelligence (EQ) work together to shape decision-making in hotel management. By looking at the link between AI data processing and human emotional skills, I aim to outline a responsible leadership model that effectively combines technology with interpersonal intuition. Managing a hotel requires navigating complex social dynamics involving guests, staff, and various stakeholders. While the rise of AI for behavioural analysis (Buhalis & Sinarta, 2019) often prompts people to question whether emotional intelligence is still needed, this analysis argues that both are indispensable.

Using a cross-cultural lens focused on Hungary and the United Kingdom, the investigation examines how regional differences affect AI adoption and EQ development. Specifically, this work provides the theoretical foundation for my upcoming empirical study on the luxury five-star hotel sector, which is a field where the balance between high-tech efficiency and high-touch personal service is most critical. The proposed framework suggests that navigating digital transformation requires a dual competency in digital literacy and emotional management. This synergy is expected to enhance guest satisfaction and bolster staff commitment. Finally, the paper offers practical frameworks and ideas for education to encourage human-focused leadership in an increasingly automated hospitality industry.

Keywords: Artificial Intelligence, Emotional Intelligence, Hotel Management, Digital Transformation, Cross-Cultural Analysis, Responsible Leadership, Hospitality Industry.

JEL Classification: L83, M10, O33, D91

Introduction

The hospitality industry is currently navigating a major transition as Artificial Intelligence (AI) and Emotional Intelligence (EQ) begin to redefine how managers make daily decisions. This rapid shift towards digital tools has sparked significant academic debate over how these systems can improve operations without losing the human leadership so central to the field (Ivanov & Webster, 2019; Tussyadiah, 2020). This study synthesises existing literature and empirical evidence on AI-EQ integration, specifically comparing the hospitality sectors in Hungary and the United Kingdom (UK). By examining how these variables influence managerial choices, staff performance and guest experiences, the paper accounts for the nuances of different cultural backgrounds.

The core of the argument is that hotel managers must strike a strategic balance between AI-driven automation and the personal touch of emotional intelligence. While AI is excellent for data insights and streamlining processes, it is empathetic leadership that continues to keep staff engaged and service quality high. This balance ensures that efficiency does not come at the cost of the "human touch", which defines hospitality. In fact, current evidence suggests that combining AI with EQ is a key driver of competitiveness today. This paper establishes the conceptual framework for my upcoming comparative study targeting the luxury five-star hotel

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markets in Hungary and the UK, where the tension between high-tech efficiency and high-touch service is most prominent.

Ultimately, such integration is expected to do more than just boost guest satisfaction: it helps create a more conscious, adaptable leadership style for an increasingly automated global market. By drawing on multiple disciplines – including hospitality management, organisational psychology, and cross-cultural research – this review proposes a practical way forward for the industry's digital transformation.

Research Questions (RQ)

1. How do AI systems currently support operational decision-making for hotel managers in Hungary and the United Kingdom?
2. In what ways do hotel managers in these two cultural contexts employ emotional intelligence (EQ) to manage guest relationships and staff dynamics?
3. How do cultural differences between Hungary and the UK influence the integration of AI and EQ in hospitality management?
4. What impact is the combined application of AI and EQ expected to have on guest satisfaction and internal staff engagement?
5. Which educational frameworks and curricula are the most effective in developing the dual digital and emotional competencies required for modern hotel management?

Research Objectives (RO):

1. To investigate the extent and nature of AI technology adoption for decision-making within the Hungarian and British hotel markets.
2. To evaluate the role of emotional intelligence in managerial practices and its effect on stakeholder relationships in both countries.
3. To identify how cultural backgrounds affect the synergy between technological tools and human-centric leadership.
4. To assess the potential impact of AI and EQ integration on guest satisfaction and staff interpersonal dynamics.
5. To propose evidence-based educational approaches and curricula that foster the necessary digital and emotional skills for hospitality professionals.

Theoretical Foundations

Artificial Intelligence in Hospitality

Artificial Intelligence (AI) refers to the capacity of machines to mimic human cognitive functions, specifically learning, reasoning, and problem-solving (Russell & Norvig, 2016). Within the hospitality sector, AI has rapidly transitioned from a "futuristic concept" to a fundamental operational tool, reshaping everything from back-of-house logistics to direct guest-facing services. Current applications range from automated check-in systems and AI-powered concierges to sophisticated sentiment analysis tools that interpret guest feedback (Tussyadiah, 2020; Buhalis & Leung, 2018).

The literature suggests that AI-driven property management systems (PMS) significantly enhance operational efficiency. By streamlining reservations and housekeeping schedules, these technologies lower overhead costs while creating a more seamless guest experience (Xiang et al., 2015; Ivanov & Webster, 2019). Furthermore, AI's ability to process vast datasets allows hotels to identify intricate patterns in guest behaviour that might otherwise remain hidden, which thus enable highly personalised marketing and upselling strategies (Buhalis & Leung, 2018). Beyond service delivery, AI plays a crucial role in sustainability; for instance, intelligent energy management systems can reduce costs by automatically adjusting environmental controls based on real-time room occupancy.

However, scholarly debate continues regarding the potential “dehumanisation” of service. A primary concern in the industry is that over-reliance on automated systems may erode the personal connection – the “human touch” – that remains the cornerstone of hospitality (Tussyadiah, 2020; Murphy et al., 2019). Moreover, implementing AI is not without its obstacles: it necessitates significant initial investment, robust data privacy governance, and continuous staff training (Ivanov & Webster, 2019). Ethical dilemmas surrounding data surveillance and job security also remain central to the academic discourse (Davenport et al., 2020). In both the Hungarian and British contexts, the challenge – and the focus of my upcoming research – is to identify the “sweet spot” where technology enhances efficiency without sacrificing the interpersonal warmth required in the luxury hotel segment.

Emotional Intelligence and Leadership

AI Application and Emotional Intelligence in Hotel Management

In an industry as people-centric as hospitality, Emotional Intelligence (EQ) is far more than a “soft skill”: it is a fundamental requirement for effective leadership. Originally defined by Salovey and Mayer (1990) as the ability to monitor and manage emotions to guide thought and action, EQ has evolved into a multi-dimensional framework encompassing empathy, self-regulation, and social proficiency (Goleman, 1998; Boyatzis et al., 2013). This is particularly vital for managing “emotional labour,” where leaders must maintain composure under pressure while navigating complex interactions with diverse teams and high-expectation guests (Grandey, 2000; Kim et al., 2017).

Empirical evidence suggests that managers with high EQ levels are better equipped to recognise emotional triggers, which enables them to resolve guest grievances and internal staff friction more effectively (Kim et al., 2007). This capacity directly shapes organisational branding and the overall quality of the guest experience. Furthermore, research by Wong and Law (2002) as well as Kim et al. (2017) demonstrates a clear correlation between emotionally intelligent leadership and reduced employee turnover: staff tends to remain longer when they feel trusted and empowered rather than strictly controlled through rigid, traditional methods (Boyatzis et al., 2013).

A critical dimension of this study is how EQ intersects with cultural differences. As Hofstede (2001) points out, the expression of emotion and the styles of conflict resolution vary significantly across cultures. Consequently, managers in Hungary and the UK require a flexible, culturally-attuned approach to leadership. Today, EQ is also increasingly tied to Corporate Social Responsibility (CSR) as modern leaders are expected to prioritise employee well-being and diversity alongside financial performance (Sigala, 2018). Even as AI-driven automation increases, the necessity for EQ has only intensified. Modern hospitality curricula now treat it as a core competency (Baum, 2019), which reflects a growing consensus that while AI can manage numbers, human intelligence remains the “heart” of the luxury service business.

Operational Optimisation and Predictive Analytics

In modern hotel management, AI-driven systems have become essential for maintaining operational fluidity. These tools take over high-volume, repetitive tasks such as inventory management, housekeeping scheduling, and energy consumption monitoring (Ivanov & Webster, 2019). Beyond simple automation, predictive analytics utilise machine learning to help managers forecast demand with greater precision. This enables more sophisticated revenue management and real-time room pricing that responds dynamically to market conditions (Xiang et al., 2015; Buhalis & Leung, 2018). Research indicates that hotels adopting AI often achieve higher occupancy rates and stronger guest loyalty, primarily by using data to personalise the stay before the guest even arrives (Tussyadiah, 2020; Ivanov & Webster, 2019).

The Synergy of Personalisation and Guest Experience

The guest experience is significantly enhanced by AI tools such as chatbots, recommendation engines, and sentiment analysis. Chatbots are effective at handling routine queries, freeing human staff to focus on more personal or complex guest needs (Tussyadiah, 2020). Simultaneously, scanning digital reviews for sentiment provides managers with a rapid method to identify service failures and address them immediately (Buhalis & Leung, 2018). However, the literature suggests that hotels should not rely exclusively on AI. While "smart room" features, such as automated climate control, are a valuable addition, they are intended to support the human side of hospitality rather than replace it.

Challenges and the Interplay with EQ

Implementing AI in a hotel environment presents several hurdles, including high initial capital expenditure, complex privacy concerns, and potential staff resistance (Tussyadiah, 2020; Ivanov & Webster, 2019). Furthermore, the efficacy of these systems depends heavily on data quality, which can vary significantly across hotel categories and target demographics (Xiang et al., 2015).

This is precisely where Emotional Intelligence (EQ) becomes a decisive factor. While AI manages the data, EQ manages the people. Effective leadership remains dependent on building trust and fostering teamwork – elements that algorithms cannot replicate (Goleman, 1998; Wong & Law, 2002). In the culturally diverse settings of Hungary and the UK, emotionally intelligent managers are essential for navigating varied communication styles and resolving internal conflicts (Hofstede, 2001).

Recent studies suggest that EQ provides greater long-term value to organisational culture than technical proficiency alone. Managers who understand the emotional dynamics of their teams tend to see higher morale and reduced friction (Kim et al., 2017). This "human element" is directly linked to job satisfaction and employee retention, which presents a critical priority for the hospitality sector in the post-pandemic landscape (Grandey, 2000; Baum, 2019).

Guest Relations, Cultural Context, and Methodology

Service Recovery and Ethical Leadership

Emotional Intelligence is perhaps most critical when operational failures occur. A manager's ability to empathise with and de-escalate a frustrated guest can transform a potential service crisis into long-term loyalty (Kim et al., 2007). Beyond immediate guest relations, EQ facilitates ethical decision-making by balancing profit motives with the welfare of both employees and guests (Boyatzis et al., 2013). As AI adoption introduces new dilemmas regarding data privacy and job displacement, emotionally intelligent leaders are essential to ensure that technological integration remains socially responsible and human-centric (Davenport et al., 2020).

Cross-Cultural Analysis: Hungary vs. United Kingdom

Cultural context significantly influences how hotels adopt AI and develop EQ (Hofstede, 2001). In the United Kingdom, the hospitality sector is highly digitised, often acting as an "early adopter" of new technologies, supported by established EQ development programmes (Baum, 2019; Ivanov & Webster, 2019). Conversely, the Hungarian context reflects a more cautious digital transformation, which is often due to different resource allocations. While British managers frequently leverage AI for rapid, data-driven decision-making, their Hungarian counterparts may place greater value on direct interpersonal relationships and group harmony (Hofstede, 2001; Ivanov & Webster, 2019). Despite these distinct paths, both regions increasingly recognise that a synergy of digital and emotional competencies is vital for modern leadership.

