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Article

From calculators to artificial intelligence: A multi-level framework for technology adoption and resistance in education and organisations

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Abstract: Technological innovations are frequently associated with enhanced efficiency and improved decision-making; however, their initial adoption has often been characterised by notable resistance. This study examined the persistence of this phenomenon by synthesising empirical evidence from the historical adoption of calculators, spreadsheets, and statistical software, and by comparing these insights with contemporary developments in artificial intelligence (AI). The findings indicated that resistance extended beyond technical limitations and reflected a complex, multi-dimensional process shaped by individual factors such as self-efficacy, perceived usefulness, and anxieties related to skill displacement as well as organisational culture and broader systemic conditions. The evidence further demonstrated that successful adoption was contingent upon structured support mechanisms, incremental exposure to new technologies, and the clear articulation of value propositions. At the organisational level, effective leadership, adequate resource allocation, and coherent policy alignment emerged as critical enablers of sustained integration. Drawing on these insights, the study proposed a multi-level conceptual framework that integrates individual, organisational, and systemic determinants to guide future technology adoption. The framework underscores that meaningful and sustainable integration depends on coordinated, cross-level interventions rather than isolated initiatives. The framework also highlights the need for further empirical research into AI adoption in under-resourced contexts. It calls for critical engagement with the ethical implications of algorithmic decision-making in evolving socio-technical systems.

Keywords: artificial intelligence; innovation diffusion; socio-technical systems; strategic integration; technology adoption; technology resistance; workplace transformation

1. Introduction

Technological innovations have continually reshaped educational and organisational practices, yet adoption is often uneven due to psychological, social, and structural barriers. Studies show that while resource constraints such as limited capital and digital literacy restrict uptake, intrinsic motivation and perceived competitive advantage can drive selective adoption of new tools [1–3]. Similarly, the adoption of artificial intelligence (AI) in higher education reveals a tension between the promise of efficiency and ethical concerns about overreliance, bias, and inequity [4, 5]. These findings highlight that adoption is influenced not only by technology itself but also by a complex interplay among user perception, institutional culture, and social context.

The role of external conditions, such as policy and governance, further mediates adoption. Xiao et al. emphasise that access to digital infrastructure, regulatory support, and digital literacy initiatives significantly affect uptake, particularly in developing contexts [6]. Notably, innovation-oriented organisational cultures and the strategic implementation of Agile practices can significantly accelerate technology integration, as Agile has been shown to serve as a critical enabler of innovation-driven organisational transformation, supporting rapid adaptation to global changes and digital disruptions [7]. United Nations Educational, Scientific and Cultural Organisation (UNESCO) extends this perspective to AI, illustrating how inequitable access and insufficient policy planning may exacerbate educational disparities, even when technological capacity exists [8]. These studies collectively underscore that adoption is contingent on an enabling ecosystem, not on individual readiness alone.

Historical evidence illustrates the importance of structured support and gradual integration. Early resistance to calculators and spreadsheet software stemmed from fears of skill erosion, workflow disruption, and accuracy concerns [9, 10]. Structured training, scaffolded learning, and iterative exposure, however, mitigated resistance and enhanced competence [11, 12]. Drawing parallels to contemporary AI adoption, these patterns suggest that user confidence, incremental exposure, and demonstrable value are crucial for successful implementation.

AI adoption in educational contexts presents both promise and caution. While AI can automate routine academic tasks and enhance personalised learning, it also raises ethical dilemmas and risks of widening inequities [4, 5, 8, 13]. These tensions highlight the need for strategies that maximise AI's benefits while addressing human, organisational, and societal considerations, emphasising that AI complements rather than replaces human expertise.

2. Study aims

This study explored the factors shaping AI adoption in education and organisations, focusing on barriers, facilitators, and lessons from past technology integrations. The study sought to provide insights to guide practical strategies for smoother, more equitable AI implementation.

