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Dear “e-mentor” readers,

I am delighted to present the latest collection of papers, which represents a significant step towards the redefined scope of our journal: higher education in management and economics.

Readers interested in business education trends can find out about the key challenges of contemporary educational digitalisation from a variety of complementary perspectives. The initial article analyses the expanding role of AI chatbots in higher education, outlining the emerging pedagogical, technological and ethical dimensions of chatbot integration. The second text focuses on the issue of information overload in online learning environments, analysing the sources of information overload and the coping strategies used by students who learn online. The third study offers a long-term policy analysis of educational digitalisation in China, tracing paradigm shifts between 1978 and 2025 through the lens of Hall’s model. The fourth article examines the factors that influence behavioural intention and the adoption of e-learning, including five key elements: accessibility, government policy, organisational support, instructor attitude and technostress.

The part dedicated to trends in management presents four texts that explore how contemporary organisations are reshaped by individual characteristics, technological transformation, and changing competence requirements. The first study examines the relationship between temperament and effective professional functioning among corporate employees, including both specialists and management staff, highlighting the human dimension of managerial performance. The second analyses the transition from smart to agentic environments, showing how AI and innovative technologies are redefining learning, work, and urban living. The third focuses on Generation Z’s concerns and perceived barriers to entrepreneurship, offering insights into managerial and policy challenges related to fostering new business creation. The fourth addresses upskilling and reskilling in the AI era, proposing a new logic of competence development essential for organisational adaptability and long-term competitiveness.

I hope you will enjoy exploring this issue. At the same time, I would like to cordially invite you to contribute to „e-mentor” and to support our efforts to internationalise the journal. Following an analysis of the results of the project financed by the Ministry of Science and Higher Education (Poland) completed in Oct 2024 (RCN/SP/0361/2021/1), we have decided to publish all articles in **English only**. Please be advised that from the beginning of 2025, there will be no further calls for manuscripts prepared in Polish. Furthermore, our goal is to make “e-mentor” a journal that serves as a forum for the presentation and discussion of research and ideas related to teaching and learning in management and economics higher education. We aim to provide a platform for the exchange of knowledge and insights on the use of technology in education, including e-learning, forms and methods of education, the verification of learning effects, and the integration of new trends in management and economics into higher education.

“E-mentor” is an open-access journal available free of charge, both online and in printed form. All scientific papers are peer-reviewed and we provide free proofreading of papers accepted for publication. Every article gets an individual DOI registered in Crossref, and the journal is indexed in several global databases, including Web of Science ESCI and EBSCO. There is **no publishing fee for the authors**. Further details are available online at http://www.e-mentor.edu.pl/eng/page/8/Info_for_Authors. Should you have any questions concerning publications in “e-mentor”, please contact the editorial team at redakcja@e-mentor.edu.pl.

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AI Chatbots in Education – the Future of Teaching and Learning

Abstract

AI chatbots in education can offer substantial benefits for both students and teachers by monitoring learners' progress, adapting to individual learning pace, supporting instruction and enhancing teachers' pedagogical practice. This study aims to outline key strategies and practical guidance for the responsible integration of chatbots into higher education. An initial evidence synthesis was conducted using a systematic–narrative hybrid review of the literature, a simplified PRISMA-style flow diagram and thematic coding of the narrative synthesis; 36 peer-reviewed articles were identified. The review makes an original contribution by mapping emerging pedagogical, technological and ethical dimensions of chatbot adoption that remain under-examined in existing secondary studies. Evolving roles of AI chatbots in learning design, student engagement, interaction and assessment, along with opportunities to strengthen their educational value, are identified. The study also offers practical implications by outlining evidence-informed strategies for instructors, curriculum designers and institutions to support the effective and responsible implementation of AI chatbots. Future work will extend the search to additional databases and examine discipline-specific applications of AI chatbots.

Keywords: chatbots, AI chatbots, education, higher education, teaching and learning

Introduction

Cutting-edge artificial-intelligence (AI) tools, including chatbots, are reshaping many aspects of life by supporting task completion, improving decision-making, and enhancing social interaction in both personal and professional contexts. Challenges facing the education sector by the COVID-19 pandemic accelerated the adoption of AI in teaching and learning. Since then, the integration of AI into educational settings has continued to expand (Ifelebuegu et al., 2023). Market analyses suggest that over 987 million people worldwide use AI chatbots, and forecasts by Research and Markets (2024) indicate that the global chatbot market will reach nearly $46.64 billion by 2029, confirming their increasing adoption across industries.

In education, the use of chatbots has increased markedly since November 2022, when OpenAI released its generative AI (GenAI) tool, ChatGPT (Razak et al., 2023). Prior to ChatGPT, AI had been used in education for many years, primarily within learning-management systems to support administrative tasks. The emergence of GenAI and large language models (LLMs) such as ChatGPT, Google Bard, Apple Siri, and IBM Watson has begun to reshape traditional pedagogical approaches (Davar et al., 2025; Gill et al., 2024; Kujundziski & Bojadjiev, 2025). Educators and institutions have experimented with chatbots not only for administrative automation but also to support learning, formative assessment, and writing and idea generation (Davar et al., 2025; Ifelebuegu et al., 2023).

At the same time, advances in machine learning and access to larger training datasets have improved chatbot performance in tasks such as summarising texts, answering student queries, and offering language-practice activities – often beyond the capabilities of earlier models such as BERT and XLNet (Davar et al., 2025). The deployment of GPT models in education can help address a key limitation of online educational platforms: delays in providing students with timely responses (Ngo et al., 2024). Such

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systems are used across a range of domains, including student support (e.g., admissions and administrative procedures), personalised learning activities tailored to learners' needs and preferences (e.g., improving speaking and writing skills), and academic assistance with tasks such as idea generation and grammar correction, sometimes functioning as 'digital supervisors' (Krumsvik et al., 2025).

The application of chatbots in teaching and learning has attracted substantial scholarly attention (McGrath et al., 2024; Mishra, 2024). This work has focused mainly on their accuracy and the benefits they may offer to students (Abdallah et al., 2024; Wang et al., 2023) and teachers (Mishra, 2024), as well as the drawbacks they may introduce into the educational process (Birenbaum, 2023; Williams, 2023). Building on this literature, our study examines strategies for integrating chatbots effectively into higher education.

Background

Chatbots are computer programs designed to simulate written and/or spoken conversation, enabling users to interact on specific topics via text or voice. They are also referred to by various names, including 'virtual assistants', 'conversational agents', 'smart personal assistants', and 'dialogue systems'. Early chatbots achieved human-like exchanges largely through keyword matching or relatively simple natural language processing (NLP) techniques (Caldarini et al., 2022; Frangoudes et al., 2021; Pergantis et al., 2025). Subsequent advances in machine learning (ML), NLP, and generative AI have enabled more sophisticated applications (Davar et al., 2025; Pergantis et al., 2025), beginning with IBM Watson in 2006. This trajectory continued in 2011 with Apple's voice-activated personal assistant Siri, although Siri is not strictly a chatbot. In 2018, Google's Duplex demonstrated the ability to manage complex, real-time interactions (Davar et al., 2025).

Released by OpenAI in 2022, ChatGPT is a prominent LLM application based on the Generative Pre-trained Transformer (GPT) architecture, specifically GPT-3.5. Owing to its ability to generate human-like text and diverse content, GPT-3.5 and subsequent versions – GPT-4 and GPT-4o ('omni'), released in March 2023 and May 2024 respectively – have gained significant popularity (Kooli, 2023; Plevris et al., 2023). Google developed its own chatbot, Bard, in 2022, with performance comparable to OpenAI's ChatGPT.

The LLM developed by the AI start-up DeepSeek has attracted attention for its competitiveness, improved performance, and lower operating costs compared with ChatGPT. The DeepSeek R1 model can understand and generate text in both Chinese and English.

LLMs now handle a wide range of tasks and are increasingly used in teaching and learning (Leite, 2024). Pre-trained on vast datasets, contemporary generative AI models are capable of understanding context and producing coherent, contextually relevant responses to user queries, reflecting advances in deep learning technology (Kooli, 2023).

AI chatbots play a multipurpose role in education. First, they can automate administrative tasks. Available at any time, AI-based chatbots can provide students with immediate responses and support, thereby improving institutional efficiency (Saleh et al., 2025). Second, through interaction with users, chatbots can map learners' patterns and pace and adjust learning materials to their capabilities. This personalises learning experiences, boosts engagement, and increases motivation (Labadze et al., 2023; Srinivasan et al., 2023). Moreover, chatbots can optimise resource allocation and serve as a critical link in the modern educational landscape (Abdallah et al., 2024). To foster an unbiased and engaging educational environment for all students, education systems need collaboration among educators, policymakers, and chatbot developers to establish principles for the responsible use of these tools, aligned with national strategies for AI implementation (Davar et al., 2025; Labadze et al., 2023).

Despite these benefits, the widespread use of AI chatbots in education also raises concerns and challenges, including academic integrity, plagiarism, and the risk of incorrect or biased outputs (often referred to as 'hallucinations'). Many publications discuss factors involved in integrating emerging AI chatbot technologies into educational settings and identify associated challenges (Annamalai et al., 2023). However, most studies focus on a single aspect of chatbot implementation in academia or on isolated instructional outcomes (e.g., educational methodologies, chatbot accuracy, academic perceptions of integration, or ethical challenges), and there remains a lack of coherent synthesis bringing together pedagogical, methodological, and ethical insights emerging alongside the rapid development of generative AI. Accordingly, this study adopts a comprehensive approach and aims to synthesise a broader set of conceptual patterns to clarify how chatbots are reshaping learning design, student engagement, interaction, and assessment practices in higher education, thereby making an original contribution. By examining current trends, conceptual developments, and implementation challenges, and by identifying the evolving roles and educational functions of AI chatbots in contemporary digital learning environments, the study also contributes to theory. In addition, it offers practical implications by outlining evidence-informed strategies and directions for the integration of chatbots by instructors, curriculum designers, and higher education institutions.

Research question: What strategies support the seamless and successful integration of AI-powered chatbots into academic curricula?

Methodology

This study undertakes an initial evidence synthesis using a systematic–narrative hybrid literature review (SNHLR), combining a structured search strategy with interpretive narrative synthesis. This design is appropriate for emerging and rapidly developing areas such as AI chatbots in higher education, where the evidence base is methodologically diverse (Greenhalgh et al., 2018; Snyder, 2019; Turnbull et al., 2023). In this context, a full systematic review – requiring exhaustive multi-database coverage and formal risk-of-bias appraisal – was neither feasible nor well aligned with the exploratory and integrative aims of the review (Turnbull et al., 2023).

The evidence synthesis comprised peer-reviewed publications investigating the integration, pedagogical applications and implications of AI-powered chatbots in education.

The literature search was conducted in the complementary databases Web of Science (WoS), Google Scholar and Semantic Scholar. As institutional access to Scopus – often considered important for comprehensive systematic coverage – was unavailable, the study was positioned as an initial evidence synthesis supported by the SNHLR design.

Comparable Boolean search strings were used across the three databases, with syntax adapted to each platform to support transparency and reproducibility (Table 1, Appendix).

A PRISMA-style flow diagram (Coupe et al., 2019) is presented in Figure 1 (Appendix). Restricting results to publications from 2021 to 2025, the searches returned 2,487 records (WoS $n = 775$; Google Scholar $n = 1{,}230$; Semantic Scholar $n = 482$). After removing 1,059 duplicates, 1,428 records proceeded to title and abstract screening, guided by predefined inclusion and exclusion criteria (Table 2, Appendix). At this stage, 1,253 records were excluded because they were not related to education, did not involve AI chatbots, focused solely on technical model development without educational application, were not peer reviewed, or were not available as full-text articles in English. A total of 175 full-text articles were then assessed for eligibility.

Full-text eligibility was assessed in relation to the research question and the inclusion criteria. Eligible studies addressed AI chatbots, conversational agents or generative AI systems (e.g. ChatGPT, Bard, Gemini) in a higher-education context; provided empirical evidence, a conceptual model or pedagogical analysis relating to teaching, learning, assessment, or student/teacher perceptions; and were peer-reviewed publications available in full text.

Of the 175 full-text articles, 139 were excluded for the reasons summarised in Table 3. Exclusions included purely technical studies focusing on chatbot architecture or algorithm design (where this could not be determined at title/abstract stage); studies outside higher education; papers that were substantively irrelevant despite keyword matches; and papers with insufficient methodological or theoretical depth. The remaining 36 studies were taken forward for thematic synthesis.

Bibliographic data and thematic content were extracted from each included study (Table 4, Appendix). Using thematic coding within a narrative analytic synthesis, the authors identified recurring patterns and emergent themes, including pedagogical integration and instructional design; student learning and engagement outcomes; educator perceptions and institutional readiness; and the ethical, motivational and evaluative dimensions of chatbot adoption. The coding framework and procedure (including Table 5) are provided in the Appendix. The coding was intended to support narrative synthesis rather than to produce quantitative reliability coefficients, consistent with qualitative interpretive approaches.

Content analysis across themes provided an integrated understanding of how AI chatbots contribute to, challenge and reshape educational practices. To enhance the reliability of the review and reduce potential bias, the two reviewers (A.P.K. and N.A.) analysed the papers independently. Disagreements were discussed and resolved by consensus.

Given the study's emphasis on an initial, structured evidence synthesis and the methodological diversity of the included studies, formal risk-of-bias tools (e.g. the Cochrane checklist or the Mixed Methods Appraisal Tool, MMAT) were not applied. This is a limitation of the review and reinforces its positioning as an initial evidence synthesis rather than a full systematic review. Nevertheless, quality was supported through clearly specified inclusion criteria, transparent screening procedures and an evidence-informed synthesis of findings (Wiboolyasarin et al., 2025).

The Integration of AI Chatbots in Education

The four emergent themes together provide a comprehensive framework for addressing the central research question: how best to integrate AI-powered chatbots into academic curricula. Each theme, synthesised through thematic content analysis, captures a distinct strategic dimension of integration – pedagogical design; learning impact, monitoring and evaluation; stakeholder readiness; and ethical and governance considerations. Taken together, these dimensions address the chatbots' roles and intended uses, pedagogical design principles, technology selection, implementation, and mechanisms for ongoing monitoring and evaluation (see Figure 2 in the Appendix). Although AI chatbots can benefit all educational stakeholders, their incorporation into education presents substantial challenges relating to reliability, accuracy, and ethical implications, which require careful scrutiny if their benefits are to be maximised (Groothuijsen et al., 2024; Ngo et al., 2024).

Identifying Chatbot Roles and Principles for Pedagogical Design

Identifying a chatbot's primary role and functions is the first step towards integrating AI chatbots into education. Depending on the intended use, a chatbot may provide administrative (service-oriented) support, act as a teaching- or tutoring-oriented platform, or support research and development by assisting with information retrieval and guidance (Baglivo et al., 2023; Moral-Sánchez et al., 2023; Okonkwo & Ade-Ibijola, 2021).

Service-oriented chatbots – designed primarily for administrative assistance – such as Ask L.U. (Abbas et al., 2022), respond to routine queries about timetables, grades, enrolment, fees, campus services, and admissions, providing efficient and timely support to users (Labrague & Sabei, 2025). They may also be used to orient students to university life, as in the cases of Lisa and Differ (Al-Abdullatif et al., 2023). Such chatbots can be integrated into an existing learning management system (LMS) (e.g., Moodle) or deployed via popular messaging applications such as WhatsApp and Twitter (Kumar, 2021), Telegram (Merelo et al., 2022), or Facebook Messenger; examples include Dina, Ask Holly, and Lola (Roca et al., 2024). This integration enables the automation of routine tasks, including responses to frequently asked questions. Performance is commonly assessed through user questionnaires or by the proportion of satisfactory responses generated, and reported results are generally encouraging (Abbas et al., 2022).

LLM-based systems that support adaptive and personalised learning can provide tailored tutoring by aligning learning materials with individual needs, learning styles, and proficiency levels, while also offering prompt feedback (Al-Abdullatif, 2023; Calonge et al., 2023; Chang et al., 2023; Lai, 2024; Liu & Reinders, 2025; Mageira et al., 2022). However, their use may reduce student–teacher interaction, encourage overreliance on chatbot responses, and expose learners to hallucinated outputs. Seamless integration in higher education therefore requires clear decisions about the chatbot's role and the pedagogical goals it serves, alongside an assessment of ethical and operational risks and strategies to minimise or mitigate them.

Although the reviewed studies highlight the instructional value of chatbots, broad generalisation is not warranted because chatbots are conceptualised differently across contexts. Several authors (Calonge et al., 2023; Chang et al., 2023; Lai, 2024; Liu & Reinders, 2025) describe chatbots as instructional partners that provide adaptive tutoring and feedback. By contrast, studies focusing on administrative or advisory applications (Abbas et al., 2022; Merelo et al., 2022; Roca et al., 2024) imply different pedagogical expectations, contributing to inconsistency across settings (Okonkwo & Ade-Ibijola, 2021).

Experimental studies (Essel et al., 2022; Mageira et al., 2022) tend to offer stronger evidence than survey-based research (Awad & Moosa, 2024; Ilieva et al., 2023), which captures perceptions rather than directly measuring chatbot performance. Multiple studies (Al-Abdullatif, 2023; Calonge et al., 2023; Chang et al., 2023) report that adaptive systems can facilitate and enhance learning. Achieving such benefits may require instructors to shift from traditional, exam-focused approaches towards learning-oriented pedagogies that promote critical thinking (Chang et al., 2023).

Some researchers report improved learning performance and critical thinking when students interact with chatbots using well-designed prompts (Chang et al., 2023; Lai, 2024). Conversely, overreliance on AI may reduce human-to-human interaction (Moral--Sánchez et al., 2023) and limit learners' critical reasoning (Husain, 2024). Taken together, these findings suggest that successful implementation depends not only on technical capability, but also on alignment between chatbot operation, pedagogical objectives, and instructor oversight.

Teaching- and learning-oriented chatbots can function as intelligent tutors. They deliver educational materials and adaptive support, helping students learn specific subjects through explanations, formative assessment tracking, and immediate, customised feedback (Abbas et al., 2022; Calonge et al., 2023; Essel et al., 2022; Ilieva et al., 2023; Mageira et al., 2022). AI chatbots can support students' self-regulated learning (Chang et al., 2023; Essel et al., 2022) and self-directed learning (Al-Abdullatif, 2023; Chang et al., 2023). They may also enhance higher-order cognitive skills (e.g., critical thinking and problem-solving) (Frangoudes et al., 2021; Moral-Sánchez et al., 2023) and metacognitive skills, as reported for the chatbot Bashayer (Al-Abdullatif et al., 2023).

Chatbots can also surface learning-analytics information – such as time spent on a page, click history, assignment deadlines, and overall progress – enabling students to take greater control of their learning and allowing instructors to encourage active learning and make informed judgements about progress (Chang et al., 2023; Lai, 2024). Because these functions involve sensitive data, there are risks relating to privacy and non-compliance with data protection regulations (Ifelebuegu et al., 2023; Ilieva et al., 2023; Kumar, 2021). The use of anonymised datasets and adherence to institutional data-governance protocols can help mitigate these risks.

Findings on the development of students' self-regulated learning are mixed (Chang et al., 2023; Hwang & Chang, 2023). Where improvements are observed, they appear to stem from chatbot designs that use structured prompts, guided questioning, and individualised feedback (Al-Abdullatif, 2023; Chang et al., 2023; Essel et al., 2022). When feedback is overly generic, students may treat chatbots as answer generators, resulting in shallow engagement (Husain, 2024). Students also often struggle to identify errors in AI-generated content, which may indicate limited critical scrutiny. Similarly, integrating chatbots within active-learning pedagogies, such as problem-based learning – often alongside gamification – can improve engagement, motivation, and learning outcomes, but may also create risks of overdependence on gameplay and a loss of learning focus (Kumar, 2021; Lin & Chang, 2023). Potential mitigations include monitoring depth of learning through engagement analytics and limiting chatbot features that are not aligned with learning goals. Overall, the literature suggests that chatbot success depends on well-designed instruction and reflective learning activities (Calonge et al., 2023), as well as students' capacity to evaluate and improve AI-generated content (Essel et al., 2022).

Regardless of the purpose for which a chatbot is used – whether to improve teaching efficiency and reduce instructors' workload (Abbas et al., 2022; Calonge et al., 2023; Essel et al., 2022; Ilieva et al., 2023; Mageira et al., 2022) or to develop particular learner skills (e.g., language learning and communication skills) (Hwang & Chang, 2023; Kim et al., 2021) – the literature recognises a range of challenges. These include plagiarism, bias in teaching materials, threats to assessment validity, language bias, contextual inaccuracies, and cultural misinterpretations. Comparable risks arise when chatbots aggregate learning materials from multiple sources and provide simultaneous access to learners across geographical locations and time zones. At the same time, such systems can support collaborative learning and offer distinctive learning experiences (Al-Abdullatif, 2023; Lai, 2024; Liu & Reinders, 2025). To mitigate these issues, the literature recommends clear disclosure policies, hybrid human–AI evaluation workflows, and plagiarism-resistant assessment formats.

Practical Implementation Factors and Transferable Implications for Curriculum Design

As the literature indicates, some of the most significant practical implementation challenges associated with integrating chatbots in education concern compatibility with existing platforms, access to chatbot-development tools, instructor readiness, digital literacy, and curriculum alignment (Al-Abdullatif et al., 2023; Essel et al., 2022; Kumar, 2021; Labadze et al., 2023; Merelo et al., 2022). In practice, this can create tensions between innovation and academic integrity: whilst chatbots may enhance formative learning, their use in summative contexts remains problematic.

In terms of curriculum design, the main implications relate to pedagogical redesign (Abbas et al., 2022; Awad & Moosa, 2024; Calonge et al., 2023), the adaptation of learning environments (Chang et al., 2023; Lai, 2024), assessment practices (Essel et al., 2022), skills development and AI literacy (Labadze et al., 2023; Liu & Reinders, 2025), and staff capacity building (Labadze et al., 2023). Building on the preceding discussion of pedagogy, curricula should adopt a blended (hybrid) model in which AI provides personalised guidance, whilst instructors retain pedagogical control (Abbas et al., 2022; Calonge et al., 2023; Chang et al., 2023; Lai, 2024; Liu & Reinders, 2025). This approach can scaffold self-regulated learning (SRL) and student autonomy (Al-Abdullatif, 2023; Lai, 2024; Liu & Reinders, 2025), as illustrated by Lin and Chang's (2023) 'CHAT-ACTS' framework. Provided that these principles are followed, chatbots can be framed as complementary instructional partners rather than replacements for teachers (Husain, 2024).

Assessment practices are another critical factor in ensuring coherent chatbot integration. It has been recognised that traditional assessment methods based on the recall of memorised facts are insufficient in AI-supported education to capture the competencies required in today's labour market. One strategy to address this gap, suggested by several authors (Abbas et al., 2022; Essel et al., 2022), is to adopt Assessment for Learning (AfL) principles. Studies indicate that shifting from paper examinations to oral examinations, group projects, portfolios, and case studies – and incorporating instructor-designed reflective components (e.g., guided self-assessment prompts, comparative analysis tasks, or ethics-focused questions) – can enable students to evaluate AI-generated content critically in terms of reliability, bias, and ethical implications (Calonge et al., 2023; Lai, 2024).

Chatbot integration is also more challenging when AI literacy among both instructors and students is low. Instructor readiness depends on understanding basic AI concepts, including how models are trained and how information is retrieved, alongside the ability to appraise AI-generated content for accuracy, bias, reliability, and ethical issues (Labadze et al., 2023; Liu & Reinders, 2025). By contrast, readily accessible no-code platforms such as DialogFlow, Flow XO, and Botsify allow educators to design and customise chatbots without extensive programming knowledge (Essel et al., 2022), thereby lowering the technical barrier to integration. Kumar (2021), for example, describes the chatbot QMT212, built using Textit and integrated with Telegram, Twitter, Facebook Messenger, and SMS.

However, no-code tools improve accessibility rather than guaranteeing pedagogical readiness. This highlights the need for hands-on training for instructors on chatbots' capabilities and limitations, potential applications, customisation, and best practices for integrating these tools into teaching methodologies (Essel et al., 2022; Labadze et al., 2023), alongside professional development programmes focused on designing AI-inclusive syllabi, developing blended teaching strategies, and establishing ethical guidelines for data use. Such professional development is necessary to retain educators' central role in a rapidly evolving technological environment (Al-Abdullatif, 2023; Labadze et al., 2023).

As previously noted, the implementation of chatbots in educational practice has faced challenges relating to the accuracy of the outputs they generate, as well as limited user familiarity with the technology. Accordingly, pre-implementation analysis and evaluation of chatbot accuracy and efficiency is an important element of integration. This may involve objective metrics derived from analytics (e.g., the proportion of correct answers provided by the chatbot, or time to task completion), whilst subjective measures rely on users' perceptions of chatbot accuracy (Frangoudes et al., 2021; Navas et al., 2024).

Beyond effectiveness and accuracy, recent studies have highlighted implications relating to transparency and ethics (Awad & Moosa, 2024; Krumsvik et al., 2025; Razak et al., 2023), the reliability of chatbots across domains (DaFonte et al., 2025; Navas et al., 2024), and broader societal impact (Gill et al., 2024). Evaluations of AI models (e.g., ChatGPT, Gemini, and Claude) suggest that reliability is task- and context-dependent, limiting transferability across domains (Husain, 2024; Lai, 2024); for instance, performance in medical knowledge does not necessarily translate into statistical reasoning or critical thinking. As shown by Navas et al. (2024), both versions of ChatGPT (GPT-3.5 and GPT-4.0) demonstrated lower accuracy in solving statistical problems than Bing. DaFonte et al. (2025) similarly found Claude 3.5 Sonnet and ChatGPT o3-mini to be more reliable in medical-surgery tests than Gemini 2.0 Flash and ChatGPT-4o mini, but to underperform in critical thinking and decision-making. Different cultural contexts and infrastructural constraints introduce additional barriers to transferability (Al-Abdullatif, 2023; Gill et al., 2024; Liu & Reinders, 2025). For example, models trained predominantly on English-language data often exhibit linguistic and cultural biases when deployed in non-English-speaking regions or culturally diverse learning environments. Moreover, limited readiness, alongside geopolitical and legal constraints (such as internet censorship), can materially affect the feasibility and transferability of AI deployment (Davar et al., 2025). Overall, the literature suggests that effective incorporation in educational contexts requires robust implementation mechanisms and monitoring frameworks, as well as policies that support contextual flexibility whilst maintaining shared international principles of fairness, transparency, and accountability in the educational use of AI (DaFonte et al., 2025; Frangoudes et al., 2021; Navas et al., 2024).

Ethical Aspects, Policies and Risk Governance

Establishing robust, transparent and human-centred frameworks for policy, curriculum and risk governance is essential for the effective integration of AI chatbots and LLMs across diverse educational settings. As the curriculum implications have already been discussed, this section focuses on ethical and policy challenges. AI-powered systems can access and process large volumes of personal data, raising concerns about privacy and data security (Ifelebuegu et al., 2023; Ilieva et al., 2023; Kumar, 2021). This highlights the urgent need to develop detailed policies, guidelines and protocols that comply with the General Data Protection Regulation (GDPR) to mitigate these risks (Williams, 2023).

AI systems may also be trained on datasets that include unethical content, gender stereotypes or other forms of discrimination, which can result in biased models (Calonge et al., 2023). Although AI systems are increasingly widespread, their underlying mechanisms and decision-making processes often remain opaque; in this sense, they function as 'black-box' models. Consequently, users may not have access to clear explanations of how a system processes their data, which can increase scepticism towards AI chatbots (Ifelebuegu et al., 2023).

An ethical framework is therefore required to ensure the responsible and transparent use of AI chatbots in research and education. Academic dishonesty and the broader ethical implications of AI technologies are additional risks associated with deploying AI chatbots in education. The use of chatbot technologies for teaching, learning and research – together with the capacity of AI-generated content to circumvent conventional plagiarism-detection tools (Sobaih & Abuelnasr, 2025) – raises questions about authorship, academic integrity, plagiarism and cheating (Mariyono & Hidayatullahet, 2025; Raptopoulou, 2025). Collectively, these publications underline the need for universities and national education agencies to develop a robust legal framework, including clear guidance and data-protection standards aligned with the GDPR, to support the ethical use of AI chatbots. Moreover, cooperation between institutions across regions, in line with UNESCO's (n.d.) recommendations on AI in education and the OECD's (n.d.) AI principles could help to develop governance models that accommodate cultural and legal variation.

On the basis of the literature reviewed, several practical implications emerge for institutions, instructors and learning designers. Instructors should treat AI chatbots as supportive tools and prioritise low-risk uses, particularly in large classes or blended-learning environments, where they can provide automatically generated explanations and just-in-time feedback. Effective implementation also requires alignment with the curriculum and the avoidance of ad hoc deployment. In addition, professional development and training programmes that build AI literacy can help staff address academic integrity issues associated with generative AI. Finally, educational institutions should establish governance arrangements that set data-protection standards, ethical-use protocols and rules for transparency.

Conclusions

This study employs a systematic literature review to identify strategies and to propose a framework for the successful integration of AI tools – particularly AI chatbots – within education. An initial evidence synthesis was undertaken using a systematic–narrative hybrid review of three complementary databases. Boolean search strings, predefined inclusion and exclusion criteria, and thematic coding within a narrative analytic synthesis were used to identify 36 peer-reviewed articles published between 2021 and 2025. The synthesis highlighted themes relating to the pedagogical integration and instructional design of AI chatbots, learning outcomes, AI literacy and institutional readiness, and the ethical and legal compliance of educational chatbots. Effective integration depends on comprehensive, human-centred institutional policies and compliance with regulations such as the GDPR, in order to mitigate academic dishonesty and algorithmic bias and to ensure adequate transparency regarding chatbot operation.

