From Generative AI to Extended Reality: Multidisciplinary Perspectives on the Challenges, Opportunities and Future of Educational Computing

Abstract

This editorial brings together the insights of fourteen members of the journal's editorial board to critically examine the evolving landscape of educational computing. In an era marked by rapid technological advancements; from generative artificial intelligence to extended reality, this editorial explores the multidimensional challenges and opportunities these developments present for education. Drawing from multidisciplinary perspectives, the contributors collectively identify four thematic areas that demand sustained scholarly attention: (1) Equity, Inclusion, and the Digital Divide; (2) Ethics, Social Sustainability, and Well-being; (3) Instructional Design; and (4) Human-Computer Interaction in Educational Technologies. Each theme reflects a convergence of urgent concerns and transformative potential and is accompanied by forward-looking research questions that aim to shape the future agenda of the field. Together, the contributions highlight critical tensions and possibilities, offering a roadmap for researchers, practitioners, and policymakers committed to harnessing educational computing technologies in socially responsible, pedagogically sound, and human-centred ways.

Keywords: Educational computing, Digital equity, Ethics in technology, Instructional design, Human-computer interaction

Introduction

We are pleased to introduce the new editorial board of the Journal of Educational Computing Research, a diverse and distinguished group of scholars whose work has shaped, and continues to shape, the evolving field of educational computing. As we mark this new chapter in the journal's trajectory, we do so with an awareness of both continuity and change: continuity in our ongoing commitment to rigorous, impactful scholarship; and change in the ways educational computing technologies are conceptualised, studied, and deployed in an increasingly complex world.

The intersection of education and computing has, over recent decades, undergone significant transformation, shaped by advances in digital technologies, shifts in pedagogical theory, and evolving societal expectations. Educational computing encompasses the application of computational tools, environments, and methodologies to support teaching, learning, and assessment. From its early roots in computer-assisted instruction and programmed learning in the mid-twentieth century, the field has developed in complexity and scope, now encompassing artificial intelligence in education, adaptive learning systems and pedagogical agents, and immersive technologies such as virtual and augmented reality.

The imperative to understand the dynamics of educational computing has been heightened by global movements towards digital transformation in education, especially in response to the COVID-19 pandemic, which accelerated the adoption of technology-enhanced learning across sectors. Technology in education is no longer a supplementary concern but has become central to educational provision and policy. Nevertheless, despite the increased presence of educational computing technologies, questions persist regarding their efficacy, equity, and the assumptions underpinning their use. Research has increasingly highlighted the complex entanglements of technology with pedagogy, policy, and social structures (Williamson, 2017), necessitating more nuanced analyses that move beyond techno-optimist discourses. This has led to changes in research agendas, with the Journal of Educational Computing Research adapting to include the ethics and social responsibility of educational computing within its aim and scope (Allison, 2025).

Some research tends to focus on the affordances of technologies and their potential to enhance learning outcomes. Early research on intelligent tutoring systems, for example, have shown potential in providing immediate feedback and adaptive support tailored to individual learners' needs (VanLehn, 2011). Similarly, virtual reality and augmented reality technologies have been explored for their capacity to create immersive learning experiences, particularly in fields requiring spatial or experiential understanding (Radianti et al., 2020). However, the integration of such technologies into everyday educational practice remains uneven, and questions about scalability, teacher preparedness, and institutional readiness persist. Hence, other work has advocated for a sociocultural understanding of educational computing, drawing attention to issues of power, access, surveillance, and data ethics (Knox, Williamson & Bayne, 2020). These diverse views have generated a heterogeneous research landscape in which educational computing innovations are both celebrated and problematised.

Future research in educational computing must therefore grapple with an expanding array of technological possibilities while attending to persistent pedagogical and ethical concerns. Considering these developments, expert insight is invaluable in understanding coherent research agendas and identifying blind spots in the current literature. Despite a rich and growing body of work in educational computing, there remains a lack of consolidated knowledge concerning how experts perceive the field's key challenges and opportunities. While meta-analyses and systematic reviews have provided important overviews of specific subfields, such as on mobile learning (Yang and Xiang, 2024), augmented reality (Lu et al., 2025), pedagogical agents (Schroeder, Davis, and Yang, 2024), or generative AI (Liu et al., 2025), few studies have sought to synthesise expert opinion across the broader terrain of educational computing.

Multidisciplinary Perspectives

This editorial adopts a multiple-perspective approach to exploring the current and future directions of educational computing, following a model developed by Dwivedi et al. (2021). The methodology centres on short, invited contributions from members of the journal's editorial board. Contributors were asked to share their individual perspectives on the key challenges, opportunities, and research directions shaping the field. The contributions were solicited via email, inviting experts to engage with a broad range of issues including methodological innovations, emerging technological trends, and critical questions confronting educational computing. While the request offered optional thematic prompts, such as the influence of AI on pedagogy, design, and inclusion, contributors were encouraged to draw upon their own expertise and concerns. The intention was not only to highlight the scholarly strengths and diverse perspectives of the editorial board but also to foster intellectual community and stimulate wider dialogue within the field.

The collected contributions are presented in largely unedited form, preserving the voice, tone, and emphasis of each author. While this may introduce some irregular narrative flow and thematic overlap, such qualities are integral to the approach, prioritising authenticity, diversity of thought, and individual voice over editorial uniformity. As such, this method foregrounds the understandings and reflective judgements of those actively shaping educational computing's present and future. Table 1 provides an overview of the topics and contributors.

By curating these scholarly reflections, this editorial seeks not merely to introduce the new editorial board and the current issues in educational computing, but to serve as a platform for intellectual engagement. These contributions underscore the richness and plurality of the field and are intended to inspire further research, discussion, and collaboration. We are grateful to our contributors for their generosity and insight and look forward to sustaining this dialogue in future issues.

Table 1: Contributions and Contributors

Contribution	**Author**
Contribution 1: Opportunities and Challenges of Designing Instruction with Computer-Based Media.	Richard E. Mayer, University of California, Santa Barbara, USA
Contribution 2: Bridging Philology and Generative AI in Educational Computing	Nikolaos Pellas, Aristotle University of Thessaloniki, Greece
Contribution 3: Do Computing Educators Really Need Code Plagiarism Detectors that are Good at Finding Semantic Similarities?	Oscar Karnalim, Maranatha Christian University, Indonesia
Contribution 4: Challenges, Opportunities, and Potential Research Issues of Generative AI-Empowered Educational Computing	Gwo-Jen Hwang, National Taiwan University of Science and Technology, Taiwan
Contribution 5: Emerging trends: Human and AI Interaction	Sara de Freitas, Birkbeck, University of London, UK
Contribution 6: Educational Computing and Mathematics: An Interdisciplinary Nexus	Oi-Lam Ng, The Chinese University of Hong Kong, Hong Kong
Contribution 7: Beyond Outcomes: Prioritizing Cognitive Processes in the Age of Generative AI	Yueh-Min Huang, National Cheng Kung University, Taiwan
Contribution 8: Responsible Artificial Intelligence for K-12 Education	Danial Hooshyar, Tallinn University, Estonia
Contribution 9: Intentional and Unintentional Consequences	Robert H. Seidman, Southern New Hampshire University, USA
Contribution 10: Generative AI and its Impact on Social Sustainability	Mostafa Al-Emran, Victorian Institute of Technology, Melbourne, Australia
Contribution 11: Extended Reality in Education: Affordances, Challenges, and Trends	Tassos A. Mikropoulos, University of Ioannina, Greece
Contribution 12: The Integration of Generative AI and Pedagogical Agents	Noah L. Schroeder, University of Florida, USA
Contribution 13: Achieving Higher Standards through Inclusive Educational Technology	Rod D. Roscoe, Arizona State University, USA
Contribution 14: Navigating the Future of Educational Computing: A Perspective from the Intersection of AI, Technology, and Global Inclusion	Ismaila Sanusi, University of Eastern Finland, Finland.

Contribution 1: "Opportunities and Challenges of Designing Instruction with Computer-Based Media", by Richard E. Mayer

My research involves applying the science of learning to education, with a special focus on how to design instructional experiences that optimize learning in computer-based environments. This work includes investigating instructional design features that increase the effectives of learning with computer-based multimedia presentations, instructional video, educational games, online pedagogical agents, immersive virtual reality, and dialogues with artificial intelligence agents. The question that motivates my research is: How can we teach students in ways so that they can take what they learned and apply it in new situations? In short, my focus is on fostering learning processes and outcomes that promote transfer.

The promise of designing instruction with computer-based media rests in its affordances for motivating generative processing in learners—that is, cognitive processing aimed at making sense of the material by attending to the relevant information in a lesson, mentally organizing it into a coherent structure, and integrating the incoming information with relevant knowledge activated from long-term memory. We want to harness the motivating power of computer-based media to help students learn in ways that yield transfer.

The challenge of designing instruction with computer-based media is that computer-based environments can be distracting for some learners leading to extraneous processing—that is, cognitive processing that is not related to the instructional goal and thereby wastes some of the learner's limited cognitive processing capacity. We want to make sure that students reflect on the core instructional message rather than on the exciting features of computer-based media. In short, the challenge of instructional design of computer-based learning is how to balance motivating features and instructional features.