3. Literature review

A complex interplay of individual, social, and institutional factors shapes the adoption of technology in educational and organisational contexts. Historical research on calculators, spreadsheets, and statistical software demonstrates that adoption is rarely determined by technical functionality alone. Teachers and professionals often resisted the use of calculators and early spreadsheet tools due to fears of errors, loss of expertise, and unfamiliarity with new workflows [9, 14, 15]. Conversely, technologies perceived to offer tangible advantages such as enhanced efficiency, improved problem-solving, or clearer analytics tended to be adopted more rapidly when accompanied by structured guidance and support [11, 16, 17]. These findings illustrate that adoption is fundamentally a socio-cognitive process in which users constantly negotiate perceived risks and benefits within their professional and social contexts.

Empirical evidence emphasises the role of structured interventions and alignment with pedagogical or organisational goals. Statistical software such as the Statistical Package for the Social Sciences (SPSS) has become dominant in the health sciences and social research, with tool selection often reflecting the methodological demands of specific study designs [10,12,18]. Scaffolding through guided instruction, step-by-step demonstrations, and hands-on exercises enhances competence and engagement, but overly prescriptive support can limit the development of independent problem-solving skills. This balance between guidance and autonomy suggests that adoption strategies must cultivate both skill acquisition and self-efficacy, reinforcing the need for thoughtful implementation rather than mere availability of tools.

Resistance to technology adoption emerges from intertwined psychological and structural dimensions. On the individual level, fear of skill loss, uncertainty, and anxiety about technological complexity inhibit uptake [13,15,19]. At the organisational level, cultural inertia, inadequate communication, and weak leadership support exacerbate these delays [1,2,20]. These dual layers indicate that successful adoption initiatives must address both users' cognitive and emotional responses and the systemic conditions that facilitate or constrain technology integration.

Contemporary AI adoption presents both continuities with, and departures from, historical technology trends. Like earlier tools, AI can enhance efficiency, support higher-order decision-making, and enable personalised learning experiences [4,8,21]. However, AI also introduces unique challenges, including ethical dilemmas, inequitable access, and risks of over-reliance, which can undermine trust and agency in professional settings [5,13,20]. This duality highlights the need to integrate AI thoughtfully into existing workflows, leveraging lessons learned from calculators and spreadsheets while remaining sensitive to the novel complexities posed by algorithmic decision-making and predictive analytics.

The sustainability of technology adoption relies on the intersection of practical utility, user support, and organisational readiness. The widespread use of Excel illustrates that familiarity and perceived convenience often outweigh concerns about accuracy, while gaps in training, infrastructure, or institutional support can limit effective integration [15,18,22]. UNESCO further underscores that equitable access and policy frameworks are essential to ensure that AI's potential benefits are realised without reinforcing existing disparities [8]. Taken together, these studies indicate that effective adoption requires a multidimensional approach, one that simultaneously addresses technological affordances, human factors, and organisational structures to foster sustained, meaningful use.

4. Methods

4.1. Research design

This study used an empirical literature review as its main research approach, analysing published empirical studies as primary data rather than merely as contextual references, and found that definitions, operationalisations, and implementation actions of scientific inquiry activities vary widely across studies, limiting the comparability and validity of their results [23]. Adopting a systematic approach allows for the comparison of findings across studies and contexts, facilitating the identification of persistent patterns of resistance and adoption throughout successive technological waves; however, a key challenge is that many postgraduate students lack the skills to conduct rigorous literature reviews, which can lead to biased or inaccurate conclusions, underscoring the necessity for structured guidance in the processes of searching, analysing, and synthesising existing research [24]. Empirical literature reviews are increasingly recognised as capable of generating theoretical insight when they move beyond description toward structured synthesis and interpretation [25–27].

Methodological literature emphasises that literature reviews constitute a rigorous research methodology when conducted transparently and analytically, particularly when inclusion criteria, analytical logic, and synthesis strategies are explicitly articulated [16, 25, 28]. Conversely, reviews that rely on implicit selection processes risk becoming narrative compilations that obscure rather than explain empirical patterns. This study, therefore, prioritised analytical depth, conceptual coherence, and reflexive interpretation over exhaustive coverage.

Insights from empirical methodological reviews further informed this design choice. Research on lean manufacturing demonstrates that empirical fields often privilege dominant methodological approaches, such as large-scale surveys, at the expense of contextual and process-oriented understanding [1, 2, 26]. These findings underscore the importance of integrating evidence from diverse empirical traditions when examining technology adoption as a socio-organisational phenomenon.