Despite providing a comprehensive overview of strategies for the seamless, unbiased and transparent integration of chatbots in education, this review has several limitations. Although three databases were consulted, the study relied on only one major indexed database (Web of Science), as restricted access prevented the inclusion of Scopus. Consequently, the authors focused on an initial evidence synthesis rather than a full systematic literature review. Moreover, given the methodological heterogeneity of the included studies, formal risk-of-bias assessment tools were not applied, which constitutes a further limitation. Future research should validate these findings using additional databases and standardised quality appraisal frameworks. Further studies could also examine the application of AI chatbots in disciplines that remain under-represented in this literature, such as economics and administrative sciences.

The appendix is available in the online version of the journal.

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Information Overload and Coping Strategies among Online Learning Students

Abstract

This study aims to analyse the sources of information overload and the coping strategies used by students who learn online. The students' opinions were analysed using a survey method, including a set of questions prepared by the authors. A sample of $N = 131$ students from various fields of study at the Nicolaus Copernicus University in Toruń (Poland) were interviewed in the survey. The findings of the study indicate that students declare more anxiety and difficulties in the form of on-site rather than online classes. The respondents primarily cited sources of information that triggered information overload, including instructions and assignments to be completed during their studies and social media content. Among the coping strategies, the highest percentage of respondents indicated making selections, reading only selected teaching materials, compiling their notes, and dividing tasks over time.

Keywords: information overload, online learning, student, digital literacy, cognitive load

Introduction

As a result of the development of digital technologies and educational experiences during the COVID-19 pandemic, interest in online learning[1] has increased dramatically among researchers and academic practitioners (Atlam et al., 2022; Khan, 2023; Zheng et al., 2020). Despite the increasing availability of technological solutions and opportunities to support the learning process, this form of learning can contribute to information overload for some individuals (Bawden & Robinson, 2020; Masrek & Baharuddin, 2023). It can also result in problems remembering large volumes of information, reduced ability to process and understand it, increasing frustration and lack of engagement in learning (Bawden & Robinson, 2020; Feroz et al., 2022). It is necessary to acquire and develop the above competencies, including those essential to managing information in different contexts, not only academic ones. Designing e-courses to avoid or minimise information overload for learners is a crucial aspect of creating motivating and valuable learning experiences. More research is still needed on this issue in Poland. Hence, there is a need to undertake the following theoretical and empirical analyses.

Cognitive Load Theory

One prominent theory presenting the limitations of learning processes resulting from digital technologies is John Sweller's cognitive load theory (Sweller, 2003; Sweller et al., 2019; van Merriënboer & Sweller, 2005). It assumes that the properties of working memory contribute to the limitation of learning processes, resulting in a so-called cognitive load. The load stems from the finite capacity of the working memory and the short-term storage of information in it (approximately 20 seconds). Processing limitations mainly concern learning processes based on acquiring new information

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[1] In accordance with Order No. 162 of the Rector of the Nicolaus Copernicus University in Toruń, the online learning referred to in this text may be conducted as e-classes, in which the entire course programme and ongoing monitoring of participants' progress are carried out remotely, or as complementary forms, in which only part of the classes is conducted using distance learning methods and techniques. For the purposes of this text, this term refers to any of the above forms of education carried out using distance learning methods and techniques.

through the senses. Organising knowledge into cognitive schemas is necessary to reduce the burden on working memory. Their construction involves interpreting, giving examples, classifying, inferring, differentiating, organising (Mayer, 2002; Mayer & Moreno, 2003) and relating processed information to knowledge structures stored in long-term memory. We can distinguish three types of cognitive load (van Merriënboer & Sweller, 2005):

- intrinsic load – describes cognitive load of an intrinsic nature. It is a result of the type and structure (complexity) of the learning material and the learner's knowledge and experience of it;
- extraneous load – describes cognitive load of an external nature. This is due to how the learning material is presented and the conditions in which the learning process takes place (distractors will intensify the cognitive load, e.g. mobile phone, television, noise, distraction effect – so-called multitasking, etc.);
- germane load – refers to the load of part of the working memory resources that results from the need for cognitive processing of educational material.

Cognitive load is the mental effort required to perform a task, depending on the volume of cognitive resources employed. Thus, attention to irrelevant information deprives the individual of cognitive resources that could otherwise influence task outcome.

According to the above theory, tasks should be designed to minimise the extraneous load, maximise the germane load and optimise the intrinsic load. The intrinsic load should also be adjusted to an appropriate level to optimise learning, taking into account the interaction between the task's difficulty and the learner's knowledge in the area (Sweller, 2010). The extraneous load can be lowered by modifying the instructional procedure accordingly – in this case, some working memory resources can be freed up to process the intrinsic load (van Merriënboer & Sweller, 2005).

An essential element of this theory is the concept of expertise. This knowledge is formed when simple structures are captured in complex cognitive schemas, and automation occurs due to repeated use of these schemas (Sweller et al., 2019). An automated schema allows memory processes to be managed efficiently, saving memory resources for other cognitive activities (van Merriënboer & Sweller, 2005). Given the critical role of cognitive schemas in the development of expertise, tasks should be structured so that new information aligns with existing knowledge (van Merriënboer & Sweller, 2010). The theory analysed assumes that the cause of working memory load is the interactivity of the learning materials (task elements). Interactivity is understood as the interaction between the structures of the information being processed and the learner's existing knowledge and experience (van Merriënboer & Sweller, 2005). The task's interactivity may vary depending on the learner's knowledge and experience. When the learner has experience solving tasks with a specific repetitive pattern, a new task in a familiar form will be perceived as less interactive than when the learner is dealing with such a task for the first time (Ciesielska & Szczepanowski, 2019). Cognitive load theory assumes that when a learner has prior knowledge of a topic, the intrinsic load is lower (Ciesielska & Szczepanowski, 2019, p. 80). A high level of previous knowledge means the information is readily available and can be retrieved quickly. For complex problems, some novices may underestimate this complexity and thus declare a lower intrinsic load than experts (Endress et al., 2022, pp. 307–309). On the other hand, Martin Valcke (2002) – in addition to the previously mentioned load types – introduced the metacognitive load. He demonstrates that some learners can cope with extraneous mental load through metacognitive activities such as monitoring, controlling, selecting, and organising sensory information (Valcke, p. 151).

Cognitive load theory is one of many approaches to analysing learning, and its application is relevant to the design of effective teaching methods and digital learning materials (cf. van Merriënboer & Sweller, 2010). It also provides a framework for understanding how people process information and what factors influence the effectiveness of the learning process. Applying this theory in education can lead to more effective and tailored educational practices for learners, thus reducing their cognitive load and information overload.

Educational technologies, by providing access to a large number of diverse information resources, contribute not only to cognitive load but also to information overload resulting from an excess of processing capacity, as will be further discussed later on (Graf & Antoni, 2021; Feroz et al., 2022; Surbakti et al., 2024).

Information Overload vs Cognitive Load

Information overload is defined in various contexts. In terms of education, it is indicated as a condition resulting from information excess beyond the learner's capacity (Feroz et al., 2022). Regarding cognitive load, information overload occurs when learners' working memory capacity is exceeded, and excessive information and stimuli in the computer-based learning environment interfere with the learning process (Chen et al., 2011).

The causes of overload can be considered under four headings: too much information; diversity, complexity, and novelty of information; pervasive and pushed information; and personal factors and individual differences (Bawden & Robinson, 2020). Research reveals the causes of information overload, which include the amount and fragmentation of information, the need to constantly log on to keep up with information in a discussion forum, the reception of information beyond one's ability to process it; information entropy occurring when there is uncertainty about the source of information or difficulty in recognising the meaning of information; stress caused by the inability to access, understand or use necessary information (Bawden & Robinson, 2020; Shahrzadi et al., 2024). Another reason may be inadequate organisation or presentation of information, or a need for more understanding of the information environment (Bawden & Robinson, 2020; Shahrzadi et al., 2024).

Researchers indicate the multiple causes of information overload, highlighting the importance of the level of information literacy, the complexity of the task, lack of prior subject knowledge, motivation level, and modes of content presentation (Arnold et al., 2024; Bawden & Robinson, 2020; Bond et al., 2021; Ritter, 2025; Roetzel, 2019). Research also shows that students with higher metacognitive skills tend to process more information and achieve deeper learning (understood as knowledge application, analysis, evaluation and synthesis) (Chen et al., 2011). To relieve the cognitive load of students, it is therefore worth employing cognitive software tools (graphical user interfaces, developed multimedia), including optimally designed animations in educational content (Chang & Yang, 2010; Dwyer & Dwyer, 2006; Le Cunff et al., 2025), digital maps and models, as well as more interactive tasks, (including collaborative tasks) (Kwiatkowska & Wiśniewska-Nogaj, 2022). Information management skills are also essential, contributing to learning effectiveness and helping to understand and cope with information overload (Shahrzadi et al., 2024).

Martin Valcke argues that information overload and cognitive load can interfere with cognitive and metacognitive processes (Valcke, 2002, pp. 103–104). Attention overload occurs when a person experiences something; the accompanying distractions result in a loss of information due to limited sensory and working memory capacity. Storage and retrieval processes become overloaded, resulting, among other things, in an inability to link new information to previously acquired knowledge (Valcke, 2002, p. 104). Valcke assumes that information overload initiates cognitive load. Furthermore, he equates information overload with external cognitive load. Finally, based on his research, he finds that those identified as 'at risk' (i.e., declaring low levels of prior knowledge, knowledge of the language of instruction and information skills) reported more significant difficulties related to information overload. He also identified their sources, i.e.: (a) *problems with the videoconferencing connection and its configuration*; (b) *navigational difficulties* with excessive hypertext structure, problem with identifying discussion authors; (c) *discomfort with online communication* – lack of computer skills, poor typing skills, time-consuming and time constraints due to work and family commitments, difficulty reading long texts from the computer screen; (d) *problems resulting from an excess of ongoing discussions* – too many incoming discussion messages, numerous resources available on the course website, insufficient information selection skills; (e) *difficulties in organising* – learning due to too many ongoing learning tasks and discussions, (f) *problems with reading comprehension* (slow reading of text due to poor language skills, need to print out extensive studies).

An analysis of existing research on information overload and cognitive load points to the need to identify the sources of these phenomena and to develop strategies for addressing them in distance learning contexts.

Research Methodology

This paper assumed the following objectives: 1) to learn about the sources of information overload in student learning, and 2) to learn how students can cope with information overload.

This paper details the following research questions:

P1. Has distance learning increased the sense of information overload?
P2. Does online learning cause more anxiety and difficulty than on-site learning?
P3. What sources of information make students feel overloaded?
P4. What coping strategies do students employ to cope with information overload?

Findings

Material and Method

The findings described below form part of a more extensive research programme (additional results can be found here: Wiśniewska-Nogaj et al., 2025). The survey was posted online in a closed system (i.e., it could only be completed via a link). The survey's authors received a favourable opinion from the NCU Research Ethics Committee. Respondents received a survey link at the e-mail address associated with their student account. The survey was conducted between April and May 2023. Before completing the survey, information was provided about respondents' rights, how the data would be used, and how to contact the person in charge of the research programme. The students were allowed to continue only after accepting this information and agreeing to participate. The landing page was visited more than 540 times, but not all visitors chose to proceed with the survey. From the entire group of respondents, those who had experienced information overload in the past four weeks were included in the study (N = 223). Subsequently, those who had not taken online classes in the last four weeks were excluded (N = 92, 41.2%)[2]. The final study group consisted of 131 people.

[2] As a result of the COVID-19 pandemic, complementary forms of education have gained significance, with an emphasis on synchronous distance learning. Currently, students can complete the entire subject in either a **synchronous** or **asynchronous** format. It is also permitted to conduct up to 20% of the teaching hours for a given course in a synchronous online format.

The research tool was a set of questions aimed at answering the following research questions:

1. Has online learning increased the sense of information overload?
2. Has online learning caused more anxiety and difficulties?
3. What do students consider to be sources of information overload?
4. What coping strategies in online learning do students present to cope with information overload?

The results obtained are presented and analysed below.

Results

The data from 131 respondents were analysed using the PS Imago 9 package (SPSS for Windows, version 29).

The first issue considered whether online learning has increased the sense of information overload. Most respondents answered that this did not happen (definitely not: $N = 20$, 15%; no: $N = 22$, 17%, rather not: $N = 36$, 27%). More than a third of respondents answered in the affirmative (definitely yes: $N = 18$, 14%; yes: $N = 13$, 10%; rather yes: $N = 16$, 12%). Only less than 5% of respondents ($N = 6$, 5%) had no opinion on this issue.

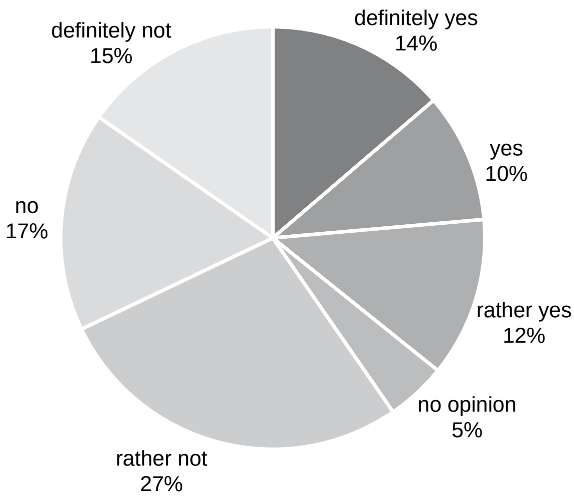
Another question concerned whether online learning causes more anxiety and difficulty than on-site learning. Most respondents answered negatively (definitely not: $N = 22$, 17%; no: $N = 22$, 17%, rather not: $N = 28$, 21%). 44% respondents answered affirmatively (definitely yes: $N = 24$, 18%; yes: $N = 16$, 12%; rather yes: $N = 18$, 14%). One respondent was undecided.

Students were then asked about different sources of information overload, including those regarding their studies, as well as their personal lives. The highest percentage of respondents (61.1%) favoured instructions and tasks to be completed during their studies. Social media content was cited by 40.5% of respondents compared to (35.1%) for Internet content and (28.2%) for traditional educational material. Interestingly, when given a choice of different sources of overload, respondents were more likely to identify on-site classes (36.6%) rather than online classes as causing a sense of information overload.

Another area concerned coping strategies. An analysis of the data in Table 2 shows that the most commonly used strategies relate to self-directed activities such as selection (chosen by 66.4% of the students) and content visualisation (54.2%), as well as activities with others – collaboration with other course participants (54.2%).

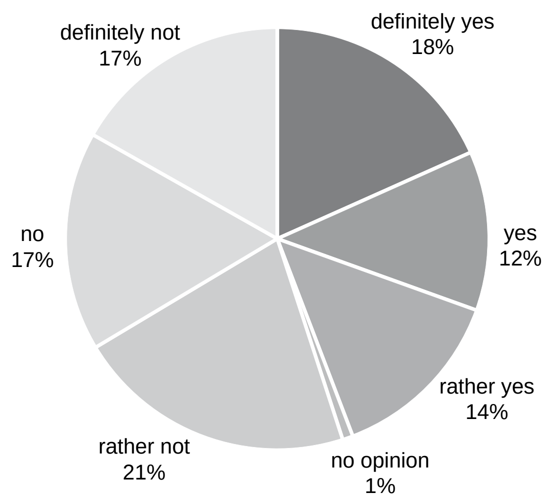
The next step was to analyse the number of strategies students employed (Figure 3). Of those surveyed, 3 persons (2%) do not use any of the proposed strategies (or propose their own). Just over a fifth ($N = 27$, 21%) use a single strategy. A similar number of students use two ($N = 43$, 33%) and three ($N = 41$, 31%) strategies. Most respondents (13%; $N = 17$) use 4 of the 6 proposed strategies.

Figure 1
Online Learning as a Form of Information Overload, as Perceived by Students



Source: authors' own work.

Figure 2
Online Learning as a Source of Anxiety and Difficulties as Perceived by Students



Source: authors' own work.

Students were also allowed to describe their ways of dealing with information overload in online learning. Nine respondents used this option, of whom three replied that they do not cope with the situation. Other responses highlighted difficulties in coping and the high emotional cost of stress and anxiety or minimising effort (downloading, learning on the fly, skipping some information).

Notably, respondents experience the adverse effects of information overload during on-site rather than online classes. In contrast, the three persons who declared they could not cope with the overload

Table 1
Different Sources of Information Triggering a Sense of Overload as Perceived by Students

Sources of information triggering a sense of overload	*N*	%
Instructions and tasks to be completed during the course of study	80	61.1
Social media content	53	40.5
On-site classes	48	36.6
Internet content	46	35.1
Traditional educational materials	37	28.2
E-mails	36	27.5
Social media notifications	34	26.0
Digital educational materials	29	22.1
Television content	21	16.0
Online classes	19	14.5
Electronic communicators	18	13.7
Telephone calls	15	11.5
Discussions and meetings with friends	12	9.2
Radio news	6	4.6

Note. * Students could select a maximum of 3 answers.
** Sources were arranged from most to least frequently selected.

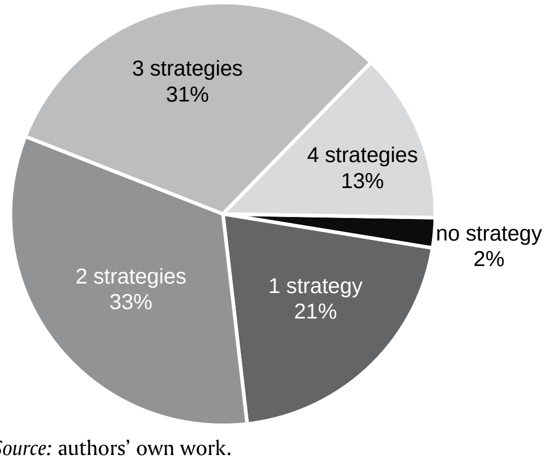
Source: authors' own work.

Table 2
Coping Strategies in Online Learning Overload

Dealing with online learning overload	*N*	%
Selection and reading only singled out teaching materials	87	66.4
Making one's own short notes, use of content visualisation techniques	71	54.2
Cooperation with other students	71	54.2
Dividing tasks over time and making sure there is time for rest	55	42.0
Avoiding action, i.e. not doing the tasks during the course	17	13.0
Report this to the academic teacher with a request to adjust the volume of learning material accordingly	3	2.3

Source: authors' own work.

Figure 3
Number of Coping Strategies in Online Learning Overload



Source: authors' own work.

described their own ways, including making their own notes, learning materials, and selecting information. Therefore, they undertake certain activities to address the problem.

The next step in the data analysis was to assess which strategies co-occurred most frequently.

Analysis of the data in Table 3 shows that more than one-third of the students select learning materials and make their notes based on them, using various visualisation methods ($N = 48$). A similar number of students familiarise themselves only with selected materials and simultaneously seek to collaborate with others ($N = 46$). In contrast, around one-fourth of students collaborate with others and 1) visualise content ($N = 35$) and 2) schedule task completion over time ($N = 35$). Slightly fewer students divide tasks over time, taking care of their resources (e.g. relaxation time) while aiming for 1) the selection of

Table 3

Co-Occurrence of Information Overload Coping Strategies

	Help	Selection	Visualisation	Division	Avoiding	Cooperation
Help	X	2	2	2	0	3
Selection	2	X	48	33	13	46
Visualisation	2	48	X	33	3	35
Division	2	33	33	X	4	35
Avoiding	0	13	3	4	X	9
Cooperation	3	46	35	35	9	X

Source: authors' own work.

learning materials (N = 33) and 2) visualisation of them (N = 33). Interestingly, just under 7% of students, on the one hand, avoid activities in an online course but simultaneously seek to collaborate with other students, and around 10% avoid assignments and select materials.

Discussion of Study Findings

Previous studies indicate that information overload is a problem experienced by online learners. In contrast, the study shows that on-site studying is a more significant source of information overload for students. This can be explained by the need to be more active, more frequent communication directly with the teacher and other students, multiple responsibilities and tasks. Presumably, factors such as the need to commute and inadequate social conditions (including lack of rest and regeneration opportunities between classes) play a role in the poorer coping with information overload in university studies. Among the sources of information, the most overwhelming sense of overload is caused by the instructions and tasks to be completed during the study, which may be due to their quantity, complexity, and the vagueness of their wording. It appears that the instructional format – whether in-person or online – does not significantly influence this. What matters is the careful assignment of tasks and the clarity and precision of the instructions provided.

In a situation of perceived information overload, the students surveyed overwhelmingly select messages, make brief notes, visualise educational content, collaborate with peers, and stagger tasks. Therefore, their actions can be considered proactive and focused on changing the situation – both through their own actions (evident in the use of strategies such as information selection, visualisation, or appropriate planning) and in collaboration with others. The latter group of remedial behaviours can be considered to enable the sharing of duties and responsibilities, perhaps resulting in a greater sense of security and a greater level of commitment or openness to new challenges. Notably, one-fifth of students in online learning use a single coping strategy, whereas two groups, each approximately one-third, use two or three. It seems that the development of remedial skills may be particularly important, as it is essential to recognise that not every method will be effective for every learning task.

Our studies indicate that instructions and assignments during the course of study are the most significant source of information overload, affecting almost two-thirds of the students surveyed. Reference can therefore be made to Sweller's cognitive load theory, which provides several insights to enable the design of learning materials that minimise learners' cognitive load and improve their mental performance and learning attitudes, regardless of the instructional form. Therefore, learners mobilise their learning resources, which positively affects their greater engagement (Sohrabi et al., 2023, p. 4).

One way stemming from Sweller's theory is to reduce the amount of text, divide it into smaller sections, eliminate unnecessary information, etc. Another is to develop the ability to select and organise information. Hence, it may be necessary for a teacher to signal applicable content, manage it, choose keywords, etc.

To help learners with information overload, teachers can also introduce a two-week preparation period in their classes, discuss work methodology and a detailed task schedule, point out specific sources of information and examples of good practice, and encourage networking with other learners (Feroz et al., 2022).

The three most commonly mentioned categories of learning support tools are cognitive, collaborative, and metacognitive. When analysing our own research findings, it is worth noting that more than half of the students surveyed indicate collaboration with others as one of the leading strategies for coping with information overload in class. Thus, it can be concluded that students deliberately choose collaboration to minimise overload by using each other's resources.

The co-occurrence of collaboration and information selection is particularly evident. It is also worth noting that students avoid assignments while striving for collaboration. This may be due to their low level of own resources and their willingness to compensate with other learners' resources. Furthermore, it is worth noting that respondents rarely ask the teacher for help. This is consistent with other research findings, which confirm that students try to reach a solution independently and, if they cannot, seek help first from their group mates and then from the teacher (Kwiatkowska, 2018).

Therefore, it is crucial to make a thoughtful and appropriate choice of tools and technologies to support the education process, characterised by interactivity, ease of use, and the possibility of collaboration and sharing on the chosen project. Thus, it can be concluded that dealing with information overload requires self-discipline and the ability to organise and plan time, as well as to prioritise tasks.

The results obtained from our own study on how to deal with information overload are supported by the literature (Shrivastav & Hiltz, 2013, p. 6), which recommends that, when receiving information, one should first specify the goal one wants to achieve, so that the relevance of individual details can be assessed (Arnold et al., 2023). Information prioritisation can also support managing information overload. The importance of mindfulness as a technique based on being consciously present, focusing on what is essential and avoiding distractions is also emphasised (Arnold et al., 2023; Ioannou, 2023; Masrek & Baharuddin, 2023; Stich et al., 2018).

The results of our study also confirmed the significant contribution of social media to the emergence of information overload among respondents. While social media offers many benefits, such as easy access to information, social support and networking opportunities, it can also lead to information overload (Koroleva & Kane, 2016; Lee et al., 2016; Melinat et al., 2014; Sasaki et al., 2015). According to the Harvard Business Review, information overload is not just about the volume of information to search, but also about the incoming information that needs to be tracked (He, 2020, p. 2). The snowballing pace of information creation and spreading on social media is increasing, while users' ability to process it effectively is not growing at the same rate. When the information shared reaches users' cognitive threshold, they will feel too exhausted to process new information (Kominiarczuk & Ledzinska, 2014; Liu et al., 2021). Moreover, the lack of logical presentation of information on social media (compilation of complex or irrelevant information) can also induce fatigue (Fu et al., 2020). Social media overload also stems from excessive social interaction (Chaouali et al., 2026; Chen & Lee, 2013; LaRose et al., 2014). Users may feel exhausted by a sense of obligation to respond to their friends or to specific content on social media (social overload), which can overburden their mental resources (Kaufhold et al., 2020).

Thus, social media is not only a place to obtain and share information but – as confirmed by the opinions of the students surveyed – a source of overload, leading to stress, feelings of overwhelm, fatigue, and pressure. Notably, the students surveyed found that coping with information overload in academia involved conscious information selection, collaboration with other learners, sharing responsibility, gaining support, and understanding, with a greater possibility of success in the educational endeavour.

In summary, the research presented above confirms the negative impact of information overload on student functioning. It also opens up new research areas related to the concept of cognitive overload described in the text. Perhaps it is not the information itself that becomes a challenge, but other factors, such as excessive assignments or instructions (Pastore, 2012). Therefore, an important question remains how to structure study programmes, individual classes, and even messages to students, both online and offline, to avoid overloading them.

An Ethics Statement

All subjects provided informed consent for inclusion in the study before participating. The Ethics Committee of NCU number 13/2023/FT approved the study.

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Chen Chen

Paradigm Evolution in Educational Digitalisation in China: A Policy Analysis Based on Hall's Model (1978–2025)

Abstract

Educational digitalisation has become central to China's higher education reform, yet existing studies often portray this process as a linear expansion of technology, overlooking deeper shifts in policy logic. This study aims to systematically examine how China's educational digitalisation policies have evolved over time and to identify the depth and nature of policy change using Hall's policy paradigm model. To achieve this, the study analyses the evolution of China's educational digitalisation policies from 1978 to 2025 through qualitative policy content analysis of key national policy documents, and distinguishes between first-order technical adjustments, second-order instrumental changes and third-order paradigm transformation. The findings identify three major stages: an initial phase of technical introduction (1978–1999), a period of large-scale ICT integration (2000–2017) and a paradigm shift towards smart, data-driven education (2018–present). The *Education Informatization 13th Five-Year Plan* (2016–2020) is identified as a transitional stage bridging second- and third-order change. Overall, this study shows that educational digitalisation in China has evolved from a supplementary teaching tool into a core driver of governance reform, pedagogical innovation and lifelong learning in higher education.

Keywords: educational digitalisation, digital education policy, Hall's policy paradigm model, Chinese higher education, smart education

Introduction

Over the past few decades, there has been a marked shift towards technology-enabled teaching and learning, driven by a new generation of students and teachers shaped by Information and Communication Technologies (ICT). Digital technologies have become an important component of high-quality education (Luo et al., 2020).

However, despite this progress, substantial disparities persist between regions and institutions, and teachers' digital competences remain uneven. Since 1978, educational digitalisation has taken a range of forms, including visual and audio-visual media-assisted teaching, synchronous and asynchronous remote teaching, computer-assisted teaching, internet- and social-tool-supported teaching, and the application of new technologies. The integration of digital technologies into education aims to embed them across all areas of the education system, to develop and utilise information resources, to facilitate information exchange and knowledge sharing, and to promote the modernisation of education.

Against this background, it is essential to examine the evolution of China's national educational digitalisation policies. In China's highly centralised and policy-driven education system, major reforms in the adoption of digital technologies have consistently stemmed from top-level policy design rather than local experimentation. National policies determine not only investment priorities and infrastructure development, but also the conceptual framing of digitalisation, the expected role of technology in teaching and learning, and the standards by which institutions are evaluated.

Studying policy evolution offers two key insights. First, it shows how the Chinese government has progressively interpreted the role of digital technologies – from supplementary teaching tools, to system-wide instruments, and, more recently, to drivers

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of intelligent and personalised education. Second, it helps to explain how shifts in policy goals and instruments have shaped the realities of higher education institutions. By tracing these policies from 1978 to the present, this study clarifies the logic, direction and intentions underpinning China's long-term digital education strategy, providing a necessary foundation for evaluating both its achievements and challenges.

For conceptual clarity, this study distinguishes between several closely related terms. 'Educational digitalisation' is used as the core analytical concept, referring to the long-term, systemic transformation of education driven by digital technologies, including changes in governance, pedagogy and institutional functions. 'Digital education policy' refers more narrowly to specific policy instruments and regulatory documents through which the state guides this transformation. Although the term 'education digitalisation' appears in some policy texts, 'educational digitalisation' is adopted here as the standardised academic expression.

This paper reviews key national policies to clarify how China has approached the digitalisation of education, with particular attention to addressing educational inequality and promoting wider technology use among teachers and students.

Research Objectives and Methodology

Research Objectives

Although there is a substantial body of research on the impact of advanced educational technologies, the effectiveness of Chinese policy interventions in this area has received comparatively little attention (Bai et al., 2016). To address this gap, this study investigates how national policies have shaped the digitalisation of higher education.

The primary research objectives of this paper are as follows:

- R01: Examine the historical evolution of China's digital-education policies using Hall's framework;
- R02: Identify and interpret first-, second- and third-order policy changes in China's educational digitalisation in line with Hall's policy paradigm model;
- R03: Evaluate the implications of these paradigm shifts for the future development of higher education.

Research Design

To meet these objectives, this study adopts a qualitative policy content analysis approach, which is particularly appropriate in the Chinese context, where education reform is strongly policy-driven. Given that digitalisation initiatives in higher education have been implemented mainly through government directives, the analysis of policy texts is essential for understanding the underlying assumptions, mechanisms and strategic implications.