In looking to the future of educational computing research, I foresee four continuing issues:

1. Formulating useful research questions. Excellent research starts by asking the right question in a way that leads to productive studies. It is tempting to ask media-comparison questions concerning which instructional medium is more effective, such as asking whether learning in immersive virtual reality is better than learning from a slideshow presentation on a desktop computer. However, the flaw in media-comparison research is that learning is caused by instructional methods rather than instructional media. An alternative is to ask value-added questions concerning how adding one feature to a computer-based lesson affects learning processes and outcomes. Future research is needed to pinpoint what works and how it works.
2. Employing appropriate research methods. Once we have a research question, the next step is to rigorously apply an appropriate research method. With experimental research this includes random assignment, experimental control, and learning outcome measures.
3. Testing foundational theories. Although we are making progress in developing theories of learning with media, more work is needed to specify the cognitive, affective, and social processes that lead to meaningful learning outcomes with instructional media.
4. Looking towards important practical applications. An exciting aspect of this line of research is that it has both theoretical and practical implications, such that practical problems in how to design computer-based instruction can lead to research that also advances learning theories.

Overall, the future is ripe for advances in educational computing research aimed at improving learning outcomes.

Contribution 2 "Bridging Philology and Generative AI in Educational Computing", by Nikolaos Pellas

Philology education, spanning Classical, Medieval, Modern Greek studies, and Linguistics, occupies a unique intersection of language history, cultural context, and close textual analysis. Unlike disciplines that emphasize rote grammar drills, philology demands interpretive rigor. Precisely, learners must situate fragmentary texts in their historical milieu, craft clear exegeses of complex syntax, and engage critically with manuscripts that survive only in pieces (Graziosi et al., 2023). Instructors thus juggle lesson planning, textual commentary, and personalized feedback, tasks that can overwhelm resources and class sizes.

Generative AI (GenAI), though nascent in philology, offers compelling potential for automating routine work, such as glossary creation, preliminary translation, or reconstructing damaged passages—while preserving scholarly depth. AI chatbots can draft annotated editions (e.g., linking Early Modern English lexicon to contemporary usage), suggest discussion prompts for Socratic seminars on Homeric verse, and generate interactive quizzes that probe syntactic shifts over time (Adamopoulou & Moussiades, 2020).

However, the methodological integration of GenAI in philology faces key challenges. Most large-scale language models are trained in modern corpora and may misinterpret archaic forms, overlook cultural nuance, or introduce bias (Pellas, 2023). Usability issues, clunky interfaces or limited accessibility, further hinder adoption in tasks requiring sustained close reading, such as paleographic analysis of medieval manuscripts. Moreover, the field lacks rigorous studies on whether AI-generated materials meet the high pedagogical standards of humanities instruction, where nuance and interpretive depth are paramount (Graziosi et al., 2023; Pellas, 2025).

To move forward, future research must interrogate how design principles (e.g., multimedia integration, adaptive feedback loops) influence learning outcomes in philological contexts. Educators and scholars should evaluate the accuracy, engagement, and AI-literacy fostered by conversational interfaces like ChatGPT or Gemini, particularly in crafting narratives and interactive assessments that respect philological rigor. Key questions include:

1. Usability: Which interface design principles of AI chatbots (e.g., integration of multimedia, interactive feedback mechanisms) best support deep learning and critical engagement in humanities contexts?
2. Pedagogical alignment: Do AI-generated glossaries, quizzes, and lesson plans accurately reflect historical and linguistic subtleties?
3. Instructional impact: Which chatbot features (e.g., scenario simulation, customized feedback) most effectively support deep textual analysis?

In sum, integrating GenAI into philology offers the promise of personalized learning pathways, immediate feedback, and innovative content creation, but demands rigorous evaluation to ensure scholarly precision and pedagogical integrity.

Contribution 3: "Do Computing Educators Really Need Code Plagiarism Detectors that are Good at Finding Semantic Similarities?", by Oscar Karnalim

Plagiarism is an emerging concern in programming education, especially with the advancement of technology and AI (Hoq et al., 2024). It is somewhat easier to copy one's code program and reuse it without proper acknowledgement. In some cases, the copied program can be disguised without much effort (Devore-McDonald & Berger, 2020). Consequently, a number of plagiarism detectors have been developed (Blanchard et al., 2022). Some of them strive for semantic similarity, where two programs having the same program flow are considered similar despite having differences in the program structure and layout (Karnalim et al., 2022).

While these detectors can be helpful in industries to prevent software intellectual property theft, they are less valuable in computing education for at least four reasons. First, many assessments are much simpler than real-world programming cases due to their educational purpose. The variation of program contents is much more limited.

Second, perpetrators involved in plagiarism cases are usually novice programmers who commit plagiarism because they cannot complete the assessments by themselves. Their ability to disguise the programs is somewhat limited to the surface level.

Third, as students are still learning to code, their programs can be easily influenced by instructors' teaching style and/or available resources. If instructors often use lambda expressions in their lectures, students are more likely to use them in their programs as well. Student programs can unintentionally share some similarities for this reason.

Fourth, in some courses, many small assessments are preferred over a few large assessments (Allen et al., 2018). Programming is somewhat similar to mathematics. To master it, students must do many exercises; knowing the theory alone is insufficient. These small assessments generally expect semantically similar solutions as they should be completed in a short time. Programs for converting temperature, for example, will share similar program flow and structure, even though they are written independently.

In such cases, instructors should employ a plagiarism detector focusing on simpler similarity algorithms, similarity in programming behaviour, or similarity in programming style. It is also suggested to search for unusual similarities, which are unlikely to result from coincidence. For instance, if two programs share strange errors or bugs while others do not, such similarity can be potential evidence of plagiarism.

Semantic similarity is also less valuable to detect GenAI-assisted plagiarism: unethical use of GenAI to complete assessments without acknowledging it (Karnalim et al., 2024). Plagiarism detectors for GenAI assistance usually look for programming style or syntax differences, which are commonly ignored by semantic similarity.

It is worth noting that this perspective does not intend to discourage the use of plagiarism detectors striving for semantic similarity in computing education. Instead, it provides more aspects to consider while selecting a suitable plagiarism detector. There is no "silver bullet" in detecting code plagiarism. The assessment design and student programming proficiency should be considered. Plagiarism detectors striving for semantic similarities are still helpful for advanced assessments (e.g., a semester-long programming project) or those dedicated to senior students (last-year undergraduates or postgraduates). The program variation might be less subtle.

Therefore, given the challenges outlined regarding code plagiarism detectors in academia, future research should consider the assessment design (in terms of complexity and purpose) and the perpetrators' background (including their programming experience and reasons for plagiarism). The research direction is different from code plagiarism detectors for intellectual property theft.

Contribution 4: "Challenges, Opportunities, and Potential Research Issues of Generative AI-Empowered Educational Computing", by Gwo-Jen Hwang

The advancements of generative artificial intelligence (GenAI) have provided new opportunities to develop new learning approaches, such as enabling a digital partner to work with human learners or providing personalized feedback to individual students working on programming tasks (Goyal, 2025; Lai & Tu, 2024; Tu, 2024; Yilmaz & Yilmaz, 2023). Meanwhile, scholars have indicated several concerns regarding the possible negative impacts of using GenAI on students' learning performance (Fui-Hoon et al., 2023). For example, Fan et al. (2025) warned that students could over rely on the assistance of GenAI, and even stop trying to complete learning tasks on their own; they called this situation "metacognitive laziness." Accordingly, scholars have made attempts to address this issue in various courses (Chang et al., 2025; Chang et al., 2024).

On the other hand, the challenges and opportunities introduced by GenAI in educational settings open up a wide range of new research directions within the field of educational computing. Several recommended research foci are listed as follows:

1. Human-GenAI collaboration in educational computing tasks.
2. Metacognitive laziness issues in educational computing: Exploring the possible negative impacts of using GenAI in educational computing tasks.
3. Learning strategies for GenAI-empowered educational computing: Developing new learning strategies for improving students' learning performance in GenAI-empowered educational computing tasks.
4. Assessment Instruments: Developing new instruments to measure students' performance in GenAI-empowered educational computing tasks.
5. Prompt engineering as educational computing: Designing tasks and strategies to promote students' computational thinking through effective use of GenAI.
6. GenAI-empowered educational computing models or frameworks: There are numerous possibilities for implementing GenAI technologies across various computing platforms and devices, such as smartphones, desktop computers, and educational robots, to support the goals of educational computing. A critical issue in this field is the development of GenAI-empowered models or frameworks that thoughtfully integrate emerging technologies with relevant educational theories and learner needs.
7. Implementation of GenAI-empowered educational computing systems: To fulfil the increasing needs of training students' programming or computational thinking, it is important to develop GenAI-empowered educational computing systems to guide

students to learn, and to provide feedback to individual students by analyzing their learning logs or performances.
8. Re-examining existing pedagogical theories from the perspective of GenAI-empowered educational computing: There could be different roles played by GenAI, such as tutor, tutee, or learning partner, in educational computing tasks. It is important to determine the roles of GenAI by referring to existing pedagogical theories. Therefore, it is suggested that additional research be conducted to perceive and interpret the pedagogy to suit the features of GenAI-empowered educational computing.
9. Investigation of ethical issues for GenAI-empowered educational computing: It should be noted that using GenAI in educational settings can not only provide opportunities to improve students' learning performance, but could also raise ethical issues, such as students using the GenAI's answers as their own work. Therefore, it is important to address this issue in future GenAI-empowered educational computing studies.

Contribution 5: "Emerging trends: Human and AI Interaction", by Sara de Freitas

From my earliest work with developing and researching AI-driven Agent technology and first publications in 2008, I have been fascinated by the potential of this technology, and not in singularly technologically deterministic ways. To understand agent technology means understanding both the technological development and the wider disciplinary challenges it presents, such as cultural and social impacts. To understand this topic area most easily, it's worth reflecting on Turing's two important papers in 1937 and 1950 (Turing, 1937; Turing 1950). While the first outlined the key challenges with web science, and shaped the discipline of computer science, the second paper focuses on 'artificial life'. As this paper asks, 'can machines think?', it has become the second most cited philosophical paper. It's one thing to build an application, it's quite another to shape a discipline – or several. While the first paper led to the development of the subject of computer science, the second, 'artificial life' has struggled to find its niche, until now, partly due to its very interdisciplinary nature and because it inherently brings together the sciences and the humanities.