Educational Frameworks for Dual Competency

The rapid pace of technological change necessitates a dual-track educational approach: digital literacy and EQ training (Pizam, 2020). Digital literacy now extends far beyond basic IT proficiency: managers must be able to interpret AI-generated data, manage CRM platforms, and na vigate cybersecurity protocols (Crawford et al., 2021). Blended learning models,combining practical simulations with theoretical instruction, are proving effective at bridging this skills gap (Buhalis & Leung, 2018). Simultaneously, EQ development is essential for managing the industry's "emotional labour". Training in self-regulation, empathy, and conflict resolution is indispensable (Wong & Law, 2002; Prentice et al., 2020). Practical methods such as 360-degree feedback, professional journaling, and role-playing real-world service recovery scenarios are particularly effective for building these interpersonal "muscles" (Boyatzis et al., 2013; Crawford et al., 2021).

Proposed Mixed-Methods Methodology

To rigorously assess managerial competencies in the upcoming empirical phase of this project, I have chosen a mixed-methods methodology. This approach will allow for a deeper understanding of both measurable performance data and the more subtle leadership behaviours that define excellence in management (Pizam, 2020). The quantitative component of the study will involve structured surveys and established diagnostic tools, such as the Wong and Law Emotional Intelligence Scale (WLEIS). By implementing experimental designs with pre- and post-training assessments, the study aims to statistically validate the efficacy of these educational interventions (Crawford et al., 2021). Complementary qualitative data – gathered through semi-structured interviews – will provide deeper insights into how managers navigate the cultural nuances and ethical dilemmas that quantitative metrics might overlook.

Conclusion

This study establishes the necessary conceptual groundwork for upcoming empirical research exploring the synergy between AI and EQ within the luxury five-star hotel sectors of Hungary and the United Kingdom. It argues that the future of hotel management is not about choosing between AI and EQ, but about finding the right synergy between them. By proposing this dual-competency framework, the study provides a sustainable pathway for hospitality organisations and educational institutions to move beyond traditional silos.

For the hospitality sector to move forward, hotels and universities must stop treating technology and soft skills as separate entities. The implementation of integrated training is the only way to develop resilient, human-focused leaders. By focusing on these dual competencies, the industry can ensure that automation strengthens the interpersonal warmth and social responsibility that define luxury hospitality. Ultimately, this balanced approach provides a strategic framework for maintaining competitive advantage in an increasingly automated global market.

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The Competency Speed Gap: How Artificial Intelligence Outpaces HR Generalists' Capability Development

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Abstract

The integration of artificial intelligence into human resource management practices has created an unprecedented temporal mismatch between the accelerating pace of competency obsolescence and the relatively fixed speed of traditional professional development mechanisms. This paper introduces the competency speed gap framework, a conceptual model that positions competency transformation as a temporal phenomenon, in which AI-induced obsolescence outpaces the ability of organizational learning systems to develop new capabilities among HR generalists. Drawing on the established theory of competency development and recent evidence on AI integration in HR functions, the goal of this paper is to propose a framework based on the summary of recent literature on the subject. The framework highlights the tendency of an exponentially growing distance: the phenomenon of structural asymmetry occurring between technology-driven and human learning cycles, as well as the multi-level impact of AI across individual, organizational, and systemic dimensions. The four theoretical predictions presented here address the topics of competency polarization, task-level transformation, hybrid collaboration models, and the primacy of organizational enablers. The paper concludes with six testable propositions that provide a basis for future quantitative research exploring the organizational conditions under which the competency speed gap tends to widen or narrow. This research adds a temporal perspective to recent degradation of skills, and emphasizes that the challenge is not a static skills gap but rather a dynamic speed difference that requires a basic reconsideration of organizational learning cycles, the infrastructure for professional development, and HR education.

Keywords: Artificial Intelligence, HR Generalists, Competency Speed Gap, Competency Obsolescence, Organizational Learning, AI-driven Change, Competency Development

Introduction

Artificial intelligence (AI) has evolved from a technological novelty into a pervasive force that is fundamentally reshaping professional practice across various occupational domains (Brynjolfsson, 2022; Russell & Norvig, 2022). Within Human Resource Management (HRM), AI systems progressively automate recruitment screening, enable predictive workforce analytics, and transform data analysis capabilities (McCartney et al., 2021; Zhang, 2023). This thus creating a phenomenon that this research refers to as the *competency speed gap*: the widening temporal disconnect between the accelerating pace of AI-induced competency obsolescence and the relatively fixed speed at which traditional professional development mechanisms can cultivate new capabilities.

Recent empirical evidence confirms that this transformation is already underway. A European Commission study (2023) examining algorithmic management across European Union (EU) member states found that between 0.7% and 21% of organizations are already using AI in HR functions such as recruitment, employee evaluation, and task allocation (European Commission, 2023, pp. 25-26). This widespread adoption provides the context for

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understanding the emergence of a competency speed gap: HR professionals must adapt to AI not only as a single technological change but also as a systemic transformation affecting multiple HR functions simultaneously.

This study aims to provide a conceptual framework that positions the transformation of competencies as a temporal phenomenon. Rather than conducting empirical research, this paper synthesizes existing literature to propose a framework for competency speed gap. This theoretical model captures the widening temporal disconnect between AI-driven competency obsolescence and traditional organizational learning cycles. The specific objectives of this paper are as follows.

5. To review and synthesize existing literature on the development of competencies, AI integration in HR and organizational learning in order to establish the theoretical foundations of the emerged competency speed gap.
6. To propose a conceptual framework that positions the competency speed gap as a multi-level, temporal phenomenon characterized by exponential divergence, structural asymmetry, and systemic impact.
7. To advance theoretical predictions as to how AI integration polarizes competency requirements, transforms task structures, necessitates hybrid collaboration models, and depends on organizational enablers rather than individual characteristics.
8. To formulate testable propositions for future quantitative research that examines the organizational conditions under which the competency speed gap may widen, narrow, or become manageable at organizational level.

The following section summarizes prior literature on competency development, the integration of AI in HR, and organizational learning systems to establish the theoretical background for the framework of competency speed gap.

Although the available literature has extensively explored the role of AI in certain HR functions – such as recruitment (Albassam, 2023; Black & Van Esch, 2020), analytics (McCartney et al., 2021) and process automation (Zhang, 2023) – and has addressed general conceptual issues in competency development (Boyatzis, 1991; McClelland, 1973; Spencer & Spencer, 1993), a critical gap persists. To the author's best knowledge, there is only a limited number of studies that have specifically addressed the temporal aspect of this phenomenon and examined whether the rate of AI-induced competency obsolescence (Allen & De Grip, 2012; Buttazzo, 2023) markedly exceeds the rate of organizational learning and professional development mechanisms (Kirkpatrick & Kirkpatrick, 2006; Kolb, 1984). Although there are international academic references to the shortening of the half-life of learned skills (Deming & Noray, 2020) and temporal asymmetries between technological change and organizational capacity (Bühler et al., 2022; Chuang et al., 2024), no comprehensive conceptual or empirical framework currently examines or addresses this accelerating speed differential, i.e. the competency speed gap specifically in the context of the HR generalist' roles (Bankins et al., 2024; Piwowar-Sulej et al., 2024).

This observation renders the present study both timely and necessary. Addressing this current research gap by reviewing prior literature on the theory of competency development (De Vos et al., 2011; Parry, 1996) and AI integration in HR (European Commission, 2023; Charlwood & Guenole, 2022), the study aims to establish a framework that views the transformation of competencies as a temporal phenomenon and offers propositions for further empirical investigation. The following question arises: *Through what mechanisms does AI generate a competency speed gap, that is, how does the temporal trajectory of HR generalists' competency development diverge from the speed of technological change and what organizational factors (Tracey et al., 1995; Ranasinghe et al., 2024) accelerate or decelerate this dynamic process?*

Literature Review

This paper adopts a narrative, theory-driven literature review strategy to support conceptual framework development in line with established guidance on narrative overviews of the literature (Green et al., 2006). The review started from seminal works in competency theory, learning theory and AI in HR, and then applied backward and forward citation tracking (snowballing) to identify additional relevant studies consistent with recent recommendations that citation tracking can usefully complement database searching (Hirt et al., 2023; Wohlin, 2014). The search focused on peer-reviewed journal articles, books and policy reports published primarily in English between 1980 and 2025 that address competency theory, AI integration in HR and organizational learning. Sources were identified through database searches (Web of Science, Scopus, Google Scholar) and citation chaining using combinations of keywords such as "competency development", "HR generalist", "artificial intelligence in HR", "skill obsolescence" and "organizational learning". Priority was given to highly cited foundational works and recent empirical or conceptual studies published in reputable journals. References were included if they directly informed the temporal dynamics of competency transformation or the multi-level impact of AI on HR roles, while purely technical AI studies without organizational or competency implications were excluded.

Building upon McClelland's (1973) fundamental concept, according to which competencies are viewed as clusters of knowledge, skills and attitudes correlating with job performance, and incorporating Dubois's (1998) reference to organizational context and environmental constraints, competency is defined here as an integrated set of knowledge, skills, behaviours, and cognitive capabilities that enable HR generalists to effectively perform their core tasks throughout the employee lifecycle and organizational functions. This definition recognizes competency as dynamic, measurable capabilities that manifest through successful task performance and must continuously adapt as organizational and technological environments change (Parry, 1996; McClelland, 1973).

This concept is consistent with broader traditions of competency theory. Boyatzis (1991) emphasizes that competencies represent "*characteristics underlying successful performance in a particular organizational role*" (p. 48). Spencer and Spencer (1993) further advance this framework by distinguishing between threshold competencies (minimum requirements for effective performance) and differentiating competencies (characteristics that distinguish superior performers). These theoretical foundations establish that competency is not static knowledge but a dynamic, context-dependent capability requiring continuous adaptation and development.

Following Caldwell's (2003) identification of multifaceted HR roles and McDonnell and Sikander's (2017) characterization of generalists as practitioners managing broad organizational activities, this research defines HR generalists as human resources professionals who manage and execute comprehensive HR functions throughout the employee lifecycle, including recruitment and onboarding, employee relations, benefits administration, compliance management, performance management, training and development, and organizational development. The comprehensive nature of these responsibilities makes HR generalists particularly relevant for examining AI's impact as their diverse duties include functions that are potentially subject to technological transformation. In this sense, HR generalists fulfil a dual role: on the one hand, they are subjects of AI-driven change, and on the other hand, they are change agents responsible for organizational adaptation (Charlwood & Guenole, 2022; European Commission, 2023).

Rather than focusing on technical specifications or degrees of artificial general intelligence, this study adopts a functional perspective, conceptualizing AI as digital technologies and systems capable of executing intellectual tasks traditionally performed by human intelligence in the professional context of HR (Russell & Norvig, 2022; McCarthy, 2007). This encompasses automated decision-making tools, predictive analytics, pattern recognition systems, natural language processing applications, and intelligent automation platforms that can augment, transform, or potentially replace human judgment and expertise in HR functions. This definition aligns with recent research by the European Commission (2023, pp. 11-18) that identifies three ways in which AI systems operate in HR: evaluation (monitoring and assessing employee performance), direction (assigning tasks and providing guidance), and discipline (determining performance-related consequences) (European Commission, 2023).