The analytical process is structured around Hall's (1993) policy paradigm model, which differentiates between incremental adjustments, shifts in policy instruments and paradigm-level transformations. This framework enables the study to capture both the technical evolution of educational technologies and the deeper transformation of the higher-education sector.

Analytical Framework: Hall's Policy Paradigm Model

Hall's (1993) policy paradigm model is particularly suitable for analysing China's educational digitalisation because it enables policy change to be examined beyond incremental adjustments, capturing shifts in instruments and underlying policy assumptions. Given the long-term, state-led and highly policy-driven nature of educational reform in China, this framework provides a systematic basis for distinguishing between different depths of policy change and identifying moments of paradigm transformation.

In this study, Hall's framework is applied through systematic analysis of national education policy documents, with particular attention to changes in policy goals, policy instruments and assumptions about the role of digital technologies in education.

Hall's model identifies three levels of policy change:

- **First-order change** involves minor technical adjustments to policy instruments without altering the underlying goals. In this study, policies issued between 1978 and 1999 – including planning for audiovisual education, early adoption of computers, network construction and initial distance-education initiatives – are categorised as first-order changes.
- **Second-order change** occurs when new instruments or mechanisms are introduced to address emerging policy needs. Chinese policies from 2000 to 2017 – such as the establishment of nationwide resource platforms, the development of the CERNET academic backbone, the expansion of MOOCs and the integration of ICT into pedagogy – fall into this category.
- **Third-order change** constitutes a transformation of the overarching policy paradigm. Policies from 2018 onwards – including the *Education Informatization 2.0 Action Plan* and the *14th Five-Year National Informatization Plan* – represent a shift towards smart education, data-driven governance, personalised learning and lifelong-learning ecosystems.

Applying this model allows the study to map the progression from incremental digitisation, to system-level integration, and finally to a new smart-education paradigm. The three-level classification is grounded in observable differences in the depth of policy change over time, as evidenced in successive policy documents, rather than being imposed in advance.

Data Sources

The analysis draws on multiple authoritative and publicly accessible sources, including:

- National-level policy documents issued by the Ministry of Education (MOE), the State Council and other central government agencies;
- The Educational Statistics Yearbooks of the People's Republic of China, which provide quantitative indicators on infrastructure, broadband access, online platforms and the use of digital resources;
- Government white papers, official reports and press briefings;
- Scholarly studies on digitalisation, smart campus construction, MOOCs, ICT integration and educational equity in China.

Only policies directly relevant to digital technology, ICT, online or blended learning, resource sharing, smart-campus development, or digital governance were selected.

Data Selection and Inclusion Criteria

Policy documents were included based on the following criteria:

1. Relevance – The policy must address digital technologies or education informatization.
2. Authority – Only policies issued at the national or ministerial level were analysed.
3. Temporal scope – Policies from 1978 to 2025 were selected to capture the full evolution of China's digital-education policy landscape.
4. System-wide influence – Major strategic documents such as Five-Year Plans, informatization action plans and major national platforms were prioritised.

Data Analysis Procedure

The analysis followed five steps:

1. Chronological categorisation
   Policies were arranged by year to identify major historical phases and shifts in state priorities.
2. Thematic coding
   Policies were coded for core themes, including digital infrastructure, teacher development, resource platforms, pedagogical innovation, equity, governance and lifelong learning.
3. Classification using Hall's framework
   Each policy was categorised as a first-, second- or third-order change, based on the nature of policy instruments, goals and paradigm assumptions.
4. Triangulation
   Policy interpretations were cross-checked against statistical data and empirical findings from academic research to support validity and reduce subjectivity.
5. Synthesis into developmental stages
   The findings were synthesised into three historical stages reflecting Hall's framework:
   - 1978–1999: Foundational and incremental digital development (first-order)
   - 2000–2017: Systemic ICT integration (second-order)
   - 2018–2025: Smart-education paradigm shift (third-order)

Within the second-order phase (2000–2017), the *13th Five-Year Plan* (2016–2020) is treated in the analysis as a transitional policy bridging second- and third-order change.

Review of Historical Policies on the Development of Digital Education in China

This section reviews the historical policies that have influenced China's educational digitalisation. 1978 is used as the starting point, as it marks a decisive turn in the development of modern Chinese education. Following the Reform and Opening-up policy, the state began to prioritise educational modernisation and issued the *Preliminary Plan for Audiovisual Education Work*, the first national directive to formalise technology-assisted teaching. In the same year, the Open University of China was established, signalling the beginning of large-scale distance education delivered through electronic media. These initiatives represent the earliest systematic efforts to integrate technological tools into education, making 1978 the most appropriate point from which to trace the evolution of China's digital education policies. The policy documents were analysed through thematic coding, focusing on infrastructure development, resource platforms, pedagogy and teacher development, equity, governance and lifelong learning. These themes informed the stage-based analysis presented below.

First-Order Changes: Foundational Introduction of Educational Technology (1978–1999)

The period from 1978 to 1999 corresponds to what Hall (1993) terms first-order policy change: incremental adjustments and the technical introduction of new tools, without altering the fundamental goals of education. This phase was initially signalled by the *Preliminary Plan for Audiovisual Education Work*, introduced at the Third Plenary Session of the 11th CPC Central Committee in 1978. The Open University of China was also established in 1978, with the aim of providing distance education. During this period, universities began to build campus networks and increase the number of computers (Gu, 2019, pp. 33–35), reflecting the importance attributed to education within broader social modernisation.

The Ministry of Education issued the *Action Plan for Revitalising Education in the 21st Century* to raise standards of technology use in education. In 1995, the first nationwide education and research computer network (CERNET) was established and connected to the global network. In 1999, the Ministry of Education launched the Modern Distance Education (DE) Project, beginning a pilot programme at four higher education institutions: Tsinghua University, Beijing University of Posts and Telecommunications, Hunan

Table 1
A Short Brief of Policies Reviewed in this Paper

Year	Department	Policy	Contents	Hall's Order of Policy Change
1978	Ministry of Education	Preliminary Plan for Audiovisual Education Work	Using radio and video in education, laying the foundation for ICT usage.	First-order change (technical introduction of educational technology)
1998	Ministry of Education	Action Plan for Revitalising Education in the 21st Century	Beginnings of distance education.	First-order change (expansion of early digital tools)
2003	Ministry of Education	Action Plan for the Revitalisation of Education (2003–2007)	Stated the process of educational informatization.	Second-order change (development of ICT instruments and systems)
2010	State Council	National Medium – and Long Term Education Reform and Development Plan (2010–2020)	Integrates educational informatization into the national informatization strategy.	Second-order change (integration of ICT into strategic policy instruments)
2012	Ministry of Education	Ten Year Development Plan for Educational Informatization (2011–2020)	Cultivating students' abilities in information-rich environments; enhancing information literacy and innovation.	Second-order change (institutionalising ICT as a core educational tool)
2016	Ministry of Education	The 13th Five-Year Plan for Education Informatization	Narrowing rural–urban gaps, expanding ICT infrastructure and applications.	Transitional policy (bridging second- and third-order change)
2018	Ministry of Education	Education Informatization 2.0 Action Plan	Eight key actions to expand access, improve quality and create personalised, innovative learning environments.	Third-order change (paradigm shift toward smart, data-driven education)
2021	Ministry of Education	The 14th Five-Year National Informatization Plan	Integrating 5G, AI, big data; building smart campuses; strengthening digital talent training and lifelong learning.	Third-order change (deepening the smart-education paradigm)

Source: author's own work.

University, and the Central Radio and TV University (CRTVU; later the Open University of China) (Baggaley & Belawati, 2010; Li & Chen, 2019).

Overall, policies in this era focused on adding digital tools to the existing education system. They adjusted parameters – more computers, greater connectivity and more remote learning – while the core framework of teaching, learning and educational governance remained unchanged.

Second-Order Changes: Expansion and Integration of Digital Technologies (2000–2017)

Between 2000 and 2017, China entered a phase of second-order policy change, in which the state introduced new policies that fundamentally expanded the role of technology within the education system. Rather than merely refining existing tools, policy began to use ICT to reshape teaching methods, resource sharing, and efforts to promote equity.

Between 1999 and 2003, the Ministry expanded the Modern Distance Education (DE) Project to include up to 68 universities, and by 2006, the pilot network had grown to include even more institutions, offering diploma, bachelor's, graduate, and non-degree continuing education programmes (Baggaley & Belawati, 2010). Collectively, these institutions established thousands of off-campus learning centres – including over 2,000 by 2003 – to support the delivery of distance education (Baggaley & Belawati, 2010).

A key infrastructure development was the enhancement of the China Education and Research Network (CERNET) – the national academic backbone – whose bandwidth surpassed 2.5 Gbit/s by the end of 2000, connecting over 2,000 research institutes and 1.2 million PCs, enabling broad Internet access across universities (Tsinghua University, 2012).

In 2004, the *Action Plan for Revitalising Education (2003–2007)* explicitly mandated the construction of digital education infrastructure in higher education, promoting high-quality computer courses and shared resources via networks (Wang, 2022).

Further institutional support followed in 2006, when the Ministry of Education established the Office of Educational Informatization, thereby centralising the planning and management of education reform initiatives across all levels, including higher education (Nong et al., 2023).

The *Outline of the National Medium- and Long-Term Education Reform and Development Plan (2010–2020)* emphasised the critical role of technology in educational development. It called for improving teachers' use of information technology, encouraging students to learn willingly with the support of technology, strengthening students' ability to analyse and solve problems through information technology, and accelerating the spread of technology. In addition, the policy stated that 'by 2020, China will construct a learning society by building a powerful, vibrant and modern education system, which can offer equal education opportunities, quality education resources and life-long education for citizens.' A learning society embodies a social culture that encourages continuous self-improvement, knowledge acquisition, and skills development, ensuring that education extends beyond schools and becomes a sustained societal norm. The goal is to enhance human capital, support social development, and promote continuous learning across all levels of society.

The *Ten-year Development Plan for Education Informatization (2011–2020)* presented technology as a key means of advancing education reform and innovation. The aim of the plan was to bring the overall level of educational digitalisation closer to that of developed countries (MOE, 2012).

In Hall's terms, this period reflects a reconfiguration of the instruments of educational policy. ICT became embedded in pedagogical strategies, administrative systems, and mechanisms for resource distribution, marking a transformative expansion beyond the incremental improvements of the previous era.

The Transitional Role of the 13th Five-Year Plan (2016–2020)

The *Education Informatization 13th Five-Year Plan*, issued by the Ministry of Education in 2016, constituted the principal policy framework for China's digital-education development in 2016–2020. The plan set out three strategic principles – popularisation, integration and innovation – and specified quantitative targets for broadband connectivity, national resource platforms and faculty training (MOE, 2016). In doing so, it consolidated earlier efforts to integrate ICT while aligning the education sector with the wider 'Internet+ Education' and innovation-led modernisation agenda.

Using Hall's (1993) policy-paradigm framework, the plan is best understood as transitional, straddling second-order and third-order change. Although its core instruments were typical of second-order reform – such as infrastructure expansion, platform development and capacity building – it also introduced policy assumptions and a governance logic that foreshadowed the paradigm-level transformation formalised after 2018. It is therefore neither simply a continuation of second-order integration nor a fully-fledged third-order shift, but an intermediate stage linking the two.

In higher education, the 13th Five-Year Plan had tangible effects. First, universities across China substantially upgraded their digital infrastructure. By 2020, almost all institutions had high-speed broadband connectivity, and many had developed 'smart campus' systems integrating teaching, administration and research functions (MOE, 2016). These developments strengthened the technical basis for flexible online and blended provision and signalled an early move towards more data-driven campus management – an initial indicator of emergent third-order change.

Second, the plan accelerated the expansion of China's Massive Open Online Course (MOOC) ecosystem. Under strong policy incentives, universities developed thousands of high-quality online courses, contributing to one of the largest MOOC systems in the world. As Zhang et al. (2019) note, this expansion was not merely quantitative but also strategic: elite universities extended their teaching reach nationwide, while rural and disadvantaged students gained greater access to high-quality digital resources.

Third, the plan promoted pedagogical innovation by encouraging blended approaches such as flipped classrooms, supported by learning-management systems. Teacher-training initiatives were expanded to strengthen digital literacy and support the routine integration of ICT into teaching, although uptake varied across regions and disciplines (British Council, 2016). These shifts further illustrate how the plan moved beyond infrastructure provision towards reshaping instructional practices.

Finally, digital technologies began to reshape university governance. Data-driven management tools introduced under the plan enabled institutions to monitor teaching quality, allocate resources more efficiently and align institutional strategies more closely with national development priorities. Scholars argue that these developments reflect a deeper embedding of digitalisation within higher-education governance, positioning universities not only as users of technology but also as active participants in China's wider digital modernisation agenda (Shen et al., 2024).

Taken together, the 13th Five-Year Plan can be read as a transitional policy: it consolidated second-order ICT integration while introducing conceptual and structural elements – such as smart-campus systems and data-driven university governance – that prepared the ground for the post-2018 third-order paradigm shift. Accordingly, this study treats the 13th Five-Year Plan as a separate analytical category, capturing the point at which China's educational digitalisation shifted from large-scale ICT integration to a more data-driven, governance-focused and system-level transformation. Analysing this plan separately also allows a clearer account of how third-order policy assumptions emerged incrementally rather than abruptly.

Third-Order Change: Smart, Data-Driven Education (2018–present)

In April 2018, the Ministry of Education of the People's Republic of China (MOE) issued the *Education Informatization 2.0 Action Plan*. This marked the onset of what Hall (1993) terms third-order policy change, as digital technologies moved from serving as external supports to becoming internal variables that reshape

Table 2
Overview of 13th Five-Year Plan's Major Features

Feature	Hall's order
Broadband expansion	Second-order
MOOC scale-up	Second-order
Smart campus governance	Proto-third-order
Data-driven management	Proto-third-order
Policy discourse on 'innovation'	Paradigm transition

Source: author's own work.

the goals, assumptions and structures of education. The Plan's declaration that 'the new era has given educational informatization a new mission and will inevitably drive educational informatization from the 1.0 era to the 2.0 era' (MOE, 2018, p. 1) signalled a new stage in China's education reform. It aims to transform not only learning environments and content, but also the wider educational ecosystem. The Action Plan sets out eight actions to accelerate the transition to the 2.0 era (Zheng, 2018).

The 2.0 phase of digital education development emphasises overcoming constraints of time, space and geography, and expanding access to high-quality educational resources. From the perspective of educational service provision, digitisation 2.0 seeks to use information technology to promote high-quality, more balanced and innovative education, thereby improving educational quality (Yang, 2018).

Key features of the 2.0 era include the deployment of 5G networks to address bandwidth and connectivity constraints; increased personalisation of teaching and learning resources; deeper integration of new technologies into in- and out-of-class activities; more flexible approaches to the evaluation of teaching; and a shift towards technology-enabled educational information management.

China's *Education Informatization Action Plan 2.0* builds on and naturally extends earlier policies. The preceding phase focused on the use of information technology equipment in classrooms and on strengthening technological connectivity between schools and institutions, whereas Action Plan 2.0 places greater emphasis on educators' and learners' experiences within a technology-rich teaching environment. Education in the 2.0 era is envisaged as operating within a more open online environment, promoting more personalised and diverse learning and providing students with access to high-quality educational resources. Unlike traditional educational models – characterised by fixed locations, curricula, pedagogies and assessment practices – education in the information age is technology-enabled and offers greater flexibility, diversity and wider accessibility.

The *14th Five-Year National Informatization Plan*, released in December 2021, further deepens this third-order paradigm shift. It situates educational digitalisation within China's wider national digital-transformation strategy and emphasises the integration of emerging technologies – such as 5G, big data, artificial intelligence (AI) and cloud computing – into economic, social and educational systems (CERNET, 2022). The plan calls for developing a comprehensive

Table 3
Eight Actions of the Education Informatization 2.0 Action Plan

No.	Action	Description
1	Popularisation of digital educational resources	Build a national public service system for educational resources.
2	Digital technologies in impoverished areas	Support the development of educational digitalisation in impoverished areas.
3	Development of online learning spaces	Build an inclusive teaching environment and strengthen system-level educational management.
4	Innovative development of smart education	Guarantee thousands of schools and millions of courses to share case studies and experiences.
5	Optimisation of educational management	Improve standards for the management of educational digitalisation.
6	Promotion of exemplary teaching cases	Standardise emerging teaching methods enabled by digital tools.
7	Development of digital campuses	Encourage schools to integrate digital technologies into teaching and to build information-rich learning environments.
8	Enhancing information literacy	Strengthen the information literacy of teachers and students.

Source: author's own work.

smart-education system, advancing digital campus initiatives in universities, and cultivating high-level digital talent through closer cooperation among industry, academia, and research sectors (CAC, 2022). In Hall's terms, this represents a continuation of third-order change, as digital technologies become central to redefining the goals and functions of higher education.

The implementation of this policy has already reshaped higher education in measurable ways. Most notably, the Ministry of Education (MOE) launched the National Smart Education Public Service Platform in March 2022. This platform integrates digital resources across disciplines, enabling universities to expand online teaching, research collaboration and student services in ways that align with the state's digitalisation goals (MOE, 2025). According to the Ministry of Education of the People's Republic of China, by the end of 2024, 'more than 30 online course platforms have been built across China, with over 97,000 MOOCs available online and 1.39 billion learners. China ranks first in the world in both the number of MOOCs and the number of learners' (MOE, 2024a).

Furthermore, higher education institutions are increasingly serving as hubs for developing talent in cutting-edge digital fields. Universities have introduced new degree programmes in artificial intelligence, the digital economy, and intelligent marine engineering, reflecting the Plan's emphasis on aligning curricula with emerging industrial needs (MOE, 2025). Pilot programmes have also supported AI-enabled teaching and the development of smart campuses, thereby advancing personalised, data-driven learning. For example, universities in Qinghai experimented with 'slice-style' digital content delivery and self-directed learning task sheets, while medical schools such as Suzhou University deployed VR-assisted surgical training (MOE, 2025). These reforms have further embedded technology in pedagogy, particularly in higher education.

The policy has also stimulated lifelong-learning initiatives, with higher education institutions playing a leading role. At the beginning of 2024, the National Open University and its branch network operated more than 55,000 learning centres for older adults, offering over 436,000 online courses to millions of adult learners (Guo, 2024; MOE, 2024b). This aligns with the Plan's explicit call to establish an inclusive and equitable digital education system that supports citizens' continuous upskilling, thereby positioning universities as key nodes within a lifelong-learning society.

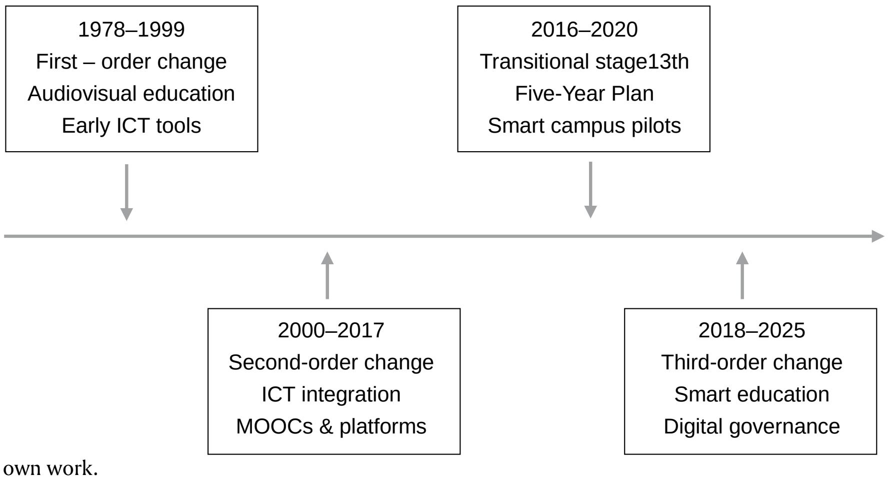
Provincial-level evidence also demonstrates the policy's impact on higher education modernisation. For instance, Hunan Province achieved universal digital connectivity across schools and universities, linked smart campuses to the national platform, and launched digital education initiatives that have generated over 16 billion learning sessions nationwide (Hunan Provincial Department of Education, 2024). Such cases show how central policy directives have translated into tangible digital infrastructure and educational innovation within universities.

In summary, the 14th Five-Year National Informatization Plan represents more than an aspirational blueprint. Together with Informatization 2.0, it represents a mature instance of third-order educational policy change, in which digital technologies reshape governance processes, redefine learning environments and reposition higher education as a critical driver of national digital transformation. Through platform expansion, talent development, pedagogical innovation, and lifelong-learning initiatives, universities have become central actors in realising the state's vision of a comprehensive smart-education ecosystem.

Timeline Summary of China's Educational Digitalisation

Figure 1 summarises the evolutionary trajectory of China's educational digitalisation identified in this study, illustrating the progression from first-order technical adjustments to a third-order policy paradigm shift under Hall's framework.

Figure 1
Timeline Summary of China's Educational Digitalisation



Source: author's own work.

Challenges of Educational Digitalisation in Higher Education

Inequity in Digital Infrastructure and Resource Allocation

Despite these advances, significant challenges remain in the modernisation of higher education within the context of the *14th Five-Year National Informatization Plan*. While flagship universities in major metropolitan areas have rapidly implemented smart-campus systems and advanced digital curricula, regional and under-resourced institutions often lag behind, perpetuating disparities in the quality of digital education (CERNET, 2022).

Although infrastructure coverage has expanded nationwide, the quality of access – such as bandwidth and device availability – varies considerably, particularly at universities in less developed provinces. Technology-led reforms can inadvertently widen the digital divide among students, especially between those from urban and rural backgrounds, unless institutions introduce targeted support mechanisms (Guo, 2024). These gaps underline the need for higher education institutions not only to align with national digitalisation objectives, but also to assess equity, inclusiveness, and long-term sustainability in their digital transformation strategies.

The *14th Five-Year National Informatization Plan* has also brought substantial investment in digitally oriented degree programmes, including artificial intelligence (AI) and big data. However, some scholars caution against over-specialisation without adequate integration into broader liberal-arts and general education, which may constrain graduates' holistic development (CFIS, 2022).

Disparities in Digital Literacy, Pedagogical Adaptation and Academic Workload

Rapid expansion has, in some cases, resulted in superficial engagement with digital learning. MOOC completion rates have remained modest, and many university students find fully online formats less engaging than blended or face-to-face provision. Moreover, not all educators are equally prepared – or willing – to integrate digital tools into their teaching, with training and uptake lagging in some disciplines.

While some argue that information technology can reduce repetitive tasks and improve efficiency, others note that digitalisation has increased demands on teachers, including continuous upskilling, expectations of innovation, and greater accountability. These pressures may lead to overtime and work interruptions, complicating the everyday realities of academic labour in higher education.

Data Governance, Privacy and Network Security Risks

The policy emphasis on large-scale platforms and national integration may facilitate resource sharing, but it has also raised concerns about data governance, privacy protection, and institutional autonomy (CAC, 2022). In particular, data-driven platforms have prompted debate about privacy and the potential for digital surveillance within higher education governance – issues likely to require further policy refinement.

Network security has likewise emerged as a significant challenge. The security of information systems is closely linked to the stability and sustainability of educational reform. In addition, teachers may struggle to identify appropriate online resources within a vast and uneven digital content environment, which further complicates effective pedagogical implementation.

Conclusion

China's efforts to promote the digitalisation of education have delivered substantial improvements in teaching and learning, while supporting the wider development of higher education. Drawing on Hall's (1993) policy-paradigm framework, this study traced the evolution of digital-education policy from first-order technical adjustments in the early period, through second-order reforms marked by the introduction of new policy instruments and the large-scale integration of ICT, to third-order changes in which digital technologies reshape educational objectives, governance arrangements and institutional functions. The historical literature and policy documents analysed here chart a progression from early audiovisual teaching and initial network construction to the establishment of digital campuses and MOOCs, and ultimately to smart, data-driven and service-oriented education supported by emerging technologies.

The *Education Informatization 13th Five-Year Plan* played an important bridging role, signalling a shift from infrastructure expansion and the wider uptake of ICT towards a more systemic and transformative agenda. Subsequently, the *Education Informatization 2.0 Action Plan* and the *14th Five-Year National Informatization Plan* indicate a clear third-order paradigm shift, emphasising personalised learning, flexible teaching, integrated online platforms and mechanisms of digital governance. Within this paradigm, digitalisation moves beyond the enhancement of classroom tools and becomes a central driver of educational modernisation and higher-education development.

Nonetheless, several issues remain unresolved and continue to shape progress. Despite strong national policies, regional disparities persist, particularly in economically underdeveloped areas where infrastructure, digital literacy and educational resources remain limited. Outdated pedagogical approaches, insufficient teacher training and uneven institutional capacity further hinder the effective integration of digital technologies. Moreover, the rapid expansion of data-driven and platform-based provision raises new concerns about data governance, privacy and the long-term sustainability of smart education initiatives. These issues suggest that achieving more balanced and higher-quality digital education will require not only technological innovation but also more substantial reforms to teacher education, curriculum design and institutional governance.

Overall, applying Hall's policy paradigm model clarifies how China's digital education policy has shifted from incremental improvement to more fundamental transformation. The framework helps to account for both the achievements and the continuing challenges of educational digitalisation, and offers insights for policymakers, universities and educators as China moves towards a more equitable, intelligent and high-quality digital education system.

Despite these contributions, this study has several limitations. First, the analysis relies primarily on national-level policy documents, which may not fully capture variations in implementation across regions and institutions. Second, although the study supplements the policy analysis with statistical data and the existing literature, it does not draw on original empirical data or fieldwork. Consequently, the findings reflect policy intentions and macro-level paradigm shifts rather than micro-level practices. These limitations point to the need for future research incorporating case studies, interviews, or quantitative evaluations to examine how educational digitalisation policies are implemented in diverse higher education contexts.

Moreover, as a qualitative and interpretive policy analysis, applying Hall's policy paradigm framework inevitably involves analytical judgement in classifying policy stages and identifying paradigm shifts. Although this study sought to remain as objective as possible by grounding these judgements in the existing literature, alternative interpretations remain possible. Future studies adopting comparative perspectives or mixed-methods approaches could help to validate and refine the analytical conclusions presented here.

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Decoding Digital Learning: Analysing Antecedents of Behavioural Intention and E-Learning Adoption

Abstract

This study seeks to identify the determinants of behavioural intention (BI) and to examine how BI influences e-learning adoption (ELA) behaviour among students. The article investigates the impact of five key factors – Accessibility, Government Policy, Organisational Support, Instructor Attitude, and Technostress – on intention to use and adopt e-learning platforms. A validated questionnaire was administered to a heterogeneous sample of 290 participants, and SmartPLS 4.0 was used for the analysis. The findings indicate that Technostress, Government Policy, and Organisational Support have a substantial and positive influence on intention and acceptance of the virtual learning platform, with Technostress emerging as the most influential factor. By contrast, Accessibility and Instructor Attitude are not significant, suggesting that access to digital infrastructure and e-learning platforms is generally good, and that students consistently report positive instructor attitudes; as a result, there is insufficient variance for these variables to meaningfully differentiate outcomes in the statistical model. The results show a strong effect of BI on e-learning adoption, with a large effect size. In addition, the model explains 53% of the variance in behavioural intention and 49% of the variance in e-learning adoption, indicating strong explanatory power. Notably, Technostress has the greatest impact, and its effects can be reduced through immersive and engaging sessions. This suggests that Technostress may sometimes function as a 'challenge stressor' rather than a 'hindrance stressor', encouraging active engagement rather than avoidance. These issues should be integrated into strategic decision-making to enhance digital education outcomes through a positive, engaging virtual learning system.

Keywords: e-learning, Learning Management System, PLS-SEM, antecedents, enablers, barriers, online education

Introduction

Online education combines classroom teaching with information and communication technologies (ICTs) and is widely regarded as an effective means of sharing knowledge (Baber, 2021). It is also referred to as virtual, distance, electronic or mobile learning, and has developed alongside the expansion of information technology (Singh & Thurman, 2019). The term is often used interchangeably with virtual education and e-learning platforms. Its widespread adoption has improved communication and teaching for both businesses and individuals, indicating considerable potential for training and education. The growing tendency for learners to choose online courses is a notable achievement of online education (Alkhalaf et al., 2012). This can help students manage their time and balance study with work, and it is now considered an integral part of the education sector. Many higher education institutions have adopted learning management systems (LMSs) to create, manage and deliver educational materials, monitor student progress, and administer assignments and quizzes, thereby facilitating interaction between learners and educators (Kim et al., 2021). Previous studies have also indicated that the implementation of LMSs has substantially transformed universities and enhanced their educational offerings (Dhapte, 2025; Singh, 2020).

Many researchers (Ahmad et al., 2018; Anwar et al., 2020; Hassanzadeh et al., 2012) have examined the features associated with successful e-learning in order to maximise

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the benefits and quality of virtual education systems. These features are considered from both human and non-human perspectives, combining technological aspects such as learning management systems (LMSs) with their users, namely educators and students.

Anwar et al. (2020), Lan et al. (2021), and Zhao and Xue (2023) identify key motivators and challenges associated with e-learning, or education delivered fully online. Enablers of e-learning include quality parameters, learners' experience and achievement level, attitude and competence level, perceived usefulness, and intention to accept virtual education. Conversely, several variables have been investigated as potential barriers to the wider acceptance of virtual learning, including technostress, the digital divide, accessibility issues, resistance to change, limited digital literacy, and financial concerns (Kong et al., 2014).