As a cross-disciplinary researcher with publications in information science, HCI journals and educational journals, I can appreciate the challenge. The learnings are captured in papers published 2008-10 from experimental work and demonstrators ranging from 2005 to today (e.g.: de Freitas, 2014, Rebolledo-Mendez & de Freitas, 2008; Rebolledo-Mendez et al., 2008; Panzoli et al., 2010 a,b), including a demonstrator for teaching space test engineers using immersive simulations. By doing whole world testing with users throughout the period, so many functionalities emerged, not least the capability for accelerated agent learning (e.g. from humans and other agents, as well as data). Significant challenges of technology acceptance and access to broad functionalities remain. These 'instances' are very technical however, and have had significant challenges now largely overcome, not least managing and integrating dynamic and real time data on-the-fly, safeguarding, and security.

What we learnt was, if we do focus on the narrower 'human and AI interaction', then we can more readily situate 'artificial life' and agent technology in the computer science sub-field of HCI. Also, the range of topics from agents as learning support, games as controllers, and cognitive systems for robots, makes a lot more sense. Specifically, if we consider that artificial life is a hybrid interaction, not a singular computer or human approach, the refinement of Hybrid-HCI helps to further refine the topic scope and disciplinary context.

Certainly, what recent research is suggesting from the research metareviews on agentic technology (e.g. Fu, Weng, Wang, 2024) is the need for:

1. shared terminology and vocabulary,
2. more robust scientific studies to show what works and what doesn't,
3. national and international standards and policies to align practices,
4. student and teacher upskilling and training,
5. strengthened technical infrastructure,
6. shared institutional AI strategies.

However, there is one major impediment to the uptake of AI technologies which is not really covered in the literature, and that is the lack of a consolidated evidence and research base, which is why elsewhere (de Freitas, 2024), I have suggested a new Research Council (for the UK): the Information and Education Sciences Research Council. This would help to support more rigorous and scientific research and help to consolidate and validate existing evidence, providing support for a closer engagement between the EdTech sector and schools, using existing frameworks and standards.

With so much at stake, surely a priority for every national government must be to consolidate our research and evidence base quickly, as many gains may be lost in the 'goldrush' if every institution has to replicate the same journey and make the same expensive mistakes that could have detrimental and unforeseen consequences. Let's learn the lesson from online education, and not squander our time and resources replicating studies, when we can use shared scientific instruments to benchmark progress and practice incrementally.

Contribution 6: "Educational Computing and Mathematics: An Interdisciplinary Nexus", by Oi-Lam Ng

Educational computing and mathematics education have long intersected in practice, from early explorations with LOGO programming (Papert, 1980) to the rise of dynamic software and today's AI-enhanced learning environments. Yet, these fields have too often operated in parallel rather than in concert. Today, as both the digitalization of society and the influence of AI accelerate, the need for stronger interdisciplinary dialogue has become pressing. I argue that computational thinking (CT) provides a powerful interdisciplinary nexus, conceptually and pedagogically, that connects educational computing and mathematics in ways that can inform both research and classroom practice (Noss & Hoyles, 1992).

CT, as a set of problem-solving competencies (Wing, 2006), including abstraction, decomposition, automation, and algorithmic design, has roots in both computing and mathematics. Importantly, it is not confined to programming. In my own research, I have documented how young learners, even without exposure to formal coding, can engage in iterative, structured reasoning within touchscreen-based mathematics environments (Yeung & Ng, 2024). Besides, the emergence of block-based programming offers powerful contexts for learners to mathematize problems and construct solutions using intuitive representations, drawing upon young learners' algorithmic and iterative thinking, pattern recognition, and use of variables (Ng & Cui, 2021; Ng et al., 2023). In doing so, CT becomes a lens through which children engage with number, structure, and pattern which are all hallmarks of early mathematical reasoning.

The rise of generative AI adds both urgency and complexity to this conversation. As AI tools increasingly automate procedural tasks, including standard mathematical operations, we must reconsider what mathematical competencies are essential for the future (Wolfram, 2020; Ng, 2025). A renewed emphasis on sense-making, problem analysis, and the ability to interpret or critique algorithmic outputs is needed. CT-enriched mathematics tasks, especially those that blend conceptual learning with digital tools, are well-positioned to cultivate these competencies. At the same time, we must remain vigilant about who benefits from such innovation. Without intentional design for inclusion, AI and CT risk reinforcing existing educational inequalities.

Looking forward, I see an urgent research agenda at the intersection of educational computing and mathematics: designing and studying equitable CT-enriched pedagogies; supporting teacher education and professional development in this space; and investigating how learners, especially from underserved communities, engage with computing as a means of mathematical empowerment. The goal is not merely to teach students to code, but to help them think computationally and critically in a world shaped by algorithms and automation.

The future of mathematics education is inseparable from the future of computing. If we are to prepare learners to navigate, shape, and challenge AI-driven systems, educational computing and mathematics must collaborate, not only at the level of tools, but at the level of ideas, values, and vision.

Contribution 7: "Beyond Outcomes: Prioritizing Cognitive Processes in the Age of Generative AI", by Yueh-Min Huang

The emergence of generative artificial intelligence tools like ChatGPT has catalyzed unprecedented discourse across educational landscapes. These technologies, with their remarkable ability to produce human-like responses and generate contextually relevant content, have transcended the status of mere technological novelties to become potentially paradigm-shifting educational instruments. Unlike previous educational technologies that primarily augmented specific capabilities, these systems potentially substitute cognitive processes previously considered uniquely human, a transformation that demands fundamental reconsideration of educational computing research priorities.

Generative AI offers substantial educational benefits that cannot be overlooked. It provides unprecedented opportunities for personalized learning experiences, adapting to individual needs and learning trajectories. Research indicates that Generative AI implementation can enhance student academic performance and engagement (Huang et al., 2025; Wu et al., 2023). The technology democratizes access to high-quality educational content generation, particularly benefiting resource-constrained contexts. Furthermore, it reduces educator workload, allowing teachers to redirect their efforts toward higher-impact instructional activities. These systems provide immediate, abundant feedback critical for learning enhancement while assisting in creating personalized materials, developing engaging content, and accelerating ideation, literature review, and complex data analysis processes (Kohnke et al., 2025).

However, current research trajectories reveal concerning patterns. Much of the existing literature fixates narrowly on easily measurable outcome metrics following Generative AI tool implementation: improved test scores, completion rates, or satisfaction indices (Lin et al., 2025; Shahzad et al., 2025; Wang et al., 2024). This narrow focus neglects a critical dimension: the impact on students' thinking processes. Empirical studies suggest that when students use Generative AI assistance for practice, their performance may improve, but subsequently declines when assistance is removed indicating a focus on short-term performance rather than fundamental concept mastery (Doleck et al., 2024; Lin et al., 2025). We observe growing evidence of overreliance, where students bypass essential cognitive engagement by outsourcing thinking to Generative AI systems (Lee et al., 2024; T.-T. Wu et al., 2025). More troublingly, frequent use of Generative AI tools correlates negatively with critical thinking abilities due to increased cognitive offloading.

This outcome fixation becomes particularly problematic in our current technological context. When Generative AI can produce seemingly sophisticated outputs with minimal human cognitive investment, the processes behind those outputs become more important, not less. Education has never been solely about end products; its fundamental purpose involves developing thinking capabilities that transfer across domains and persist throughout lifetimes. Research must pivot toward exploring how Generative AI can enhance these fundamental cognitive skills rather than merely focusing on learning products. Evidence suggests that excessive software dependence for problem-solving can impede students' deep understanding of fundamental concepts, affecting their performance without software assistance (Lee et al., 2024). When individuals overly rely on Generative AI for information retrieval and decision-making, their capacity for reflective problem-solving and independent analysis may diminish.

In the era of widespread Generative AI use, several critical thinking frameworks demand renewed research attention:

- **Higher-order thinking skills** such as analyzing, evaluating, and creating transcend simple memorization (Krathwohl, 2002). The advent of AI necessitates these capabilities for learners to effectively analyze and evaluate AI-generated content, moving beyond mere information retrieval (Wang et al., 2025). These cognitive processes are increasingly at risk of AI substitution rather than augmentation.
- **Systems thinking** emphasizes understanding interconnections and holistic perspectives in complex educational contexts involving AI (Arnold & Wade, 2015). Both research and practice require systems thinking approaches to comprehend the intricate interactions between Generative AI, learners, educators, and the broader educational ecosystem. This framework offers students approaches for understanding complex problems that Generative AI struggles to model holistically.
- **Computational thinking** involves problem-solving methods using algorithmic thinking and abstraction to interact with AI (Lee et al., 2023; C.-H. Wu et al., 2025). These skills are crucial for effectively designing prompts for AI, understanding its outputs, and leveraging its capabilities in structured, logical ways, ironically essential for students to meaningfully interact with AI systems.
- **Design thinking** represents a user-centered approach for designing and implementing AI tools and pedagogies in education (Liu et al., 2024; C.-H. Wu et al., 2025). This methodology ensures AI tools and their integration in educational environments are human-centered and effectively address the needs and challenges of learners and educators. It engages creative problem-solving capacities distinct from AI's pattern-matching strengths.

- **Reflective thinking** emphasizes self-assessment and learning from experiences using AI in education (Lin et al., 2025). Encouraging learners and educators to engage in reflective thinking about their experiences with AI can promote deeper understanding and inform more effective integration strategies. This metacognitive awareness of one's learning processes and how they're being mediated by technology is perhaps most crucial in an AI-saturated landscape.