Traditional competency development frameworks, as presented by De Vos et al. (2011) in their integrated model, position competency development as a cyclical process centred on Personal Development Plans (PDPs), which coordinate three core pathways: training, on-the-job learning, and career management, as shown in Figure 1. These interconnected processes can improve individual employability within relatively table organizational and socio-economic environment. The temporal architecture of traditional development cycles operates on relatively fixed timescales.

The implementation and evaluation of personal development plans can unfold over a longer period of time with regular monthly or quarterly check-ins to assess progress and recalibrate the goals (Kirkpatrick & Kirkpatrick, 2006; Guskey, 2002). Training programme impact evaluation unfolds over extended periods: immediate feedback measures initial reactions, but significant behavioural changes or knowledge transfer can only be measured after 3 to 12 months (Garavaglia, 1993; Kirkpatrick & Kirkpatrick, 2006). This longer time span reflects the basic learning theory.

Kolb's (1984) experiential learning cycle requires repeated reflection, conceptualization, and active experimentation – a process that unfolds over extended periods. Knowles' (1984) Adult Learning Theory emphasizes self-directed learning and contextual engagement, both of which require significant investment of time. Similarly, Schön's (1983) theory of reflective practice views professional development as a continuous, repetitive, cyclical process of learning and adaptation rather than an immediate outcome. These learning theories agree on a fundamental principle: meaningful competency development operates on extended temporal scales, typically measured in months or years rather than weeks.

Figure 2 illustrates the AI-enhanced competency development model which was built on the model of De Vos et al. (2011), and shows how the traditional personal development plan (PDP)-centred approach – which includes training, on-the-job learning, and career management – operates in an organizational context. This framework is essential for analysing how AI disrupts traditional development cycles.

Unlike previous technological transitions that primarily affected manual or routine cognitive tasks (Frey & Osborne, 2017), AI's impact extends comprehensively across knowledge work domains, affecting professional roles traditionally isolated from automation (Brynjolfsson & McAfee, 2014). Human resource professionals occupy a particularly complex position within this transformation: they simultaneously serve as subjects of the AI-driven change – requiring adaptation of their own competency profiles – and as agents responsible for managing organizational adaptation to AI integration (Charlwood & Guenole, 2022).

AI fundamentally disrupts the temporal logic of traditional competency development. Building on the integrative model of competency development by De Vos et al. (2011), Figure 2 illustrates how the AI-Enhanced Competency Development Model disrupts traditional frameworks by introducing rapid, systemic change across multiple organizational levels.

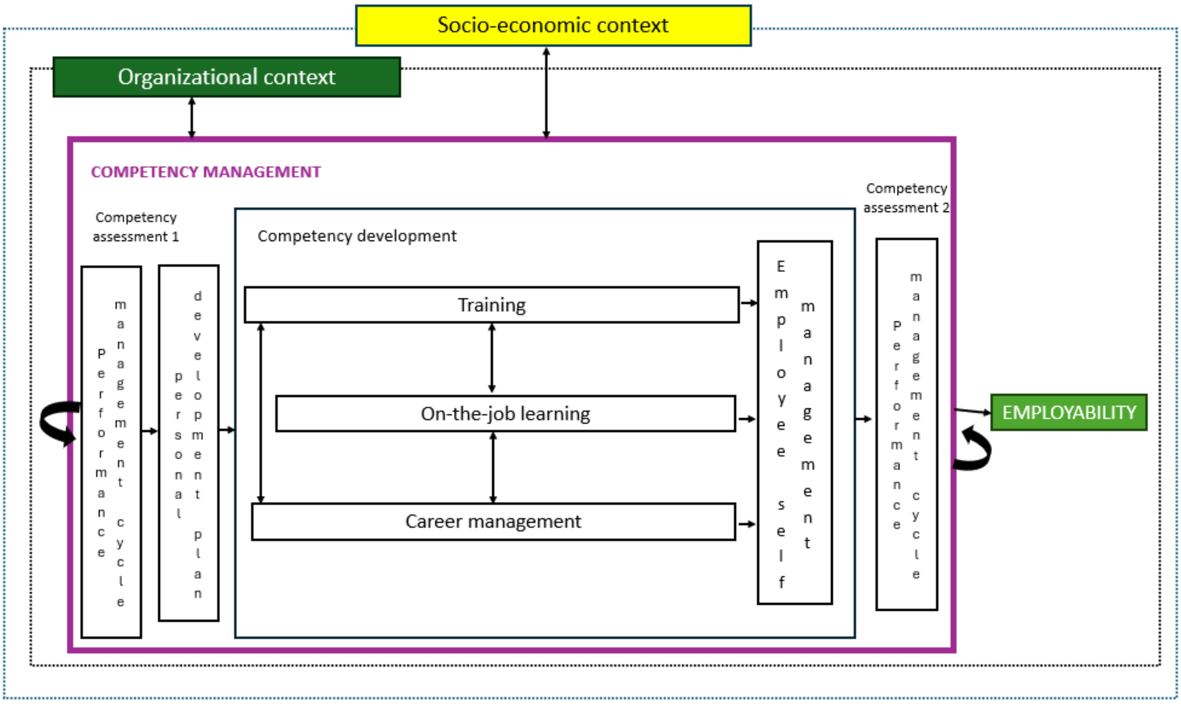

Figure 1: *Integrative model of competency development*
Source: *De Vos et al., 2011*

This AI disruption cuts across all levels of organizational functioning: the individual level as daily professional routines and learning are shaped by AI applications; the level of practitioners as HR professionals must both use and manage AI tools; and the strategic level since leaders must adapt to the broader organizational and societal impacts of AI. As shown in Figure 2, this leads to three simultaneous outcomes: accelerated obsolescence of existing competencies (Vezeteu & Năstac, 2024), constant demand for new AI-relevant skills (Babashahi et al., 2024), and a widening gap between current capabilities and market requirements undermining employability (Goulart et al., 2022).

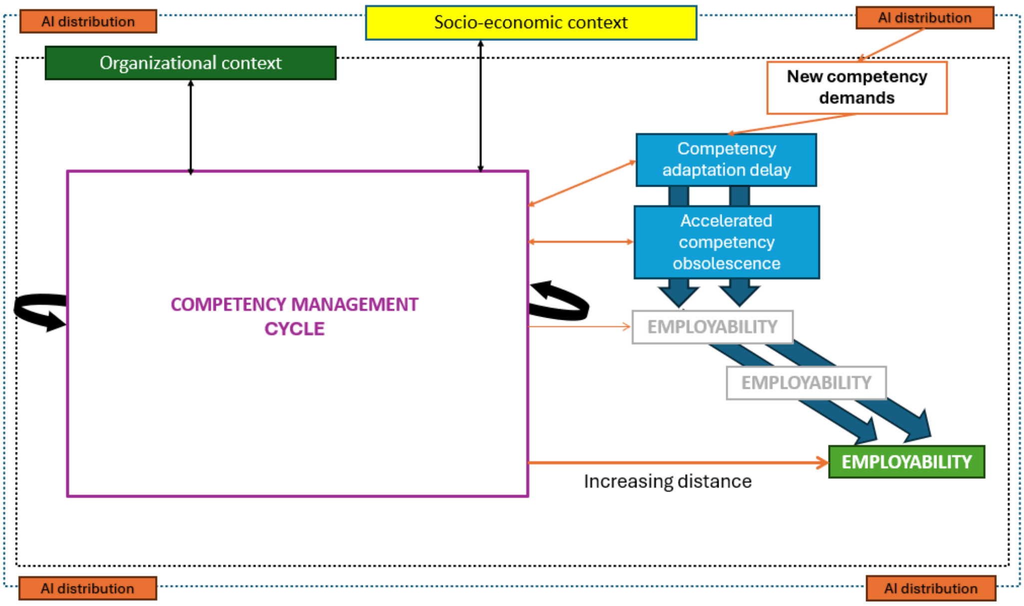

Figure 2: *The AI-Enhanced Competency Development Model is built on the model by De Vos et al. (2011)*
Source: *The author's own.*

Academic research demonstrates that skill obsolescence has intensified with technological changes. Traditional estimates of competency half-life – the period after which skills lose half their value – range from 5 to 15 years (Allen & de Grip, 2012; Deming & Noray, 2020). However, AI integration further accelerates this obsolescence timeline through two mechanisms. First, AI systems evolve at an accelerated pace. Historically, computing power doubles approximately every 18-24 months, which is a phenomenon known as Moore's Law (Buttazzo, 2023). This rapid technological advancement means that HR professionals face constantly evolving AI tools, platforms, and capabilities that require continuous skill updates. Second, organizational adoption cycles are compressing as AI tools become more accessible and integrated into HR workflows (European Commission, 2023). This creates a fundamental structural mismatch: while traditional professional development operates on annual or multi-year cycles (training programmes, career progression, and certification renewal), AI-driven competency requirements change on a quarterly or even monthly basis as new systems are introduced and existing systems are updated.

While extensive research examines AI's impact on various occupational domains (Frey & Osborne, 2017; Brynjolfsson & McAfee, 2014) and specific HRM functions such as recruitment (Albassam, 2023; Black & Van Esch, 2020) and talent management (Jacob et al., 2023), the latest research provides critical evidence on AI's transformative power on professional competencies. Arshad et al. (2025) demonstrate that AI serves as an augmentation tool rather than a replacement mechanism, and reshapes skill composition towards non-routine cognitive and interpersonal domains. Amayreh et al. (2025) provide evidence that AI experience, use, technical ability, and perceived usefulness have a significant positive effect on employee self-competence. Piwowar-Sulej et al. (2024) examine AI's influence on future competencies, while Raman et al. (2024) evaluate AI's performance in HR queries, highlighting its complementary role. Aguinis et al. (2024) emphasize the diverse competencies needed to manage HR roles with AI assistance.

These studies collectively demonstrate that AI integration imposes dual competency requirements: on the one hand, there is a demand for new technical capabilities, while on the other hand, the importance of interpersonal, ethical, and strategic competencies persists and even grows. Evidence suggests that organizations cannot achieve adaptation through technical upskilling alone; instead, they require comprehensive competency transformation spanning technical, interpersonal, and strategic domains.

Effective competency development depends on the organizational context, and not merely on individual effort. As documented in basic learning theories, competency development requires structured organizational support. Kolb's experiential learning cycle requires structured reflection and practice opportunities; Knowles' adult learning theory emphasizes self-directed learning in supportive contexts; and Schön's reflective practice states that professional development requires organizational conditions enabling continuous experimentation and feedback (Tracey et al., 1995).

The structural timing gap identified through the analysis of traditional development mechanisms (annual or multi-year operating cycles) versus AI-driven requirements (quarterly or monthly schedules) suggests that individual HR professionals – regardless of age or familiarity with digital technologies – are struggling to overcome systemic organizational barriers to rapid learning, such as inadequate training infrastructure, misalignment between AI deployment and the timing of training, and organizational culture barriers that discourage risk-taking and experimentation. This creates a multi-level adaptation challenge where organizations must align learning infrastructure, training programs, and psychological safety mechanisms with the accelerated pace of AI-driven transformation (Ranasinghe et al., 2024; European Commission, 2023, pp. 87-98).