The instructor, course design, student characteristics, university support, and information technology are five key dimensions of online education. Rodríguez-Ardura and Meseguer-Artola (2016) validated that instructors' efforts are critical for the effective application of information systems and the success of online learning. Hou et al. (2022) and Teo et al. (2008) proposed instructor characteristics that influence effectiveness, such as expertise, commitment, status, priorities, fundamental values, training, IT competence, mindset, and teaching style. Furthermore, El Alfy et al. (2017) note that students' characteristics – including expectations, engagement, media competence, personal competence (self-regulated learning), motivation, course compatibility, flexibility, and satisfaction – also contribute to e-learning adoption. Another pillar is the institution's characteristics, including organisational leadership, readiness, institutional policy, staff training, organisational culture, technical support facilities, and change management systems. Information technology attributes encompass information quality, ease of use, system quality, accessibility, security, privacy, and service quality (Teo et al., 2020). Lastly, course design includes course structure and content, information quality, subject area, knowledge tests, competency tests, feedback, quizzes, and assessment modes and levels of difficulty (Karimian & Chahartangi, 2024; Kong et al., 2014; Nguyen et al., 2024). Considering all of the above variables, the current study sets the following research objectives:

- RO1 – To study the impact of accessibility on behavioural intention of learners to use e-learning platforms.
- RO2 – To test the effect of organisational support on the behavioural intention of learners to embrace e-learning.
- RO3 – To determine the influence of government policy to gauge the behavioural intention of learners towards the use of e-learning.
- RO4 – To assess the role of instructor attitude in creating behavioural intention of learners.
- RO5 – To examine how Technostress affects behavioural intention for e-learning in learners.
- RO6 – To identify the influence of behavioural intention on actual adoption of e-learning platforms.
- RO6 – To study the impact of accessibility on behavioural intention of learners to use e-learning platforms.
- RO7 – To generate and test a conceptual framework that incorporates institutional, psychological, and contextual antecedents to explain e-learning adoption.

Hypothesis Generation based on Literature Review and Theoretical Background

Adoption of online education in HEIs is rooted in several complementary theoretical foundations. Perceptions of practicality, effectiveness, ease, and convenience in virtual education are commonly examined through established frameworks. Davis's (1989) Technology Acceptance Model (TAM) focuses on perceived usefulness and perceived ease of use as predictors of adoption. By contrast, UTAUT incorporates facilitating conditions and social influence (Venkatesh et al., 2003). Accessibility aligns with perceived ease of use (TAM) and facilitating conditions (UTAUT). Where there is access to platforms (low bandwidth requirements, mobile-friendly design, intuitive interfaces, interactive features), the likelihood of adoption is higher.

Nevertheless, instructor attitude can be mapped to the social influence construct in UTAUT and to the educational and emotional support elements of Social Support Theory (House, 1981). Instructors' support (encouragement, feedback, and guidance) has been reported to positively affect students' satisfaction and their willingness to continue using e-learning tools. This support may be direct (through teaching behaviour) or indirect (by creating a positive learning context).

Government support enhances enabling conditions through infrastructure, subsidies, or requirements that minimise barriers to e-learning. This increased support is expected to improve users' behavioural intention to use the e-learning platform (Kaur & Sehajpal, 2025; Sehajpal et al., 2025; Singh & Sehajpal, 2025). The theory supports the proposed hypotheses that government policy relates to intention through constructs such as Social Influence (norms, perceived pressure) and Facilitating Conditions (availability of resources), which are conducive to positive behavioural intention and use.

Institutional Theory also explains how government policy can act as a coercive pressure and as normative organisational support in shaping intention to use e-learning (DiMaggio & Powell, 1983). Institutional Theory focuses on how external forces influence organisations and individuals (e.g., government regulations, policies, and mandates that incentivise particular behaviours to secure legitimacy and compliance).

Technostress, on the other hand, captures negative pressures and is commonly treated as a deterrent to adoption behaviour. Technostress is grounded in the Stress–Strain–Outcome framework (Koeske & Koeske, 1993), which conceptualises technology overload, complexity, and continual updates as stressors that lead to strain (fatigue, frustration, dissatisfaction), which may reduce learners' intention to adopt or use e-learning.

The discussion above provides a theoretical rationale for examining variables such as Accessibility, Government Policy, Organisational Support, Instructor Attitude, Technostress, and E-learning Adoption within a single framework. Together, these elements form a multi-level ecosystem that influences technology adoption in learning environments. Based on TAM, UTAUT, Institutional Theory, Social Support Theory, and the Stress–Strain–Outcome framework, technology adoption is shaped not only by individual user perceptions (e.g., instructor attitude and technostress) but also by structural enablers (e.g., accessibility and government policy) and organisational conditions (e.g., institutional support). Such models suggest that psychological, environmental, and institutional factors jointly determine behavioural intention and actual usage. The literature relevant to the constructs used in the current study is reviewed below:

Accessibility and Psychological Framework to Accept Virtual Platforms for Education

With a range of technologies and devices used to access learning resources – mobile phones, laptops, tablets, and desktop computers – e-learning has experienced rapid growth. Making e-learning accessible also depends on integrating technologies such as speech-to-text, alternative text for images, captions, screen readers, and keyboard navigation. Technology has fundamentally transformed education, teaching methods, and learning environments (Kithsiri et al., 2018). Traditionally, educational resources were not easily accessible to many people, and limited collaboration and information exchange were also observed among students seated in the same classroom (Rodríguez-Ardura & Meseguer-Artola, 2016). Many learning tools are now available in multiple formats – text, audio, video with subtitles, and transcripts – allowing students to select what best fits their skills and preferences and making learning more inclusive (Wen et al., 2008). Studies have found that accessibility and overall usability depend critically on logical structure, clear instructions, and straightforward navigation (Lyukevich et al., 2020). Accessible e-learning systems stimulate greater engagement and participation among all students, including those from underprivileged or underrepresented groups (Gibreel & Abdalla, 2024). System accessibility influences perceptions of intuitiveness and manageability of virtual platforms. Users are likely to view such platforms as useful and requiring less effort when they are easy to access, navigate, and use. Thus, we hypothesise:

H1: Accessibility has a significant impact on the likelihood of adoption of virtual platforms.

Organisational Support and Willingness for Embracing Virtual Platform

Learners' intention to implement and use online education platforms in a dynamic environment is strongly influenced by organisational support (Alajmi et al., 2018). Dedicated leadership, learning opportunities, sufficient funding, and a supportive culture all contribute to this support. Leadership, resources, technical assistance, and training are directly instrumental in achieving positive outcomes. In addition, reducing barriers, addressing resistance, and shaping attitudes can also improve acceptance. Successful and comprehensive endorsement of online education across institutions depends on strong, visible, and consistent organisational support (Alkhalaf et al., 2012; Rowell, 2010). By removing barriers and enabling students and staff to engage, supportive environments foster a culture that values technology. Thus, we hypothesise.

H2: Organisational Support has a positive relationship with propensity for adoption of virtual platforms

Government Policy and Willingness for Adopting Virtual Platform

The extensive implementation of the NEP, the establishment of virtual laboratories, financial assistance policies for acquiring digital devices, and unified platforms such as Diksha and Swayam have supported wider acceptance of digital learning and, in turn, contributed to changes in social norms. This social influence can shape behavioural intention through learners' perceptions of support and approval from society and peers (Elameer, 2021). Integrating digital learning into the curriculum fosters awareness and a preference for interacting with digital tools. Enabling conditions, including guidelines that ensure digital literacy training, adequate resources, and technical assistance, are known to influence behavioural intention (Kanwal & Rehman, 2014). Consequently, learners who perceive themselves as equipped and supported in using virtual educational tools may be more motivated. Thus, we hypothesise:

H3: Government Policy has a significant relationship with behavioural intention to use the e-learning platform.

Instructor Attitude and Readiness to Embrace Virtual Platform

Instructor Attitude is widely regarded as an important variable in determining intention to use online and digital learning mechanisms (El Alfy et al., 2017; Yi et al., 2024). A positive attitude towards e-learning is likely to increase an instructor's willingness to adopt and use these platforms in their teaching. Willingness to engage may be shaped more by attitude than by convenience; among experienced instructors, perceived usefulness, satisfaction, and positive affect indicate a favourable attitude, which in turn predicts stronger intention to use e-learning. Institutional and social factors also influence educators' attitudes. Accordingly, it is hypothesised that:

H4: Instructor Attitude is significantly related to behavioural intentions to use the online learning platform.

Technostress and Willingness for Embracing Virtual Platform

Technostress refers to stress or anxiety associated with the use of digital technologies and can undermine willingness to use digital educational platforms (Tarafdar et al., 2011). Several forms of technostress have been identified in the literature, including techno-invasion (disturbances to personal life), techno-overload (being forced to work faster), and techno-uncertainty (feeling left behind by rapid technological change). Several studies show that greater technostress is associated with lower intentions to use, or continue using, e-learning platforms (Penado Abilleira et al., 2020). Students who experience technostress may feel overwhelmed, anxious, and dissatisfied, which reduces their motivation to engage with online learning resources (Chu & Chen, 2016). Reduced participation, lower memory retention, and anxiety resulting from technostress can influence academic achievement and satisfaction with online education (Lal et al., 2024). Students experiencing technostress may also be less likely to participate in group projects or communicate with instructors or peers. Based on these findings, we hypothesise:

H5: Technostress has a significant relationship with behavioural intention to use e-learning platforms

Behavioural Intention to use E-learning Platform Relationship with Adoption Behaviour

Behavioural intention is widely acknowledged as a crucial determinant of adoption behaviour, thereby enhancing the effectiveness of virtual learning methods (Al-Hunaiyyan et al., 2021). Numerous studies and theoretical models (including TAM and UTAUT) consistently indicate a strong relationship between the propensity to adopt and the actual adoption of online education platforms (Jameel et al., 2022; Xian, 2019). Behavioural intention reflects learners' readiness or willingness to use virtual learning platforms in the knowledge acquisition process and is frequently identified as the main antecedent of actual adoption. Strong intentions are likely to translate into actual use behaviour. Thus, we hypothesise:

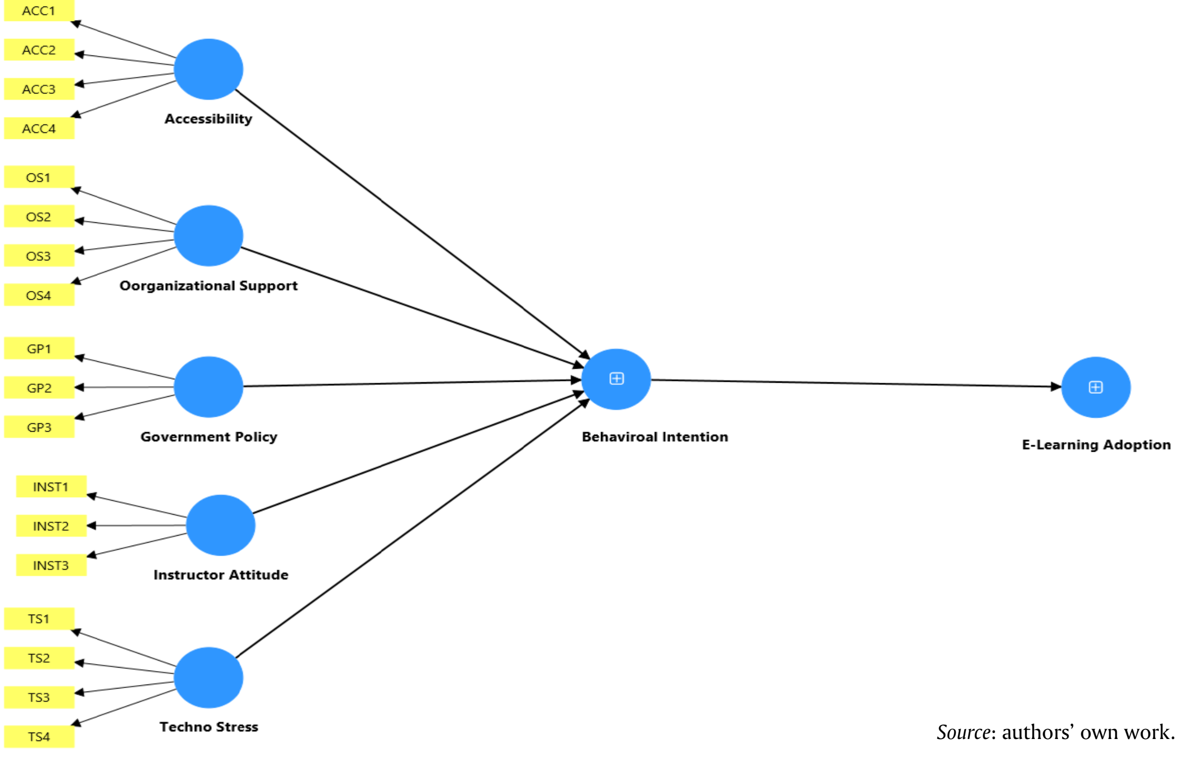
H6: Behavioural intention has a significant relationship with actual usage of e-learning platforms

Only a limited number of studies have investigated these constructs within a single empirical framework, particularly in developing countries where infrastructure and pedagogical practices may differ. The current literature seldom addresses how these variables collectively influence students' perceptions. These gaps underscore the need for an integrated analysis that evaluates the relative contribution of technostress, accessibility, government policy, organisational support, and instructor attitude to students' e-learning experience. The present study seeks to address this gap by developing a conceptual model and providing empirical evidence, thereby extending understanding of factors that shape effective and sustainable online learning.

Development of Conceptual Model

A conceptual model of e-learning adoption has been developed using the variables shown in Figure 1.

Figure 1
Conceptual Model



Source: authors' own work.

Research Methodology

Quantitative methods were used to test the hypotheses in the conceptual framework. SmartPLS 4 (Ringle et al., 2024) was used to assess the measurement and structural models. Data collected through surveys of users of an e-learning educational platform were analysed using PLS-based Structural Equation Modelling (PLS-SEM). This is a robust quantitative technique for evaluating complex relationships among latent constructs, particularly in exploratory work and in social science research involving non-normal data. The analysis includes two stages: first, the measurement model is assessed (i.e., the relationships between indicators and constructs); second, the structural model is assessed (i.e., the hypothesised causal relationships between constructs). Following data screening for outliers, multicollinearity, and average variance extracted (AVE) (Coluci et al., 2015), the approach prioritises maximising explained variance in dependent variables rather than overall model fit indices. The methodology was selected to ensure a robust basis for generating insights into the facilitators and barriers associated with e-learning platforms. Measurement items were drawn from an extensive review of the literature (Hwang & Kim, 2022; Karimian & Chahartangi, 2024; Rahayu et al., 2021). The questionnaire was validated by industry experts and professionals before responses were collected, as shown in Table 1. Overall, this approach provides a credible basis for generating results that extend the existing evidence base.

Table 1
Survey Questionnaire

Construct	Code	Measurement Item	Reference
Accessibility	ACC1	I own a suitable device for e-learning	Ssemugenyi & Nuru Seje, 2021
	ACC2	I have reliable internet access for e-learning	Alyoussef, 2022
	ACC3	These platforms are easy to use	
	ACC4	LMSs are compatible with mobile devices	
Organisational Support	OS1	My institute provides sufficient IT infrastructure for e-learning	Tom et al., 2019
	OS2	University leadership allocates sufficient funds for e-learning tools	Herath et al., 2015
	OS3	Technical support for e-learning is readily available	
	OS4	My institute regularly updates digital learning technologies	
	OS5	Administrative processes support e-learning	
Government Policy	GP1	The government provides grants for e-learning infrastructure	Singh et al., 2021
	GP2	National policies mandate the integration of digital education	Elameer, 2021
	GP3	Government agencies monitor e-learning quality standards	
	GP4	Government initiatives promote faculty training, development, and accessibility	
Instructor Attitude	INST1	My instructor is confident in delivering content through an online platform	Ssemugenyi & Nuru Seje, 2021
	INST2	My instructor enjoys using the e-learning system for teaching	Hernández-Ramos et al., 2014
	INST3	My instructor promotes active student participation	Sangwan et al., 2021
Technostress	TS1	Technology compels me to work faster	Tarafdar et al., 2011
	TS2	I am worried about technology interfering with my personal time	Penado Abilleira et al., 2020
	TS3	Sometimes it is hard to learn how to use new educational technologies	
	TS4	Technology fails me when I need it most	

Table 1 – continue

Construct	Code	Measurement Item	Reference
Behavioural Intention	BI1	I will use online education tools frequently in the future	Yang & Qian, 2025
	BI2	I believe that e-learning enhances students' engagement	Ameen et al., 2019
	BI3	I am comfortable adopting new e-learning technologies	Jamil, 2017
	BI4	I intend to recommend adoption of the online education platform to my peers	
E-learning Adoption	ELA1	I find online education tools useful for improving my learning performance	Al-Maroof et al., 2021
	ELA2	Understanding virtual learning tools is easy for me	Shah et al., 2025
	ELA3	I possess the necessary resources for the learning management system	Mashroofa et al., 2023
	ELA4	My peer group influences me to use the virtual learning system	

Source: authors' own work.

Data Analysis

A dataset was compiled from responses provided by 290 participants via a structured questionnaire designed to capture a heterogeneous audience, thereby supporting scalability and efficiency, as shown in Table 2. Convenience sampling was used, and respondents were higher education students in the State of Uttaranchal. The sample was drawn from 33 universities, comprising 11 state universities, one central university, and 18 private universities. Participation was voluntary; informed consent was obtained online and completed before data collection began, and no personally identifiable information was collected. Given the limitations of convenience sampling – including possible sample bias and variation in responses – preventive measures were implemented to mitigate these issues.

Measurement Model Assessment

Following Taber (2018), assessment of the outer model examines construct reliability and internal consistency through indicator loadings (λ), composite reliability (CR), and Cronbach's alpha (α), with values above 0.7 generally considered acceptable; CR is often regarded as the more appropriate reliability metric. Convergent validity is assessed using the average variance extracted (AVE), which should exceed 0.5, as shown in Table 3. Campbell and Fiske (1959) suggested assessing discriminant validity to confirm that constructs are empirically distinct, using approaches such as the HTMT ratio, cross-loadings, and the Fornell–Larcker criterion; recommended thresholds typically lie between < 0.850 and 0.90, as shown in Tables 4 and 5. The measurement model meets the reliability and validity criteria reported in Table 3.

Table 2
Demographic Data

User's Age	Frequency	Percentage	Educational Qualification	Frequency	Percentage
Less than 25	77	26.5	Undergraduate	69	23.8
Between 25 to 35	174	60	Postgraduate	128	44.1
More than 35	39	13.5	Ph.D./Others	93	32.1
Gender	**Frequency**	**Percentage**	**Experience**	**Frequency**	**Percentage**
Male	102	35.2	Positive	167	57.5
Female	188	64.8	Negative	123	42.4

Source: authors' own work.

Table 3
Factor Loading, Reliability, Validity and Collinearity of Outer Model

		Alpha	CR	AVE	VIF
ACC1	0.766	0.85	0.898	0.687	1.746
ACC2	0.82				2.132
ACC3	0.825				1.935
ACC4	0.9				2.378
BI1	0.769	0.785	0.861	0.608	1.57
BI2	0.755				1.476
BI3	0.808				1.635
BI4	0.785				1.574
ELA1	0.821	0.784	0.86	0.607	1.655
ELA2	0.803				1.65
ELA3	0.741				1.502
ELA4	0.748				1.503
GP1	0.889	0.81	0.882	0.715	1.729
GP2	0.89				2.099
GP3	0.749				1.685
INST1	0.863	0.79	0.877	0.704	1.795
INST2	0.872				1.826
INST3	0.779				1.497
OS1	0.836	0.868	0.91	0.716	1.961
OS2	0.867				2.463
OS3	0.805				1.811
OS4	0.877				2.35
TS1	0.737	0.782	0.859	0.605	1.376
TS2	0.794				1.814
TS3	0.805				1.597
TS4	0.773				1.633

Source: authors' own work from PLS-SEM software.

The reliability measures (CR, loading values, and Cronbach's alpha) all exceed 0.70, indicating that items such as ACC1, ACC2, ACC3, and ACC4 collectively represent the Accessibility latent construct effectively; the same criteria are met by indicators for the other constructs, establishing internal consistency. AVE reflects the proportion of variance captured by the construct relative to measurement error and provides evidence of convergent validity. Table 3 shows that the AVE for ACC, GP, OS, TS, and INST exceeds 0.50, meeting the validity threshold.

The bold diagonal entries report the square roots of the average variance extracted (AVE) for each construct, while the remaining values represent inter-construct correlations. Discriminant validity refers to the extent to which the items associated with a given construct measure that construct rather than other constructs, thereby indicating clear separation between constructs. Discriminant validity was assessed using cross-loadings (Table 4) and the Fornell–Larcker criterion (Table 5). In Table 5, the diagonal values (√AVE) exceed the corresponding inter-construct correlations, indicating that TS, GP, OS, INST and ACC are empirically distinct. Accordingly, each construct is measured using a distinct set of indicators.

Structural Model Assessment

Structural model assessment is a vital step in testing hypotheses about latent constructs (Bagozzi & Yi, 1988). Structural relationships are evaluated by analysing path coefficients, p-values, and t-values, together with f^2 (effect size) and R^2, after establishing reliability and validity of the outer model. The

Table 4
Discriminant Validity: Using Cross Loadings

	ACC	BI	EL	GP	INST	OS	TS
ACC1	0.766	0.252	0.169	0.628	–0.189	0.428	0.138
ACC2	0.820	0.208	0.269	0.401	–0.236	0.383	0.089
ACC3	0.825	0.320	0.328	0.403	–0.097	0.459	0.243
ACC4	0.900	0.377	0.363	0.475	–0.164	0.508	0.239
BI1	0.282	0.769	0.479	0.367	0.079	0.472	0.515
BI2	0.314	0.755	0.523	0.396	0.167	0.481	0.466
BI3	0.354	0.808	0.613	0.387	0.109	0.510	0.509
BI4	0.179	0.785	0.561	0.321	0.195	0.409	0.534
ELA1	0.362	0.632	0.821	0.333	0.167	0.485	0.551
ELA2	0.207	0.563	0.803	0.237	0.129	0.426	0.508
ELA3	0.274	0.468	0.741	0.263	0.105	0.314	0.399
ELA4	0.245	0.497	0.748	0.271	0.197	0.372	0.423
GP1	0.531	0.484	0.334	0.889	–0.064	0.578	0.279
GP2	0.455	0.415	0.348	0.890	0.004	0.531	0.329
GP3	0.468	0.221	0.173	0.749	–0.140	0.371	0.049
INST1	–0.107	0.155	0.135	–0.005	0.863	0.024	0.238
INST2	–0.210	0.160	0.183	–0.092	0.872	0.039	0.297
INST3	–0.181	0.125	0.170	–0.061	0.779	–0.007	0.208
OS1	0.550	0.524	0.421	0.572	–0.001	0.836	0.475
OS2	0.397	0.461	0.401	0.465	0.049	0.867	0.510
OS3	0.445	0.467	0.391	0.537	0.006	0.805	0.406
OS4	0.444	0.567	0.531	0.471	0.030	0.877	0.521
TS1	0.392	0.516	0.535	0.350	0.163	0.469	0.737
TS2	0.056	0.432	0.399	0.098	0.309	0.420	0.794
TS3	0.187	0.550	0.491	0.280	0.157	0.493	0.805
TS4	0.051	0.503	0.457	0.155	0.316	0.371	0.773

Source: authors' own work.

Table 5
Discriminant Validity: Using Fornell Lacker Criterion

	ACC	BI	EL	GP	INST	OS	TS
ACC	**0.829**						
BI	0.363	**0.780**					
EL	0.352	0.700	**0.779**				
GP	0.569	0.472	0.356	**0.845**			
INST	0.196	0.176	0.193	0.062	**0.839**		
OS	0.544	0.600	0.520	0.603	0.024	**0.846**	
TS	0.228	0.649	0.610	0.292	0.297	0.567	0.778

Source: extracted from PLS-SEM Software.

current model assesses the relationships between ACC and BI, OS and BI, TS and BI, INST and BI, GP and BI, and BI and ELA.

The empirical assessment of the hypothesised structural paths in the PLS-SEM model (Table 6) indicates mixed effects of the latent constructs on behavioural intention and e-learning adoption. The path from Accessibility to Behavioural Intention (H1: $\beta = 0.055$, $p = 0.357$) is not statistically significant, suggesting that the mere availability of, or ease of access to, technological infrastructure does not, in itself, materially increase users' intention to engage with online education systems. This is consistent with UTAUT (Venkatesh et al., 2003), which implies that facilitating conditions may not exert a direct effect when other antecedents are more salient. By contrast, Organisational Support has a statistically significant positive effect on Behavioural Intention (H2: $\beta = 0.197, p = 0.007$), underscoring the importance of responsive and robust support in strengthening user confidence, technological self-efficacy, and perceptions of platform reliability; this, in turn, fosters stronger behavioural intention. Literature emphasised the role of academic and technical scaffolding in virtual learning environments.

Furthermore, Government Policy shows a significant positive effect on Behavioural Intention (H3: $\beta = 0.194$, $p = 0.002$), indicating that macro-level regulatory and institutional frameworks that endorse, incentivise, or mandate digital transformation act as important external motivators that legitimise e-learning and align stakeholders with national priorities, consistent with Alshammari et al. (2016) on the enabling role of policy interventions in technology assimilation. In contrast, Instructor Attitude does not show a significant direct effect (H4: $\beta = 0.061$, $p = 0.184$), suggesting a diminished, indirect, or mediated role of instructors in shaping behavioural intention in contexts where students are comparatively autonomous and technologically experienced, which challenges the traditionally central role emphasised by Rodríguez-Ardura and Meseguer-Artola (2016).

Technostress has a strong and highly significant positive association with Behavioural Intention (H5: $\beta = 0.450$, $p = 0.000$), indicating that students may experience technology-related challenges as manageable and even motivating when supported by adequate digital literacy and institutional infrastructure; this implies that technostress may sometimes function as a 'challenge stressor' rather than a 'hindrance stressor', prompting engagement rather than avoidance.

This reinforces the central premise of the TAM and its extensions (Davis et al., 1989): enhancing users' competence and reducing technological anxiety through structured pedagogical interventions and user-empowerment initiatives have a pronounced and unambiguous effect on the formation of intention. This, in turn, indicates that institutional administrators should invest strategically in sustained training provision and proactive technical assistance protocols. Finally, H6 shows a strong statistical association between *Behavioural Intention* and *E-learning Adoption* ($\beta = 0.700$, $p = 0.000$), confirming intention as the most proximal antecedent of actual behaviour and underscoring the importance of cultivating positive attitudinal, normative and control beliefs to catalyse active engagement with e-learning platforms.

Existing evidence suggests that when access to digital infrastructure and devices is highly standardised within an institution or region, it varies little and is therefore a weaker statistical predictor (Aboagye et al., 2021; Adarkwah, 2021). Similar findings have been reported in multiple pandemic-related studies: once a baseline level of access has been achieved, students tend to treat accessibility as an expected factor rather than a differentiator, and psychological variables such as technostress or self-efficacy become more important in shaping the learning experience (Hodges et al., 2020; Mohammadi, 2015). Our sample reflects the same pattern: institutional provision and the general availability of devices have resulted in most students reporting uniformly high accessibility scores, producing a limited range effect.

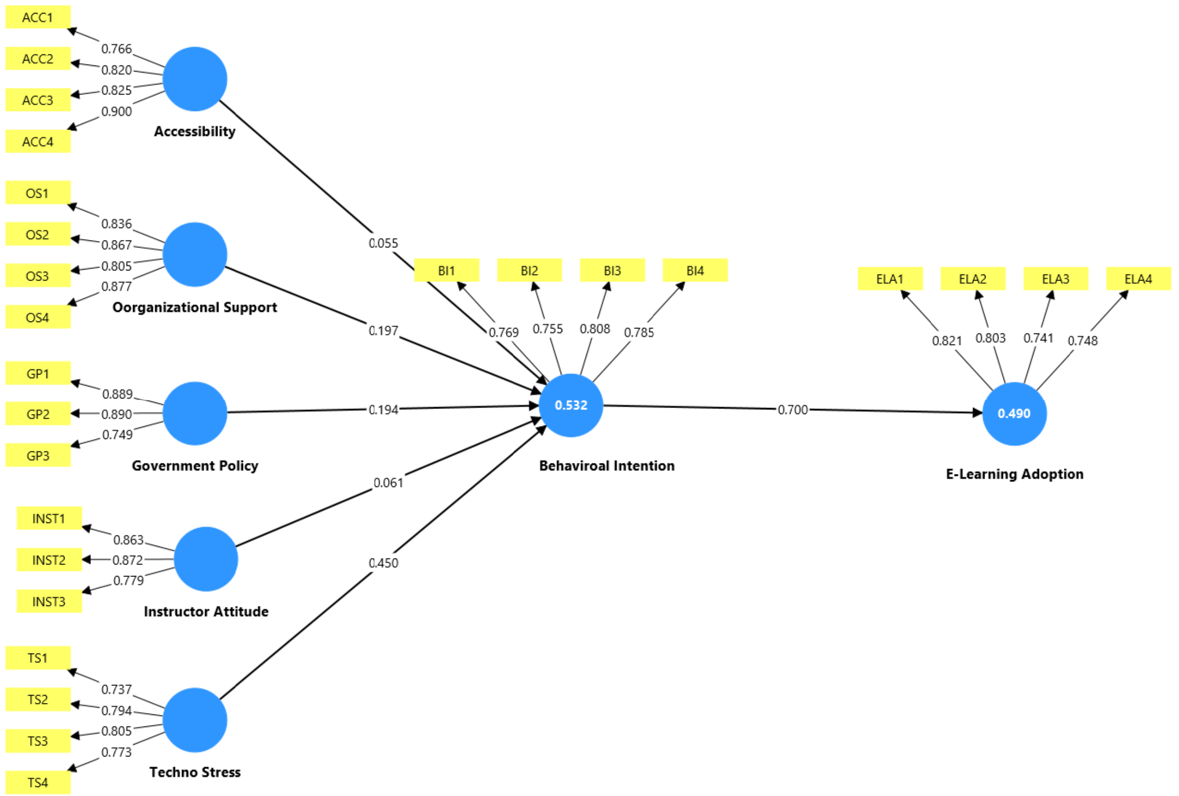
To assess the model's predictive capacity, R^2 values were examined. The R^2 for Behavioural Intention is 0.530, indicating that 53.2% of the variance is explained by accessibility, organisational support, government policy, instructor attitude, and technostress, as shown in Figure 2, reflecting moderate-to-substantial predictive power. The R^2 for E-Learning Adoption is 0.490, indicating that behavioural intention alone

Table 6
Hypothesis Testing

Hypothesis	Relationship	*β*	*SD*	*t*-value	*p*-value	Decision
H1	ACC > BI	0.055	0.060	0.922	0.357	Rejected
H2	OS > BI	0.197	0.073	2.686	0.007	Supported
H3	GP > BI	0.194	0.062	3.142	0.002	Supported
H4	INST > BI	0.061	0.046	1.330	0.184	Rejected
H5	TS > BI	0.450	0.054	8.268	0.000	Supported
H6	BI > ELA	0.700	0.035	20.118	0.000	Supported

Source: authors' own work from PLS-SEM software.