4.2. Search strategy

To identify relevant studies, we conducted a careful, iterative search across several leading academic databases, including Scopus, Web of Science, IEEE Xplore, ERIC, and Google Scholar. This approach helped us identify 126 studies exploring technology adoption, resistance, and use in both educational and organisational settings. The findings show that while smart digital technologies can greatly improve teaching, learning, and overall organisational efficiency, their success often depends on infrastructure, digital literacy, and the specific context in which they are implemented [16,21,27,29]. We used search terms that captured key ideas in adoption research, such as perceived usefulness, resistance mechanisms, learning integration, organisational change, and emerging digital tools, ensuring that our review covered a wide range of technologies, from well-established systems to the latest innovations.

Citation chaining complemented keyword searching by tracing influential empirical studies over time, thereby linking foundational work on calculators and spreadsheets to contemporary studies on artificial intelligence and digital transformation [9, 14, 15]. This process supported conceptual continuity and reduced fragmentation across disciplinary boundaries, a common challenge in technology adoption research [5,8].

Iterative refinement of the search strategy occurred alongside preliminary analysis, allowing emerging themes to guide the identification of subsequent studies. This reflexive approach aligns with qualitative synthesis principles, where analytical sensitivity develops in tandem with evidence engagement [4,13,28].

A total of 203 sources were initially identified for this literature review. After removing duplicates and screening titles and abstracts, sixty full-text articles were assessed for eligibility. Thirty-four primary studies were included in the analysis (**Figure 1**). The final studies spanned diverse geographies, with sixteen from the Global North and eighteen from the Global South, and varied sectors: ten from K-12 education, fourteen from higher education, and ten from corporate or organisational contexts. Most sources were peer-reviewed (28), with six master's theses included to capture additional perspectives.

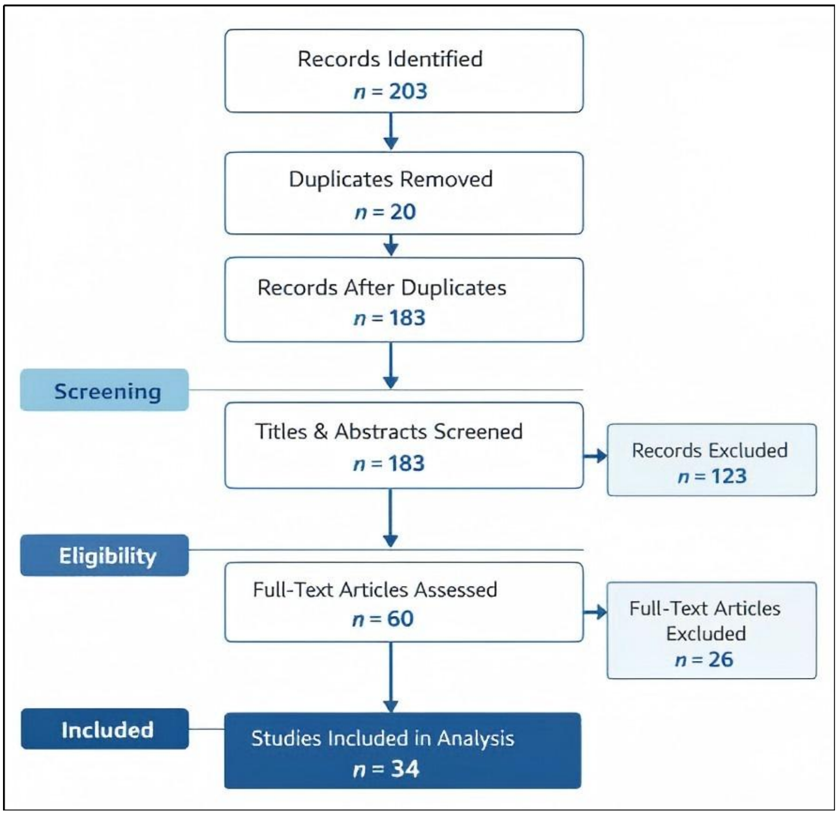

Figure 1. PRISMA flow diagram showing the selection of studies.