Through the literature reviewed above it is possible to establish several converging insights:

1. Transformation of competencies is fundamentally temporal. Traditional development mechanisms operate on relatively fixed, extended timescales (3-12 months for training evaluation, annual or multi-year career progression), and reflect underlying learning theory principles.
2. AI disruption accelerates obsolescence across skills, jobs and organizational models. Evolution of computing power (Moore's Law) and reduced adoption cycles on organizational level create rapidly changing competency requirements with a shift to quarterly or monthly timescales.
3. There isa structural timing mismatch. The divergence between slow organizational learning cycles and rapid technological change creates conditions where continuous professional development efforts may prove insufficient to maintain employability.
4. The impact is multi-level. The disruption caused by AI affects individual competency development, organizational workforce planning and training infrastructure as well as systemic educational and professional standards.
5. The organizational context is crucial. Individual adaptability primarily depends on organizational enablers – such as learning infrastructure, psychological safety, and the coordination and scheduling of training programs – rather than on individual characteristics alone.

The literature review is organized around five interlinked building blocks that jointly underpin the competency speed gap framework. First, competency theory frames competencies as dynamic, context-dependent capabilities. Second, the role of HR generalists is specified, and their broad functional remit and dual position as both subjects of AI-driven change and agents of organizational adaptation are emphasized. Third, a functional definition of AI in HR is outlined focusing on how AI systems support evaluation, direction and discipline in HR processes. Fourth, traditional competency development and learning theories show that competency growth unfolds through PDP-based, multi-pathway processes on extended temporal scales. Finally, AI's impact on these temporal dynamics is analysed, which reveals a structural misalignment between rapidly accelerating AI-driven competency obsolescence and the slower pace of organizational learning. Building on these insights, the following section introduces the competency speed gap framework as a conceptual model that formalizes these temporal dynamics and positions them both as a critical research challenge and as a phenomenon that can be addressed at the organizational level.

Conceptual Framework

As we have seen, in contrast to AI-induced acceleration of competency obsolescence, traditional organizational learning cycles have relatively fixed timescales. This section attempts to establish a framework for the emerging competency speed gap, which is crucial for the formal representation of the temporal dynamics of competency transformation. In doing so, the author will seek to identify the mechanisms through which AI integration creates an increasing gap between the rate of competency obsolescence and organizational learning capacity.

The competency speed gap framework captures the widening temporal disconnect between two competing speeds: the accelerating rate of competency obsolescence driven by AI-powered innovation and the relatively fixed pace of organizational learning and development cycles. This framework extends beyond existing constructs of skill obsolescence (Frey & Osborne, 2017) and skills gaps (Novak et al., 2015; Ravi & Sumathi, 2023; Sartori et al., 2022) by specifically addressing the temporal dimension of competency disruption. The competency speed gap creates a structural condition where even continuous professional development efforts may prove insufficient to maintain employability, as target competency requirements shift faster than development mechanisms could respond.

Competency speed gap is distinguished by three main characteristics:

Exponential divergence: the gap widens over time as AI capabilities advance faster than human adaptation mechanisms (Buttazzo, 2023).

Structural asymmetry: traditional development pathways (training cycles, career progression, experiential learning) operate at fundamentally different temporal scales than AI-driven change (Bühler et al., 2022; Chuang et al., 2024).

Multi-level impact: the gap manifests simultaneously at individual (personal capability development), organizational (workforce planning and training), and systemic (educational curricula and professional standards) levels (Bankins et al., 2024).

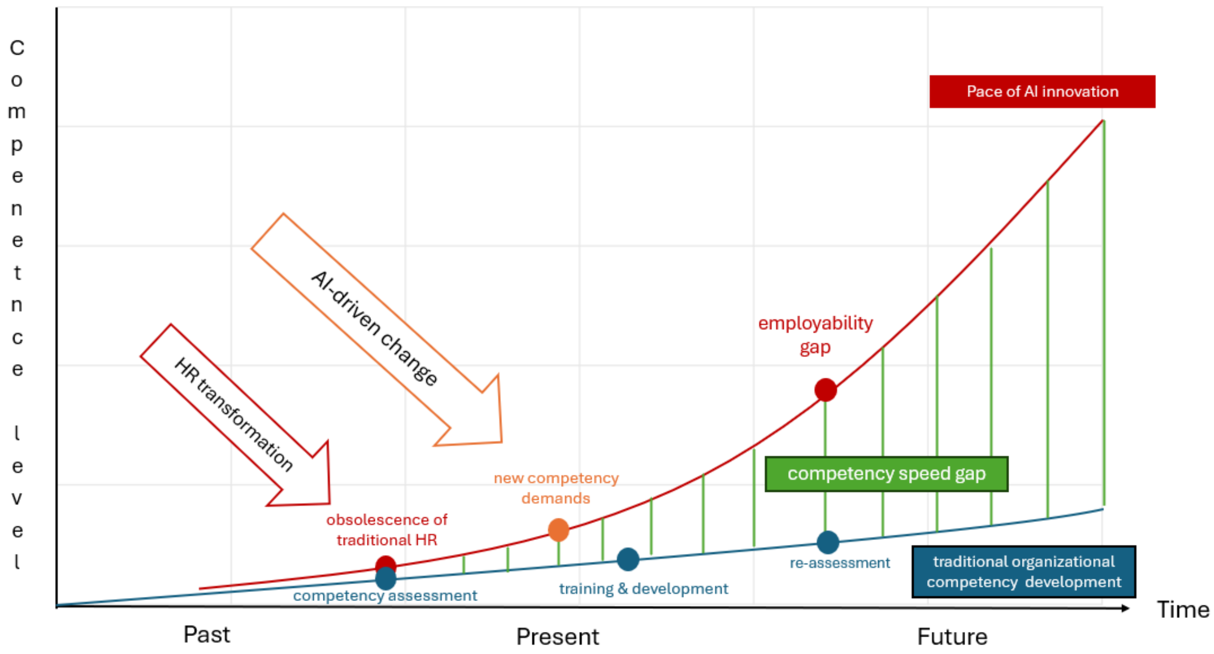

Figure 3: *The core mechanism of the competency speed gap.*
Source: *The author's own.*

Figure 3 illustrates the basic mechanism of the competency speed gap, and shows how the pace of AI-powered innovation (indicated by the rising red line) diverges exponentially from the pace of traditional organizational competency development (indicated by the rising blue line). This exponential divergence creates an expanding employability gap over time, where the distance between current capabilities and market requirements continuously widens despite the ongoing professional development efforts.

Four Theoretical Predictions: Mechanisms of Competency Transformation

This temporal divergence manifests through four distinct but interconnected mechanisms. The following predictions specify how AI integration will reshape competency requirements at different levels of analysis from the structure of work itself to the organizational and individual conditions that shape the adaptation process.

P1: Competency Polarization: Based on the literature review's discussion on the multi-level disruptive effect of AI, which shows that AI-powered innovation creates a demand for new technical skills while maintaining the strategic importance of relational skills, this research predicts that AI integration will polarize competency requirements between demands for new technical abilities and improved interpersonal skills.

In practice, this means that HR professionals will be faced with a simultaneous demand for new technical skills, such as prompt engineering, data interpretation, and the use of AI-powered collaboration tools (Babashahi et al., 2024; Korzynski et al., 2023) while relational and social-emotional skills will gain more strategic importance in contexts requiring trust, ethical judgment, and complex interpersonal navigation (Bobitan et al., 2024). As noted in the literature review, AI systems can execute evaluation, direction, and discipline functions, yet employees often prefer human engagement for decisions involving emotional support, trust, or vulnerability (Rubin et al., 2025). This creates a polarized competency landscape in which both technical and relational capabilities are essential yet develop at different paces.

P2: Task-Level Transformation: Drawing on the framework of the competency speed gap presented in Figure 3, which shows exponential divergence between technology and learning cycles, this study predicts that AI will transform HR work at the task level rather than at the job level, and will automate certain (routine and repetitive) task elements while creating space for higher-value activities requiring creativity, critical thinking, strategic planning, and human judgment. The literature review established that traditional competency development operates as a multi-pathway process where training, on-the-job learning, and career management operate in concert. However, disruptions caused by AI show that routine, administrative tasks, such as screening job applications, scheduling interviews, or processing routine compliance checks have become prime candidates for automation while opportunities for higher-value activities like strategic consulting, complex problem-solving and change management continue to expand (Sundari et al., 2024). Rather than eliminating HR roles, this task-level transformation encourages the evolution of different roles, with competency requirements shifting from administrative and routine analytical tasks towards strategic, interpersonal, and complex cognitive domains (Nishar, 2023).

P3: Hybrid Collaboration Models: Building on the analysis of organizational learning cycles presented in the literature review, which reveal a slower pace for traditional development mechanisms (3-12 months for training evaluation), this research predicts that optimal HR performance will emerge from the collaboration of human with AI rather than humans' substitution by artificial intelligence. This is so as empirical evidence demonstrates that the highest productivity gains can be reached when humans and AI operate in complementary roles. The temporal dynamics outlined in the competency speed gap framework shows that organizations are currently facing a structural timing gap where the development of human skills unfolds in annual or multi-year windows while AI-driven requirements shift quarterly or monthly. This mismatch creates a necessity for a paradigm shift away from automation-focused models (where AI replaces human judgment) towards partnership-focused models (where humans and AI work together to enhance their complementary strengths). Evidence from studies on human-AI teams demonstrates that complementarity – where humans represent judgment, context interpretation, and ethical decision-making while AI handles data processing and pattern recognition – tended to outperform humans or AI working independently (Przegalińska et al., 2025; Vaccaro et al., 2024). This hybrid collaboration paradigm requires new competencies in managing hybrid workflows, validating AI outputs, and allocating tasks appropriately between humans and machines (Sidra & Mason, 2025; Hemmer et al., 2025).

P4: Organizational Enabler Primacy: Based on the multi-level analysis of competency transformation presented in Figure 2, which demonstrates that AI-induced disruption extends to multiple levels including the individual, HR professionals, and the strategic level, this research predicts that successful adaptation to the accelerating competency requirements depends more on organizational enablers than on individual characteristics such as age or previous technical experience. As documented in the literature review, learning theory emphasizes that competency development depends not merely on individual effort but on organizational context: Kolb's experiential learning cycle requires structured reflection and practice; Knowles' adult learning theory emphasizes self-directed learning in supportive contexts; and according to Schön's reflective practice, professional development requires organizational conditions enabling continuous experimentation and feedback. The structural timing gap identified in the competency speed gap framework, as presented in Figure 3, suggests that individual HR professionals, regardless of age or technical familiarity, cannot overcome systemic organizational barriers to rapid learning such as inadequate training infrastructure, misalignment between AI deployment and the scheduling of training programmes, or organizational cultures that discourage risk-taking and experimentation. Therefore, while individual HR professionals cannot overcome these obstacles on their own, adaptability is managed at the organizational level through institutional redesign of learning systems, training infrastructure, and psychological safety, thus turning the competency speed gap into a manageable organizational challenge rather than an inevitable individual shortcoming (Tracey et al., 1995; Ranasinghe et al., 2024; European Commission, 2023, pp. 87-98).