As educational computing researchers navigate this transformative period, we must reorient our research questions from "What outcomes does AI enable?" to "How does AI reshape the thinking processes that ultimately matter most?" By prioritizing research into how AI influences and potentially enhances cognitive skills like critical thinking, problem-solving, and creativity, the educational computing research community can provide valuable insights for educators and policymakers on leveraging generative AI's potential while safeguarding education's core values and objectives. Only by understanding these deeper cognitive impacts can we ensure generative AI becomes a tool for intellectual empowerment rather than unintentional diminishment.

Contribution 8: "Responsible Artificial Intelligence for K-12 Education", by Danial Hooshyar

The integration of AI into K-12 education offers significant potential to enhance teaching, support learning, and improve school administration. However, it also raises critical concerns around ethics, trust, and transparency (e.g., Hooshyar et al., 2025).

One major concern is the increasing reliance on generative AI—especially domain-agnostic, commercially developed large language models (LLMs)—as the primary representation of educational AI. While LLMs show promise in enhancing learning outcomes and teaching efficiency (e.g., Alsofyani & Barzanji, 2025), their alignment with pedagogical goals and curricular needs remains limited. Emerging research highlights critical limitations, including persistent biases and a lack of contextual understanding (Warr et al., 2024; Resnik, 2024). In math education, for example, an LLM may learn that algebra is a core subject (a fact), that students struggle with word problems (a contingent but neutral fact), and that boys tend to excel in advanced math (a contingent but problematic bias). If such biases shape an AI tutor's behaviour, the system could unintentionally discourage girls by offering easier tasks or less encouragement to tackle challenging material. In addition, many AI systems overlook essential learning processes such as motivation, emotion, and (meta)cognition, and are often developed without meaningful involvement of domain experts and stakeholders. There is also widespread reliance on unreliable explainable AI methods to interpret black-box models, and ethical issues such as data inconsistencies and algorithmic bias are frequently ignored during development (Hooshyar et al., 2025). Moreover, current AI systems frequently overemphasize automated, individualized instruction, often neglecting the development of metacognitive and self-regulated learning skills.

These challenges highlight the urgent need for responsible AI; approaches that emphasize human-centred design, ensuring users' trust through ethical decision-making, promoting explainable outcomes, and preserving privacy through secure implementation (Goellner et al., 2024). Despite growing research efforts to address these principles in educational contexts, much of the current discourse remains theoretical, with limited real-world implementation of ethical, trustworthy, and interpretable AI systems. To move forward, research should not only examine how to responsibly use current AI systems in K-12 settings but also how to design AI methods that align with responsible AI principles.

Regarding the former, more attention is needed to evaluate existing AI systems through the lens of responsible AI principles and regulations like the EU AI Act, while considering stakeholder concerns around trust, privacy, and ethics. Research should also investigate how these tools affect not just learning outcomes but student wellbeing–cognitive, emotional, and social developments. Moreover, responsible use of AI requires avoiding over-automation through hybrid human-AI regulation of learning practices where learners are not just consumers but active participants in their learning journey. As for the latter, we need to move beyond purely data-driven models towards hybrid human-AI methods that incorporate both training data and symbolic domain knowledge, enabling more human-centred design (Hooshyar et al., 2024). This approach: (i) facilitates the involvement of practitioners in both the development and interpretation of AI systems; (ii) helps address existing data inconsistencies and biases in AI models; and (iii) supports the integration of essential learning processes into computational models.

Contribution 9: "Intentional and Unintentional Consequences", by Robert H Seidman

The first issue of this *Journal* was published 40 years ago and included articles such as "Logo and Intelligent Videodisc Applications for Pre-Readers," "Computer Anxiety: Definition, Measurements, and Correlates," and "Fifth Generation Computing: Introducing Micro-Prolog into the Classroom." This period marked the rise in the educational use of micro-computers as a precursor to personal computers.

Over the years, the *Journal* has published a diverse array of high-quality research articles. Even a brief review of recent issues demonstrates just how far the field has advanced. Who could have predicted the emergence of large language generative AI models like ChatGPT and the use of big data models in tailoring learning experiences? In another 40 years, when looking back at this *Journal* issue, readers will undoubtedly marvel at the significant strides made in the field.

However, some enduring concerns are likely to persist as we move forward into an unpredictable future. What are the unintentional individual and societal consequences of educational computing-based direct instruction and ancillary learning assistance in formal and informal educational settings? What role will "intelligent" machines play in the emotional well-being of students and teachers? How will the human bond between teachers and learners be affected in the short and long term? What are the psychological emotional benefits and costs to the quality of life? Most importantly, what does it mean to be a human teacher and learner in a world increasingly populated by quasi-sentient non-human intermediaries?

This *Journal* serves as an important venue for an international research community committed to rigorous scholarship in advancing educational computing. The research published here reflects and affects evolving trends in the field. As such, the *Journal* can provide a dynamic platform for discussions that span a broad range of cognitive and affective learning modalities. These scholarly discussions can broaden the scope of research and inform and enhance knowledge and practices in the field.

As a research community, it would serve our field well to explore the indirect effects and unintended consequences of our work in parallel with the many ways that educational computing can contribute to critical thinking, lifelong learning, and the cultivation of the little studied area of "wonder." (Green, 1971).

This *Journal* has always had and continues to have a distinguished Editorial Board. Three of the founding members, luminaries in their own right, were especially supportive in my role as founding Executive Editor. They were Richard Mayer (Mayer, 2025), Seymour Papert (Seidman, 2017), and Joseph Weizenbaum (Sarnof, 2023). I am sure that that the new Board members will be as helpful to Dr. Allison as they were to me.

Contribution 10: "Generative AI and its Impact on Social Sustainability", by Mostafa Al-Emran

Opportunities

Generative AI, encompassing technologies like large language models and content generation tools, presents transformative opportunities for educational computing by fostering social sustainability. These systems can democratize access to education through personalized learning experiences, tailoring content to diverse learner needs across linguistic, cultural, and socioeconomic contexts (Al-Emran et al., 2025). For instance, AI-driven tools can generate accessible educational materials, such as multilingual resources or content adapted for students with disabilities, promoting inclusivity. Additionally, Generative AI can support collaborative learning environments by facilitating simulations and virtual environments that encourage cross-cultural dialogue and empathy, aligning with social sustainability goals of equity and community-building. By automating routine instructional tasks, these technologies free educators to focus on fostering critical thinking and social-emotional skills, enhancing the human-centric aspects of education.

Challenges

The integration of Generative AI into educational environments poses challenges to social sustainability, as outlined in Table 2.

Table 2: Key challenges of Generative AI in promoting social sustainability in education.

Challenges	**Description**
Algorithmic bias	Generative AI systems may produce biased outputs due to limitations in training data, leading to content that misrepresents or excludes diverse groups, hindering equitable education.
Digital divide	Unequal access to AI tools, particularly in low-income or rural areas, risks widening educational disparities, limiting inclusivity and equitable learning opportunities.
Inconsistent output reliability	AI-generated educational content may vary in accuracy or relevance, potentially misleading learners and undermining trust in technology-driven education.

Data privacy risks	Collection of sensitive student data by AI systems raises concerns about unauthorized access or misuse, eroding trust and safety in educational environments.
Over-reliance and disengagement	Excessive dependence on AI tools may reduce student initiative and interpersonal engagement, weakening social connections critical for collaborative learning.

Future research agenda

To advance the understanding of Generative AI's impact on social sustainability in educational settings, future research must move beyond treating social sustainability as a singular construct and instead explore its sub-dimensions, such as quality of life, inclusivity, community cohesion, and social equity (Al-Emran, 2023). These sub-dimensions are deeply interconnected, with improvements in one potentially enhancing others. For example, enhancing inclusivity can help foster a better quality of life and promote greater social equity (Levidow & Papaioannou, 2018). By disaggregating social sustainability, research can better capture these interrelations and interdependencies, providing a more nuanced understanding of how Generative AI can promote equitable and inclusive education. The following is the research agenda to investigate these sub-dimensions and their interplay in the context of Generative AI:

- How can reliable and valid metrics be developed to measure the sub-dimensions of social sustainability (quality of life, inclusivity, community cohesion, social equity)?
- What are the long-term effects of AI-driven educational interventions on students' mental health and well-being?
- How can AI-driven simulations foster inclusive learning experiences that accommodate students with disabilities?
- How can Generative AI facilitate collaborative virtual learning environments that strengthen community cohesion among students from diverse backgrounds?
- How can Generative AI address the digital divide to ensure equitable access to educational resources in low-income or rural communities?
- How do improvements in inclusivity through Generative AI (e.g., multilingual content) influence quality of life and social equity in educational contexts?

Contribution 11: "Extended Reality in Education: Affordances, Challenges, and Trends", by Tassos A. Mikropoulos

Extended Reality (XR) is one of the emerging learning technologies with a significant impact on education (Samala et al., 2024). XR includes Virtual Reality (VR), which immerses the user into a digital world; Augmented Reality (AR), which brings digital elements onto the real world; Mixed Reality (MR), which enables reciprocal interaction between real and virtual elements; other forms of realities between real and virtual worlds.

The contribution of XR to education comes from its affordances, like other implementations of Information Technologies. Its three-dimensional spatial representations transform users into participants, enhancing pedagogical interaction. XR enables first-order experiences across diverse temporal and spatial scales, combining multisensory, intuitive, and real-time interactions. These unique features facilitate the exploration of concepts and phenomena that are otherwise beyond human experience or difficult to investigate. The above technological affordances give rise to specific learning affordances; activities participants may enact. Educators and learners can create environments, objects and code, navigate freely, model and simulate, deliver content, communicate, and collaborate.