4.3. Inclusion and exclusion criteria

The review encompassed empirical studies utilising qualitative, quantitative, or mixed method designs that examined human, organisational, or pedagogical aspects of technology adoption, revealing that integrating quantitative and qualitative approaches enables a more nuanced and comprehensive understanding of complex phenomena by capitalising on the complementary strengths of both methods [30]. Eligible studies addressed either established digital tools or advanced technologies and reported empirical evidence on barriers, enabling conditions, or adoption outcomes [10,20,22]. This ensured that the review remained grounded in observed practice rather than speculative projection. Studies were excluded where the focus was limited to technical system performance without engagement with users, institutions, or social processes. Conceptual papers lacking empirical grounding were also excluded, as they offered limited insight into adoption dynamics shaped by lived experience and organisational context [5,13,28].

4.4. Data extraction and analytical procedure

Data extraction followed a structured framework that captured the research context, technology type, methodological approach, reported challenges, facilitating conditions, and adoption outcomes. This framework enabled systematic comparison across studies while preserving contextual specificity [10, 12, 18]. Extracted data were organised to allow iterative engagement rather than one-off coding.

The analysis employed thematic synthesis to identify recurring patterns, contrasts, and tensions across empirical findings. Attention was paid to contradictory outcomes, such as cases where training improved competence but failed to produce sustained integration, highlighting the conditional nature of adoption processes [2, 11, 17]. This approach prioritised explanation and sensemaking over aggregation. Constant comparison across studies supported the refinement of analytical categories, allowing themes to evolve in response to empirical variation rather than being imposed a priori. This interpretive stance aligns with qualitative synthesis methodologies that emphasise analytical flexibility and theoretical sensitivity [4, 13, 28].

4.5. Theoretical anchoring and analytical rigour

The proposed framework draws on Socio-Technical Systems (STS) theory, emphasising the dynamic interaction between social and technical subsystems and the need to align individual behaviour with organisational infrastructure [1, 3]. While Diffusion of Innovations (DOI) theory effectively explains adoption patterns [16, 27], explicitly linking the framework to STS enhances its explanatory power at the systemic level, where organisational structures and readiness shape outcomes [6, 13]. Unlike calculators or spreadsheets, AI exhibits autonomous decision-making, creating an interpretability gap that can heighten resistance [4, 9, 14], highlighting the need to consider both human agency and technological capability alongside user skills, perceptions, and support structures [3, 19].

DOI provided a primary analytical lens, guiding interpretation of how relative advantage, complexity, and compatibility influence adoption trajectories [16, 27, 28]. Historical cases of calculators, spreadsheets, and statistical software illustrated how familiarity and institutional normalisation can outweigh accuracy or ethical concerns [9, 14, 15], informing the understanding of contemporary AI adoption. Analytical rigour was reinforced through iterative theme refinement, explicit evidence-claim linkage, and careful consideration of empirical contradictions, ensuring that theoretical insights remained grounded in observed practice and transferable across contexts [4, 5, 8].

5. Results and development of an adoption framework

5.1. Patterns of adoption and resistance

Empirical analysis revealed recurring patterns in technology adoption across educational and organisational contexts. Individual perceptions, such as confidence in using new tools, perceived utility, and fear of skill loss, strongly shaped adoption decisions [3, 15, 19]. Organisational culture and leadership also played a crucial role: supportive communication, clear governance, and agile management practices facilitated smoother uptake, whereas inertia and poor guidance impeded it [1,2,7]. The broader ecosystem, including access to digital infrastructure, equitable opportunities, and policy support, further influenced adoption, demonstrating that technology uptake depends on a complex interaction of individual, organisational, and systemic factors [5,6,8].

Resistance was most pronounced where these factors were weak or misaligned. Anxiety, uncertainty, and mistrust frequently slowed adoption, particularly when tools threatened existing skills or disrupted familiar workflows [9,14,17]. Limited training and insufficient institutional support compounded these barriers, delaying integration despite the availability of functional technology [10,15,20]. Contemporary AI adoption highlighted additional resistance points, including ethical concerns and inequitable access, illustrating that promising technologies require careful attention to human, cultural, and policy considerations [4,5,13].