Figure 2
E-Learning Adoption Model



Source: extracted from PLS–SEM Software.

explains 49% of the variance in adoption. The f^2 values for each predictor indicate the contribution of each factor to the explained variance (Table 7).

Table 7
F^2 Values

Predictor →	Dependent	f^2
ACC → BI	0.004	Very small (almost negligible)
BI → EL	0.96	Very large effect
GP → BI	0.044	Small effect
INST → BI	0.007	Negligible
OS → BI	0.035	Small effect
TS → BI	0.258	Medium-to-large effect

Source: authors' own work from PLS-SEM software.

Managerial Implications

The findings indicate that organisational support, government policy, and technostress are particularly important in shaping learners' intention to use e-learning, whereas accessibility and instructor attitude do not show direct effects. Institutions should therefore focus on building strong support systems. Organisational assistance (administrative support, specialist help, training, and resource provision) has clear implications for learners' ability to use e-learning effectively and to build competence. Supportive environments enable faculty and students to reduce hurdles and foster a culture that values technology (Baber, 2021). Continuous professional development and readily available support can increase users' confidence and capability when using e-learning platforms.

Policy-makers should also ensure that e-learning policies are clear, stable, and backed by appropriate resources, as such policies create an enabling ecosystem that supports platform use and long-term adoption (Nagy & Duma, 2023). Since technostress emerged as a strong positive predictor, managers should adopt structured digital competency training, balanced workload practices, and stress-reduction measures so that students experience technology as manageable and beneficial rather than overwhelming (Penado Abilleira et al., 2020).

Although baseline accessibility and instructor attitude were not statistically significant, institutions must still ensure minimum standards of digital infrastructure and provide professional development for instructors, as these remain prerequisites for sustainable e-learning provision (Ramhith & Lallmahomed, 2024).

Finally, since behavioural intention is a key predictor of actual uptake, strengthening user motivation and the perceived value of online learning should be central to institutional strategy. The present study considers these variables to assess their influence on improving e-learning adoption and supporting equitable access to education.

Conclusion and Future Scope

E-learning is an important aspect of contemporary education, as it supports flexibility and accessibility and helps to overcome geographical, economic, and social boundaries. By integrating technology into teaching and learning environments, institutions can provide more inclusive and efficient educational experiences. This shift highlights the importance of identifying the main factors that determine the effective implementation of virtual learning environments, as understanding these determinants is crucial to improving student engagement and the overall e-learning experience.

This article examines the antecedents of behavioural intention to use e-learning platforms—Accessibility, Government Policy, Organisational Support, Instructor Attitude and Technostress—which, in turn, influence E-Learning Adoption behaviour. The measurement model was assessed for reliability and validity, and the results were satisfactory: all constructs met the recommended thresholds (Cronbach's alpha (α) > 0.7; composite reliability (CR) > 0.85; average variance extracted (AVE) > 0.6), and the VIF values for all measurement items were below 5 (Table 3), indicating no multicollinearity concerns. This suggests that the indicators represent their respective constructs well. Discriminant validity was also supported, indicating that the items for each construct relate to that construct only and not to other constructs; hence, each construct is clearly differentiated. None of the constructs (TS, GP, OS, INST and ACC) overlaps with the others. This was established using the Fornell–Larcker criterion, whereby all diagonal values exceed the inter-construct correlations, suggesting that each construct is distinct from the others, as shown in Tables 4 and 5. Thus, each construct differs from the others and is measured by different indicators/items.

The structural model indicates that Government Policy ($\beta = 0.194, p = 0.002$), Technostress ($\beta = 0.450$, $p < 0.001$), and Organisational Support ($\beta = 0.197$, $p = 0.007$) have significant and positive effects on behavioural intention to use e-learning platforms.

With respect to Hypothesis 3, the relationship between Government Policy and behavioural intention aligns with elements of Institutional Theory such as coercive pressures, compatibility, and observability. Clear policies, mandates, or incentives from government bodies create an environment in which e-learning is perceived as legitimate, necessary, and aligned with broader educational reforms. Learners respond to this institutional climate by forming stronger intentions to adopt e-learning. Government Policy therefore emerges as a structural antecedent that reinforces the institutional layer of the conceptual model.

Organisational Support is grounded in UTAUT's facilitating conditions and Institutional Theory's normative pressures. This result confirms that when institutions provide training, technical support, and encouragement, learners feel more confident and motivated to use e-learning. Organisational support signals legitimacy and reduces perceived effort, thereby strengthening intention. The finding supports the framework's institutional dimension by showing that organisational structures and norms meaningfully shape learner behaviour, thus addressing research objective 2.

Among these factors, Technostress has the largest effect, with a medium-to-large effect size ($f^2 = 0.258$; Table 7), indicating that higher levels of technology-related pressure are associated with stronger intentions among students to continue using e-learning platforms. The results show that, although technology can create stress – such as pressure to work faster, difficulty learning new tools, interference with personal time, and system failures – Technostress still significantly increases intention to use e-learning ($\beta = 0.450$, $p < 0.001$). In line with Stress–Strain–Outcome theory, these technology-related stressors create strain, but the outcome is not necessarily withdrawal; instead, students may feel compelled to continue using technology because it is essential for completing coursework, accessing materials, and meeting academic expectations. This can be described as necessity-driven or compliance-driven adoption. BI **acts as** the bridge between stress and **actual** behaviour. Thus, Hypothesis 5 is supported, validating the psychological dimension of the conceptual framework and highlighting Technostress as a critical factor shaping e-learning adoption.

By contrast, the current study found non-significant effects for Instructor Attitude ($\beta = 0.061, p = 0.184$) and Accessibility ($\beta = 0.055$, $p = 0.357$), with weak effect sizes ($f^2 = 0.007$ and 0.004, respectively).

Although accessibility is often linked to perceived ease of use in TAM and facilitating conditions in UTAUT, the non-significant effect suggests that learners may no longer perceive accessibility as a barrier. In many educational contexts, baseline access to devices and internet connectivity has become normalised. Accessibility may therefore function as a hygiene factor – necessary, but not sufficient to shape intention. Once minimum access is in place, other motivational and institutional factors appear to become more decisive. This finding refines the conceptual framework by indicating that contextual enablers such as accessibility do not automatically translate into intention unless accompanied by institutional or psychological drivers. Accordingly, Hypothesis 1 is not supported.

Instructor attitude is identified as a key social influence within UTAUT, but the non-significant result suggests that learners may not rely heavily on instructor cues when forming intentions. This may occur when learners are already familiar with digital tools or where peer and institutional influences outweigh instructor attitudes. It may also indicate that instructor endorsement is not strongly communicated. This finding nuances the psychological dimension of the framework by showing that not all sources of social influence carry equal weight in shaping intention. Accordingly, Hypothesis 4 is not supported.

The non-significant results for accessibility and instructor attitude may reflect uniformly high accessibility enabled by institution-wide digital infrastructure provision, together with consistently positive instructor behaviour reported by most students. Where such variables show limited variation, their predictive relationship with learning outcomes is weakened.

Behavioural intention has a significant impact on E-Learning Adoption behaviour, with a large effect size ($f^2 = 0.96$), highlighting its central role in translating the effects of exogenous constructs into actual use behaviour. The R^2 value for BI is 0.530, indicating that 53.2% of the variance is explained by Accessibility, Organisational Support, Government Policy, Instructor Attitude, and Technostress (Figure 2), which represents moderate-to-strong explanatory power. The R^2 value for E-Learning Adoption is 0.490, indicating that behavioural intention alone explains 49% of the variance in adoption. The f^2 values for each predictor (Table 7) indicate the contribution of each independent variable to the dependent variables' explained variance, which is acceptable in behavioural research.

Consistent with TAM, UTAUT, and DOI, intention remains the most powerful proximal determinant of actual behaviour. This confirms that the antecedents examined in this study i.e. organisational support, government policy, and technostress are ultimately influence adoption by affecting intention. This finding completes the conceptual framework by validating the intention–behaviour link central to technology acceptance theories.

In summary, the results highlight Technostress, Government Policy, and Organisational Support as key antecedents of behavioural intention to use an online learning platform in both initial and continued practice. These findings can guide policy-makers and higher education institutions in strengthening such capabilities to support e-learning adoption as technology-mediated learning becomes increasingly essential. Such progress requires personalised and adaptive learning systems that improve educational effectiveness by tailoring content to learners' specific needs. The integration of gamification tools and other interactive engagement methods may also improve outcomes without the environmental costs associated with physical infrastructure or printed materials.

Overall, the results show that e-learning adoption is shaped by a multi-layered system of influences. First, institutional antecedents such as government policy and organisational support significantly strengthen intention, whereas instructor attitude does not exert the expected social influence. Second, psychological antecedents such as Technostress are the strongest predictors, underscoring the importance of emotional and cognitive strain in technology acceptance. Third, contextual antecedents such as accessibility do not significantly shape intention, suggesting that contextual readiness alone is insufficient. Finally, behavioural intention strongly predicts actual adoption, supporting the theoretical foundations of the model.

Future research could explore the moderating role of government policies and schemes in colleges' and universities' initiation and implementation of online education, as such measures can encourage HEIs to respond more rapidly and expand the reach of virtual education. During COVID-19, certain government bodies provided mobile phones and computers to eligible students through higher education institutions to facilitate access to learning platforms. Further work could also examine causal relationships between government initiatives and institutional readiness.

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Effective Professional Functioning and Temperament in Corporate Employees – Specialists and Management Staff

Abstract

This study examined differences in temperament and occupational effectiveness between corporate employees in specialist and managerial roles, and tested whether temperamental traits were associated with occupational effectiveness. A cross-sectional survey was conducted using standardised psychological questionnaires: the Pavlovian Temperament Survey (PTS) and the Bochum Inventory of Personality Determinants of Work (BIP). Statistical significance was set at $p < 0.05$. No significant between-group differences in temperament were found. Across the full sample, however, temperamental traits showed positive associations with indices of occupational effectiveness. Managers reported higher self-rated effectiveness than specialists, a pattern that may reflect stronger motivation, flexibility, conscientiousness, social skills and emotional stability – attributes that are particularly salient for decision-making and team leadership. These findings suggest that incorporating assessment of temperamental traits into organisational recruitment, selection, and development processes may help to enhance occupational effectiveness, support job satisfaction, and build team capability.

Keywords: temperament, corporate employees, effective professional functioning, work performance, psychological predictors

Introduction

Work occupies a central place in the life course, shaping patterns of living and affording opportunities to deploy and develop skills. Although the nature and intensity of engagement vary over time, work remains a major arena for meeting needs and pursuing interests and passions (Kubat, 2015). Work-related activity spans the full spectrum of occupational participation, from the development and application of professional qualifications to the performance of work roles. Czechowska-Bieluga (2010) defines occupational functioning as employees' activity and participation in the workplace arising from the performance of professional roles; these roles are shaped by the interplay between employees' competences and working conditions, as well as the organisation's goals and tasks (Klimkowska, 2019). Czapiński (1992) further emphasises the role of happiness – understood as subjective well-being – as an integral element of occupational functioning and a cornerstone of success in life; he regards happiness as foundational to overall life satisfaction (Wirkus & Stasiak, 2018).

Kubat (2015) understands functioning as the enactment of roles in relation to others and to tasks. In this vein, occupational functioning comprises several interrelated components, including competences, formal qualifications, skills, duties and decision-making authority (Kossowska & Sołtysińska, 2002). These terms are often used interchangeably in everyday discourse, but they warrant careful distinction. Competences are not fixed traits; they evolve with professional and life experience.

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Extended education and continuous learning foster the development of competences and, in turn, enhance occupational functioning. Qualifications refer primarily to formal education and certified credentials, typically complemented by relevant experience and skills. Authority denotes the decision rights attached to a post, while duties (obligations) flow from the terms of the employment contract (Kubat, 2015).

Temperament has attracted sustained attention across multiple disciplines. Theoretical and empirical work converges on the view that it is a complex, multidimensional construct with significant implications for individual functioning, including occupational domains. It is amenable to objective assessment via behavioural and neurobiological indices, yet it is also shaped by genetic, biological, cognitive, and environmental influences. Temperamental traits constitute innate dispositions and vulnerabilities, including levels of emotional reactivity and resilience, that condition individuals' capacity to regulate their responses to adverse and favourable environmental contingencies. Crucially, these traits also calibrate susceptibility to environmental influence, shaping responses to stimuli and to the demands of the workplace (Kagan, 2003).

This article examines the association between temperament and effective occupational functioning amongcorporate employees, comparing specialists with managerial staff. We combine a critical review of the literature with a questionnaire-based survey using validated psychological instruments. Temperament and work-related functioning were assessed using the Pavlovian Temperament Survey (PTS) and the Bochum Inventory of Personality Determinants of Work (BIP), respectively.

Literature Review

Theories of **individual functioning at work** are a central concern in organisational psychology and human resource management. A prominent strand focuses on work-life balance (Work-Life BalanceTheory). It is concerned with how employees can integrate paid work with other life domains, including family, relationships, leisure and health. Evidence indicates that sustaining such balance is associated with higher job satisfaction, better mental health and improved performance (Greenhaus et al., 2003). Work–life balance is dynamic, shaped by individual preferences, values and life goals (Kelliher & Anderson, 2010). Achieving balance typically requires control over working time and flexibility in how tasks are undertaken. Employers can support this by providing flexible scheduling, maternity and paternity leave, childcare support and time off for personal matters. Shen and Joseph (2021) emphasise that developing digital skills has become indispensable for effective professional performance, particularly in the context of rapid changes in the labour market.

A central challenge is the growing expectation that employees be constantly available and immediately responsive, especially in a digital era in which work and private life are increasingly intertwined (Gajendran & Harrison, 2007). Nevertheless, establishing clear boundaries between work and non-work and honing time-management skills are important individual strategies for sustaining balance (Matthews & Barnes-Farrell, 2010).

Recent research on work–life balance in the context of the shift to remote working during the COVID-19 pandemic suggests that greater flexibility in where and when work is done can help employees manage work and non-work domains, with positive effects on balance. However, remote working can also erode boundaries, blurring work and personal life and generating conflict. As a result, remote workers – particularly those who are highly engaged– may experience fatigue as demands from both domains intensify and accumulate (Bhat et al., 2023).

This and other theories in the literature emphasise that careers are dynamic and evolve over time, and that individuals and organisations must make deliberate choices and adopt varied strategies to foster professional success. In this context, career success is often operationalised in terms of effectiveness, a construct widely used to describe individual and team performance (Skrzypek, 2012). Effectiveness shapes organisational performance and development and is influenced by both intra- and extra-organisational factors.

Employee motivation and commitment are key determinants of work performance and quality of life. Intrinsic motivation – grounded in one's interests and competencies – is associated with higher overall quality of life. Work, with its physiological and psychological dimensions, therefore plays a central role in human development and affords opportunities for personal growth (Sillamy, 1995).

An employee's effectiveness also depends on the workplace climate, the motivation system and working conditions. The motivation system is a key element of management, comprising mechanisms that initiate, direct and sustain behaviour. Different types of motivation can be identified; a common distinction is between extrinsic motivation, linked to rewards and benefits. The achievement of satisfactory results depends on the employee's effectiveness (Łukaszewski, 2002). Alongside extrinsic motivation, there is also intrinsic motivation, which stems from the activity itself and an interest in work. It arises when an individual is engaged in the type of work they do and seeks to develop in the role they hold, without necessarily expecting rewards. Humanistic psychology also emphasises motivational aspects related to development, fulfilment and self-realisation. These types of motivation coexist with characteristics such as openness to new experiences, being present in the moment, perceiving the world as a source of inspiration, a sense of control over one's own life, self-confidence, and the ability to think creatively and solve problems (Łukaszewski, 2002).

Effective employee motivation is central in contemporary organisations, hence supervisory roles are pivotal (Dworzecki, 2001). Managers should understand their employees, including their needs and the stimuli that motivate them, so that they can deploy motivational mechanisms judiciously and thereby enhance employees' motivation (Czarnecka, 2011). Securing robust motivational outcomes, high levels of engagement and identification with the organisation's mission and objectives, whilst sustaining mutual satisfaction, requires strategies tailored to the specific characteristics of the organisational unit and to its processes (Steinerowska-Streb & Wronka-Pośpiech, 2022).

Beyond motivation, overall quality of life and job satisfaction are also important determinants of occupational effectiveness. Quality of life is a multidimensional construct grounded in both individuals'expectations and objective indicators (Ratajczak, 2006). Job satisfaction denotes the affective evaluation associated with performing one's work roles and tasks (Płaczkiewicz, 2016).

Temperament is a term used primarily to denote the formal properties of reaction and behaviour. It encompasses parameters such as energy level, tempo, intensity, strength, variability, speed and mobility (Strelau, 2001). From a predominantly biological (constitutional) perspective, Strelau characterises temperament in terms of the strength of excitation (an index of endurance, low reactivity and emotional resilience), the strength of inhibition (the capacity for behavioural self-control), the mobility of nervous processes (the ability to adapt behaviour rapidly to environmental change) and the balance of nervous processes (the relation between excitation and inhibition, often operationalised as the difference between them).

Within Jan Strelau's framework, the ratio of excitation to inhibition – the relative strength of these two processes – serves as an index of temperamental balance. It indicates whether an individual's functioning is characterised predominantly by excitation (energy, reactivity, impulsivity) or by inhibition (self-regulation, the capacity to suppress responses, resistance to overload).

The model posits that a predominance of excitation facilitates rapid, intense responding but increases vulnerability to disorganisation under high levels of stimulation, whereas a predominance of inhibition is associated with stronger behavioural control and greater stability of action. In general, a relative equilibrium between the two processes is the most adaptive configuration.

Temperament, understood as a biologically grounded disposition shaping patterns of reaction and behaviour, has significant implications in corporate settings, influencing how employees accommodate organisational demands. In organisational contexts, temperamental diversity can enhance efficiency and support adaptation to dynamic change and to the differentiated requirements of functions and departments. Sensitivity to temperamental profiles enables more effective team management by aligning roles, workflows and expectations with individuals' propensities for adaptation and self-regulation, thereby contributing to organisational performance.

The effective functioning of a corporation depends fundamentally on its workforce. In line with their strategic objectives, firms employ specialists from a wide range of disciplines and typically organise their activities into functional departments. Common functions include general management, finance, marketing, research and development (R&D), human resources (HR), information technology (IT), and legal affairs. Depending on the sector and the firm's priorities, additional functions may be established, such as engineering, architecture, design, data analytics or logistics, staffed by the relevant professionals.

Employees commonly work in teams, a mode of organisation that can be more effective than individual effort because it brings together diverse skills, experiences and perspectives (Katzenbach & Smith, 1993). Teams are often understood as small groups of individuals with complementary skills who are committed to a shared purpose and performance goals, and who hold themselves mutually accountable (Katzenbach & Smith, 1993).

Professional expertise and career satisfaction develop over time through the acquisition of relevant competences. Early career is a formative phase in which newcomers and organisations learn from one another. During organisational socialisation, new employees come to understand both the formal requirements of the job and the tacit expectations associated with the role (Forbes & Piercy, 1991). It is common for new hires to experience 'reality shock' or 'culture shock' when their initial expectations collide with the lived realities of the work (Forbes & Piercy, 1991).

Schein (1978) identifies four principal challenges facing new entrants to organisations: the need to improve performance continuously; to hone technical competencies; to be ready to assume a range of organisational roles; and to make informed career decisions. Although demanding, meeting these challenges can lay the foundations for a productive and fulfilling early career (Schein, 1978). Ultimately, expertise is built through sustained investment of time, cumulative learning, and engagement with stretching assignments that generate valuable experience (Forbes & Piercy, 1991).

Individuals who deepen their knowledge across specialist and managerial domains are more likely to progress to the upper tiers of the organisational hierarchy and join the managerial ranks. The *Encyclopedia of management* defines the managerial cadre as those responsible for directing organisational units and achieving results through the work of others (Listwan, 2004). Managers operate in both commercial and non-profit contexts and can be classified along several dimensions, including organisational type, functional area, hierarchical level, and the nature of their involvement in delivering organisational tasks (Listwan, 2004).

The most familiar typology classifies managers by hierarchical level. Top management – typically chief executives and directors – sets organisational goals, formulates strategy, and makes pivotal decisions, such as approving mergers or entering new markets (Listwan, 2004). Middle management – such as departmental and operations managers – translates strategic direction into policies and coordinates the work of first-line managers (Griffin, 1993). First-line management –team leaders, supervisors, and forepersons – oversees day-to-day operations and the work of operational staff (Griffin, 1993).

Effective managerial practice rests on the capacity for situational analysis, goal-setting, effective communication and sound decision-making. It is equally important to understand the varieties of leadership behaviour and their organisational effects, and to use decision-making models judiciously in dynamic business contexts (Griffin, 1993; Robbins & Judge, 2017). Managerial effectiveness is critical to organisational success. It is shaped by managerial skill, professional experience, leadership style and organisational culture, and it can be assessed using methods such as 360-degree feedback. Understanding these factors informs HRM strategy and decisions about management development. Ongoing monitoring of managers' performance and the implementation of targeted improvement initiatives are essential to achieving organisational goals.

Analysing employees' performance – across both specialist and managerial roles – assumes particular salience when temperament is taken into account. Appreciating how temperament shapes job performance enables the tailoring of managerial approaches and the development of relevant capabilities within the organisation. Research in this area can generate robust practical implications for optimising performance at both team and individual levels.

Research Method

This study examined temperamental traits and professional effectiveness among corporate employees, specifically specialists and managers. Its specific aim was to test the association between temperamental traits and professional effectiveness in these two occupational groups. The study employed a questionnaire-based survey design using standardised psychological instruments (see Bryman & Bell, 2015). To address the research questions and test the hypotheses, statistical analyses were conducted in IBM SPSS Statistics.

In line with the study objectives, we formulated the following hypotheses:

H1. Specialists and managers differ significantly in professional effectiveness.

H2. Specialists and managers differ significantly in temperament.

H3. Professional effectiveness is positively associated with temperament.

Research tools are instruments that enable scientists to measure and analyse research phenomena (Bryman & Bell, 2015). Two main instruments were used: the **Pavlovian Temperament Survey (PTS)** and the **Bochum Inventory of Personality Determinants of Work (BIP)**.

The Pavlovian Temperament Survey (PTS), developed by Strelau and Zawadzki (1998), comprises 57 items assessing three temperamental properties: Strength of the Excitation Process (SPP), Strength of the Inhibition Process (SPH), and Mobility of Nervous Processes (RPN). The instrument is grounded in Pavlov's theory of the properties of the nervous system (Strelau, 2001). Reported internal consistency is good (Cronbach's alpha: SPP = 0.88; SPH = 0.77; RPN = 0.82), with evidence of construct validity (Strelau & Zawadzki, 1998).

The Bochum Inventory of Personality Determinants of Work (BIP), developed by Hossiep and Paschen (2006), is an instrument for assessing personality in a professional context. It comprises 220 questions and measures the following scales: professional orientation (MOM – achievement motivation, MW – power motivation, MP – leadership motivation), professional behaviour (SU – conscientiousness, EL – flexibility, OD – action orientation), social competences (WS – social sensitivity, OR – openness to relationships, TO – sociability, OZ – team orientation, AS – assertiveness) and psychological characteristics (SE – emotional stability, PP – working under pressure, PS – self-confidence). Psychometric testing has confirmed high reliability (coefficients ranging from .80 to .95) and the validity of the instrument (Jaworowska & Brzezińska, 2014).

Research Results

The study used a random sample drawn from a clearly defined sampling frame comprising employees of international corporations based in Warsaw. The sampling frame was compiled in collaboration with selected organisations, which provided anonymised lists of employees who met the predefined inclusion criteria. The sample was selected using simple random sampling based on the principle of equal probability of selection, meaning that every individual meeting the inclusion criteria had the same random chance of being invited to participate.

The inclusion criteria were: (1) current employment in an international corporation headquartered in Warsaw, (2) full-time employment status, (3) at least one year of tenure in the current organisation, and (4) provision of informed and voluntary consent to participate in the study. Individuals employed on temporary contracts, interns, and employees with less than one year of organisational tenure were excluded in order to ensure a relatively homogeneous level of professional experience and organisational adaptation among participants.

The study was conducted electronically at the turn of 2023/2024 and included 80 participants. Women constituted the majority of the sample, accounting for 61.3% of respondents (n = 49), while men represented 38.8% (n = 31). The vast majority of participants had higher education (91.2%; n = 73), whereas 8.8% (n = 7) reported secondary education. In terms of occupational position, the sample was evenly divided between specialists and individuals in managerial roles, with each group comprising 50.0% of participants (n = 40).

Verification of Assumptions

The significance level was set at $p < 0.05$. The Shapiro–Wilk test was used to assess the normality of the variable distributions and indicated that all analysed variables were normally distributed. Equality of variances between the compared groups was assessed using Levene's test, which confirmed homogeneity of variances for all analysed variables. Parametric tests were therefore used.

To determine the significance of differences between the two groups (independent variable: 'Position'), Student's *t-test* was used. The results are presented in Table 1.

To determine the significance of differences between the two groups (independent variable: 'Position'), Student's *t-test* was used. The results are presented in Table 2.

The *t-tests* did not indicate any statistically significant differences in the analysed variables (RPN, SPH, and SPP) when the sample was divided according to the 'Position' variable.

To determine the strength and direction of the relationship between the RPN variable and the other selected variables, Pearson's *r* correlation coefficient was used. The results are presented in Table 3.

The *r* correlation analysis indicates a significant positive relationship between the variables.

To determine the strength and direction of the relationship between the SPH variable and the other selected variables, Pearson's *r* linear correlation coefficient was used. The results are presented in Table 4.

The *r* correlation analysis indicates a significant positive relationship between the variables.

To determine the strength and direction of the relationship between the SPP variable and the other selected variables, Pearson's *r* correlation coefficient was used.

The Pearson's *r* correlation analysis revealed statistically significant positive relationships between the strength of the excitation process and several dimensions of professional and psychological functioning. The strongest correlations were observed

Table 1
Results of Student's t-test – Significance of Differences between Two Groups (Independent Variable: 'Position')

						95% CI	
Variable	***T***		***Df***	***p***	**Cohen's *d***	**Lower**	**Upper**
AS	–2.10	*	76.91	0.039	–0.47	–0.93	–0.04
EL	–2.19	*	77.66	0.032	–0.49	–0.94	–0.06
MO	–2.06	*	72.37	0.043	–0.46	–0.99	–0.02
MP	–5.74	***	75.06	<0.001	–1.28	–1.84	–0.88
MW	–2.34	*	77.08	0.022	–0.52	–1.01	–0.10
OD	–0.58		75.48	0.562	–0.13	–0.59	0.31
OR	–0.10		76.11	0.921	–0.02	–0.48	0.41
OZ	–2.47	*	77.81	0.016	–0.55	–0.98	–0.12
PP	–0.65		73.56	0.516	–0.15	–0.60	0.30
PS	–1.99	*	77.63	0.050	–0.45	–0.90	–0.03
SE	–2.25	*	76.71	0.027	–0.50	–0.92	–0.07
SU	–0.75		77.60	0.453	–0.17	–0.67	0.24
TO	0.13		75.63	0.899	0.03	–0.42	0.47
WS	–0.11		74.68	0.910	–0.03	–0.47	0.42

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: authors' own work.

Table 2
Results of Student's t-test – Significance of Differences between Two Groups (Independent Variable: 'Position')

					95% CI	
Variable	***T***	***Df***	***p***	**Cohen`s *d***	**Lower**	**Upper**
RPN	0.53	77.88	0.601	0.12	–0.33	0.55
SPH	0.14	77.39	0.885	0.03	–0.40	0.51
SPP	–0.60	77.46	0.548	–0.14	–0.57	0.30

Source: authors' own work.

Table 3
Results of Pearson's r Correlation Analysis

					95% CI		p
Variable 1	Variable 2	n	r		Lower	Upper	
RPN	AS	80	0.39	***	0.22	1	<0.001
RPN	EL	80	0.46	***	0.30	1	<0.001
RPN	MO	80	0.07		–0.11	1	0.261
RPN	MP	80	0.18		–0.01	1	0.060
RPN	MW	80	0.08		–0.11	1	0.247
RPN	OD	80	0.35	***	0.18	1	0.001
RPN	OR	80	0.60	***	0.47	1	<0.001
RPN	OZ	80	0.27	**	0.08	1	0.009
RPN	PP	80	0.25	*	0.06	1	0.014
RPN	PS	80	0.61	***	0.47	1	<0.001
RPN	SE	80	0.36	***	0.18	1	0.001
RPN	SU	80	0.00		–0.18	1	0.492
RPN	TO	80	0.22	*	0.04	1	0.025
RPN	WS	80	0.31	**	0.14	1	0.002

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: authors' own work.