XR has inspired research not only in education but also across social sciences and humanities. Studies have investigated how virtual environments affect attention, meditation, flow, and creativity by examining electrical brain activity, thus offering insights into how we can design effective learning environments (Yang et al., 2018). VR has shown positive cognitive and affective results in educational settings since 2000 (Mikropoulos & Natsis, 2011). A growing body of research supports similar benefits from other XR technologies (Hanid et al., 2025). XR has also shown promise in developing academic skills in special needs education (Iatraki & Mikropoulos, 2025).

Other emerging technologies are also shaping the future of XR in education. Generative Artificial Intelligence (GAI) has been integrated into virtual environments to support university students with brainstorming and personalized learning pathways (Hemminki-Reijonen et al., 2025). Internet of Things (IoT) has been used to develop mixed reality environments for architecture education, where physical shading influences spatiotemporal virtual illuminance in real rooms (Zhao et al., 2022).

Beyond its advances in education, literature also highlights challenges in the use of XR in education, which can be grouped into two main categories. The first relates to educational settings. These involve technology integration, teacher training and professional development, curriculum design, and information literacy for both teachers and students. While much relevant research has been conducted, its proposals still need to be effectively applied and evaluated in practice. The second category concerns research challenges and trends. Research methodology is critical for generating valid, evidence-based findings. Effective empirical studies of XR learning environments require not only appropriate use of XR's affordances but also sound pedagogical frameworks. The well-established Technological Pedagogical Content Knowledge (TPACK) framework provides a strong foundation for both research designs and practical applications. To advance the field, empirical studies reporting effect sizes are essential for enabling meta-analyses that inform future research. Key research topics include the role of immersion levels, interaction methods such as haptic interfaces, gestures, and eye tracking, as well as the impact of presence on learning. XR can also move theoretical research forward. Studies using brain measures may deepen our understanding of human-computer interaction and guide the design of more effective learning environments. Finally, research on XR affordances can help identify principles for creating impactful learning experiences.

In summary, this brief report demonstrates that Extended Reality (XR) has the potential to serve as a transformative cognitive tool in education. By integrating XR with other emerging technologies, applying cognitive and social learning theories, and fostering innovative teaching and learning practices, we can unlock new educational possibilities. Furthermore, XR presents rich research opportunities across a variety of fields, offering a powerful platform for advancing both theory and practice.

Contribution 12: “The Integration of Generative AI and Pedagogical Agents”, by Noah L. Schroeder

Research around pedagogical agents (PAs, virtual characters designed to help people learn) has been ongoing for nearly three decades (Siegle et al., 2023), but is seeing increased interest with the emergence of generative artificial intelligence (GenAI). GenAI enables PA researchers to overcome many technical challenges when creating fully conversational PAs, creating opportunities to support the “whole learner” (Mannekote et al., 2024) and neurosymbolic approaches to PA-based educational interventions (Jaldi et al., 2025). GenAI-powered PAs open opportunities to deeply explore questions around social processes in learning (see CASTLE theory, Schneider et al., 2022) and long-term interactions between learners and PAs (Veletsianos & Russell, 2014). This comment highlights two areas I feel that researchers should consider as they begin integrating GenAI and PAs, acknowledging that this list is only the starting point.

First, as researchers build more conversational PAs that can sustain conversations and memory over time, questions arise regarding the ethics and impact of long-term learner-agent interactions. For example, should we encourage learners to develop long-standing relationships with PAs? What happens if there are changes to this relationship not initiated by the learner (e.g., change to the underlying model)? Imagine a child developing a trusting relationship with a knowledgeable peer-like PA over the course of an academic year, only to have that “friend” drastically change overnight due to an unannounced change in the underlying model. Such changes could have dramatic socio-emotional impacts on the child, potentially impacting more than just their learning experience. It is critical to understand these dynamics before conducting research to ensure responsible and ethical implementation of GenAI-powered PAs, and collaborations with experts in child development and psychology will be essential.

Second, prioritizing privacy is critical. While data privacy always holds a priority for researchers, the ease of accessibility of many GenAI tools via API opens doors to data privacy issues. I encourage researchers to explore small language models (SLMs) that can be run on consumer-grade hardware. This approach could help address some data privacy issues, provides proof of concept for schools or educational institutions to host their own artificial intelligence solutions locally, and helps ensure model stability by controlling updates. SLMs can be fine-tuned for educational use cases and the field of SLMs is innovating quickly. For example, the forthcoming Granite 4 family is claimed to use a hybrid Mamba-2/Transformer architecture that increases efficiency (Soule & Bergmann, 2025). The continued advancement of SLMs, in combination with the advantages for data privacy, position SLMs as a potential focal point for educational computing with GenAI models and PAs.

Integrating GenAI and PAs allows tremendous opportunities to expand our understanding of current theoretical perspectives and provides a way to potentially bring individualized learning opportunities to all learners. However, it is essential that we keep ethical considerations at the forefront of our mind as these technologies continue to evolve.

Contribution 13: "Achieving Higher Standards through Inclusive Educational Technology", by Rod D. Roscoe

Every participant in educational systems—spanning learners, teachers, parents, and administrators—deserves access to authentic opportunities to succeed. As demonstrated by publications in this journal and beyond, carefully designed and personalized educational technologies (Bernacki et al., 2021) can serve these lofty goals. However, the development and implementation of educational technologies also encounter several problems. Despite our best intentions, tools can be created that exclude relevant populations and data, and which replicate human biases or prejudices (Baker & Hawn, 2021; Goldshtein et al., 2024). Consequently, I challenge educational computing scholars to embrace principles of inclusive design, equitable education, and human variability to guide their work (Roscoe, 2023; Roscoe et al. 2019) and hold themselves to higher accountability.

In support of this request, I have previously co-articulated (hopefully) useful guidance and heuristics. For example, I have shared 'who-ristic' questions (Roscoe, 2023) that encourage forethought about technology design. These interrelated questions invite developers to think proactively about intended beneficiaries, participatory design, and potential impact or harm. Contending with these queries throughout design and evaluation is difficult—the pursuit of inclusion and equity raises standards rather than lowering them—but the results empower more learners and attract more customers (for those who care about marketability).

My colleagues have also advocated for asset-based approaches to educational technology and artificial intelligence (AI) in education (Ocumpaugh et al., 2024). We have described how typical approaches to learner modeling (e.g., representations of student knowledge, skill, and growth) tend to adopt deficit mindsets. Learners are often characterized and assessed based on divergence from expert performance, knowledge gaps, ineffective strategies, disengagement, and so on. In other words, the emphasis is on what learners "lack." Importantly, deficits are meaningful. Students do need to know things and perform tasks, and it helps if they care about it. However, deficit-based approaches are also incomplete. Deficit framing ignores that students already possess a wealth of ideas, experiences, and resources that could enable success if we recognize and leverage them.

Ocumpaugh and colleagues shared several guiding recommendations for emphasizing assets in future educational technology research and development. First, we must recognize that students have valid assets that can emerge from formal (e.g., schooling) as well as less formal sources (e.g., family, friends, jobs, recreation, and culture). Second, adopting more expansive definitions of learner assets enables developers to explore how to detect them, and then to build tools that acknowledge, adapt to, and cultivate those assets. Finally, we should also make students' assets visible in ways that communicate value (e.g., dashboards that celebrate relevant student hobbies that they could discuss with peers). Empirical studies can then examine how and when asset-based technologies and features achieve the most positive outcomes for diverse learners.

Ultimately, there are myriad frameworks and evidence-based resources for pursuing inclusive and equitable educational design. The central challenge is thus choosing to adopt these principles and methods in the pursuit of better products. I encourage contributors to the journal to advance the success of all educational participants through impressive, innovative, and inclusive educational computing.

Contribution 14: "Navigating the Future of Educational Computing: A Perspective from the Intersection of AI, Technology, and Global Inclusion", by Ismaila Sanusi

As an editorial board member of JECR with research interests spanning AI education, educational technology, and computing education, I am both excited and reflective about the evolving landscape of educational computing. The field stands at a pivotal juncture; where rapid technological advancements intersect with pressing global educational needs.

One of the most significant challenges we face is ensuring equitable access to educational computing innovations. While AI and emerging technologies offer transformative potential, their benefits are not evenly distributed. This is particularly evident in underrepresented regions such as Africa, where infrastructure, policy, and resource constraints often limit access to cutting-edge educational tools. As someone originally from Africa with research experience across diverse regions, I see a critical need for scholarship that bridges global divides; exploring how context-sensitive, culturally relevant, and low-resource innovations can be designed and scaled.

Another challenge lies in preparing educators and learners to meaningfully engage with AI and computing technologies. The integration of AI into education is not just a technical endeavor—it requires pedagogical rethinking, ethical considerations, and a deep understanding of how learners interact with intelligent systems. Research must move beyond tool development to investigate how AI can support inclusive, personalized, and human-centered learning experiences.

Generative AI, in particular, is rapidly reshaping the field of computing education and educational technology. Tools like large language models and AI-powered content generators are transforming how students learn to code, how educators design curriculum, and how assessments are conducted (Feng et al., 2025). These technologies offer unprecedented opportunities for adaptive learning, automated feedback, and creative exploration. However, they also raise critical questions about academic integrity, digital literacy, and the evolving role of the educator (Shailendra et al., 2024). As researchers, we must examine not only the capabilities of generative AI but also its implications for equity, agency, and the future of learning.

Looking ahead, I see three key directions for future research: (1) the development of AI-powered tools that are transparent, ethical, and adaptable to diverse learning contexts; (2) the exploration of computing education models that are inclusive of learners from historically marginalized communities; and (3) the cultivation of global research collaborations that prioritize equity and sustainability particularly through the inclusion of developing regions.