5.2. Facilitators of successful integration

Empirical studies consistently emphasised the importance of structured support and gradual exposure in fostering adoption. Scaffolded learning, mentoring, and iterative practice have been shown to enhance student confidence and competence while mitigating anxiety, with effective scaffolding requiring the deliberate design of learning activities and support materials that are closely aligned with learners' current abilities and potential developmental levels [11, 12]. Tools offering clear advantages in efficiency, decision-making, or analytical power were adopted more readily, particularly when aligned with professional goals and organisational priorities [10, 16, 18]. Institutional policies, governance, and resource allocation also proved critical, helping to sustain adoption over time and bridge equity gaps in access [1,6,8].

Adaptability emerged as another key facilitator. Flexible training, context-sensitive guidance, and opportunities for autonomous exploration promoted long-term uptake [2,11,18]. Rigid or overly prescriptive interventions, on the other hand, often limit engagement and innovation. These findings suggest that successful adoption requires a balance between standardisation and flexibility, allowing technology to enhance human and organisational capacity rather than constrain it.

5.3. Development of an integrated adoption framework

Research shows that successful technology adoption depends on a combination of individual readiness, organisational support, and systemic facilitation (see **Figure 2**). At the individual level, people are more likely to embrace new tools when they perceive clear value, feel confident, and understand the risks, reflecting the socio-cognitive negotiation that drives engagement. Organisational factors such as leadership, culture, communication, and resource allocation can support or hinder adoption, while broader systemic elements, such as policy, infrastructure, and equitable access, provide the conditions for sustainable adoption. These levels interact dynamically: positive experiences can boost organisational confidence and accelerate uptake, whereas systemic inequities may limit engagement even when individuals are ready. Lessons from calculators, spreadsheets, and statistical software show that structured support, gradual exposure, and visible demonstrations of value consistently facilitate adoption. To make this framework actionable, leaders can use a structured checklist to guide implementation. At the individual level, they should ensure users understand the value of AI beyond its technical functions and feel confident in applying it in their work. At the organisational level, leadership should provide support for experimentation, allowing teams to learn through trial and error without fear of failure. The framework also highlights the emerging "Digital Divide 2.0," where differences in AI literacy, such as familiarity with advanced tools or techniques, can create new inequities.

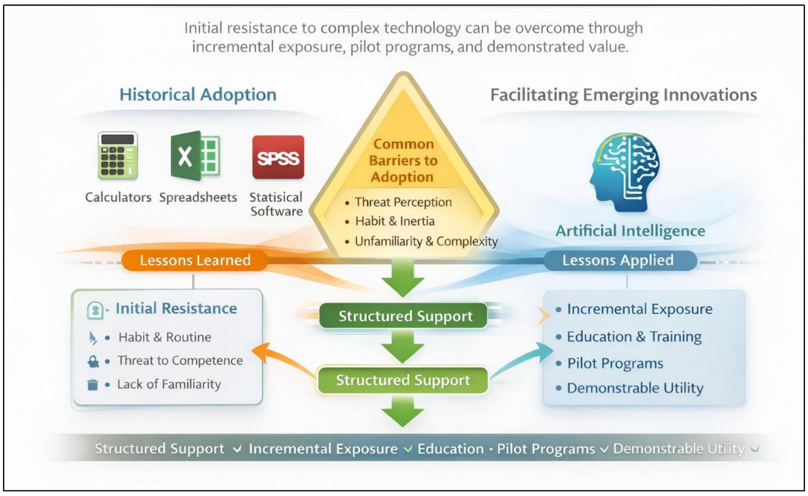

Figure 2. Technology Adoption and Lessons for Emerging Innovations.

6. Discussion

The study examined how technology adoption unfolded across educational and organisational contexts, focusing on barriers, facilitators, and lessons from past technologies, from calculators and spreadsheets to contemporary AI. It aimed to provide insights to guide practical strategies for smoother, more equitable technology integration. The synthesis of empirical evidence highlights that technology adoption is not a single event, but a multi-level process shaped by individual readiness, organisational support, and systemic facilitation. This study confirms that individual perceptions of usefulness, confidence, and risk remain central to adoption decisions, reinforcing established socio-cognitive theories of technology uptake [9, 14, 15]. However, the findings extend this understanding by emphasising that individual readiness alone is insufficient; organisational and systemic conditions are equally decisive. In practice, this means that even when individuals perceive clear benefits from technology, adoption may stagnate if organisational leadership fails to provide supportive structures or if policy and infrastructure barriers persist. This aligns with existing literature that highlights organisational culture, leadership, communication, and resource allocation as pivotal enablers or inhibitors of adoption [1,2,7].