Table 4
Results of Pearson r Correlation Analysis

					95% CI		p
Variable 1	Variable 2	n	r		Lower	Upper	
SPH	AS	80	0.10		–0.09	1	0.190
SPH	EL	80	0.21	*	0.03	1	0.029
SPH	MO	80	0.16		–0.03	1	0.082
SPH	MP	80	–0.09		–0.27	1	0.787
SPH	MW	80	–0.07		–0.25	1	0.736
SPH	OD	80	0.51	***	0.36	1	<0.001
SPH	OR	80	0.11		–0.08	1	0.166
SPH	OZ	80	0.15		–0.03	1	0.088
SPH	PP	80	0.38	***	0.21	1	<0.001
SPH	PS	80	0.12		–0.07	1	0.143
SPH	SE	80	0.25	*	0.06	1	0.014
SPH	SU	80	0.20	*	0.01	1	0.038
SPH	TO	80	0.51	***	0.36	1	<0.001
SPH	WS	80	0.40	***	0.23	1	<0.001

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: authors' own work.

with flexibility ($r = 0.62$, $p < 0.001$), self-confidence ($r = 0.60$, $p < 0.001$), and the ability to work under pressure ($r = 0.58$, $p < 0.001$). A high level of strength of the excitation process was also significantly associated with emotional stability ($r = 0.49$, $p < 0.001$), assertiveness ($r = 0.44$, $p < 0.001$), achievement motivation ($r = 0.38$, $p < 0.001$), and leadership motivation ($r = 0.34$, $p = 0.001$).

Moderate but statistically significant relationships were also found with openness to relationships ($r = 0.26$, $p = 0.010$), social sensitivity ($r = 0.23$, $p = 0.022$), and power motivation ($r = 0.21$,

$p = 0.034$). By contrast, the associations between the strength of the excitation process and team orientation, conscientiousness, and the remaining variables were not statistically significant ($p > 0.05$); the weak negative relationship observed for conscientiousness was also not statistically significant.

Overall, the findings indicate that strength of the excitation process is an important predictor of effective functioning in contexts that require flexibility, emotional resilience, the ability to perform under pressure, and self-confidence, whilst showing weaker and non-significant associations with traits related to teamwork and conscientiousness.

Conclusions and Practical Implications of the Study

The study found no statistically significant differences in temperament between specialists and managers, but did identify a significant positive association between temperament and effective occupational functioning. Managers reported higher self-rated effectiveness than specialists, a pattern consistent with attributes commonly associated with leadership roles – motivation, adaptability, conscientiousness, social competence and emotional stability. This pattern plausibly reflects the distinctive demands of managerial work, including decision-making and team leadership. It is important to note that the BIP instrument used in this study assesses personality characteristics relevant to occupational functioning – potential psychological predictors of effectiveness – but does not directly measure effectiveness itself. Accordingly, the findings speak to predispositions for effective functioning rather than to participants' actual performance outcomes.

Psychometric assessment, including measures of temperament, may support improved person-role matching, with potential benefits for career success and job satisfaction. The evidence also underscores the value of cultivating leadership-relevant attributes such as assertiveness, adaptability and achievement motivation. However, the present results do not warrant definitive recommendations for selection practice, nor do they justify using temperament scores as standalone decision criteria in recruitment or human resource management. Nonetheless, they provide a basis for further inquiry into temperament as one of several contributors to effective professional functioning.

Psychometric instruments, such as temperament inventories, can usefully inform developmental processes, particularly the design of training, mentoring and coaching programmes intended to cultivate competencies critical to managerial practice. However, further research across sectors, incorporating objective performance indicators, is required to delineate more precisely the scope and nature of the association between temperament and professional functioning.

This study has several limitations. The sample comprised only corporate employees in Warsaw, which may limit the generalisability of the findings to other occupational groups, sectors and cultural or organisational contexts. In addition, both temperament and professional effectiveness were assessed via self-report. While self-report is widely used in research on temperament and occupational functioning, such methods are vulnerable to self-presentational bias and social desirability effects, and may have limited validity as proxies for actual behaviours and achievements.

In conclusion, the study offers valuable, albeit limited, insights into the role of temperament in professional contexts. Further in-depth analyses are required to clarify the practical implications of these findings for human resource management.

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Dominika P. Brodowicz

From Smart to Agentic Environments: AI and Innovative Technologies Transforming Learning, Work and Urban Living

Abstract

This article examines agentic environments, an emerging paradigm that moves beyond the conventional smart city model by embedding artificial intelligence across diverse settings. Unlike earlier systems, which were technologically advanced, yet siloed, agentic environments integrate generative AI (GenAI) with edge computing and multi-agent frameworks to create adaptive, privacy-preserving, context-aware and sustainability-oriented systems. They bridge personal, professional and public spheres to support proactive decision-making, sustainable resource management and personalised user experiences across daily activities, including learning, work, commuting and civic participation. The study uses an exploratory design that combines theoretical modelling with empirical methods to assess this evolving concept. Primary data come from a survey and a focus group with AI and machine-learning experts, used to validate the conceptual framework through practical applications. Ethical, social and environmental considerations are foregrounded, including data sovereignty, algorithmic transparency and the energy demands of large AI models. The findings suggest that modularity, cross-domain integration and ethical governance are foundational to agentic systems, while significant challenges remain around privacy, individual autonomy and environmental impact. Overall, the research positions agentic environments as key building blocks for human-centred, sustainable and resilient urban ecosystems.

Keywords: agentic environments, generative AI, smart cities, privacy, urban sustainability

Introduction

In recent years, the smart city concept has evolved beyond its early emphasis on optimising digital infrastructure and data-driven governance. Traditional smart environments, focused on smart mobility, smart governance and smart living, have struggled with siloed operations and limited responsiveness. The lack of integration between systems constrains the adaptability of urban infrastructure. At the same time, evolving societal needs and advances in digital technologies, most notably generative AI (GenAI), edge computing and autonomous multi-agent systems, have catalysed the emergence of agentic environments. This new paradigm links interconnected systems with context-aware capabilities to enable proactive, personalised and ethically aligned user engagement across work, learning and everyday urban life.

This article examines how agentic environments redefine urban intelligence by shifting from reactive automation to dynamic collaboration among AI agents across personal, professional and public domains. By integrating modular AI systems, edge-based processing and multimodal interfaces, these environments point towards cities that are not merely efficient but adaptive and human-centred. Drawing on theoretical foundations and empirical research – including surveys and expert focus groups – the study shows how agentic systems can uphold data privacy, support sustainability and enhance user wellbeing. Through real-world examples in transport, education and civic participation, we position agentic environments as central to the next wave of urban innovation. We also recognise that progress depends as much on governance and

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equity as on technical capability, and that solutions must operate within diverse regulatory frameworks while responding to varied social needs.

Theoretical Foundations of Smart and Agentic Environments

Over the past two decades, the notion of the 'smart city', and, more broadly, the 'smart environment' has evolved considerably. The term initially referred to urban areas that used digital technologies and data-driven governance to improve the efficiency of infrastructure management, service delivery and resource utilisation (Komninos, 2002). In practice, smart cities apply information technologies across domains such as transport, communication, education and public administration to foster sustainability, innovation and citizen engagement. According to Giffinger et al. (2007), smart cities comprise six interrelated dimensions: smart economy, smart people, smart governance, smart mobility, smart environment and smart living. Subsequent frameworks have expanded and refined this perspective.

The concept of Ambient Intelligence (AmI) emphasised environments that sense human presence and adapt to it through unobtrusive, background operations, reducing the need for direct human interaction (Aarts, 2005; Weber et al., 2005). This work led to the development of intelligent environments that move beyond automation by incorporating cognitive and responsive capabilities which learn from user behaviour to optimise operations and better meet user needs (Wrede et al., 2010). Despite their transformative potential, most current models still operate independently and are largely reactive. This is often described as the silo effect, referring to the lack of integration and communication between different data owners (Soe, 2018) – for example, across departments responsible for transport, education and social services. Such fragmentation constrains overall efficiency and adaptability, impeding the creation of truly interconnected and responsive urban management. These limitations provide the impetus for agentic environments, which aim to bridge silos through integrated, context-aware and proactive systems across domains.

Nearly a decade ago, Wolter and Kirsch (2017) observed that many 'smart' solutions optimise discrete local functions, while devices such as smart meters and traffic lights still operate in isolation, with little or no inter-system communication or co-operation. Generative AI (GenAI) and multi-agent systems (MAS) offer a response to this limitation, shifting from static, reactive technologies to active, goal-directed ecosystems. GenAI denotes AI models that can produce original content – text, images and video – by learning from data (Brown et al., 2020). Edge computing reduces latency by bringing computation and data storage closer to data sources (for example, sensors and devices), enabling real-time decision-making (Shi et al., 2016). Autonomous agents are self-governing software entities that perceive their environment and pursue objectives through automated processes with minimal human oversight (Wooldridge & Jennings, 1995). Agentic environments combine large language models (LLMs), multimodal interfaces, decentralised edge inference and modular AI agents (Guo et al., 2024). They differ from conventional smart systems by supporting cross-domain reasoning, contextual awareness and predictive personalisation (Bibri & Krogstie, 2017).

Current research increasingly treats agentic systems as a distinct paradigm that extends beyond the smart-city model. Tiwari (2025) distinguishes between automation, which executes pre-defined tasks; autonomy, which allows systems to optimise themselves within specified limits; and agency, which enables systems to achieve goals through cross-domain co-ordination, negotiation among AI agents and contextual understanding. On this view, agentic environments surpass data-driven, personalised smart cities by enabling purposeful co-ordination across personal, professional and urban systems. Whereas smart infrastructure prioritises operational efficiency and data-driven service delivery within discrete functional areas, agentic environments allow systems to work together through negotiated decision-making.

The significance of this approach lies in reframing the human-technology-urban relationship from a narrow focus on service optimisation and energy efficiency to a co-operative ecosystem that advances sustainability while maintaining high standards of user privacy. In essence, agentic environments are AI-driven, adaptive urban systems that integrate personal, professional and public domains through autonomous agents and context-aware decision-making. Throughout, we refer to urban areas rather than cities, recognising that post-COVID patterns of work, learning and daily life increasingly extend beyond traditional municipal boundaries through remote work and online provision. Privacy is a central concern. In many contexts, ostensibly smart systems have enabled excessive and opaque data practices, including facial recognition and mass surveillance. For example, in China, extensive closed-circuit television (CCTV) networks and other tools are used to monitor public behaviour, apply facial recognition in public spaces and track individuals in real time without explicit consent (Keegan, 2019). A more recent case is Amsterdam's decision to withdraw from a smart traffic-light scheme that collected data from citizens' smartphones, due to concerns about tracking and a lack of transparency regarding subsequent data use and sharing (Ioplus, 2025). Such examples highlight the need for alternative approaches based on agentic environments, which by design are more secure and privacy-preserving, minimising the transmission of data to central hubs. However, agentic solutions can also introduce new structural governance challenges. Technologies that span personal, professional and public domains risk reinforcing algorithmic exclusion, making decision processes opaque and entrenching inequalities in the distribution of benefits. Accordingly, new safeguards are required – ensuring accountability, distributional fairness and robust public oversight – and must be developed in parallel with the deployment of agentic systems.

Practical Applications of Agentic Environments in Urban Life, Work, and Learning

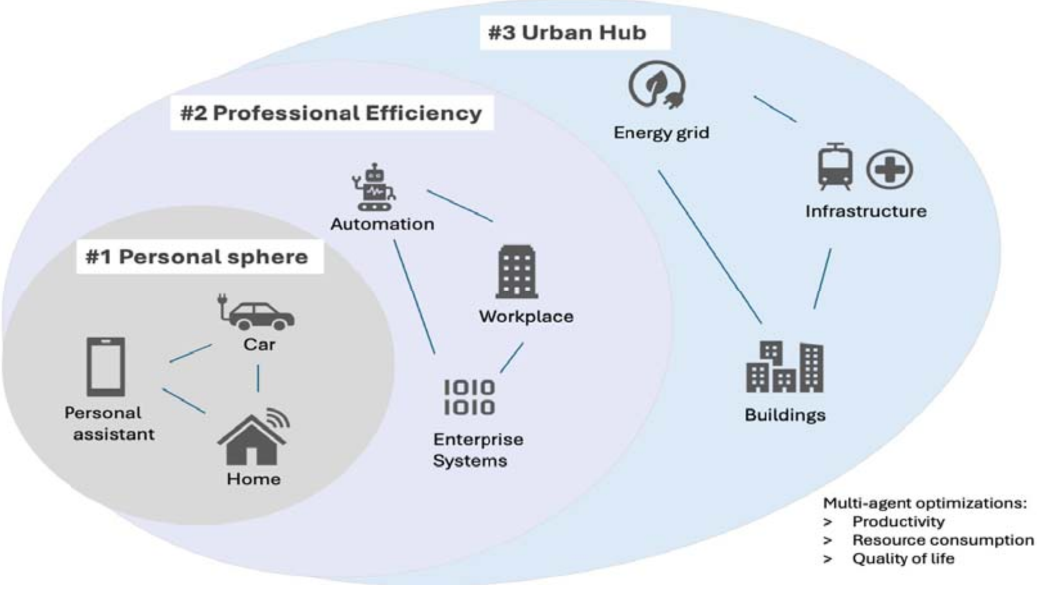
The shift from smart to agentic environments is unfolding at both theoretical and practical levels. AI-driven systems are moving from passive automation to proactive orchestration across domains such as mobility, education, governance and healthcare. The Estonian Zelos platform – analysed by the author as part of intelligent solutions deployed during COVID-19 (Brodowicz, 2021) – illustrates decentralised, agent-based civic engagement by matching isolated residents with volunteers. By co-ordinating logistics, communication and emotional support, such platforms exemplify a move beyond isolated smart-city applications towards responsive, co-ordinated systems. Agentic environments have potential to reshape commuting. Vehicle-to-everything (V2X) systems integrate personalised agents that co-operate with vehicles (Ding et al., 2022). Platforms developed by firms such as Qualcomm and Huawei enable vehicles to interoperate with home and city systems, with the aim of reducing driver stress and emissions during journeys (Rehman et al., 2023). For example, an in-mirror vision system can detect driver fatigue by tracking eye movement, prompt rest breaks via a voice agent, check responsiveness and even offer to book a nearby hotel or restaurant. Deployed thoughtfully, these AI-enabled agents can enhance personal safety and improve travel efficiency. Similar dynamics are evident in work and learning. Productivity in coding, document generation and process automation is being transformed by tools such as Microsoft Copilot, IBM Watson, GitHub Copilot and OpenAI's ChatGPT, which provide interactive support for writing, research, brainstorming and problem-solving across disciplines (Mosaiyebzadeh et al., 2023; Susnjak, 2022). The evolution of these tools' merits close attention: they are shifting from basic, reactive interfaces to personalised agents that understand context, orchestrate optimised workflows and help to reduce cognitive overload – a growing concern in both educational and workplace settings (Durst et al., 2024). Taken together, these examples demonstrate how agentic environments extend beyond single-purpose smart applications to deliver integrated, context-aware and user-centred capabilities across everyday urban life.

Workplaces adopting agentic environments allow personal AI agents to orchestrate calendars across work and home, recommend sustainable commuting options and manage home-office energy use – capabilities that are particularly valuable for remote and hybrid arrangements (Tawalbeh, 2025). Similar advances are evident in education. As lifelong learning and frequent career transitions become the norm – especially for urban residents who may reskill or change sectors multiple times – more adaptive support is required. The education sector already employs generative AI for tutoring, assessment and content creation, but agentic frameworks go further. For example, a student learning assistant can combine city transit data to recommend less crowded routes aligned with class schedules, while monitoring stress via wearables to adjust workload (Benkhalfallah et al., 2023). Pilot projects in Amsterdam and New York have tested AI-assisted urban classrooms, where multimodal AI agents (Mischos et al., 2023) dynamically adjust temperature, lighting and task difficulty in response to student feedback and behaviour.

Contemporary urban areas face environmental and social challenges that demand solutions beyond isolated 'smart' products and services. Agentic environments offer a holistic route to resilience and sustainability (see Figure 1). Building management systems (BMS) from Siemens and Johnson Controls already deploy AI agents to optimise HVAC, lighting and space use in real time, responding to occupancy patterns (Burzagli et al., 2022). These agents can scale to neighbourhood level, co-ordinating energy consumption with waste and transport operations. Barcelona's 'City OS' platform links environmental data with social services, illustrating multi-agent co-ordination in practice (Alam et al., 2012). The adoption of such systems supports circular-economy principles, defined by the European Commission as 'a model of production and consumption, which involves sharing, leasing, reusing, repairing, refurbishing and recycling existing materials and products as long as possible' (European Commission, 2020). Agentic environments address efficiency and effectiveness alongside data privacy and security. By using edge computing for local data processing, they can reduce reliance on the cloud and minimise exposure to security risks – as exemplified by devices such as Meta's smart glasses and Google's edge Tensor chips (Shen et al., 2024).

Large-scale AI systems are highly energy-intensive. The IEA (2024) estimates that a single generative-AI query on ChatGPT can use roughly as much electricity as a 60-watt light bulb running for 17 minutes. Training a single large language model can emit hundreds of tonnes of CO (Luccioni et al., 2022). Agentic environments offer an alternative pathway by prioritising small language models (SLMs), on-device edge inference and modular AI agents with adaptive scaling, alongside hybrid architectures that dynamically offload computation. Moving towards this design could reduce the carbon footprint of urban AI while maintaining personalised services and strong operational performance. Figure 1 presents the Agentic Environment Lenses, showing how agents integrate across personal, professional and urban spheres. These domains can operate independently to safeguard privacy and data security, while still enabling information exchange and seamless collaboration with the user's explicit knowledge and consent.

Figure 1
The Agentic Environment Lenses with Agents' Integration Across Personal, Professional and Urban Sphere



Source: „The agentic environment lenses with agents' integration across personal, professional and urban sphere" [working paper], P. Pospieszny, & D. P. Brodowicz, 2025 (dr2.ai).

Methodology and Results of the Study

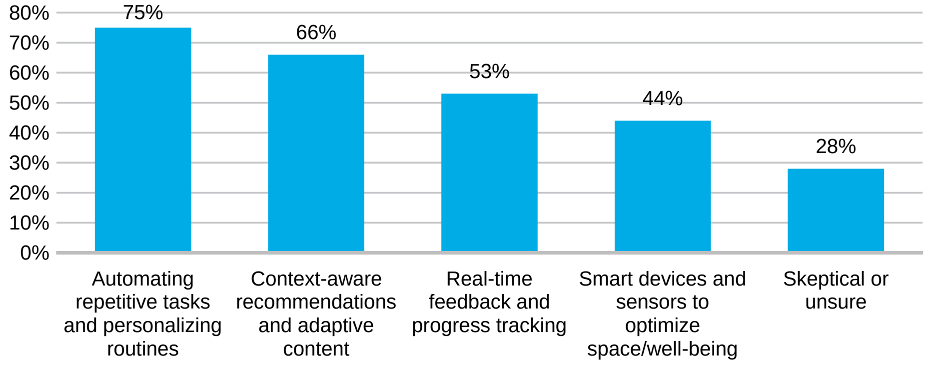
Given the nascent state of theory in this field, the study adopts an exploratory design to analyse the interplay between generative AI and agentic environments. A three-stage methodology combined secondary and primary data. Stage one comprised a desktop review of the literature, drawing on peer-reviewed sources indexed in IEEE Xplore, Scopus and Web of Science, alongside white papers, industry reports and relevant regulatory documents. This phase mapped the technological evolution of smart environments and current AI applications, establishing the conceptual basis for the empirical work.

Stage two comprised an online survey administered via Google Forms between January and February 2025. Participants were recruited through LinkedIn and the dr2.ai team's professional networks, using purposive sampling to reach experts in artificial intelligence, machine learning and related fields. Eligibility required at least three years' experience with AI/ML systems to ensure respondents were likely to have completed a full implementation cycle – from development and deployment through to user feedback. Respondents brought hands-on experience of technical performance as well as governance, privacy and user-acceptance challenges, across projects involving wearables, smart-home systems, in-car interfaces and other consumer technologies in Europe, North America and the Asia–Pacific region. Stage three consisted of an online focus group held in February 2025, bringing together eight expert participants and two researchers representing dr2.ai and the Warsaw School of Economics. The session assessed the emerging framework for clarity, relevance and cross-domain applicability, generating practical feedback used to validate and refine it for real-world use.

The study applied data triangulation, combining a literature review, a survey of AI/ML experts and a focus group. The primary research aimed to elicit insights into current conditions and anticipated developments in agentic environments. The survey targeted professionals with hands-on experience of AI deployment and analysis in commercial and urban settings, as these practitioners are central to the development and operation of emerging agentic infrastructure. In total, 32 experts responded (out of 50 contacted via LinkedIn and email). Selection did not consider gender, as the emphasis was on qualifications and topic relevance. Respondents reported international project experience developing AI-based products for major global technology firms, including Google, and leading IT consultancies such as EPAM and Cognizant. The questionnaire covered five domains aligned with the study framework: language models, ethics, capabilities, services and sustainability.

In relation to the first question on daily use of language models (see Figure 2), most respondents (75%) expected agentic environments to enhance learning and professional activities. The mechanisms most frequently cited were the automation of repetitive tasks and delivery of context-aware, personalised content and routines (66%). Real-time feedback mechanisms were also highlighted as important (53%). A notable minority (28%) were sceptical about the practical impact of these technologies, likely reflecting first-hand implementation experience.

Figure 2
Language Models in Daily Use

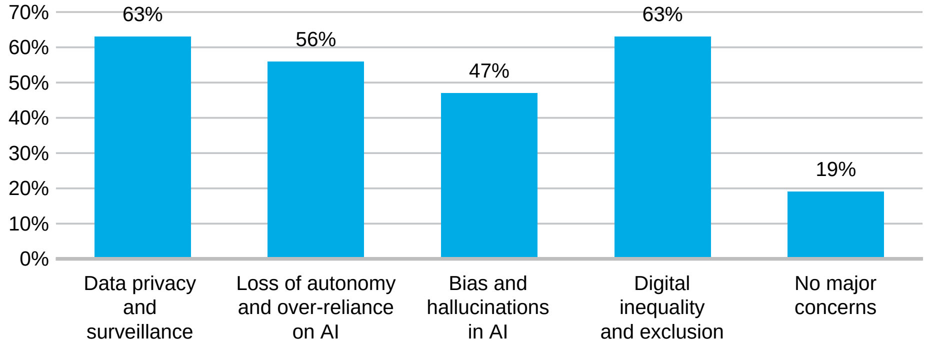


Source: author's own work.

The second survey question examined anticipated challenges in implementing AI-based agentic environments (see Figure 3). Respondents' concerns were chiefly ethical and societal: data privacy and surveillance (63%); erosion of human autonomy due to dependence on AI systems (56%); and the risk of algorithmic errors or bias (47%). These responses indicate a sophisticated understanding of AI integration into public and civic infrastructure, extending beyond technical issues to encompass social, political and regulatory considerations.

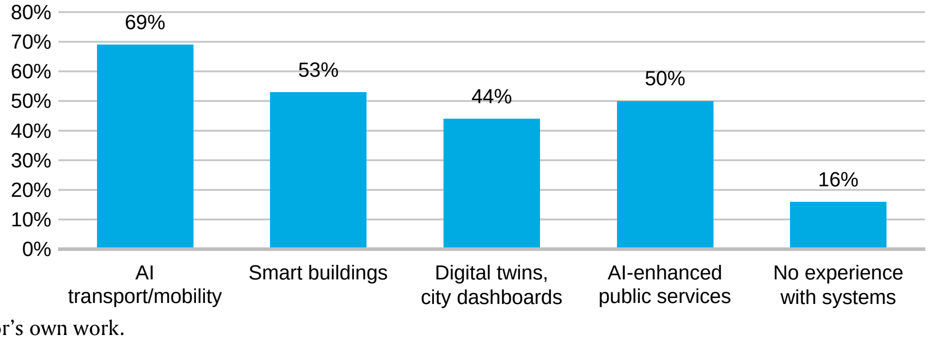
Experts were also asked which AI-enabled urban services they had personally used (see Figure 4). Most had experience of AI-supported mobility systems (69%) and intelligent building management (53%). These findings suggest that, for this cohort, agentic technologies are already part of everyday urban life rather than abstract concepts. Engagement with citizen-facing dashboards and AI-enhanced public services was also common (44–50%), indicating broad familiarity with emerging smart-city applications.

Figure 3
Ethical and Societal Concerns in AI Integration



Source: author's own work.

Figure 4
AI-Enabled Urban Services and Smart City Applications



Source: author's own work.

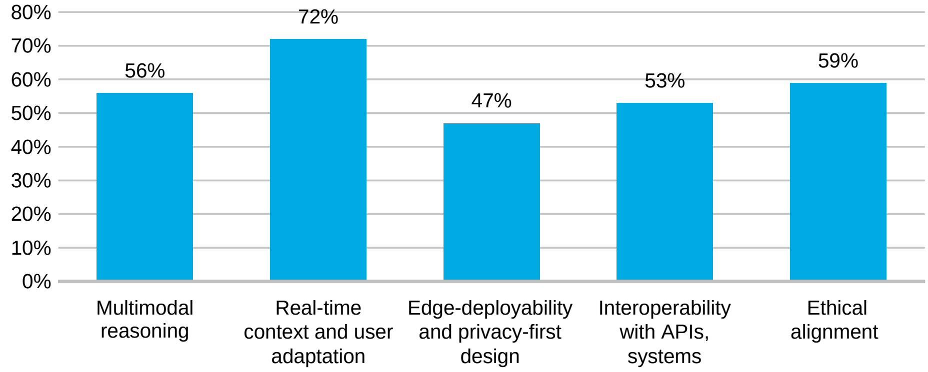
The survey also asked about the technical and ethical features of AI agents in agentic environments (see Figure 5). Respondents' top choices for future capabilities were real-time contextual adaptation (72%), ethical alignment and explainability (59%), and multimodal reasoning across diverse input types (56%). These findings suggest that participants expect agentic environments to marry advanced technical performance with transparency, accountability and human-centred design.

Finally, experts were asked about the environmental sustainability of AI systems (see Figure 6). Most participants emphasised the need to conduct environmental impact assessments (66%), to use small, energy-efficient AI models (47%) and to establish standardised certifications for environmentally responsible AI infrastructure (59%). These priorities indicate a growing recognition of the environmental costs of large-scale AI, alongside a commitment to sustainable practices in intelligent urban development.

The responses indicate that practitioners combine technological expertise with critical judgement. Participants recognised the transformative potential of agentic environments, particularly for enhancing urban intelligence, but consistently stressed that ethical, social and environmental considerations must underpin responsible innovation. To probe these issues further, researchers at dr2.ai ran an additional online focus group in February 2025 with eight participants and members of the dr2.ai research team. The session examined practical use cases and concerns not fully covered by the survey, especially those relating to learning environments and AI-supported education. It highlighted the need for agentic systems to personalise learning pathways while remaining adaptable, inclusive and transparent in lifelong learning contexts.

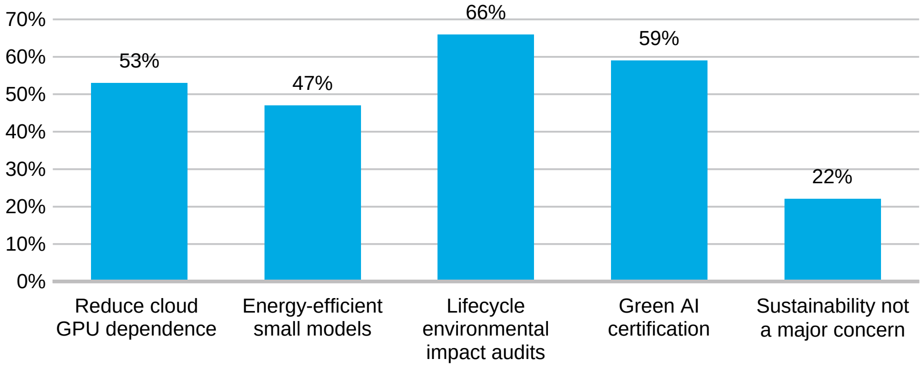
The Agentic Environments focus group generated both visionary and actionable insights, centred on agent collaboration and governance mechanisms to steer the development of intelligent, sustainable ecosystems. Findings underscored that modularity, personalisation, ethical governance and cross-domain integration are essential to realising the potential of agentic environments across personal, professional and urban domains. The group also examined collaboration models for complex cross-domain systems. Participants strongly favoured co-operative agent teams and hierarchical structures, and expressed particular interest in hybrid approaches that can be tailored to specific contexts. Such models enable agents to switch between independent operation and team-based co-ordination as environmental demands change.

Figure 5
Key Capabilities for Future AI Agents in Agentic Environments



Source: author's own work.

Figure 6
Enhancing the Environmental Sustainability of AI Systems



Source: author's own work.