It is my hope that through continued dialogue and research, we can collectively envision a future where educational computing not only advances technology but also advances equity, inclusion, and the holistic development of learners.

Discussion and Implications

Throughout this editorial, the contributors have raised several important questions regarding the challenges, opportunities, and future research directions shaping the field of educational computing research. Based on the contributions, several themes have been created to reflect the key areas of focus for the future of educational computing, as outlined below.

Theme 1: Equity, Inclusion, and the Digital Divide.

The first theme focuses on equity, inclusivity, and the responsible design of AI-enhanced educational technologies. Though contributors may approach the problem from slightly different angles; ranging from pedagogical agents (contribution 12) to learner modelling (contribution 13) and global collaboration and inclusivity (contribution 14), contributors are unified by a central concern: how educational technologies, especially those enhanced by AI, can be leveraged to create more inclusive, equitable, and socially just learning environments. Key research directions based on this theme as indicated by the contributors include:

- How can pedagogical models and design principles ensure AI-enhanced educational technologies address the digital divide and promote equitable access for underserved communities?
- How do improvements in inclusivity through Generative AI (e.g., multilingual content) influence quality of life and social equity in educational contexts?
- How can principles of inclusive design and equitable education be systematically integrated into the development and evaluation of educational technologies?
- In what ways can educational technologies be designed to detect, represent, and leverage learner assets from both formal and informal contexts?
- How do deficit-based versus asset-based learner modelling approaches influence student engagement and achievement within educational computing systems?
- How can global research collaborations be structured to prioritise equity and sustainability in educational computing, particularly through the involvement of developing regions?

Theme 2: Ethics, Social Sustainability, and Well-being.

This theme relates to how contributors have shared concerns regarding the ethical, emotional, and socio-cultural impacts of AI in education, particularly in long-term, human-centred, and diverse learning contexts. While each contributor may target a specific sub-issue, ranging from social sustainability (contribution 10) to regulatory alignment (contribution 8), they all contribute to a broader inquiry into the responsible and sustainable integration of AI in educational environments. Key research directions based on this theme include:

- What are the long-term effects of AI-driven educational interventions on students' mental health and well-being?
- How do intelligent educational technologies influence the emotional well-being of both students and teachers, and what implications do these effects have for the sustainability of human-centred education?

- How can existing AI systems in K-12 education be evaluated and adapted to align with responsible AI principles, including ethical standards, trust, and regulatory frameworks like the EU AI Act?
- What are the ethical implications of using GenAI in educational computing, and how can educational institutions ensure responsible and fair use?
- What are the ethical and socio-emotional implications of long-term learner-agent relationships, especially when changes to the agent occur without the learner's consent or awareness?
- What are the unintended individual and societal consequences of widespread adoption of educational computing technologies across formal and informal educational settings?

Theme 3: Instructional Design.

This theme focuses on understanding how specific design features within computer-based learning environments can facilitate deep learning and knowledge transfer by engaging learners' cognitive, affective, and social dimensions (e.g. contribution 1). Contributors reflect on the dynamic interplay between these learner processes and adaptive instructional strategies that not only enhance sustained understanding but also prevent overreliance on technology (contribution 7). By investigating how learners interact with educational technologies, this theme encapsulates design elements that optimize learning experiences, promote critical thinking, and support meaningful knowledge construction, ultimately contributing to more effective and personalized technology-enhanced education. Key research directions based on this theme could include:

- What instructional design features in computer-based environments best support deep learning and transfer, and through which learner processes do they work?
- How do cognitive, affective, and social processes interact in students' learning with [*e.g. specific technology*], and what adaptive instructional strategies can promote sustained understanding while mitigating overreliance?
- What models or frameworks best support the design and implementation of GenAI-empowered educational computing systems across various platforms and learning contexts?
- How do challenges related to technology integration, teacher training, curriculum design, and information literacy affect the effective implementation of [*e.g. specific technology*] in educational settings?
- How can assessment design be optimized to support effective and pedagogically appropriate GenAI-plagiarism detection through educational technologies?
- How can AI-generated learning tools (e.g. glossaries, quizzes, and chatbots) be designed to reflect disciplinary depth?

Theme 4: Human-Computer Interaction in Educational Technologies.

This theme encapsulates how contributors consider how advanced technologies are reshaping educational computing by transforming human-technology relationships. The first dimension mentioned by contributors focuses on the integration of GenAI and intelligent digital agents as collaborative partners in learning (e.g. contribution 5), examining their pedagogical potential, impact on learner autonomy, motivation, and the need to adapt existing educational theories to accommodate these evolving roles. The second dimension investigates the sensory, cognitive, and affective effects of immersive XR environments, emphasizing how interaction modalities and physiological measures enrich understanding of learner experiences and outcomes (contribution 11). Both areas highlight the multidimensional influence of intelligent and immersive technologies on education, thus reshaping human-computer interaction. Key research directions based on this theme include:

- How can GenAI be effectively integrated as a collaborative partner in educational computing to support students' learning without diminishing their autonomy or motivation?
- How can prompt engineering be used as a pedagogical tool to develop students' computational thinking and problem-solving skills?
- In what ways do existing pedagogical theories need to be adapted or reinterpreted to account for GenAI's role in educational computing as tutor, tutee, or partner?
- How is the presence of AI-enhanced digital agents transforming the nature of the teacher-learner relationship, and what does this shift reveal about the evolving role of human identity and agency in educational contexts shaped by intelligent technologies?
- How can brain-based measures (e.g., electrical brain activity) be used to deepen our understanding of human-computer interaction in learning environments with [*e.g. specific technology*]?
- What are the effects of immersion levels, interaction types (e.g., haptic feedback, gestures, eye tracking), and presence on learners' experiences and outcomes in XR environments?

Concluding Comments

This editorial brings together a diverse yet interconnected set of contributions from our editorial board that collectively highlight the evolving landscape of educational computing in an era increasingly defined by generative AI and shifting pedagogical priorities. From theoretical explorations to pragmatic considerations, the contributions presented show the growing complexity and opportunity that emerge when education, technology, and society intersect. Whether discussing the ethical imperatives of responsible AI in K-12 contexts (contribution 8), the cognitive implications of AI-enhanced instruction (contribution 7), or the interdisciplinary bridges between philology (contribution 2), mathematics (contribution 6), and computing, the contributors communicate a shared urgency: to reimagine educational computing not merely as a technical endeavour, but as a deeply humanistic and socially embedded field.

The integration of extended reality, intelligent pedagogical agents, and inclusive technologies creates a period of rapid technological change which requires a renewed examination of how we teach and learn. Educators, researchers, and policymakers need to consider not only how such tools can enhance learning outcomes, but also how they may reshape educational values, norms, and access. Notably, several contributions challenge long-standing assumptions, such as the overreliance on plagiarism detection technologies (contribution 3), or outcome-based metrics (contribution 13), and advocate instead for a renewed focus on cognitive processes, ethical deliberation, and global inclusivity.

Collectively, the contributions invite a critical reflection on the future directions of educational computing research. They challenge us to adopt more nuanced, interdisciplinary approaches while remaining vigilant about the socio-technical predicaments that define contemporary educational systems. As we navigate this rapidly evolving terrain, it becomes clear that our responsibility lies not only in designing effective and innovative educational computing technologies but also in cultivating a reflective and inclusive discourse that ensures these tools serve the broader aims of equity, sustainability, and well-being.

References

Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications, 2*, 100006. https://doi.org/10.1016/j.mlwa.2020.100006

Al-Emran, M. (2023). Beyond technology acceptance: Development and evaluation of technology-environmental, economic, and social sustainability theory. Technology in Society, 75, 102383. https://doi.org/10.1016/J.TECHSOC.2023.102383

Al-Emran, M., Al-Qaysi, N., Al-Sharafi, M. A., Khoshkam, M., Foroughi, B., & Ghobakhloo, M. (2025). Role of perceived threats and knowledge management in shaping generative AI use in education and its impact on social sustainability. The International Journal of Management Education, 23(1), 101105. https://doi.org/10.1016/J.IJME.2024.101105

Allen, J. M., Vahid, F., Downey, K., & Edgcomb, A. D. (2018). Weekly programs in a CS1 class: experiences with auto-graded many-small programs (MSP). *ASEE Annual Conference & Exposition*.

Allison, J. (2025). Beyond Innovation: Centring Ethics and Social Responsibility in Educational Computing. Journal of Educational Computing Research, 0(0). https://doi.org/10.1177/07356331251331851

Alsofyani, A. H., & Barzanji, A. M. (2025). The Effects of ChatGPT-generated feedback on Saudi EFL learners' writing skills and perception at the tertiary level: A mixed-methods study. *Journal of Educational Computing Research*, *63*(2), 431-463. https://doi.org/10.1177/07356331241307297

Arnold, R. D., & Wade, J. P. (2015). A Definition of Systems Thinking: A Systems Approach. Procedia Computer Science, 44, 669-678. https://doi.org/10.1016/j.procs.2015.03.050

Baker, R.S., & Hawn, A. (2022). Algorithmic bias in education. International Journal of Artificial Intelligence in Education, 32, 1052–1092. https://doi.org/10.1007/s40593-021-00285-9

Bernacki, M.L., Greene, M.J. & Lobczowski, N.G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose(s)? Educational Psychology Review, 33, 1675–1715. https://doi.org/10.1007/s10648-021-09615-8

Blanchard, J., Hott, J. R., Berry, V., Carroll, R., Edmison, B., Glassey, R., Karnalim, O., Plancher, B., & Russell, S. (2022). Stop reinventing the wheel! Promoting community software in computing education. *Working Group Reports on Innovation and Technology in Computer Science Education*, 261–-292. https://doi.org/10.1145/3571785.3574129

Chang, C. Y., Lin, H. C., Yin, C., & Yang, K. H. (2025). Generative AI-assisted reflective writing for improving students' higher order thinking. *Educational Technology & Society*, *28*(1), 270-285. URL: https://www.jstor.org/stable/48810719

Chang, C. Y., Wang, P. L., Li, C. J., & Hwang, G. J. (2024). From empathy to quality long-term care: a generative AI-based art therapy approach based on the self-directed learning model. *Interactive Learning Environments*, 1-21. DOI: 10.1080/10494820.2024.2443072

de Freitas, S. (2014) Education in Computer Generated environments. London and New York: Routledge. https://doi.org/10.4324/9780203094709

de Freitas, S (2024) Podcast for Times Higher (Campus+). Last retrieved online on 6th May 2025 at: https://www.timeshighereducation.com/campus/authors/sara-de-freitas.