A key contribution of this study is demonstrating how these levels interact dynamically, producing feedback loops that shape adoption trajectories over time. The framework shows that positive experiences at the individual level can reinforce organisational confidence, leading to expanded implementation and greater diffusion. At the same time, systemic inequities can limit uptake even in otherwise supportive environments [4, 13, 20]. This dynamic is particularly relevant to AI adoption, where the technology's complexity and novelty often amplify uncertainty and resistance. Historical examples of calculators, spreadsheets, and statistical software illustrate that structured support, incremental exposure, and clear demonstrations of value consistently facilitate successful technology adoption. Similarly, the Technology-enhanced Supportive Instruction (TSI) model, which integrates Microsoft Excel with intentional teacher–student interactions, has been shown to effectively engage students and support learning in both face-to-face and remote statistics education, suggesting that AI adoption should likewise be conceptualised as an iterative, adaptive process rather than a one-time implementation [11, 12, 17]. This perspective is reinforced by evidence from small and medium-sized enterprises in developing countries, which reveal that opportunities and challenges in digital technology adoption are closely tied to organisational readiness, resource availability, and contextual factors [31].

The study also underscores the importance of systemic enablers, including policy alignment, infrastructure readiness, and equity considerations. While organisational readiness can address many internal barriers, sustainable adoption requires external conditions that support scalability and fairness [5, 6, 8, 31]. Without these conditions, adoption may remain limited or exacerbate existing inequalities, particularly in resource-constrained settings. Therefore, the findings reinforce the need for multi-level strategies that align individual training and support with organisational capacity-building and broader policy reforms. The framework offers a practical guide to AI and technology adoption, showing that success depends on coordinated actions across individuals, organisations, and systems. Grounded in STS theory, it highlights the need to align user readiness and organisational structures for effective integration. Importantly, it addresses AI's autonomous decision-making, which creates trust and interpretability challenges, emphasising that adoption strategies must tackle both human and systemic factors to ensure sustainable, meaningful use. The study contributes a multi-level framework that links individual readiness, organisational support, and systemic infrastructure, offering both theoretical insight and practical guidance for sustainable, equitable, and effective AI and technology adoption.

7. Study limitations and recommendations for future research

While this study offers a valuable synthesis of adoption patterns across historical and contemporary technologies, it is limited by its reliance on published empirical literature, which may be subject to publication bias and overlook adoption experiences in under-resourced or non-academic settings. In addition, the evidence base spans contexts with varying levels of digital infrastructure and organisational capacity, making it difficult to determine how consistently the identified factors operate across regions and institutions. Although the framework emphasises systemic enablers such as policy, infrastructure, and equity, the literature does not yet provide uniform evidence on how these dimensions unfold in low-resource or highly unequal settings, and the historical comparisons with calculators, spreadsheets, and statistical software may not fully capture the ethical and governance complexities unique to AI. Consequently, the framework should be viewed as a guiding lens rather than a definitive model. Future research should broaden empirical investigations into underexplored contexts, particularly examining AI adoption in low-resource educational and organisational environments to assess the systemic dimensions of adoption frameworks. Longitudinal studies are needed to capture how adoption trajectories evolve, while comparative analyses across sectors could clarify whether adoption dynamics vary according to professional culture and regulatory context. Evidence suggests that modern computing presents transformative opportunities across industries, yet its adoption is often limited by technical complexity, ethical concerns, and the need for scalable, secure infrastructure [32]. In education, AI integration faces similar barriers, including limited digital literacy, infrastructure gaps, and ethical challenges, highlighting the need for practical, context-sensitive strategies to support implementation [33]. Moreover, spreadsheet tools have been shown to improve assessment practices by providing structured, instrumented approaches that enhance accuracy, analysis, and feedback [34]. Taken together, these findings underscore the imperative of embedding ethical considerations such as trust, bias, and governance at the heart of technology adoption strategies to ensure that AI and digital innovations are implemented responsibly and equitably.