Urban infrastructure can be orchestrated by distributed, swarm-like agents that control local traffic lights, while supervisory agents analyse city-wide traffic patterns to optimise overall flow. Building resilient, real-time adaptive environments depends on this dynamic, layered system of co-ordination. Experts noted that such agentic systems achieve seamless interaction across domains through composite AI architectures that include multimodal LLMs. A personal AI assistant might combine professional calendars with urban mobility data to plan energy-efficient commutes and collaborate with healthcare agents to monitor wellbeing and adjust work schedules. These collaborative systems overcome traditional silos to deliver highly contextual, cross-domain support for individuals and communities. The need for edge computing as a foundation for privacy-preserving personalisation emerged as a recurring theme in the responses. The analysis identified three interconnected spheres that intersect and influence one another while maintaining clear boundaries for security, privacy and user comfort:

1. Personal sphere: human-centred optimisation. The personal sphere sits at the core of the agentic environment, encompassing everyday settings and devices such as homes, vehicles and personal assistants. AI agents aim to enhance comfort, health and convenience through adaptive systems that safeguard user privacy. By analysing user behaviour, personalised agents co-ordinate device actions to automate routines, support wellbeing and reduce energy use. Edge computing keeps data within local systems, while intelligent agents learn and adapt through federated learning and contextual interaction.
2. In the professional sphere – covering work, learning and lifelong development – AI agents already boost productivity through tools such as GitHub Copilot, Microsoft 365 Copilot and Atlassian Rovo. In an agentic environment, this becomes a context-aware, integrated knowledge system that is central to academic learning and ongoing skills development. LLM-powered agents can deliver immediate, multimodal tutoring and rapid data retrieval for students and researchers; support educators and professionals with curriculum planning, research synthesis and grant writing; and enable continuous learning via goal-based routines that recommend courses and adapt content to a user's cognitive capacity and available time. They also tailor their operation to organisational workflows and individual development goals by drawing on personal signals – such as energy levels and concentration patterns – to enhance performance and wellbeing.
3. Finally, the urban hub addresses infrastructure and systemic intelligence across buildings and public services. Multi-agent systems co-ordinate complex operations including energy-grid management, traffic control and emergency response. AI agents optimise resource use, cut emissions and strengthen city resilience. Crucially, agents in this sphere can interact with the personal and professional domains: a workplace agent might share commute information with urban systems to trigger adaptive traffic-light timing; a home system can use grid price forecasts to decide whether to pre-heat or pre-cool; and educational institutions can adjust digital learning environments in response to city-level disruptions such as extreme weather.

LLM-based multi-agent systems weave these three spheres together, optimising information flows, time, connectivity and environmental sustainability. They lift productivity through automation and orchestration, reduce resource use via edge computing and distributed intelligence, and improve quality of life through anticipatory, context-aware personalisation. In this way, agentic environments mark a shift from isolated digital experiences to ecosystem-level intelligence oriented towards a sustainable, human-centred future.

Conclusions

The shift from smart to agentic environments marks a fundamental reorientation from infrastructure optimisation towards sustainable, human-centred ecosystems. Established smart-city and ambient-intelligence frameworks now converge with compound AI, edge computing and multi-agent orchestration to create a new generation of urban systems. Early implementations show practical benefits across workplaces, education, transport and public health. However, realising this potential depends on privacy-first architectures, decentralised models and sustainability-led design to address the ethical and environmental challenges inherent in large-scale AI.

Agentic solutions point towards more liveable, resilient and inclusive urban environments, but protecting individual privacy requires robust transparency, safety and accountability. Scaling these systems depends not only on technical capability but also on regulatory frameworks, infrastructure, governance and, increasingly, social acceptance. The EU's privacy-by-design stance helps to build trust but can slow experimentation, while the United States – and many Asian jurisdictions – tend to favour faster, market-led deployment under lighter oversight. Accordingly, future research should look beyond technical readiness to focus on regulatory alignment and effective public oversight, so that agentic environments can progress from promising pilots to widely adopted, trustworthy urban infrastructure.

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Anna Kowalczyk--Kroenke

Concerns and Potential Barriers to Running Own Business – The Perspective of Generation Z in the Podlaskie Region

Abstract

This study aims to identify barriers perceived by Generation Z to establishing and running a business, with particular attention to gender differences. The study is set in a regional context. It presents the perspective of Generation Z operating in a peripheral region characterised by a high rate of human capital outmigration to larger cities. The research problem addressed the identification of factors (economic/organisational and psychosocial) that, from the perspective of Generation Z representatives in the Podlaskie region, hinder or prevent the creation and operation of their own businesses, taking into account the gender dimension. The results presented in this study constitute an unpublished fragment of a project conducted at the University of Lomza. The study presents results from a survey of 340 Generation Z respondents (students and graduates up to 3 years after completing their higher education) in the Podlaskie region (Bialystok, Lomza, and Suwalki subregions). The empirical section utilises a proprietary CAWI survey questionnaire.

Keywords: Generation Z, entrepreneurship, own business, peripheral region, career

Introduction

Entrepreneurship is what drives the economy. There is no doubt that without entrepreneurs, the labour market essentially doesn't exist. They not only produce specific goods and services but also create jobs, thereby boosting a region's employment dynamics. This is particularly important in peripheral regions, where access to employment can be significantly limited by various factors and relatively rapid job changes are very difficult. In this context, the question arises not only how to create jobs that reflect the specific conditions of a given region, but also how young people in peripheral regions – often lacking experience and resources – can shape their professional careers. An analysis of the literature on youth entrepreneurship identifies several important research topics. Key research areas include predictors of entrepreneurship among students across fields of study, with particular emphasis on entrepreneurial intentions, competencies, the factors that influence them, and the profiles or characteristics of young entrepreneurs. Analyses of various forms of entrepreneurship that offer opportunities to avoid failure, as well as of business financing, are also important (Dorina, 2025, p. 305).

This study aims to identify barriers perceived by Generation Z to establishing and running a business in Podlaskie region, which is considered a peripheral region. The peripheral regions are defined as the five voivodeships of Eastern Poland: Podlaskie, Warmian-Masurian, Lublin, Podkarpackie, and Swietokrzyskie. Regional disparities in socioeconomic development can be traced to historical factors, particularly in the context of the economic transformation after 1989. The voivodeships of Eastern Poland developed more slowly than those in other parts of the country. These voivodeships have consistently ranked last in GDP per capita since the beginning of the

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transformation period (Leszczewska, 2011, p. 380). According to Jegorow, a reliable quantitative study of entrepreneurship that accounts for the spatial dimension requires analyses that capture the regional context. This is caused by existing development disparities, particularly noticeable in the voivodeships of Eastern Poland – the Lublin, Podkarpackie, Podlaskie, Swietokrzyskie, and Warmian-Masurian Voivodeships (Jegorow, 2015, p. 103).

In the Podlaskie Voivodeship, the registered unemployment rate at the end of December 2024 was 6.9%, up from the previous month (by 0.1 percentage points) and down year-on-year (by 0.1 percentage points). At the end of the month, there were 37 unemployed people per job offer (compared to 34 the previous month and 62 the year before) (Statistical Office in Bialystok, n.d.). Although the number of national economic entities in the REGON register at the end of December 2024 increased both monthly (by 0.1%) and year-on-year (by 2.5%), most entrepreneurs assessed the economic situation negatively in January 2025 (Statistical Office in Bialystok, n.d.).

The main barriers to running a business in 2025, regardless of the region, include: rising labor costs, uncertainty about the general economic situation and, most importantly, high tax burdens (Adamska et al., 2025, p. 5).

Data from third-quarter 2024 reports also show that the highest unemployment rate in the region was recorded among the youngest participants in the labour market (aged 15–24) – 10.9%. In the second quarter of 2024, the unemployment rate increased in the two youngest age groups – by 1.6 percentage points in the 15–24 age group and by 0.5 percentage points in the 25–34 age group (Biały et al., 2025, p. 11). It's worth noting that the vast majority of employees are employed by public companies/institutions or private employers – a staggering 81.1%, while 18.3% are self-employed (Biały et al., 2025, p. 9).

These data only marginally indicate that youth employment in the region is a problem with consequences, including population migration to other voivodeships and beyond Poland's borders. This contributes to the outflow of human capital – specific competencies, skills, and knowledge. There's also the issue of young people remaining in the region but lacking access to employment, or to employment that does not align with their capabilities and preferences. In this context, self-employment may be an alternative. Therefore, this study addresses the following research question: Which factors, from the perspective of Generation Z representatives in the Podlaskie region, hinder the creation and operation of one's own business? This problem opens the door to a broader discussion of what might discourage and weaken young people's motivation to start and run their own businesses in the Podlaskie region, and which aspects might be crucial to building entrepreneurial potential in this region.

The Specificity of Generation Z and Entrepreneurship among Young Generations – Outline of the Issue

Although there is no rigid framework defining the birth date of Generation Z or a methodology for establishing boundaries between it and other generations (Moore et al., 2017, p. 111), the literature generally places the birth date between 1995 and 2012. Generation Z, also referred to as iGen, Gen Z, or post-millennials (Barhate & Dirani, 2022, p. 140; cf. Cilliers, 2017, p. 190), is increasingly entering the modern labour market.

One opportunity associated with undertaking professional activity is establishing one's own business, which is particularly important in regions where access to employment is limited and outflows of human capital are relatively high. Entrepreneurship can therefore provide an opportunity to build a workplace not only in response to economic needs but also by taking into account one's own professional preferences, competencies, skills, expectations, and ultimately interests. It enables individuals to shape their careers in accordance with one of Generation Z's most important needs: autonomy. In the literature, this generation is referred to as the Do-It-Yourself Generation (Singh & Dangmei, 2016, p. 2), and research conducted by Dan Schawbel indicates that its members tend to be more entrepreneurial, trustworthy, tolerant, and less motivated by money than Generation Y (Singh & Dangmei, 2016, p. 2, cited in Schawbel, 2014).

The entrepreneurial intentions of younger generations are shaped by a range of factors, including attitudes toward private entrepreneurship, risk-taking tendencies, subjective norms regarding private entrepreneurship in society, entrepreneurial self-efficacy, and family business experience (Rachwał & Wach, 2016, p. 411). They are also expressions of individual ambitions, values, and needs that determine the most appropriate career path. Research shows that a lack of enjoyment in work, a poor team atmosphere, workload, and a lack of a sense of purpose at work are the most common barriers to work motivation (Fratrièová & Kirchmayer, 2018, p. 28). This is why the ability to create a workplace that accounts for individual preferences may serve as an alternative to traditional employment, in which the terms and conditions of work are dictated by the employer.

When analysing Generation Z, it's important to remember the key trends shaping it. These include social media, interpersonal connections, and skills gaps, where Generation Z will suffer more than any other from the growing divide between the highly skilled and the unskilled. The gap in technical skills is enormous, but the gap in non-technical skills is even wider. It's also a global mindset, a local reality – more knowledge of distant parts of the world than Generation Y knew, but less courage in the geographical sense. Here, the key to tactically engaging them in their environment is a focus on what's local and, finally, on infinite diversity – an entirely new way of thinking about differences (see Tulgan, 2013, p. 6).

On the one hand, there is a perception of high competence, especially in the digital sphere (Gaidhani et al., 2019, p. 2804). However, there are many concerns about what the professional reality should look like and which direction it should take. Generation Z doesn't want to be just a number, but wants to make a significant contribution. The most important aspects in the professional context are a pleasant workplace, a flexible schedule, and paid time off (Gabrielova & Buchko, 2021, p. 492). Research shows that this is a self-confident generation that wants to secure its future. They know that work plays a crucial role in fulfilling their dreams, and if it doesn't, they won't feel happy. If Generation Z doesn't find happiness in the workplace, they will leave it. This generation values its independence and dislikes authority (Ozkan & Solmaz, 2015, p. 480).

As research by Slovak researchers Papulová and Papula shows, entrepreneurship is perceived positively among younger generations as a way to increase employment, improve living standards, and promote common interests and goals. It's not easy to navigate today's world, and it's challenging to understand which path to choose for the future. However, a better future requires not leaving everything to chance. It's necessary to utilise all skills and abilities to create favourable conditions, especially for younger generations, so that they can prepare for the future; the main challenges and responsibilities here rest with teachers, the government, and relevant institutions (Papulová & Papula, 2015, p. 520). It is widely accepted that entrepreneurship is a risky activity that encompasses not only economic aspects but also psychological factors, such as an individual's personality and motivations, which can be a driving force towards the entrepreneurial path (see Mihalcea et al., 2012, p. 280).

Economic and psychological factors will be crucial not only in deciding whether and what kind of business to pursue, but also in addressing specific challenges as an entrepreneur. The modern world is undergoing rapid, significant transformations that often defy accurate forecasting and effective management (Syamsir et al., 2025, p. 1). The COVID-19 pandemic, recession, and geopolitical threats related to the Russian-Ukrainian war all require companies to be flexible, to adapt quickly, and to reconfigure resources to remain competitive. In a volatile, uncertain, complex, and ambiguous (VUCA) environment, leaders face increasingly greater challenges (Atanassova et al., 2025, p. 12). Today's environment, characterised by volatility, uncertainty, complexity, and ambiguity, has influenced and continues to influence the business environment. Next-generation (digital) technologies are accelerating the emergence of new business models and transforming organisational structures, requiring diverse management skills. In this respect, the contemporary business environment requires today's leaders to have a deep understanding of both the world and their organisation, and, importantly, the ability to engage the organisation in changing and transformative processes (Telli, 2025, p. 196).

Changing social, economic, cultural, and technological conditions mean that modern entrepreneurs must be courageous enough to take risks amid volatility and unpredictability. Innovation, expressed in the creation of products and services that are more creative and differentiated than what is already available on the market, remains crucial. Potential entrepreneurs are also expected to develop entrepreneurial skills, market orientation, and sales orientation (Ashari et al., 2025, cited in Rizan & Utama, 2020). This volatile environment is constantly evolving. In the years following the pandemic, the global business landscape is further shaped by geopolitical conflicts (including the Russian-Ukrainian war and the war in the Middle East), inflationary pressures, rising interest rates, supply chain disruptions, and climate-related disasters. The implications, especially for micro, small, and medium-sized enterprises, are profound (Millar et al., 2018).

The multitude of changes and transformations in the modern world also pose numerous challenges for entrepreneurs. Literature indicates that factors hindering the initiation of entrepreneurship among young people include, among others, a lack of entrepreneurial education, lack of social support, limited social capital, limited access to credit, a lack of business support centres and facilities, inappropriate government policies, and a hostile legal framework (see, e.g., Ofosu-Appiah et al., 2025, p. 1). Importantly, these can be both strictly economic and psychosocial. Among the barriers to the development of small and medium-sized enterprises, Matejun lists external threats, including market, personnel, and financial barriers, as well as those stemming from government economic policy, legal barriers arising from limited access to information, educational barriers, and infrastructure-related barriers.

There is no doubt that the development of the SME sector depends primarily on the amount of capital available, sourced from both internal and external sources. Further barriers include inappropriate economic policies, complex business regulations for establishing and operating a business, instability in the legal system, and the high costs of adapting to regulatory changes (Matejun, 2003, p. 236). In this context, and particularly importantly, a key factor influencing the success of micro and small businesses is entrepreneurial orientation. It should be understood that innovation, proactivity, and a willingness to take risks are considered necessary in an unpredictable environment. (see, e.g., Karnowati et al., 2023). However, societal expectations can be problematic, as they often prioritise formal employment over entrepreneurship. Many younger generations feel pressured to seek traditional jobs rather than start their own businesses. Difficulties also arise from cultural preferences that can discourage risk-taking and innovation, especially among young people, who at this stage often lack sufficient self-confidence to evaluate entrepreneurship as a viable career option (Makina, 2022).

A flawed assumption in entrepreneurship policy is that anyone can be trained to be an entrepreneur. This approach, despite its noble intentions, often overlooks key differences among types of entrepreneurial activity and the conditions under which entrepreneurship training can be effective. Risk-taking alone does not drive entrepreneurship, but motivation and skills are cited as key factors (Brixiova et al., 2025, p. 5, cited in Baumol, 1990). The number of existing barriers is not limited to those listed above; they collectively indicate the multitude of problems entrepreneurs often face, regardless of the specific nature of the business. Although discussions of entrepreneurs' challenges and barriers have long been part of public debate, they often overlook the perspectives of the youngest members of the labour market. From this perspective, self-employment can serve as a means of avoiding unemployment, particularly when the unemployment rate is relatively high, and a lack of experience or appropriate skills further complicates the process of choosing a career path. In peripheral regions, entrepreneurship – it's worth noting – can not only provide opportunities for self-employment but also potentially create jobs for the local community.

Methodological Assumptions and Characteristics of the Research Sample

The research presented in this paper aimed to identify the barriers perceived by Generation Z representatives from the Podlaskie region in creating and running their own businesses, with gender as a differentiating factor. The research problem was formulated as follows: Which factors (economic/organisational and psychosocial) from the perspective of Generation Z representatives in the Podlaskie region hinder or prevent the creation and operation of their own business, and what are the differences between the perspectives of women and men? This objective dictated the purposeful selection of respondents for the sample. The key inclusion criterion was age: Generation Z (individuals born between 1997 and 2006, i.e., adults on the date of the study), which is essential for considering their actual activity in the context of entrepreneurship and professional career. A total of 340 respondents from the Podlaskie region (Bialystok, Lomza, and Suwalki subregions) participated in the study. 55.3% were women and 44.7% were men. Respondents represented the following places of residence: rural areas (31.8%), small towns (population below 20,000 inhabitants) – 20.3%, medium-sized towns (20,000–100,000 inhabitants) – 34.1%, large cities (over 100,000 inhabitants) – 13.8%. The detailed distribution is presented in Table 1.

The survey included respondents with secondary education (40.3%), higher engineering education (7.0%), higher bachelor's degree (32.4%), and higher master's degree (20.3%). A detailed breakdown is presented in Table 2.

The empirical section of this paper presents a previously unpublished fragment of research on factors perceived as barriers or difficulties in establishing and operating one's own business, as reported by the respondents surveyed. This paper presents the results obtained in the main research sample (without respondents from the pilot group).

Table 1
Distribution of the Place of Residence of the Surveyed Respondents

Respondent's place of residence	*N*	%
Village	108	31.8
Small town – population below 20,000 inhabitants	69	20.3
Medium city – 20,000-100,000	116	34.1
Large city – over 100,000	47	13.8
Total	340	100.0

Source: author's own work.

Table 2
Distribution of Respondents' Education

Education	*N*	%
Secondary education	137	40.3
Higher engineering	24	7.0
Bachelor's degree	110	32.4
Master's degree	69	20.3
Total	340	100.0

Source: author's own work.

The study utilized a proprietary online CAWI questionnaire, which was made available for respondents between July and September 2024 via social media, career offices, and the USOS systems of universities in the Podlaskie Voivodeship.

The survey questionnaire contained 17 closed questions (cafeteria of answers), and in the case of 11 of them the respondent also had the opportunity to provide his/her own additional answer (outside the available cafeteria).

The questionnaire covered the following areas: propensity for entrepreneurial behaviour; risks, concerns, and difficulties (economic/organisational and psychosocial); traits and soft skills conducive to entrepreneurship; challenges associated with entrepreneurship; education; and support for entrepreneurship development. The research was conducted online and maintained complete anonymity.

Statistical processing of the data collected during the study was performed using IBM SPSS Statistics. To compare women and men regarding the importance of economic, organisational, and psychosocial factors hindering business activity, the Mann-Whitney U test was used. This test examines whether there is a statistically significant difference between two groups for ordinal or ratio variables that are not normally distributed. The following abbreviations are used in the tables containing this test: *M* – arithmetic mean, *Me* – median, *SD* – standard deviation, *Z* – test statistic, *p* – test significance. Three levels of statistical significance were adopted (from highest to lowest: $p < 0.001$ – marked with ***, $p < 0.01$ – marked with **, and $p < 0.05$ – marked with *). In this case, the groups differ statistically significantly. The level of measurement of the variables (scale 1–5) supported the use of this test in this analysis.

Research Results – Analysis and Discussion

This paper presents selected excerpts from quantitative research conducted as part of a large project in the Podlaskie region (subregions: Bialystok, Lomza, Suwalki), demonstrating differences between women and men in their perceptions of barriers and difficulties hindering business activity. The analyses conducted as part of the study indicate that Generation Z members perceive a range of concerns related to starting and running their own businesses. In the first part, respondents rated the importance of economic and organisational factors hindering business activity on a scale of 1–5, where 1 = not difficult, 2 = slightly difficult, 3 = moderately difficult, 4 = very difficult, and 5 = impossible. Therefore, the higher the mean and median on a 1–5 scale, the greater the difficulties associated with a given factor as perceived by respondents.

The collected data show that, among the economic and organisational factors, women found the high costs of running a business the most challenging. In contrast, the lack of appropriate professional contacts was the least challenging. Among the economic and organisational factors, the greatest challenge for men was the high cost of running a business. In contrast, the lowest were posed by the lack of institutional support. The Mann-Whitney U test revealed statistically significant differences between groups in perceived importance of the lack of institutional support and perceived difficulty in obtaining funding for business development. Both of these factors are significantly more important for women than for men. Additionally, for the factor "difficulty in obtaining funding for starting a business", the difference is close to the level of statistical significance. This factor is more important for women than for men. Detailed data are presented in Table 3.

In the next section, respondents rated the importance of psychosocial factors that hinder business activity on a 1–5 scale, where 1 = very low, 2 = low, 3 = average, 4 = high, and 5 = very high. Therefore, the higher the mean and median on a 1–5 scale, the greater the difficulties associated with a given factor in the respondents' assessment. The data obtained indicate that, from the perspective of women, high stress is the most challenging of the psychosocial factors, while lack of trust in others is the least challenging. From the perspective of men, conflict management is the most challenging psychosocial factor, whereas a lack of trust in others is the least challenging. The Mann-Whitney U test revealed statistically significant differences between the groups in the importance of high stress and high future uncertainty, as well as in the associated mental and emotional states. Both of these factors are significantly more important for women than for men. Additionally, for three factors: lack of trust in others, maintaining high motivation and energy for hard work, and managing relationships, the difference is statistically significant – they are more important for women than for men. Detailed data are presented in Table 4.

The collected data shows that respondents consider high business costs, a lack of appropriate professional contacts, and a lack of support from external institutions to be important economic/organisational factors. Psychosocial factors include high stress, a lack of conflict-management skills, and concerns about uncertainty, which can ultimately affect one's psychophysical well-being. Meanwhile, the realities of the modern world are inherently linked to unpredictability, instability, and uncertainty (see, e.g., Mirakyan, 2022). Since eliminating uncertainty

Table 3
Comparison of Women and Men in Terms of the Importance of Economic and Organisational Factors Hindering the Conduct of Business Activity

Economic and organisational factors	Sex						U Mann-Whitney Test	
	Female			Male				
	M	*Me*	*SD*	*M*	*Me*	*SD*	*Z*	*p*
Complicated laws and regulations	3.61	4.00	0.67	3.55	4.00	0.83	–0.309	0.758
Lack of support from institutions	3.48	4.00	0.76	3.12	3.00	0.91	–3.590	<0.001***
Difficulty in obtaining funding for starting a business	3.83	4.00	0.93	3.60	4.00	1.13	–1.673	0.094
Difficulty in obtaining funding for business development	3.62	4.00	0.81	3.34	4.00	0.98	–2.663	0.008**
Lack of appropriate professional contacts	3.42	4.00	0.86	3.28	3.00	0.94	–1.392	0.164
High costs of running a business	3.88	4.00	0.66	3.73	4.00	0.83	–1.514	0.130

Source: author's own work.

Table 4
Comparison of Women and Men in Terms of the Importance of Psychosocial Factors Hindering the Conduct of Business Activity

Psychosocial factors	Sex						U Mann-Whitney test	
	Female			Male				
	M	*Me*	*SD*	*M*	*Me*	*SD*	*Z*	*p*
High stress	3.94	4.00	0.87	3.58	4.00	0.97	–3.340	0.001**
Lack of trust in people	3.34	3.00	0.87	3.17	3.00	0.87	–1.824	0.068
Maintaining high motivation and energy for hard work	3.60	4.00	0.97	3.43	3.00	0.97	–1.796	0.072
Managing relationships with people	3.67	4.00	0.86	3.47	4.00	0.96	–1.764	0.078
Conflict management	3.80	4.00	0.88	3.60	4.00	1.08	–1.522	0.128
High uncertainty about the future and the associated mental and emotional state	3.76	4.00	0.96	3.40	3.00	1.02	–3.370	0.001**
Fast pace of work	3.47	3.00	0.83	3.30	3.00	0.96	–1.370	0.171
The need to adapt to many, rapid changes	3.68	4.00	0.88	3.56	4.00	0.84	–1.005	0.315

Source: author's own work.

is impossible, it is preferable to support young generations in developing competencies that will enable them to function in this reality. Mental resilience, assertiveness, communication, negotiation skills, and conflict and crisis management are among the aspects to consider when building young people's entrepreneurial potential. This is also crucial in the context of developing educational programs, where practicality is a key consideration, as demonstrated by Seemiller and Grace (2017, p. 22).

Generation Z students clearly prefer practical learning opportunities that enable them to apply what they learn immediately in real-world contexts. This "confrontation" between knowledge and practice enables them to adapt more effectively to a real-world business environment and to develop and master specific skills. There is also no doubt that entrepreneurship is a high-risk activity, in which outcomes are difficult to predict, and the changes the socio-economic environment may bring are uncertain. On the one hand, autonomy, independence, and the ability to combine work and hobbies are essential values for Generation Z. However, the issue of understanding what running a business is, what challenges and difficulties it entails, and consequently, what challenges may arise at various stages of one's business development remains problematic.

Research findings suggest that the need for stability, predictability, and security is so important. Similar conclusions emerge from research conducted by Samul, Kobylińska, and Rollnik-Sadowska (2018, p. 94). The authors point out that among young people (15–29 years old) in the Podlaskie region, job satisfaction is the most important factor in their careers, rated higher than salary alone. Notably, employment stability and the security associated with long-term employment remain crucial; for young people, these are more important than mere development opportunities. This raises the question of what constitutes the attractiveness of entrepreneurship and how to promote it so that it is perceived as a compelling alternative to a career based on one's own values. Research conducted among Generation Z in Bucharest by Iorgulescu (2016, p. 51) also indicates that, as with Polish Generation Z respondents, they have a strong need for security, as reflected in their desire for secure jobs. Other important aspects include good professional relationships, generous remuneration, and the opportunity to work in a team.

In the context of economic factors, one particularly problematic area is the cost of running a business. However, the problem lies not only in the costs themselves, but also in obtaining financing for business development. This is one of the barriers that can particularly limit the activation of younger generations in this area, a finding echoed in other studies across regional contexts (see, e.g., Kropelnytska et al., 2025, p. 118; Matlhake & Kalitanyi, 2025). Support from external institutions for employment also remains an important issue, particularly at the regional level. Appropriately tailored programs that account for the real needs and capabilities of young people could provide significant support in establishing their own businesses. The research conducted covers only a fraction of the area related to potential barriers and difficulties in the context of building and developing one's own entrepreneurship. However, it can also serve as a starting point for scientific exploration of youth entrepreneurship development, especially in the context of the Podlaskie region in the current socio-economic reality.

In response to the research question, it should be noted that women and men differ in their perceptions of economic/organisational and psychosocial factors as barriers/difficulties in running a business. This is particularly evident in relation to psychosocial factors. Research indicates that one of the most important barriers (an economic/organisational factor common to both groups) is the cost of running a business. For women, a significant barrier is the lack of institutional support and difficulty obtaining funding for business development. In terms of psychosocial factors, women are dominated by high stress. In contrast, men struggle to manage conflicts, which are inherent to every business, regardless of its specific nature.

Summary

Establishing and running your own business is a significant challenge but also an opportunity, especially for those seeking to create a workplace aligned with their values, needs, capabilities, and expectations, while accounting for individual preferences across multiple dimensions. It certainly requires courage and a certain openness to the risks inherent in this career model. While it's difficult to avoid certain risks, it's possible to shape specific educational programs to provide real value and significant support for potential young entrepreneurs. It's also worth paying attention to the individual factor – offering specific assistance that takes into account individual needs, expectations, and capabilities. This is especially true, as Slovak researchers suggest, because the younger generation is expected to bring new energy, knowledge, and insights to their specialisation, thereby enhancing the economy's competitiveness (see Papulová & Papula, 2015, p. 516). In this context, youth entrepreneurship can be viewed as a new energy in the labour market and an impetus for its development. In the peripheral regions that constitute the context of this research, opening and running one's own business can potentially be an excellent opportunity to avoid unemployment and possible migration among young people, making it all the more important to build support programs that will address the challenges faced by the youngest participants in the labour market.

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Upskilling and Reskilling in the AI Era: A New Logic of Competence Development

Abstract

Generative artificial intelligence (GenAI) is reshaping professional education, hastening the obsolescence of competences and unsettling traditional, linear approaches to upskilling and reskilling. This article advances a new logic of competence development to characterise this shift. Drawing on institutional reports (DeVry University, 2024; World Economic Forum, 2023, 2025) and established theoretical traditions, it shows that the competence landscape is moving towards hybrid models that combine technical expertise with adaptive capabilities such as resilience, reflective judgement and AI literacy. A comparative analysis of employers' and employees' perspectives reveals both opportunities and risks, notably gaps in recognition, digital inequalities and a shifting of responsibility for learning. Using the gAI-PT4I4 prototype as an illustrative case, the article demonstrates how GenAI can serve as a vehicle for adaptive, personalised learning and training, while raising questions about scalability, ethics and deskilling. The conceptual contribution is to define competence development as an iterative, co-created and adaptive process, in contrast to static, competence-based models. At the same time, AI can itself provide a pathway for developing new competences, supporting the complex processes of upskilling and reskilling. The gAI-PT4I4 case connects the conceptual argument to a concrete example of AI-enabled adaptive learning.