Propositions for future research

The competency speed gap framework and the above described four predictions (P1-P4) require empirical validation through quantitative research. To advance from conceptual foundation to measurable construct, future research should test the following propositions.

T1: HR professionals working in AI-integrated environments will report significantly higher demand for both technical competencies (e.g., data interpretation, AI tool proficiency, prompt engineering) and interpersonal competencies (e.g., emotional intelligence, ethical judgment, trust-building) compared to HR professionals in environments without AI integration.

T2: Organizations with rapid AI deployment will exhibit greater competency speed gaps than organizations where AI integration is carried out gradually. This proposition examines whether faster technological change creates greater differences in learning systems regardless of the industry or organizational size.

T3: The competency speed gap will be greater when organizations deploy AI systems before establishing training infrastructures, compared to instances when training programs are implemented simultaneously with or prior to the introduction of AI. This proposition examines how the sequencing of AI adoption and the preparation of learning systems affects the pace of competency adjustment.

T4: HR professionals in organizations with a culture of continuous learning will adapt faster to AI-driven competency changes than those in organizations that use traditional training approaches. This difference is unrelated to individual factors such as age or previous technical experience. This proposition highlights that organizational context has a more powerful impact than personal characteristics.

T5: Organizations that emphasize human-AI partnership models will achieve better outcomes (employee satisfaction, role clarity, performance) than organizations focused on AI-driven automation or task substitution. This assumption explores whether collaboration frameworks moderate the relationship between AI integration and the transformation of HR roles.

T6: The rate of competency obsolescence – the speed at which skills lose their practical value – will increase as AI system updates become more frequent and the adoption of technology accelerates. This proposition captures the core temporal mechanism of the speed gap.

Table 1 shows how theoretical predictions align with operationalized propositions and highlight how organizational enablers, temporal dynamics, and competency transformation mechanisms can be measured and tested in HR practice and research.

Table 1: *Theoretical Predictions and Testable propositions in the competency speed gap framework*

Prediction	Core claim	Testable proposition
P1: Competency Polarization	AI creates a simultaneous demand for technical and interpersonal skills.	T1
P2: Task-Level Transformation	AI transforms tasks (not entire jobs); automates routine work while expanding higher-value activities.	T5
P3: Hybrid Collaboration Models	Human-AI partnership outperforms substitution; complementarity between human judgment and AI data processing.	T5
P4: Organizational Enabler Primacy	Organizational factors are stronger predictors than individual characteristics (age, prior technical experience).	T2, T3, T4
Core Mechanism: Temporal Dynamics of the Speed Gap	The speed gap widens as AI accelerates; the obsolescence rate increases and skill half-life decreases.	T6

These claims can be verified through cross-sectional surveys comparing organizations using different AI adoption strategies, longitudinal studies tracking changes in competencies over time, or experimental plans testing specific training interventions. Quantitative validation would establish the competency speed gap as a measurable framework for organizational practice and the development of specific HR policies.

Conclusion

This paper has introduced the competency speed gap as a conceptual framework for understanding the temporal dynamics of competency transformation in AI-integrated HR environments. By synthesizing existing literature on competency development, AI integration, and organizational learning, the framework captures the widening difference between the accelerating pace of AI-driven competency obsolescence and the relatively fixed speed of traditional professional development mechanisms. The four theoretical predictions (P1–P4) and six testable propositions (T1–T6) presented above provide a foundation for future quantitative research examining the conditions under which the competency speed gap emerges, widens, or becomes manageable at the organizational level.

The competency speed gap framework makes three contributions to existing theory. First, it introduces a temporal dimension to the competency literature positioning the challenge not as a static skills gap but as a dynamic speed differential. Second, it extends the AI-in-HRM literature by conceptualizing HR generalists as occupying a dual position – simultaneously subjects of AI-driven change and agents responsible for organizational adaptation. Third, the framework synthesizes learning theory (Kolb, Knowles, Schön) with technology adoption research, and highlights the structural asymmetry between human learning cycles and AI-driven requirement changes.

For HR practitioners and organizational leaders, the competency speed gap framework suggests several actionable priorities. Organizations should align AI deployment timelines with training infrastructure development, and ought to ensure that learning systems are established before or simultaneously with technology introduction (as proposed in T3). Investment in continuous learning cultures – rather than episodic training interventions – appears critical for managing accelerating competency requirements (T4). Additionally, prioritizing human-AI partnership models over substitution-focused automation may yield superior outcomes in employee satisfaction, role clarity, and performance (T5). For HR education institutions, the framework implies a need to reconsider curriculum design, incorporating both technical AI literacy and interpersonal competencies that remain strategically important in AI-integrated environments.

This study has several limitations that must be acknowledged. As a conceptual paper, the competency speed gap framework and its propositions require empirical validation through quantitative research. The framework was developed primarily through literature synthesis rather than primary data collection, which limits the specificity of the claims. Additionally, the analysis focuses on HR generalists in organizational contexts, and the applicability of the framework to other professional domains or to HR specialists remains to be examined. Finally, the propositions assume relatively stable organizational environments; the framework may require adaptation for organizations undergoing simultaneous transformations (e.g., mergers, restructuring) beyond AI integration. Several research directions emerge from this framework. First, longitudinal studies tracking competency evolution in organizations with different AI adoption strategies would provide direct tests of propositions T2, T3, and T6. Second, comparative research across industries with varying AI penetration rates could illuminate contextual moderators of the competency speed gap. Third, scale development research is needed to operationalize the competency speed gap as a measurable construct potentially incorporating both objective measures (skill currency, training lag) and subjective assessments (perceived obsolescence, learning anxiety). Fourth, intervention studies testing specific organizational strategies – such as accelerated learning cycles, AI-literacy programs, or hybrid collaboration training – would establish evidence-based practices for managing the speed gap. In conclusion, the competency speed gap represents not an inevitable individual shortcoming but an organizational challenge that can be addressed through institutional transformation. Organizations that recognize this temporal dynamic and invest in aligned learning infrastructure, continuous development cultures, and human-AI collaboration models will be better positioned to turn AI integration from a disruptive threat into a catalyst for strategic competency development.

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Mapping the Landscape of Artificial Intelligence in Marketing: A Literature-Based Study

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Abstract:

Artificial intelligence (AI) has become a widely adopted technology in companies, with marketing emerging as one of its most dynamic areas of application. Its adoption is expected to grow further driven by AI's potential to enhance efficiency, enable personalization, and support strategic decision-making. This study synthesizes recent academic research on AI in marketing. To provide context, a historical perspective traces the evolution of AI in marketing from early implementations to contemporary practices. It also identifies the key marketing domains where AI is most commonly applied. The study highlights the primary focus areas that receive the most attention in contemporary scholarly work as reflected in the keywords that appear most frequently across publications. Based on the keywords, EU-related AI marketing research is structured into six thematic clusters covering technology, performance, adoption, human–AI interaction, digitalisation and organisational decision-making. Compared to the US, EU research is broader and more nuanced, while US studies focus primarily on technological and performance aspects. In CEE, emphasis lies on management, adoption, and digitalisation. By synthesizing findings, the study offers actionable insights for scholars and practitioners. Future research will explore AI adoption among small and medium-sized enterprises in Hungary and its implications for organizational efficiency and competitiveness.

Keywords: Artificial Intelligence, Marketing-purpose Application, Literature Review, Web of Science, Keyword Co-occurrence Network

JEL Classification: M31, O33

The evolution of the use of AI in Marketing

Marketing has traditionally focused on understanding customers and creating value. It has gone through several major transformations including the rise of digital marketing, and many studies now identify artificial intelligence (AI) as the next stage in this evolution (Davenport et al., 2020).

Its corporate use is also widespread: according to McKinsey's global study with around 1500 participants, 78% of businesses use AI in at least one business function with marketing and sales among the top areas of application (Singla et al., 2025). This shows that AI has become a widely adopted technology in companies.

Historical evolution of AI in marketing

To understand how artificial intelligence is applied in contemporary marketing, it is important to consider its historical evolution as shown in Figure 1. In general, the origins of AI can be traced back to the 1940s, when Alan Turing, through his test demonstration of machines being capable of producing human-like responses, and Isaac Asimov, introducing the Three Laws of Robotics, laid the early groundwork for the discipline. However, AI did not appear in marketing

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until the early 2000s, when marketers began adopting data-mining tools to analyse large datasets, which enabled them to gain deeper insights into customer behaviour. A major development in the use of AI emerged in the mid-2000s with the rise of Search Engine Optimisation (SEO) and Pay-Per-Click (PPC) advertising. The technologies behind these tools allowed marketers to target consumers more precisely and to track user preferences more effectively. By the 2010s, the advent of Big Data enabled AI techniques to advance further supporting more sophisticated forecasting of customer behaviour, trend identification, and predictive analytics. In the 2020s, AI has become a central component of marketing (Kumar et al., 2023). It has transformed how companies engage with customers and make data-driven decisions (Labib, 2024).

It must be noted that the integration of AI into marketing functions require a strong digital infrastructure with digital marketing playing a critical role in creating the technological and organizational conditions necessary for AI development. The COVID-19 pandemic further accelerated this digital transformation, which led to increased adoption of AI-driven tools and strategies across industries (Cioppi et al., 2023). As a result, marketing now not only incorporates AI but AI is becoming increasingly specialized for distinct marketing functions (Kumar et al., 2023).

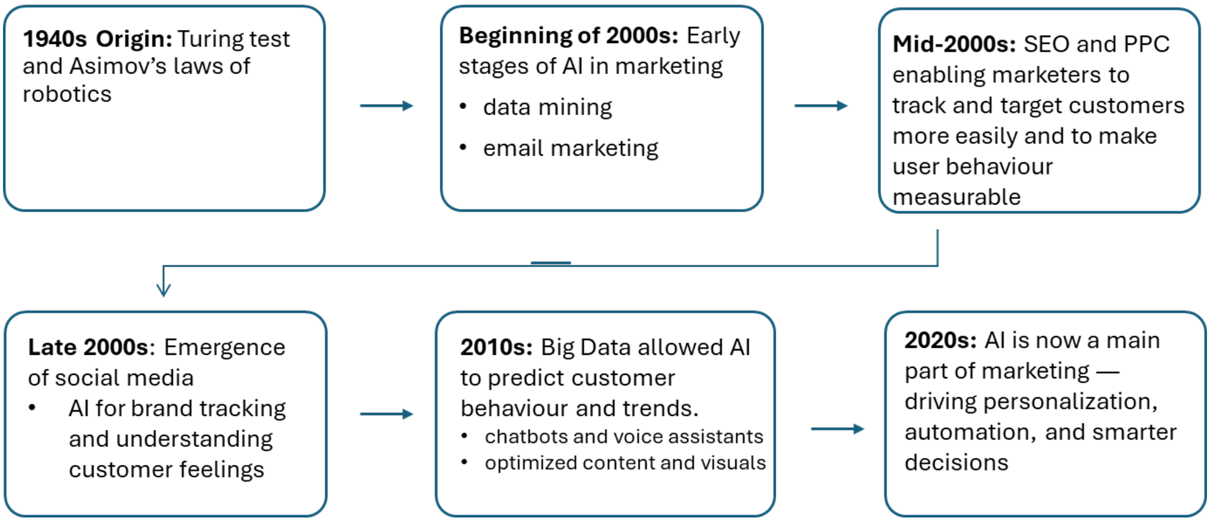

Figure 1: *History of the use of AI in Marketing*
Source: *based on the 2023 publication of Kumar et al. 'AI-powered marketing: What, where, and how?'*

Classification of AI

AI can be classified in multiple ways. Based on a **functional and structural approach,** we can distinguish AI by intelligence levels, task types, and whether it is embedded in a robotic system (Davenport et al., 2020). Additionally, AI can be categorized based on **technological capabilities,** including machine learning, computer vision, robotics, speech recognition, and natural language processing, as well as supporting technologies such as cloud computing, Augmented Reality (AR), and Virtual Reality (VR) (Cioppi et al., 2023).