Devore-McDonald, B., & Berger, E. D. (2020). Mossad: defeating software plagiarism detection. *ACM on Programming Languages, 4, 1-28. https://doi.org/10.1145/3428206*

Doleck, T., Agand, P., & Pirrotta, D. (2024). Integrating generative AI in data science programming: Group differences in hint requests. Computers in Human Behavior: Artificial Humans, 2(2), 100089. https://doi.org/10.1016/j.chbah.2024.100089

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International journal of information management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., ... & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, *56*(2), 489-530. DOI: 10.1111/bjet.13544

Feng, T. H., Luxton-Reilly, A., Wünsche, B. C., & Denny, P. (2025). From Automation to Cognition: Redefining the Roles of Educators and Generative AI in Computing Education. In Proceedings of the 27th Australasian Computing Education Conference (pp. 164-171). doi: 10.1145/3716640.3716658

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of information technology case and application research*, *25*(3), 277-304. DOI: 10.1080/15228053.2023.2233814

Fu, Y., Weng, Z., & Wang, J. (2024). Examining AI Use in Educational Contexts: A Scoping Meta-Review and Bibliometric Analysis. International Journal of Artificial Intelligence in Education, 1-57. https://doi.org/10.1007/s40593-024-00442-w.

Goellner, S., Tropmann-Frick, M., & Brumen, B. (2024). Responsible Artificial Intelligence: A Structured Literature Review. arXiv Preprint arXiv:2403.06910. https://doi.org/10.48550/arXiv.2403.06910

Goldshtein, M., Alhashim, A. G., & Roscoe, R. D. (2024). Automating bias in writing evaluation: Sources, barriers, and recommendations. In M. D. Shermis & J. Wilson (Eds.), The Routledge international handbook of automated essay evaluation (pp. 421-444). Routledge. https://doi.org/10.4324/9781003397618

Green, T. (1971). Wondering and the Roots of Motivation (Chapter 9). In T. F. Green, The Activities of Teaching. McGraw-Hill.

Graziosi, B., Haubold, J., Cowen-Breen, C., & Brooks, C. (2023). Machine Learning and the Future of Philology: A case study. *TAPA, 153*(1), 253–284. https://doi.org/10.1353/apa.2023.a901022.

Goyal, A. (2025). AI as a Cognitive Partner: A Systematic Review of the Influence of AI on Metacognition and Self-Reflection in Critical Thinking. *International Journal of*

Innovative Science and Research Technology, *10*(3), 1231-1238. DOI: 10.38124/ijisrt%2F25mar1427

Hanid, M.F.A., Zakaria, M.I. & Hassan, R. (2025). The advancement of extended reality in education: Insights from a 2019–2024 bibliometric analysis. Multimedia Tools and Applications. https://doi.org/10.1007/s11042-025-20821-2

Hemminki-Reijonen U., Hassan, N.M.A.M., Huotilainen, M., Koivisto, J.M., Cowley, B.U. (2025). Design of generative AI-powered pedagogy for virtual reality environments in higher education. NPJ Science of Learning, 10(1):31. https://doi.org/10.1038/s41539-025-00326-1.

Hoq, M., Shi, Y., Leinonen, J., Babalola, D., Lynch, C., Price, T., & Akram, B. (2024). Detecting ChatGPT-generated code submissions in a CS1 course using machine learning models. *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, 526–532. https://doi.org/10.1145/3626252.3630826

Hooshyar, D., Azevedo, R., & Yang, Y. (2024). Augmenting deep neural networks with symbolic educational knowledge: Towards trustworthy and interpretable ai for education. Machine Learning and Knowledge Extraction, 6(1), 593-618. https://doi.org/10.3390/make6010028

Hooshyar, D., Šír, G., Yang, Y., Kikas, E., Hämäläinen, R., Kärkkäinen, T., ... & Azevedo, R. (2025). Towards responsible AI for education: Hybrid human-AI to confront the Elephant in the room. *arXiv preprint arXiv:2504.16148*. https://doi.org/10.48550/arXiv.2504.16148

Hoyles, C., & Noss, R. (1992). A pedagogy for mathematical microworlds. Educational Studies in Mathematics, 23, 31–57. https://doi.org/10.1007/BF00302313

Huang, Y.-M., Chen, P.-H., Lee, H.-Y., Sandnes, F. E., & Wu, T.-T. (2025). ChatGPT-enhanced mobile instant messaging in online learning: Effects on student outcomes and perceptions. Computers in Human Behavior, 168, 108659. https://doi.org/10.1016/j.chb.2025.108659

Iatraki, G., Mikropoulos, T. A. (2025). Using Immersive Augmented Reality to Teach Physics to Students with Intellectual Disabilities. Journal of Computer Assisted Learning, 41(3). https://doi.org/10.1111/jcal.70040.

Jaldi, C. D., Ilkou, E., Schroeder, N., & Shimizu, C. (2025). Education in the era of Neurosymbolic AI. Journal of Web Semantics, 85, 100857. https://doi.org/10.1016/j.websem.2024.100857

Karnalim, O., Simon, & Chivers, W. (2022). Layered similarity detection for programming plagiarism and collusion on weekly assessments. *Computer Applications in Engineering Education*, *30*(6), 1739–1752. https://doi.org/10.1002/cae.22553

Karnalim, O., Toba, H., & Johan, M. C. (2024). Detecting AI assisted submissions in introductory programming via code anomaly. *Education and Information Technologies*, 29, 16841–16866. https://doi.org/10.1007/s10639-024-12520-6

Kohnke, L., Zou, D., & Su, F. (2025). Exploring the potential of GenAI for personalised English teaching: Learners' experiences and perceptions. Computers and Education: Artificial Intelligence, 8, 100371. https://doi.org/10.1016/j.caeai.2025.100371

Knox, J., Williamson, B., & Bayne, S. (2019). Machine behaviourism: future visions of ‘learnification’ and ‘datafication’ across humans and digital technologies. *Learning, Media and Technology*, *45*(1), 31–45. https://doi.org/10.1080/17439884.2019.1623251

Krathwohl, D. R. (2002). A Revision of Bloom's Taxonomy: An Overview. Theory Into Practice, 41(4), 212-218. https://doi.org/10.1207/s15430421tip4104_2

Lai, C. L., & Tu, Y. F. (2024). Roles, strategies, and research issues of generative AI in the mobile learning era. *International Journal of Mobile Learning and Organisation*, *18*(4), 516-537. DOI: 10.1504/IJMLO.2024.141836

Lee, H.-Y., Chen, P.-H., Wang, W.-S., Huang, Y.-M., & Wu, T.-T. (2024). Empowering ChatGPT with guidance mechanism in blended learning: effect of self-regulated learning, higher-order thinking skills, and knowledge construction. International Journal of Educational Technology in Higher Education, 21(1), 16. https://doi.org/10.1186/s41239-024-00447-4

Lee, H.-Y., Wu, T.-T., Lin, C.-J., Wang, W.-S., & Huang, Y.-M. (2023). Integrating Computational Thinking Into Scaffolding Learning: An Innovative Approach to Enhance Science, Technology, Engineering, and Mathematics Hands-On Learning. Journal of Educational Computing Research, 62(2), 211-247. https://doi.org/10.1177/07356331231211916

Levidow, L., & Papaioannou, T. (2018). Which inclusive innovation? Competing normative assumptions around social justice. Innovation and Development, 8(2), 209–226. https://doi.org/10.1080/2157930X.2017.1351605

Lin, C.-J., Lee, H.-Y., Wang, W.-S., Huang, Y.-M., & Wu, T.-T. (2025). Enhancing reflective thinking in STEM education through experiential learning: The role of generative AI as a learning aid. Education and Information Technologies, 30(5), 6315-6337. https://doi.org/10.1007/s10639-024-13072-5

Liu, Y.-L. E., Tseng-Pin, L., & and Huang, Y.-M. (2024). Exploring Students' Continuance Intention Toward Digital Visual Collaborative Learning Technology in Design Thinking. International Journal of Human–Computer Interaction, 40(11), 2808-2821. https://doi.org/10.1080/10447318.2023.2172904

Liu, X., Guo, B., He, W., & Hu, X. (2025). Effects of Generative Artificial Intelligence on K-12 and Higher Education Students' Learning Outcomes: A Meta-Analysis. Journal of Educational Computing Research, 0(0). https://doi.org/10.1177/07356331251329185

Lu, Z., Chiu, M. M., Wang, S., Mao, W., & Lei, H. (2025). Effects of Augmented Reality on Students' Higher-Order Thinking: A Meta-Analysis. Journal of Educational Computing Research, 63(3), 728-747. https://doi.org/10.1177/07356331241309644

Mannekote, A., Davies, A., Pinto, J. D., Zhang, S., Olds, D., Schroeder, N. L., Lehman, B., Zapata-Rivera, D., & Zhai, C. (2024). Large Language Models for Whole-Learner Support: Opportunities and Challenges. Frontiers in Artificial Intelligence, 7. https://doi.org/10.3389/frai.2024.1460364

Mayer, R. (2025). Richard Mayer. UC Santa Barbara. https://psych.ucsb.edu/people/faculty/richard-mayer#:~:text=Richard%20E.,and%20computer%20games%20for%20learning

Mikropoulos, T.A., Natsis, A. (2011). Educational virtual environments: A ten-year review of empirical research (1999–2009). Computers & Education, 56(3), 769-780. https://doi.org/10.1016/j.compedu.2010.10.020.