8. Conclusion

Resistance to adopting new technologies is a persistent challenge, shaped not only by individual psychology but also by social norms and institutional structures. Historical examples, from calculators to Excel and statistical software, show that initial scepticism can give way to widespread adoption when users clearly see the value and receive proper guidance, education, and support for integration. Today, organisations face similar challenges with AI adoption, and lessons from these past experiences offer practical guidance. Incremental exposure, hands-on training, pilot programs, and transparent demonstrations of utility can help ease the transition and foster acceptance among users. However, the pace of AI development after 2024 means that the opportunity to build this positive engagement is closing quickly. Future research should assess these strategies in a variety of organisational settings to identify what works best in practice. More importantly, acting promptly is critical: without coordinated, multi-level interventions, organisational inertia may set in, making it harder to implement AI effectively and sustainably. Establishing supportive environments now can ensure AI adoption is not only successful but also resilient in the long term.

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Data availability statement: All data generated or analysed during this study are included in the published article and its referenced sources. No additional datasets were created.

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References

1. Ebrahim AQ, Van den Berg CL. The barriers to technology adoption among businesses in Cape Town's informal economy. South African Journal of Information Management. 2024; 26(1): a1872. doi: 10.4102/sajim.v26i1.1872
2. Jr. Pimentel Singun A. Unveiling the barriers to digital transformation in higher education institutions: A systematic literature review. Discover Education. Research Square Preprint. 2024. doi: 10.21203/rs.3.rs-4970233/v1
3. Noriega Del Valle M, Łaba K, Mayer CH. Unlocking technology acceptance among South African employees: A psychological perspective. South African Journal of Industrial Psychology. 2024; 50: a2177. doi: 10.4102/sajip.v50i0.2177
4. Yurdunkulu A, Bulut MA, Göçen A. From academics to Aidemics: Unpacking the human–AI symbiosis in higher education. Acta Psychologica. 2025; 261: 105796. doi: 10.1016/j.actpsy.2025.105796
5. Brandao PR. The impact of artificial intelligence on modern society. AI. 2025; 6(8): 190. doi: 10.3390/ai6080190
6. Xiao J, Xu Z, Xiao A, et al. Overcoming barriers and seizing opportunities in the innovative adoption of next-generation digital technologies. Journal of Innovation and Knowledge. 2024; 9(4): 100622. doi: 10.1016/j.jik.2024.100622
7. Tshabalala M, Marnewick C. Agile as an enabler towards innovation-based organisational transformations. South African Journal of Information Management. 2021; 23(1): 1–10. doi: 10.4102/sajim.v23i1.1309
8. UNESCO. AI and the Future of Education: Disruptions, Dilemmas, and Directions. UNESCO; 2025. doi: 10.54675/KECK1261
9. Banks SA. A Historical Analysis of Attitudes Toward the Use of Calculators in Junior High and High School Math Classrooms in the USA Since 1975 [Master's thesis]. Cedarville University; 2011.
10. Masuadi E, Mohamud M, Almutairi M, et al. Trends in the usage of statistical software and their associated study designs in health sciences research: A bibliometric analysis. Cureus. 2021; 13(1): e12639. doi: 10.7759/cureus.12639
11. Taber KS. Scaffolding learning: Principles for effective teaching and the design of classroom resources. In: Effective Teaching and Learning: Perspectives, Strategies and Implementation. Nova Science Publishers; 2018. pp. 1–43.
12. Al-Haddad S, Chick N, Safi F. Teaching statistics: A technology-enhanced supportive instruction (TSI) model during the COVID-19 pandemic and beyond. Journal of Statistics and Data Science Education. 2024; 32(2): 129–142. doi: 10.1080/26939169.2024.2315939
13. Übellacker T. Making Sense of AI Limitations: How Individual Perceptions Shape Organisational Readiness for AI Adoption. arXiv preprint. 2025. doi: 10.48550/arXiv.2502.15870
14. Rebman CM, Booker QE, Wimmer H, et al. An industry survey of analytics spreadsheet tools adoption: Microsoft Excel vs Google Sheets. Information Systems Education Journal. 2023; 21(5).
15. Gonçalves RA, Rodrigues SJ. Error in the technological resources used for mathematics education. Modern Sciences