Keywords: reskilling, upskilling, competence development, capability approach, generative artificial intelligence

Introduction

The release of ChatGPT in November 2022 marked a turning point in the worldwide diffusion of large language models (LLMs) as a transformative form of artificial intelligence. Within weeks, it had attracted more than 100 million users, making LLMs the fastest-adopted technology in history and reshaping approaches to learning, work and competence development. Unlike earlier waves of digital transformation, which were predominantly institution led (Brynjolfsson & McAfee, 2014), GenAI has diffused more democratically, lowering barriers to access and fostering more personalised learning.

From a labour market perspective, competences are increasingly regarded as strategic assets, consistent with the resource-based view in management studies (Barney, 1991). The challenge, however, lies less in foreseeing which competences will matter than in acquiring them quickly and effectively, as their life cycles grow ever shorter. Traditional, linear approaches cannot keep pace with this acceleration. Whilst fears of job displacement dominate public debate, recent studies paint a more nuanced picture: GenAI complements human capacities such as reasoning, creativity and problem solving (Noy & Zhang, 2023). The ability to collaborate with AI, whilst retaining judgement and ethical responsibility, is fast becoming a defining competence for the future of work.

At the same time, GenAI is a disruptive force, destabilising competence frameworks, career paths and education systems. Existing validation mechanisms, such as diplomas and occupational classifications, often fail to recognise competences acquired informally, thereby reinforcing inequalities of opportunity. Addressing these challenges demands not only technological solutions but also conceptual and institutional reform.

International reports, including the *Future of Jobs* (2023, 2025) and DeVry University's *Closing the Gap* (2024), offer valuable forecasts and underscore the role of employers

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in upskilling and reskilling. Yet their vantage point is often one-sided, privileging the cataloguing of skills over analysis of the qualitative transformation of competence development. Academic debate shows similar limitations, frequently overlooking the systemic implications of AI-driven change. Consequently, the discourse is dominated by lists of skills and roles, laying bare the inadequacy of traditional validation systems.

The research gap is clear: although future competences have been widely identified and are intuitively recognised as qualitatively different, this awareness has not yet translated into substantive change in upskilling and reskilling programmes. The pressing task is to design pathways that are not only effective but also agile and adaptive, capable of keeping pace with the next wave of change already on the horizon.

This paper advances the notion of a new logic of competence development to capture the qualitative shift in how competences are created, validated and sustained in the AI era. In contrast with the traditional linear model, this new logic is iterative, distributed and relational. It treats competences not as static assets but as dynamic capabilities co-shaped through continuous interaction with intelligent technologies. This perspective foregrounds adaptability, critical judgement and ethical responsibility, whilst recognising AI as an active partner in the learning process.

The paper combines the stability of competence-based approaches with the flexibility of capability-oriented perspectives (Kolb, 1984; Nonaka & Takeuchi, 1995; Schön, 1992) and emphasises the enabling role of AI technologies. The argument proceeds on two levels: conceptually, by clarifying this shift; and illustratively, through the gAI-PT4I4 prototype. The prototype serves as an empirical anchor for the proposed logic of competence development rather than a mere technological illustration. It shows how AI-enabled learning can foster adaptive, co-creative competence building. For analytical clarity, the paper adopts the definition of competence used in the European Qualifications Framework (EQF): 'Competence means the proven ability to use knowledge, skills and personal, social and/or methodological abilities, in work or study situations and in professional and personal development' (Council of the European Union, 2017). The analysis is confined to the professional context, with particular focus on upskilling and reskilling in workplace settings.

The article is structured as follows. The first section outlines the competence landscape in the AI era, followed by a review of key theoretical approaches. The next section analyses the *Future of Jobs* surveys, examining changes in the qualities and rankings of competences, evolving perceptions of AI, acquisition pathways and the shifting logic of upskilling and reskilling, and concludes by drawing out systemic implications. The subsequent section introduces the employee perspective based on the DeVry survey. An illustrative case of AI-supported learning via the gAI-PT4I4 prototype then follows. The paper ends with conclusions that synthesise these insights into a new logic of competence development and identify directions for future research.

Methodology

This study adopts a conceptual design grounded in secondary sources and reflective analysis. It draws on institutional reports treated as grey literature with demonstrable influence on labour and education policy. Source selection was guided by three criteria: large-scale employer surveys, direct relevance to competence development and evidence of policy uptake. On this basis, two datasets were selected: the World Economic Forum's reports (2023 and 2025 editions) and DeVry University's *Closing the Gap* (2024).

The primary focus was the WEF reports, examined through a comparative analysis of the two editions and the systematic coding of competences. Each skill constituted a unit of analysis: every identified competence was recorded as a single entry and assigned an orientation. Coding was undertaken by a single researcher to ensure consistency, but this also constitutes a methodological limitation, as inter-coder reliability could not be assessed.

The coding scheme was organised around three dimensions: orientation, acquisition pathway and learning context. The reports themselves do not explicitly classify competences by competence- or capability-based orientations. This distinction reflects an analytical lens introduced by the study rather than an explicit feature of the data. The orientation dimension was therefore coded latently, guided by the theoretical framing rather than by labels used in the reports. Such an interpretive approach inevitably entails a degree of theory led categorisation; however, this is consistent with qualitative research practice, provided it is made explicit. Table 1 presents the coding scheme.

In addition, the reports were analysed at the textual level, with particular attention to framing and shifts in language.

This made it possible to trace not only changes in rankings but also the underlying patterns of transformation. For triangulation, the DeVry University study was included to highlight differences between employer and employee perspectives.

The guiding research question was: *How do competence- and capability-based framings emerge in institutional reports, and what are their implications for upskilling and reskilling?*

The conceptual framing drew on established perspectives: experiential learning (Kolb, 1984), reflective practice (Schön, 1992), knowledge creation (Nonaka & Takeuchi, 1995) and capability theory (Nussbaum, 2011; Sen, 1999). The gAI-PT4I4 prototype is presented as an illustrative example of AI-supported competence development. Given its limited empirical validation ($n = 20$, no control group, short term scope), it should be read as an exploratory demonstration rather than conclusive evidence.

Table 1
Codebook for Skills Outlook (WEF 2023 & 2025)

	Code	Operational definition (anchored in WEF language)	Inclusion / Exclusion rules	Example terms / phrases
Orientation	Competence-based	Frames workforce needs in terms of discrete, measurable skills (e.g., core skills, skills gaps, skills disruption); emphasis on possession of competences.	Include when text lists specific skills. Exclude when adaptability is emphasised.	core skills; skills gaps; skills disruption
	Capability-based	Emphasises adaptive potential, resilience, and lifelong learning. Focus on becoming and adapting.	Include resilience, adaptability, continuous learning. Exclude fixed technical lists.	resilience, flexibility and agility; curiosity and lifelong learning; lifelong learning as the lifecycle of skills decreases
Acquisition Pathways	Formal education	Universities, schools, structured qualifications.	Include 'higher education teachers', 'education systems'. Exclude short courses.	higher education teachers; public education systems
	Workplace training	Employer-led learning: on-the-job training, apprenticeships, coaching.	Include 'on-the-job training', 'apprenticeships'. Exclude self-learning.	on-the-job training and coaching; employer-sponsored apprenticeships
	Micro-credentials	Short, modular certifications or digital courses.	Include 'short courses', 'certifications'. Exclude full degrees.	short courses; certifications
	Experiential / / project learning	Learning through project work, rotations, applied practice.	Include 'project-based learning', 'job rotation'.	project-based learning; job rotation
	Communities & peer learning	Mentoring, peer-to-peer networks, communities of practice.	Include 'peer learning', 'mentorship'. Exclude formal education.	peer learning; mentorship
	AI-enabled / / adaptive learning	Technology- and AI-driven personalised training.	Include AI-driven platforms, GenAI training.	Generative AI training; adaptive learning platforms
Learning Context	Individual	Self-learning, personal initiative to build skills.	Include 'self-learning', 'individual learners'.	individual learners focused on GenAI skills
	Team	Collaborative learning within small groups.	Include 'team upskilling', 'collaborative learning'.	team upskilling; collaborative learning
	Organisational	Company-wide workforce development strategies.	Include 'corporate training initiatives', 'workforce strategies'.	upskilling their workforce; organisations identify skills gaps
	Ecosystemic	Sector-wide, regional, or policy-driven approaches.	Include 'public policies', 'Reskilling Revolution'.	funding for reskilling and upskilling; Reskilling Revolution

Source: author's own work.

This study also acknowledges several limitations: reliance on grey literature, the absence of primary data triangulation, a single-coder design for the coding process, and the interpretive nature of the analysis, shaped not only by the data but also by the researcher's perspective. Nevertheless, the methodology offers a transparent and replicable framework for examining transformations in competence development in the AI era.

The Competence Landscape in the AI Era

Any considered reflection on the future of competences benefits from a brief survey of the models that have shaped their definition and development in recent decades. In Europe, debate has been strongly influenced by the Bologna Process and by instruments such as the European Qualifications Framework (EQF) and ESCO (European Skills, Competences, Qualifications and Occupations), which together have institutionalised a competence-based approach. This model emphasises measurable, observable skills mapped to defined proficiency levels, thereby supporting standardisation and comparability across education systems and labour markets. A similar philosophy underpins the Skills Framework for the Information Age (SFIA), widely applied in the IT sector. Increasingly, however, this competence-oriented view is being challenged by a capability-based approach, which highlights foregrounds adaptability, problem solving and reflective practice in volatile, uncertain environments.

The accelerating digital transformation and the spread of artificial intelligence are reshaping the very foundations of competence development. The rapid diffusion of generative AI has both heightened the salience of competences as strategic resources whilst exposing the limitations of traditional, static frameworks. Competence development can no longer be conceived as a linear process of skill accumulation; it must be understood as a dynamic interplay between stability and adaptability.

These debates crystallise into two dominant perspectives. The competence-based approach conceives competences as measurable sets of skills, knowledge and behaviours required to perform specific tasks. It underpins most international reports and labour market policies because it enables standardisation, benchmarking and comparability across sectors. By contrast, the capability-based approach emphasises adaptability, reflective practice and the ability to navigate uncertainty. Capabilities are not reducible to discrete skills; rather, they denote the capacity to integrate knowledge, exercise judgement and co-create solutions in evolving contexts.

The coexistence of these approaches reveals a structural tension in competence development. On the one hand, employers and policymakers seek frameworks that deliver measurable outputs and facilitate certification. On the other, the volatility of the AI era exposes the limits of such frameworks and highlights the need for competences that cannot be pre-defined in catalogues but emerge dynamically through practice. In this light, competences and capabilities are better seen as complementary dimensions: competence-based approaches supply stability and structure, while capability-based approaches confer adaptability and resilience.

The advent of AI reinforces this dual logic. Generative systems support competence acquisition by widening access to knowledge, accelerating problem solving and enabling real-time feedback. Yet their responsible use demands capabilities such as critical reflection, creativity and ethical judgement. AI thus operates both as a driver of change and as an enabler of new learning architectures. This double role calls for a reconceptualisation of competence development in which the balance between competences and capabilities becomes a defining feature of future education and labour market systems.

Competence Development – A Review of Theoretical Approaches

Building on the contrast between competence-based and capability-based perspectives, it is useful to revisit the theoretical traditions that support these models. For decades, the competence-based approach has dominated both research and practice, particularly in policy settings where standardisation, benchmarking and certification are prized. Yet it is often criticised for being static and reductionist, tending to overlook the dynamic processes of learning, reflection and adaptation.

As a counterpoint, the capability approach, rooted in the work of Amartya Sen (1999) and Martha Nussbaum (2011), focuses not on predefined competences but on the freedoms and opportunities available to individuals. Development is framed as the ability to exercise agency, to adapt and to learn continuously in changing environments. Education within this perspective cultivates resilience, autonomy and reflective practice, enabling individuals to respond creatively and ethically to new challenges.

At the organisational level, these ideas converge with the theory of dynamic capabilities introduced by Teece, Pisano and Shuen (1997) and further developed by Teece (2007). Dynamic capabilities describe how firms integrate, build and reconfigure competences in rapidly changing contexts. They provide the strategic foundations for renewing individual and collective competences, helping organisations remain innovative and competitive amid disruption. In the AI era, they also influence how employers design learning infrastructures and create the conditions for continuous upskilling and reskilling.

Further theoretical contributions broaden this view of competence development. Kolb's (1984) model of experiential learning, Schön's (1992) notion of the reflective practitioner and Nonaka and Takeuchi's (1995) theory of knowledge creation all understand learning as an iterative, context-sensitive and co-creative process. These perspectives are especially pertinent in periods of rapid technological change, when competences are continually reshaped by new tools and evolving professional environments.

Taken together, these theories suggest that competence development cannot be reduced to the accumulation of isolated skills. It is better understood as a process that combines measurable competences with capabilities that sustain adaptability, creativity and ethical judgement. This synthesis provides the conceptual foundation for analysing how technological transformation is reshaping the logic of upskilling and reskilling.

The Emerging Competence Landscape in Light of the *Future of Jobs 2025*

The distinctions set out above underscore the need to examine how competence- and capability-based framings surface in empirical sources. The World Economic Forum's *Future of Jobs* reports, based on large-scale employer surveys, catalogues of skills and track their rankings over time. Although the reports offer little in the way of theoretical reflection, their data reveal how competence priorities are evolving amid accelerating technological change.

The 2023 edition was largely competence-oriented, emphasising analytical thinking, technological literacy and attention to detail. Attributes closer to a capability-based logic, such as creativity and resilience, were present but less prominent.

By contrast, the 2025 edition presents a more balanced picture. Whilst analytical and technical skills remain central, adaptability, motivation to learn and social influence have gained in importance. This shift signals a growing recognition of the limits of static competence catalogues and the need for capabilities that enable continuous adaptation.

Taken together, the reports reveal not only an expansion but also a qualitative transformation of the competence landscape. An emerging hybrid model combines the stability afforded by competences with the adaptability conferred by capabilities, laying the groundwork for the analysis of acquisition pathways and learning contexts in the next section.

Changing Perceptions of Artificial Intelligence

Findings from the *Future of Jobs* reports also chart a shift in how artificial intelligence is understood. Whilst earlier debates cast AI chiefly as a disruptive force, recent editions adopt a more nuanced view that recognises risks and opportunities in tandem.

The 2023 edition captured widespread ambivalence: AI was frequently characterised as a disruptive technology linked to automation, job displacement and social inequality. Employers acknowledged its promise but voiced strong concerns about its destabilising effects on established professional structures.

By 2025, the tone had shifted. The *Future of Jobs 2025* report increasingly portrayed AI not only as a source of disruption but also as an enabler of new learning opportunities. Generative AI, in particular, was credited with lowering barriers to access, facilitating problem solving and supporting real-time training. Employers expressed rising expectations that AI would serve as a vehicle for competence development, making learning more personalised, adaptive and responsive to individual needs.

This reframing signals a broader shift in the discourse on AI. An initial preoccupation with threats and uncertainty has given way to a more balanced narrative, in which risks and opportunities are considered in tandem. Employers increasingly regard AI not merely as a challenge but as a resource to be woven into upskilling and reskilling strategies.

The shift matters for two reasons. First, it attests to organisations' capacity to recast technologies once seen as disruptive as instruments of value creation. Second, it signals a growing expectation that AI will not only shape demand for competences but also support their acquisition. In this dual role, AI emerges both as a driver of change and as a partner in competence development. This evolving view also reshapes assumptions about where and how learning should take place, opening the way to new blends of formal education, workplace training and self-directed learning, which are examined in the following section.

Acquisition Paths and Context

As perceptions of AI have shifted from disruption to partnership, attention has also turned to the contexts in which competences are acquired. When coded, the *Future of Jobs* reports reveal not only which competences are prioritised but also where and how they are most often developed. This dimension is crucial for understanding how upskilling and reskilling are embedded in organisational and educational practice, and how responsibility for competence development is distributed across institutions, workplaces and individuals. Importantly, these pathways are highly context-sensitive, reflecting broader structural conditions that shape access to learning opportunities.

Coding of the 2023 edition showed that on-the-job training was the dominant pathway. Employers consistently identified workplace learning as the most effective mechanism for addressing rapidly emerging competence gaps. This reflects recognition that competences need to be developed in environments closely aligned with practical tasks, where new technologies and processes can be integrated directly into daily routines. Workplace learning thus offers immediacy and relevance, but it also remains strongly contingent on organisational culture and the resources available within particular sectors.

At the same time, formal education retained an important role, particularly in providing foundational knowledge and qualifications. Universities and vocational colleges deliver structured programmes that equip graduates with core competences. Yet the pace of technological change often outstrips education systems' capacity to update curricula. As a result, their contribution is increasingly complemented by workplace-based initiatives and shorter, more flexible formats such as micro-credentials. The effectiveness of these pathways, however, varies across national systems, institutional arrangements and professional fields.

Coding of the 2025 edition confirmed and consolidated these trends. Workplace learning remained the dominant context, while formal education retained its significance largely as a provider of foundational competences and a validator of qualifications. The analysis also highlighted the growing salience of self-directed learning, supported by digital platforms and, increasingly, AI-enabled tools. This shift underscores the contextual nature of learning: the ability to benefit from self-directed and AI-supported pathways depends on individual resources, digital infrastructure and workplace recognition. It also signals a redistribution of responsibility, with individuals now expected to engage in continuous, autonomous learning alongside institutional and organisational support.

Taken together, these pathways illustrate the hybrid and context-sensitive character of competence development in the AI era. Formal education supplies foundational competences and certification; workplace learning offers immediacy and sector-specific relevance; and self-directed learning provides flexibility and personalisation but depends heavily on access to digital tools and supportive environments. In combination, they form a multi-layered ecosystem in which competences and capabilities are acquired, validated and transformed.

An ecosystemic perspective underscores the need to integrate diverse pathways into coherent strategies for upskilling and reskilling. It also points to the importance of institutional arrangements that can bridge the gaps between formal education, workplace practice and individual agency, ensuring that competence development remains inclusive, adaptive and aligned with technological change.

Because these acquisition pathways are inherently contextual, no single model of upskilling and reskilling can be universally applied. Effective strategies must adapt to sectoral, organisational and national conditions, while also addressing differences in individual resources. Without such sensitivity to context, competence development risks deepening existing inequalities, privileging those with access to supportive infrastructure and excluding those without. The challenge, therefore, is to design ecosystemic approaches that balance diversity with inclusivity.

Evolving Logic of Reskilling and Upskilling

Findings from the *Future of Jobs* reports indicate a substantive shift in the logic of reskilling and upskilling. Employers continue to stress the urgency of competence renewal, but their strategies are moving away from a narrow transfer of discrete skills towards cultivating adaptability and the capacity for continuous learning.

In 2023, reskilling and upskilling were framed chiefly within a competencebased perspective. Training was conceived as the delivery of predefined sets of competences designed to meet emerging organisational needs. This followed the traditional view of education and training as instruments for filling competence gaps in a predictable, measurable fashion.

By 2025, the framing had shifted towards a more dynamic, capability-oriented logic. Employers recognised that competences acquired through formal programmes can lose relevance quickly, and that the ability to adapt, reflect and learn continuously is at least as important as technical expertise. The reports highlighted the rising role of self-directed learning, short and iterative training formats, and flexible pathways that allow workers to weave together formal education, workplace experience and informal learning.

This shift also signals a redistribution of responsibility for competence development. In earlier models, the burden fell largely on schools, universities and employer led training. Under the new logic, employees are expected to play a more active role in steering their own learning trajectories. At the same time, organisations are expected to create enabling conditions, including access to digital platforms, mentoring and mechanisms for recognising learning. Competence development thus becomes a shared responsibility among employees, employers and institutions.

Yet tensions remain. Employers expect workers to take greater initiative, but not all individuals have equal access to resources and opportunities. Without adequate safeguards, this emphasis on individual responsibility risks deepening inequalities and entrenching digital exclusion. The central challenge, therefore, is to design frameworks that balance personal initiative with organisational and institutional support, so that upskilling and reskilling in the AI era advance inclusive and sustainable competence development.

Consequences for Upskilling and Reskilling

Analysing competence trends and the evolving logics of development reveals significant implications for how upskilling and reskilling are conceived and delivered. These implications affect employees, employers and educational institutions alike, reshaping the wider ecosystem of lifelong learning.

The first consequence is a redefinition of training priorities. As competence life cycles shorten, training can no longer be treated as a discrete episode; it must become a continuous, iterative process. Employers are expected to cultivate environments that support ongoing adaptation rather than sporadic interventions. This shift also complicates assessment and validation. Traditional mechanisms, such as diplomas and certificates, do not readily capture competences acquired informally or with AI-supported tools. New systems of recognition are therefore required, capable of validating dynamic, experience-driven learning whilst preserving credibility and comparability.

A second consequence is the redistribution of responsibility for competence development. Workers are encouraged to exercise greater agency over their learning trajectories, while employers are expected to provide access to resources, mentoring and recognition mechanisms. Public institutions retain a vital role in ensuring access and safeguarding equality of opportunity. Yet this redistribution brings risks. An intensified emphasis on self-directed learning can entrench inequalities, as not all individuals enjoy equal access to digital tools, infrastructure or institutional support. Without adequate safeguards, digital exclusion and uneven opportunity may erode the inclusiveness of competence development.

Finally, the integration of artificial intelligence into learning processes presents both opportunity and challenge. AI is increasingly expected not only to shape demand for competences but also to enable their acquisition through personalisation and adaptability. At the same time, growing reliance on

AI-based tools raises the risk of deskilling: as routine tasks are automated or delegated to intelligent systems, workers may have fewer opportunities to practise and sustain core competences. This dual role demands careful integration into learning ecosystems, supported by ethical oversight, regulatory compliance and transparent governance.

Taken together, these consequences call for a fundamental reconsideration of the architecture of competence development. The future of upskilling and reskilling will hinge on the design of systems that are flexible, inclusive and ethically grounded, balancing individual initiative with organisational and institutional responsibility.

The Employee Perspective

Whilst employer surveys dominate institutional reports such as the *Future of Jobs*, the employee voice is far less frequently represented. DeVry University's *Closing the Gap* (2024) helps to fill this gap by examining how workers themselves perceive the challenges of competence development in the AI era. This perspective is crucial, as it brings to light tensions between institutional expectations and the lived realities of employees.

The study shows that workers recognise the necessity of continuous learning and accept that responsibility for competence development is increasingly shifting towards the individual. Many report engaging in self-directed learning, particularly via digital platforms, to remain employable in rapidly changing environments. At the same time, they express concern about the resources required for such efforts, time, financial investment and access to adequate infrastructure. This reveals a clear tension between the expectation of individual initiative and the unequal distribution of opportunities that may limit workers' ability to meet these demands.

Employees also place strong emphasis on recognition and validation. Informal learning, though central to competence renewal in the AI era, often remains invisible within formal systems of certification and career progression. Workers fear that without institutional mechanisms to validate competences acquired outside traditional settings, their learning efforts will not translate into professional mobility or security. This highlights a persistent asymmetry between employer-driven competence frameworks and employee-driven learning practices.

The DeVry findings confirm that competence development in the AI era cannot be understood solely from the standpoint of employers or policymakers. Employees may assume greater responsibility for their own upskilling and reskilling, but their capacity to do so is shaped by structural factors such as recognition systems, workplace support and access to digital resources. These tensions underscore the broader challenge of designing competencedevelopment infrastructures that are both inclusive and sustainable. They also provide a necessary counterpoint to institutional narratives, reminding us that the future of work will be shaped not only by employers' strategies but also by the everyday practices and constraints experienced by workers themselves.

AI-Supported Dynamic Education Path

The question of whether artificial intelligence can support competence development in practice has become increasingly pressing amid rapid technological change and shortening competence life cycles. The gAI-PT4I4 prototype illustrates the new logic of competence development in action, showing how AI can help to transform learning into an adaptive, interactive process. Developed by Lin et al. (2025), it offers a concrete example of how AI may be integrated into educational infrastructures for Industry 4.0. Rather than treating AI solely as a source of disruption, the prototype 'fights fire with fire', deploying generative systems to address the very challenges they help to create.

The prototype rests on a modular architecture comprising four technical elements: a generative AI module; a retrieval-augmented generation mechanism,; digital twin and virtual-reality environments; and sentiment analysis capabilities. Together, these components create an adaptive and immersive educational system. The generativeAI module produces training content in real time and adjusts it to the user's level and professional context through natural language interaction. The retrieval-augmented generation mechanism ensures the integration of external knowledge so that training materials remain contextually relevant and current. Digital twins and virtual reality provide simulated work environments that mirror real world conditions, enabling learners to experiment and acquire competences without the risks or costs of actual production. Finally, the sentiment analysis module tracks emotional engagement and adjusts the intensity, pace and format of instruction accordingly. Each component maps onto a dimension of the proposed framework, from iterative learning cycles to adaptive feedback that supports learner agency.

The prototype was evaluated under controlled experimental conditions with a cohort of 20 participants. They completed the training tasks successfully in 80 per cent of cases, suggesting the system's effectiveness. The time required to acquire competences was reported to be shorter than under conventional training, although precise comparative data were not provided. These preliminary findings indicate that AI-supported pathways can enhance both the efficiency and the personalisation of learning. They also point to a shift from competence acquisition to competence co-creation, consistent with the proposed new logic.

At the same time, the experiment exposes clear limitations and challenges. The small sample precludes generalisation, and the absence of a control group or detailed baseline measures weakens the strength of any causal claims. Moreover, the controlled conditions do not mirror the complexities of real world learning environments, where workplace constraints, learner motivation and organisational culture materially shape outcomes. The incorporation of sentiment analysis raises additional ethical concerns, particularly in relation to the collection of sensitive data and the potential for behavioural manipulation.

Despite these limitations, the gAI-PT4I4 prototype represents an important conceptual advance. It demonstrates the possibility of moving beyond rigid, standardised training models towards adaptive systems that respond dynamically to learner needs. The case confirms that competence development is relational and adaptive, and can be co-created through human-AI collaboration. In this sense, it exemplifies a broader paradigm shift in competence development, in which AI is viewed not solely as a source of risk but as an enabling infrastructure for future upskilling and reskilling. Nevertheless, the results remain exploratory and call for further validation through larger-scale, longitudinal studies capable of assessing long-term effectiveness and ethical implications.

Conclusion

Key Insights for Upskilling and Reskilling in the AI Era

The analysis presented in this article demonstrates that upskilling and reskilling in the AI era can no longer be understood as the transfer of predefined skills within static frameworks. The accelerating pace of technological change, together with the shortening life cycles of competences, calls for a new architecture of learning that integrates competence-based stability with capability-based adaptability. This hybrid logic recognises not only the measurable acquisition of technical competences but also the cultivation of reflective practice, creativity, resilience and the ability to collaborate with intelligent systems.

Artificial intelligence plays a pivotal role in this transformation. As illustrated by the gAI-PT4I4 prototype, AI can serve as an enabling infrastructure for personalised, iterative and context-sensitive learning. Such systems have the potential to lower barriers to access, provide real-time feedback and adapt training dynamically to a learner's professional context. The gAI-PT4I4 case shows how the new logic of competence development can be put into practice. At the same time, such systems bring new challenges. The integration of generative AI requires significant investment in infrastructure and capability, while the use of highly sensitive data, such as emotional feedback, raises ethical concerns. Without appropriate safeguards, these technologies may undermine trust, infringe upon autonomy or even facilitate behavioural manipulation.

Limitations of Upskilling and Reskilling in the AI Era

Despite its promise, upskilling and reskilling face critical limitations. Access to learning opportunities remains highly uneven, constrained by time, financial means and digital infrastructures. Recognition systems still lag behind practice, leaving competences acquired through informal or AI-supported learning invisible in many professional contexts. The pace of technological change often outstrips the adaptive capacity of organisations and education systems, placing workers under sustained pressure to renew their competences. Moreover, while AI can enable learning, excessive reliance on automated systems risks contributing to deskilling, eroding human expertise and reflective judgement. These limitations make it clear that upskilling and reskilling are not purely technical endeavours; they require institutional safeguards, a commitment to social equity and robust ethical governance.

Broader Implications and Future Directions

The future of upskilling and reskilling in the AI era hinges on shared responsibility. Employees must exercise agency in shaping their development pathways; employers must enable continuous learning and recognise competences acquired through diverse channels; and public institutions must act as guarantors of inclusion, preventing digital exclusion and ensuring access to the necessary infrastructure. Together, these actors can cultivate competence ecosystems that are flexible, ethical and sustainable.

Several avenues for future research emerge. From the employer perspective, it is important to examine how organisations operationalise competence requirements in recruitment and performance management, and how they design reskilling strategies that balance stability with adaptability. From the employee perspective, further studies should investigate which competences workers themselves regard as most salient for the future, what motivates engagement in learning and how processes of deskilling manifest in the context of AI adoption. It is also essential to monitor the persistent gap between institutional expectations and employee realities. The DeVry survey reminds us that enthusiasm for continuous learning is tempered by concerns about resources, recognition and unequal access, issues that must be addressed if upskilling and reskilling are to be inclusive. At the systemic and macroeconomic levels, future research should explore how public institutions cooperate with business to shape inclusive competence ecosystems, and how informal, AI-supported competences can be recognised and validated. Critical questions also arise about the longterm impact of adaptive AI systems: can they accelerate competence renewal without eroding reflective judgement, and how can they support both individual agency and collective resilience?

Seen in this light, the findings affirm the relevance of the new logic of competence development advanced in this article. Rather than a linear transfer of predefined skills, competence development in the AI era emerges as a dynamic, iterative process of renewal, co-shaped through human-AI collaboration. Recognising future competences as grounded in capabilities underscores the need for adaptive and inclusive pathways capable of sustaining learning amid accelerating technological change.

Ultimately, despite the uncertainties of a complex and volatile world, artificial intelligence should not be understood merely as a disruptive force. If responsibly governed, it can extend human capacities to learn, adapt and co-create knowledge. In this sense, AI offers not only a new logic of upskilling and reskilling but also an opportunity to open up roles to people whose competences are not captured by formal qualifications.

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