Thirdly, AI can be classified according to **marketing functions**. AI can support a wide range of marketing functions thanks to its ability to process large amounts of data quickly and accurately (Haleem et al., 2022). AI can be used throughout the whole marketing process from the early stages of market research and strategic planning to the implementation and evaluation of marketing activities.

AI enables personalized customer experiences, optimizing digital advertising, improving customer engagement through chatbots. It can be also applied to optimize market and competitive analysis, and can be used for predictive analytics, dynamic pricing as well as to automate content creation and to carry out sentiment analysis. Furthermore, AI enhances voice and visual search optimization, and marketing automation. Not the least, it can also be implemented in e-commerce and social media, which currently represent the fastest-growing fields (Kumar et al, 2023; Ziakis & Vlachopoulou, 2023).

Strategic planning: AI technologies, such as machine learning and statistical algorithms, are often implemented to support the planning of data-driven, integrated marketing campaigns. They enable forecasting based on historical data, analysis and synthesis of customer preferences and market trends, and allow businesses to proactively adjust their strategies, moving beyond decisions based on intuition or past experience. AI can also be used to predict product attributes, such as design preferences, and to optimize marketing decisions like media planning and scheduling. (Verma et al., 2021); (Durmuş Senyapar, 2024)

Social media: AI can process massive amounts of data in real time, therefore it enables marketers to create dynamic campaigns including personalized and customized messaging based on individual customer preferences (Huang & Rust, 2020). Algorithms allow companies to track what customers like or dislike and align their strategies with customer interests. Additionally, by analysing content performance, AI helps improve message relevance and impact (Verma et al., 2021),

Customer relationship management (CRM): It focuses on building and maintaining long-term customer relationships by using information technology (IT) to effectively store, manage, and apply data across the customer lifecycle. AI has significantly transformed CRM systems by advanced data analysis, which subsequently enables increasingly personalized customer experiences and improved customer journey as a result. Additionally, key developments such as chatbots and virtual assistants have further optimized processes by enabling real-time interaction with customers. At the same time, the integration of AI into CRM requires careful consideration because of data privacy and ethical issues linked to the sensitive nature of customer information. (Ledro et al., 2025)

Budget optimization: AI can be also used to increase efficiency and cost-effectiveness by optimizing marketing strategies in line with available budgets. With AI, businesses can develop their own dynamic pricing strategies, where AI adjusts product prices in real time based on demand, competitor pricing, and consumer behaviour thus ensuring optimized revenue (Haleem et al., 2022); (Verma et al., 2021).

E-commerce: AI adoption in e-commerce opens new strategic avenues. With AI, e-commerce platforms can run real-time campaigns, retarget users, dynamically adjust offers and prices, and respond fast to changing consumer behaviour or external conditions. Additionally, by implementing chatbots, virtual assistants, and computer-vision–based applications businesses can further increase customer experience. Studies suggest that while the use of AI provides a strong competitive advantage in the digital marketplace it is also becoming increasingly inevitable (Zhuk & Yatskyi, 2024).

Performance: Research indicates that AI can improve both marketing and organizational performance by supporting both automated processes and human decision-making. By automating repetitive tasks, extracting insights from and synthesizing large volumes of data, AI enables more effective value creation and drives improved sales outcomes (Vlačić et al., 2021).

As detailed above, research highlights that AI's integration in marketing brings numerous benefits, including increased efficiency, improved customer targeting, and more precise market predictions. It is also shown that AI is increasingly integrated across multiple marketing functions from planning to the end and evaluation of marketing campaign. AI supports activities ranging from customer relationship management to social media to campaign optimization and predictive analytics. Its adoption is widespread, which reflects its growing importance in contemporary marketing practice.

Methodology

After taking a glance at how the use of AI evolved over time and how it is used in marketing, the next goal was to identify sources and key research areas on the use of AI in marketing. For this, we started by identifying and analysing scientific articles from the Web of Science database focusing specifically on publications that included the terms „AI"; "marketing" and either the term "application" or "use" in their titles or topics. The study centred on sources that belong to the following categories in the Web of Science database: "business", "economics", or "management". Recognizing that AI is a rapidly evolving field, and at the same time to incorporate the most current insights, the study considered publications from 2020 to 2025. It focused on scholarly publications from three geographic regions: the European Union (EU), the United States (US), and Central and Eastern Europe (CEE). Three separate searches were conducted for each region, and then the resulting findings were compared to identify similarities and differences. The search identified 350 scientific sources originating from the EU, 75 from the US, and 170 from the CEE region. Keywords extracted from the resulting dataset were visualized using VOSviewer, a software platform for creating and visualizing bibliometric networks. Relying on the keyword visualization function of the software a co-occurrence network was created, which highlights the main research domains and their interconnections within each region.

A minimum co-occurrence threshold of five was applied, which means that only keywords appearing at least five times in the analysed sources were included in the visualization. This threshold was set in order to only highlight concepts that are recurrent within the research field. Non-relevant terms such as geographical names that do not belong to either of the studied regions were excluded, and terms with the same meaning such as "artificial intelligence" – "AI" were regrouped and listed in a thesaurus file, which enabled the software to treat these items as a unified concept to avoid duplications. Through the keyword visualization of the Web of Science publications for the EU that appeared between 2020 and 2025, six color-coded clusters were identified with each representing distinct thematic areas (see Figure 2).

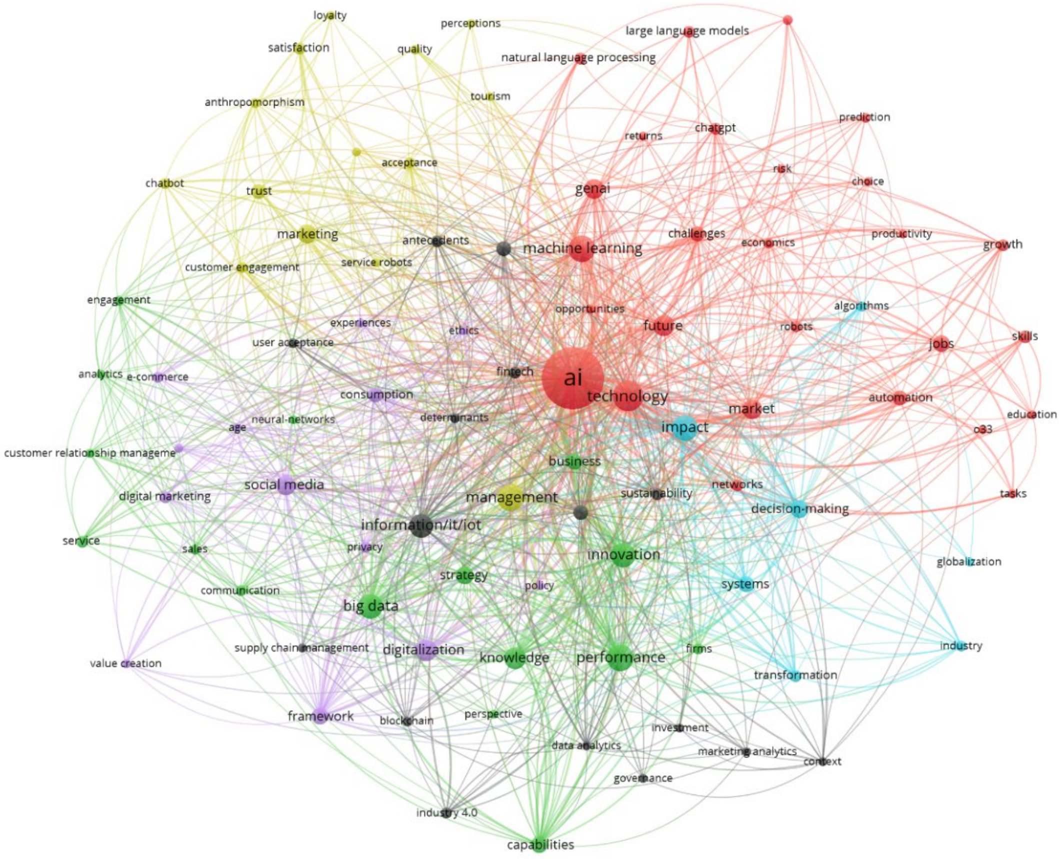

Figure 2: *Co-occurrence network visualization for the EU*
Source: *own visualization based on Web of Science publications for the EU, from 2020-2025, using VOSviewer*

The six color-coded clusters emerging within the co-occurrence network for the EU are the following:

- The **red cluster** *"AI Technologies"* is the most central and extended cluster, and focuses on the use of AI in marketing from a technological perspective. The main research themes include the development of AI technologies, the spread of machine learning and generative models.
- The **green** *"AI-enabled Performance, Innovation & Knowledge development"* **cluster,** with keywords like *performance, innovation, big data* and *knowledge*, covers corporate and performance-oriented applications of AI focusing on the integration of AI and big data to support organizational decision-making, management, and performance measurement. It also centres on how AI and data-driven technologies contribute to organizational performance and competitive advantage and on investigating knowledge and skill development required for the efficient use of AI.
- The **"dark" cluster** *"Information, Adoption & User Behaviour*" examines the human and organizational response to AI and IT systems. Publications that belong to this cluster investigate how individuals and institutions adopt new technologies as well as addresses behavioural factors influencing usage and the determinants of acceptance or resistance.
- The **yellow cluster** highlights how *human–AI relationships* influence co*nsumer experience* and *trust.* Publications in this cluster address how users perceive AI, how

much trust they have in AI, and how AI promotes service management and customer relationship practices and what role service robots play in customer relationship.

- The **purple** *(Digitalization, Social Media & Consumption Patterns)* **cluster** includes sources that examine how *digitalization* and *social media* shape consumer behaviour, and how consumption patterns evolve in the online space. The inclusion of ethical considerations (ethics is the 5th most common keyword as shown by Table 5) points to growing concerns surrounding privacy, data use, and responsible marketing practices in digital spaces.
- The **light blue cluster** with keywords like *systems, industry,* and *globalization* examines how AI-enabled systems and algorithms drive organizational transformation, industry wide modernization and global integration.

As indicated in Tables 1–6, within each cluster the five most important keywords were selected based on their occurrence, which means how often these keywords appeared in the literature, and their total link strength (TLS), which reflects how frequently a keyword appears together with others.

Keywords that scored well on both measures were ranked highest. When two keywords had similar occurrence counts, TLS was used to guide the final selection. This approach ensures that the chosen keywords are not only common in the literature but are also closely connected to other topics.