Journal. 2023; 12(2): 38–42.
16. Sahin I. Detailed review of Rogers' diffusion of innovations theory and educational technology-related studies based on Rogers' theory. Turkish Online Journal of Educational Technology. 2006; 5(2): 14–23.
17. Chaamwe N, Shumba L. ICT integrated learning: Using spreadsheets as tools for e-learning, a case of statistics in Microsoft Excel. International Journal of Information and Education Technology. 2016; 6(6): 435–440. doi: 10.7763/IJIET.2016.V6.728
18. Pabilario L. Impact of technological tools on mathematics pedagogy: Data-driven insights into educators' practices in math classrooms. Engineering Proceedings. 2025; 107(1): 5. doi: 10.3390/engproc2025107005
19. Amaliah A, Linggi TT, Suyuthi NF. A comprehensive literature review on the factors influencing resistance to organisational change and strategies for effective management. Journal of Development Management and Economics. 2025; 3(1): 1–9. doi: 10.71435/604109
20. Eltaiba N, Hosseini S, Okoye K. Benefits and impact of technology-enhanced learning applications in higher education in the Middle East and North Africa: A systematic review. Global Transitions. 2025; 7: 350–374. doi: 10.1016/j.glt.2025.06.004
21. Dlamini R, Simuja C, Feldman J, et al. AI in education: Challenges, opportunities, and possibilities. Journal of Education. 2025; 98: 1–4.
22. Abdul Hasim SN, Abu Bakar K. Challenges and impacts of technology adoption in education: A systematic literature review. International Journal of Research and Innovation in Social Science. 2025; 3(5): 7536–7548. doi: 10.47772/IJRISS.2025.903SEDU0558
23. Rönnebeck S, Bernholt S, Ropohl M. Searching for a common ground – A literature review of empirical research on scientific inquiry activities. Studies in Science Education. 2016; 52(2): 161–197. doi: 10.1080/03057267.2016.1206351
24. Chigbu UE, Atiku SO, Du Plessis CC. The science of literature reviews: Searching, identifying, selecting, and synthesising. Publications. 2023; 11(1): 2. doi: 10.3390/publications11010002
25. Snyder H. Literature review as a research methodology: An overview and guidelines. Journal of Business Research. 2019; 104: 333–339.
26. Jasti NVK, Kodali R. A literature review of empirical research methodology in lean manufacturing. International Journal of Operations and Production Management. 2014; 34(8): 1080–1122. doi: 10.1108/IJOPM-04-2012-0169
27. Rogers EM. Diffusion of Innovations, 5th ed. Free Press; 2003.
28. Scholkmann AB. Resistance to (digital) change: Individual, systemic and learning-related perspectives. In: Ifenthaler D, Hofhues S, Egloffstein M, et al. (editors). Digital Transformation of Learning Organisations. Springer; 2020. pp. 219–236. doi: 10.1007/978-3-030-55878-9_13
29. Mhlongo S, Mbatha K, Ramatsetse B, et al. Challenges, opportunities, and prospects of adopting and using smart digital technologies in learning environments: An iterative review. Heliyon. 2023; 9(6): e16348. doi: 10.1016/j.heliyon.2023.e16348
30. Sarwono J. Quantitative, Qualitative and Mixed Method Research Methodology, 1st ed. Independently published; 2022.
31. Díaz-Arancibia J, Hochstetter-Diez J, Bustamante-Mora A, et al. Navigating digital transformation and technology adoption: A literature review from small and medium-sized enterprises in developing countries. Sustainability. 2024; 16(14): 5946. doi: 10.3390/su16145946
32. Gill SS, Wu H, Patros P, et al. Modern computing: Vision and challenges. Telematics and Informatics Reports. 2024; 13: 100116. doi: 10.1016/j.teler.2024.100116
33. Novianti I. An exploratory study on the challenges of AI technology in education and its practical recommendations. International Journal of Social Science Research and Review. 2025; 8(3). doi: 10.47814/ijssrr.v8i3.2481
34. Winnberg M. The use of spreadsheet tools in assessment: an instrumented technique perspective. NOMAD Nordic Studies in Mathematics Education. 2025; 30(1): 83–102. doi: 10.7146/nomad.v30i1.152932