Table 1: *Red - Cluster 1 - AI Technologies*
Source: *own research, based on VOSviewer keyword visualization*

Red - Cluster 1 —AI Technologies			
Rank	**Keyword**	**Occurrence**	**TLS**
1	**AI**	222	744
2	**Technology**	53	247
3	**Machine learning**	42	145
4	**Future**	25	107
5	**Market**	23	101

In the red cluster (see Table 1), ‘AI’ and ‘technology’ are the most common keywords and are represented with the largest nodes (see Figure 3). They are also the central elements of the whole network. Several keywords in the cluster – including ’AI’, ’technology’ as well as ‘future’, ‘market’, or ‘machine learning’ – show strong interconnections both within the cluster and across clusters representing the technological base which, in conjunction with other focus areas, draws further scholarly attention. As illustrated in Figure 3, the centrality of “AI” is demonstrated by its extensive interconnections across the network.

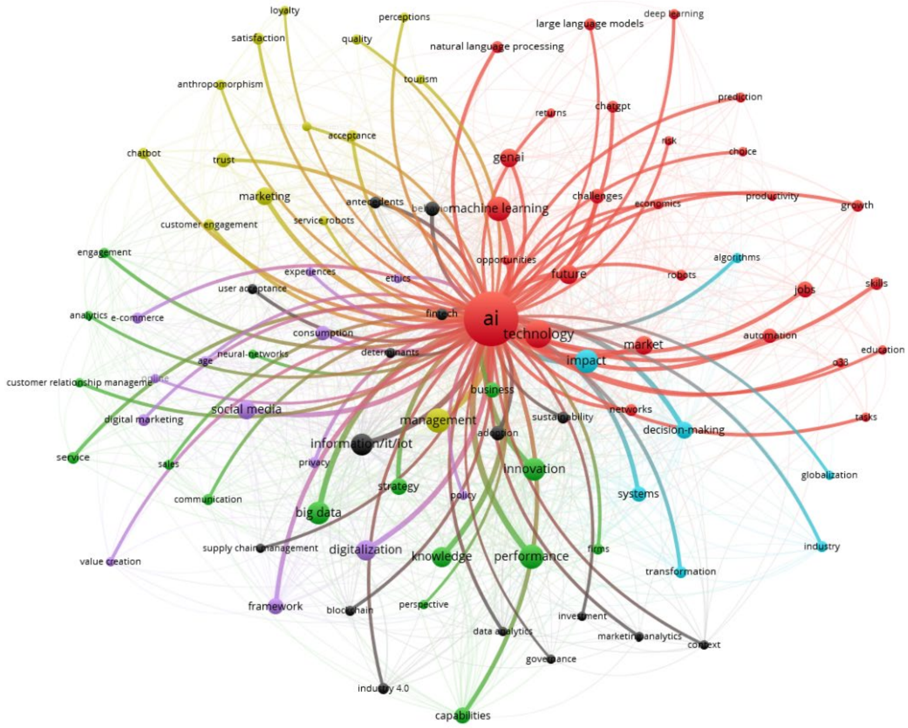

Figure 3: *Co-occurrence network for the EU highlighting AI's connection with other keywords*
Source: *own visualization based on Web of Science publications from 2020-2025, using VOSviewer*

Table 2: *Green - Cluster 2 - AI-enabled Performance, Innovation & Knowledge development*
Source: *own research, based on VOSviewer keyword visualization*

Green - Cluster 2 AI-enabled Performance, Innovation & Knowledge development			
Rank	**Keyword**	**Occurrence**	**TLS**
1	**Performance**	41	197
2	**Innovation**	36	161
3	**Big data**	35	163
4	**Knowledge**	27	143
5	**Business**	15	68

In the green cluster, all central concepts are strongly connected within the cluster, which most probably indicates that these terms are studied together and several publications examine how these phenomena impact each other e.g. how innovation and knowledge influence performance (see Figure 2). Additionally, prominent keywords of the cluster (shown in Table 2) including 'performance', 'innovation' and 'knowledge' are all directly connected to the keyword ‘management’ despite its location in another cluster indicating the corporate oriented applications of AI. Furthermore, ‘innovation’ and ‘knowledge’ also show a direct link with ‘marketing’ (also from another cluster), which signals that contemporary marketing research is strongly focused on knowledge creation and innovation.

Table 3: *Dark - Cluster 3 — Information, Adoption & User Behaviour*
Source: *own research, based on VOSviewer keyword visualization*

Dark - Cluster 3 — Information, Adoption & User Behaviour			
Rank	**Keyword**	**Occurrence**	**TLS**
1	**Information / IT / IoT**	33	144
2	**Adoption**	13	48
3	**Behaviour**	14	47
4	**Data analytics**	5	33
5	**Determinants**	6	23

In the dark cluster, ‘information’ the most prominent keyword of the cluster (see Table 3) shows links to multiple other clusters, including ‘AI’ and ‘technology’ from the red cluster, ‘innovation’ and ‘performance’ from the green cluster, ‘management’ from the yellow cluster, ‘impact’, ‘systems’ and ‘decision-making’ from the blue cluster, as well as ‘digitalization’ and ‘social media’ from the purple cluster (see Figure 2). This pattern highlights the highly integrative function of information. The keyword ‘adoption’ is strongly connected to ‘behaviour’ and ‘user acceptance’ in the dark cluster, which might suggest that information is being explored through the lens of human responses to emerging technologies, as well as through AI- and technology-oriented perspectives. Interestingly, no direct connection between behaviour and information is visible in the network. Moreover, adoption is linked to both ‘management’ and ‘marketing’ despite the fact that these terms belong to different clusters, which indicates that AI adoption-related issues are discussed across both organizational and market-oriented contexts.

Table 4: *Yellow - Cluster 4 - Human–AI Interaction*
Source: *own research, based on VOSviewer keyword visualization*

Yellow - Cluster 4 - Human–AI Interaction			
Rank	**Keyword**	**Occurrence**	**TLS**
1	**Management**	43	206
2	**Marketing**	20	73

3	**Trust**	13	49
4	**Customer engagement**	7	37
5	**Service robots**	5	20

In the yellow cluster, both 'management' and 'marketing' – the most important keywords of the cluster as shown in Table 4 – form many cross-cluster links. Within this cluster AI is strongly linked to concepts such as 'customer engagement', 'trust', and 'acceptance', which reflects the human-centred aspects of technology adoption in marketing (see Figure 2). Additionally, beyond its own cluster, marketing also connects to the red cluster through AI, 'machine learning', 'generative AI' and 'future' with the notion of 'future' further tied to 'innovation' in the green cluster, which shows a direct connection to marketing. Other links of marketing to the green cluster include 'knowledge' and 'big data', which highlight that modern marketing relies significantly on data. Marketing also connects to the blue cluster through decision-making, and to the purple cluster through consumption, experiences, ethics, and e-commerce, which indicates the broader consumer and ethical implications associated with AI-enabled marketing practices (see Figure 2).

Table 5: *Purple - Cluster 5 Digitalization, Social Media & Consumption Patterns*
Source: *own research, based on VOSviewer keyword visualization*

Purple - Cluster 5 Digitalization, Social Media & Consumption Patterns			
Rank	**Keyword**	**Occurrence**	**TLS**
1	**Social media**	23	108
2	**Digitalization**	28	82
3	**Framework**	17	83
4	**Consumption**	13	50
5	**Ethics**	5	33

In the purple cluster, as indicated in Table 5, the main keywords: 'social media', 'digitalization', 'framework', and 'consumption' centred around digital consumer behaviour and are closely linked within the cluster. In addition, they are all linked to management, which is situated in the yellow cluster (see Figure 2). This indicates that digital consumption patterns and social media dynamics appear as important managerial concerns and prominent topics within current research. Additionally, 'social media', 'consumption', and 'framework' show significant connections with 'ethics', which suggests that ethical considerations play a central role in discussions related to digital platforms and consumer practices. These keywords show strong links to multiple other clusters, which highlight their multidisciplinary nature.

In the sixth, light blue cluster 'impact', appears as the central element within this hub (see Table 6) connecting the keywords of this cluster with each other, which also show strong internal connectivity. Beyond its own cluster, as shown in Figure 2, 'impact' also demonstrates significant links to the AI-focused red cluster, as well as to business-oriented keywords such as 'management', 'business', 'performance', 'innovation', and 'knowledge', which emphasizes organizational implications. Additionally, 'impact' shows links to marketing-related terms including 'social media' and 'customer engagement', as well as to 'chatbots', which latter indicates intersections with customer-facing and digital marketing domains. Overall, this positions *'impact'* as a central integrative concept thus bridging technological advancements with managerial, organizational, and marketing considerations.

Table 6: *Light-blue - Cluster 6 AI Impact on Organisational Decision-Making and Systems Transformation*
Source: *own research, based on VOSviewer keyword visualization*

Light-blue - Cluster 6 AI Impact on Organisational Decision-Making and Systems Transformation			
Rank	**Keyword**	**Occurrence**	**TLS**
1	**Impact**	39	175
2	**Decision-making**	18	104
3	**Systems**	15	80
4	**Transformation**	9	54
5	**Industry**	7	35

The clusters demonstrate that research on the use and application of AI in marketing within the European Union is well-developed and is characterized by a diverse range of sub-topics and focus areas. These results align with the literature overview, which pointing out that AI can be applied in marketing in various ways, based on different AI technologies and across distinct marketing areas. The clusters show that research spans technological, corporate-focused, strategic, and behavioural aspects. The interconnected nature of these clusters illustrates that AI in marketing constitutes an integrated system, and its impact extends beyond technical innovation thereby introducing structural transformations including new organizational practices, and new ways of interaction between businesses and consumers. Consequently, AI's social implications are also topical.

Regarding **keyword co-occurrence in the US,** the Web of Science shows a smaller research base, with 75 articles identified, compared with 350 in the EU. As shown in Figure 4, the focus of US research is on the technological, performance-related and impact-driven aspects of AI as reflected in frequent keywords such as 'AI', 'technology', 'machine learning', 'performance', 'management', 'big data' and 'impact'. Although four clusters are present, the keyword network is less diversified than in the EU, and the themes are more closely interconnected. Researchers in this field are primarily interested in the technological, performance-related aspects of AI, and focus on how innovations like machine learning and big data influence management, organizational outcomes and strategic value.

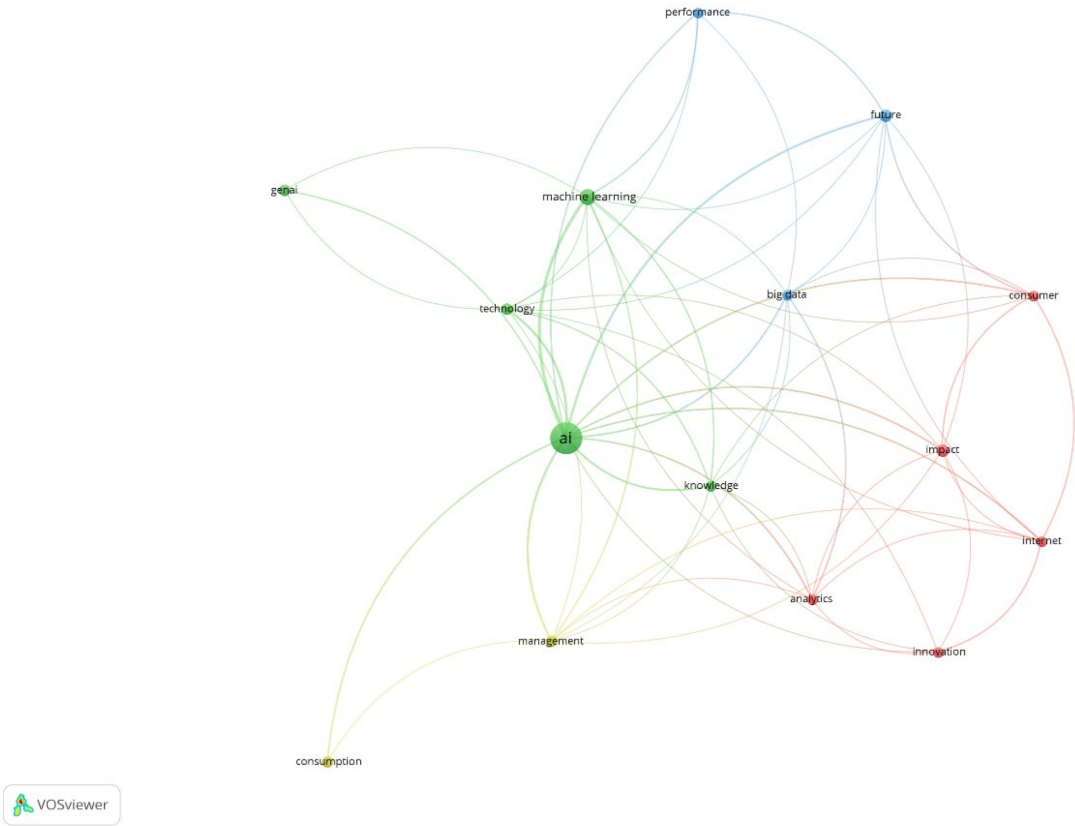

Figure 4: *Co-occurrence network visualization for the US*
Source: *own visualization based on Web of Science publications from 2020-2025, using VOSviewer*

In CEE, the research base is broader than in the United States with 170 sources identified in the Web of Science database. Sources are also more diversified than in the US and there is a stronger focus on the marketing and management perspective (see Figure 5). The network shows that 'AI' is closely linked to 'management' as these two terms are in the same cluster. This shows that these two terms frequently co-occur in the same publications, and scholars in this region tend to study AI primarily through a managerial lens.

AI's link to 'adoption' also indicates that AI is primarily examined from an organizational rather than a technical perspective.

A strong emphasis on 'digitalization' and 'digital transformation' appears in a related cluster, where 'competitiveness', 'automation', and 'technology' are tightly linked. This suggests that AI is often studied within the broader context of digital change and its impact on organizational and regional competitiveness. Overall, the structure of the network indicates that while these themes are strongly interconnected, the CEE literature remains less extensive than in the wider EU research landscape.

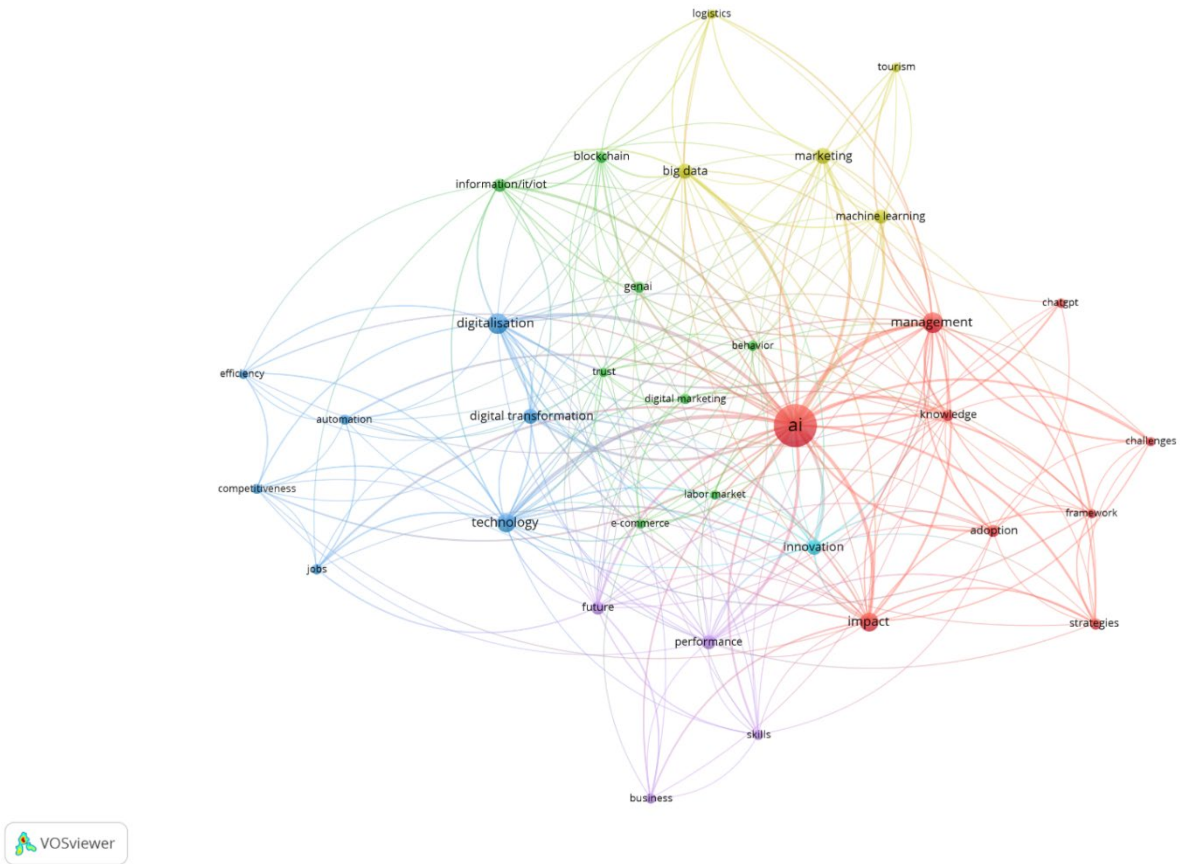

Figure 5: *Co-occurrence network visualization for the CEE region*
Source: *own visualization based on Web of Science publications from 2020-2025, using VOSviewer*

Comparison with other literature reviews

The six clusters identified for the EU show notable similarities with previous literature syntheses including Labib's bibliometric study, which analysed a corpus of 522 publications from 2015-2023 indexed in the Web of Science database. The study also identified six clusters: 1-*Psychosocial dynamics of AI*, 2-*AI-enhanced market dynamics and strategies*, 3-*AI for consumer services*, 4-*AI for decision-making*, 5-*AIov for value transformation*, and 6-*AI for ethical marketing* (Labib, 2024).

The most significant overlap is between Labib's *AI for consumer services* cluster and the yellow cluster, as both frameworks converge on themes related to Human–AI interaction, consumer engagement, trust, and marketing communication.

The light-blue cluster likewise demonstrates strong correspondence with Labib's *AI for decision-making*, as both focus on AI-supported systems, decision processes and their implications for marketing and organizational effectiveness.

The red cluster converges with Labib's *AI-enhanced market dynamic strategies*. However, it differs at some points. While Labib adopts a more explicitly market-oriented and strategic perspective, the current review reflects a technology-centred focus rather than emphasising AI development and technical capabilities.

The green cluster aligns with Labib's *AI for value transformation* as both address innovation, knowledge creation, and performance. Nevertheless, Labib's approach places stronger emphasis on transformative value creation, whereas the current review emphasizes performance, and shifts the focus towards a more corporate, efficiency-driven and results-oriented interpretation of AI's role in marketing.

As for further differences, in the current review ethical considerations appear embedded within broader thematic categories, particularly those related to consumer behaviour and digitalisation in the purple cluster. While this cluster partially overlaps with Labib's ethical focus, it extends its scope to digitalisation and consumption patterns.

It is also to be noted that clusters in this study arise from the co-occurrence patterns, which means that themes are formed based on how topics are directly connected in the literature in terms of keywords. This produces thematic groupings that differ from those derived through theoretical reasoning. Finally, the divergence is reinforced by the fact that AI is a rapidly evolving field, and by the study's methodological choice to analyse the literature across distinct geographical regions.

The clusters identified in this study also show a degree of convergence with the systematic literature review conducted by Mariani and Wirtz (2022). The latter is a multidisciplinary research with a significant focus on consumer research and psychology that identifies eight thematic areas: (1) memory and computational logic; (2) decision-making and cognitive processes; (3) neural networks; (4) machine learning and linguistic analysis; (5) social media and text mining; (6) social media content analytics; (7) technology acceptance and adoption; and (8) big data and robots.

While Mariani and Wirtz place a stronger emphasis on cognitive processes, neural networks, and psychological mechanisms, several of these themes are also visible in the keyword co-occurrence clusters of the present study although they are regrouped or framed under different topics. In contrast, the current analysis demonstrates a relatively stronger focus on systems, technological infrastructures as well as broader corporate and organisational dimensions of AI adoption.

The observed divergence can be attributed to the broader and more business-oriented scope of the present study. This is coupled with the identification of some new research streams that were less visible at the time of earlier reviews such as the spread and recent emergence of large language models, generative AI, and more advanced machine-learning techniques that has brought renewed focus to technological themes within the research landscape.

Conclusion

Following an overview of how the use of AI evolved in marketing and how it is applied currently, a study based on scientific sources from the Web of Science database published from 2020 to 2025 was carried out. The keyword co-occurrence network, based on extracted keywords, reveals the core topics and main focus areas in the EU and the US-based publications.

For publications from the EU, keywords were regrouped into six distinct clusters, representing the main thematic areas within AI-marketing research. The six clusters include (1) AI technologies, (2) AI-enabled Performance, Innovation & Knowledge development, (3) Information, Adoption and User Behaviour, (4) Human - AI interaction, (5) Digitalisation, Social Media and Consumption Patterns, and (6) AI Impact on Organisational Decision-Making and Systems. Core keywords were also defined for each cluster, which highlights the main thematic areas within each grouping. The findings also reveal the key areas of research focus in the EU and the US, and highlight differences between the two regions. Research in the EU spans technological, corporate-focused, strategic and behavioural aspects with a larger number of studies. In the US researchers are primarily interested in the technological, performance-related aspects of AI.

This study also examined how the previously identified focus areas within the EU specifically appear in the CEE region. This was studied as a preliminary step to provide context for further research on Hungary. Analysis of the CEE co-occurrence network indicates that research in marketing and AI is concentrated on management, adoption and digitalization.

Overall, the visualization highlights the prevalence of topics such as the technological aspects of AI, consumer behaviour and technology adoption as well as organizational adoption and implications to management in recent-current research while also highlighting a shift towards more recent technological developments related to generative AI, large language models, advanced machine-learning techniques.

It is to be noted that this study includes publications from a single database, which entails certain limitations, and a more detailed analysis of content is planned to further refine research results.

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