Ng, O., & Cui, Z. (2021). Examining primary students' mathematical problem-solving in a programming context: towards computationally enhanced mathematics education. ZDM Mathematics Education, 53(4), 847–860. https://doi.org/10.1007/s11858-020-01200-7

Ng, O., Leung, A., & Ye, H. (2023). Exploring computational thinking as a boundary object between mathematics and computer programming for STEM teaching and learning.

ZDM Mathematics Education, 55(7), 1315–1329. https://doi.org/10.1007/s11858-023-01509-z

Ng, O. (2025). Problem solving with discrete variables from a computational thinking perspective. For the Learning of Mathematics 45(2).

Ocumpaugh, J., Roscoe, R.D., Baker, R.S., Hutt, S., & Aguilar, S. J. (2024). Toward asset-based instruction and assessment in artificial intelligence in education. International Journal of Artificial Intelligence in Education, 34, 1559–1598. https://doi.org/10.1007/s40593-023-00382-x

Papert, S. (1980). Mindstorms: Children, computers, and powerful ideas. Basic Books.

Panzoli, D., Peters, C. Dunwell, I., Sanchez, S., Petridis, P., Protopsaltis, A., Scesa, V. & de Freitas, S. (2010a). Levels of Interaction: A User-Guided Experience in Large-Scale Virtual Environments, IEEE 2nd International Conference in Games and Virtual Worlds for Serious Applications (VS GAMES10), Braga, Portugal, March 26-27, IEEE, pp. 87-90, ISBN: 978-0-7695-3986-7. https://doi.org/10.1109/VS-GAMES.2010.27

Panzoli, D., Peters, C., Dunwell, I., Sanchez, S., Petridis, P., Protopsaltis, A., & de Freitas, S. (2010b). A level of interaction framework for exploratory learning with characters in virtual environments. In Intelligent Computer Graphics 2010 (pp. 123-143). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-15690-8_7

Pellas, N. (2025). The role of students' higher-order thinking skills in the relationship between academic achievements and machine learning using generative AI chatbots. *Research and Practice in Technology Enhanced Learning, 20,* Article 36. https://doi.org/10.58459/rptel.2025.20036.

Pellas, N. (2023). The effects of generative AI platforms on undergraduates' narrative intelligence and writing self-efficacy. Special Issue "Trustworthy Artificial Intelligence in Education." *Education Sciences*, *13*(11), 1155. https://doi.org/10.3390/educsci13111155.

Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. Computers & education, 147. https://doi.org/10.1016/j.compedu.2019.103778

Rebolledo-Mendez, G. & de Freitas, S. (2008) Attention modeling using inputs from a Brain Computer Interface and user-generated data in Second Life. In Proc. of the Workshop of Affective Interaction in Natural Environments (AFFINE) 2008. In association with ACM Tenth International Conference on Multimodal Interfaces (ICMI), Crete, Greece.

Rebolledo-Mendez, G., Burden, D. & de Freitas, S. (2008). A Model of Motivation for Virtual-Worlds Avatars. In H. Prendinger, J. Lester, and M. Ishizuka (Eds.): IVA 2008, LNAI 5208, pp. 535–536. Berlin, Heidelberg: Springer-Verlag. https://doi.org/10.1007/978-3-540-85483-8_76

Resnik, P. (2025). Large language models are biased because they are large language models. *Computational Linguistics*, 1-21. https://doi.org/10.1162/coli_a_00558

Roscoe, R. D. (2023). Building inclusive and equitable artificial intelligence for education. XRDS: Crossroads, The ACM Magazine for Students, 29(3), 22-25. https://doi.org/10.1145/3589637

Roscoe, R. D., Chiou, E. K., & Wooldridge, A. R. (2019) (Eds.). Advancing diversity, inclusion, and social justice through human systems engineering. CRC Press. https://doi.org/10.1201/9780429425905

Roscoe, R. D., Salehi, S., Nixon, N., Worsley, M., Piech, C., & Luckin, R. (2022). Inclusion and equity as a paradigm shift for artificial intelligence in education. In F. Ouyang, P. Jiao, B. M. McLaren, & A. H. Alavi (Eds.), Artificial intelligence in STEM education (pp. 359-374). CRC Press. https://doi.org/10.1201/9781003181187

Samala, A.D., Rawas, S., Criollo-C, S., Bojic, L., Prasetya, F., Ranuharja, F., & Marta, R. (2024). Emerging Technologies for Global Education: A Comprehensive Exploration of Trends, Innovations, Challenges, and Future Horizons. SN Computer Science, 5, 1175 https://doi.org/10.1007/s42979-024-03538-1

Sarnof, B. (2023, July 25). Weizenbaum's nightmares: how the inventor of the first chatbot turned against AI. The Guardian. https://www.theguardian.com/technology/2023/jul/25/joseph-weizenbaum-inventor-eliza-chatbot-turned-against-artificial-intelligence-ai

Schneider, S., Beege, M., Nebel, S., Schnaubert, L., & Rey, G. D. (2022). The Cognitive-Affective-Social Theory of Learning in digital Environments (CASTLE). Educational Psychology Review, 34(1), 1–38. https://doi.org/10.1007/s10648-021-09626-5

Schroeder, N. L., Davis, R. O., & Yang, E. (2024). Designing and Learning With Pedagogical Agents: An Umbrella Review. Journal of Educational Computing Research, 62(8), 1907-1936. https://doi.org/10.1177/07356331241288476

Seidman, R. (2017). Tribute to Seymour Papert (1928-2016). Journal of Educational Computing Research. 55(4). 447-448. https://doi.org/10.1177/0735633117710860

Siegle, R. F., Schroeder, N. L., Lane, H. C., & Craig, S. D. (2023). Twenty-five Years of Learning with Pedagogical Agents: History, Barriers, and Opportunities. TechTrends, 67(5), 851–864. https://doi.org/10.1007/s11528-023-00869-3

Shahzad, M. F., Xu, S., & Zahid, H. (2025). Exploring the impact of generative AI-based technologies on learning performance through self-efficacy, fairness & ethics, creativity, and trust in higher education. Education and Information Technologies, 30(3), 3691-3716. https://doi.org/10.1007/s10639-024-12949-9

Shailendra, S., Kadel, R., & Sharma, A. (2024). Framework for adoption of generative artificial intelligence (GenAI) in education. IEEE Transactions on Education, 67, 5, pp. 777-785, Oct. 2024, doi: 10.1109/TE.2024.3432101

Soule, K., & Bergmann, D. (2025, May 2). IBM Granite 4.0 Tiny Preview: A sneak peek at the next generation of Granite models. https://www.ibm.com/new/announcements/ibm-granite-4-0-tiny-preview-sneak-peek

Tu, Y. F. (2024). Roles and functionalities of ChatGPT for students with different growth mindsets. *Educational Technology & Society*, *27*(1), 198-214. URL: https://www.jstor.org/stable/48754851

Turing A.M. (1937) On Computable Numbers, with an Application to the Entscheidungsproblem" in The Proceedings of the London Mathematical Society, ser. 2, vol. 42 (1937), pp. 230–265 Turing Alan M. Computing Machinery and Intelligence" in Mind LIX, (2236), 433-460. https://doi.org/10.1112/plms/s2-42.1.230.

Turing, A.M. (1950) Chapter on: Computing Machinery and Intelligence in Mind. Mind, 59 (236), pp. 433-460. Last retrieved online on 6th May at https://www.cs.colostate.edu/~howe/cs440/csroo/yr2015fa/more_assignments/turing.pdf. https://doi.org/10.1007/978-1-4020-6710-5_3.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educational Psychologist, 46(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Veletsianos, G., & Russell, G. S. (2014). Pedagogical Agents. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), Handbook of Research on Educational Communications and Technology (pp. 759–769). Springer New York. https://doi.org/10.1007/978-1-4614-3185-5_61

Wang, W.-S., Chia-Ju, L., Hsin-Yu, L., Ting-Ting, W., & and Huang, Y.-M. (2024). Feedback Mechanism in Immersive Virtual Reality Influences Physical Hands-on Task Performance and Cognitive Load. International Journal of Human–Computer Interaction, 40(15), 4103-4115. https://doi.org/10.1080/10447318.2023.2209837

Wang, W.-S., Lin, C.-J., Lee, H.-Y., Huang, Y.-M., & Wu, T.-T. (2025). Enhancing self-regulated learning and higher-order thinking skills in virtual reality: the impact of ChatGPT-integrated feedback aids. Education and Information Technologies. https://doi.org/10.1007/s10639-025-13557-x

Warr, M., Oster, N. J., & Isaac, R. (2024). Implicit bias in large language models: Experimental proof and implications for education. Journal of Research on Technology in Education, 1-24. https://doi.org/10.1080/15391523.2024.2395295

Williamson, B. (2017). Big data in education. SAGE Publications Ltd, https://doi.org/10.4135/9781529714920

Wing, J. M. (2006). Computational thinking. Communications of the ACM, 49(3), 33–35. https://doi.org/10.1145/1118178.1118215

Wolfram, C. (2020). The math(s) fix: An education blueprint for the AI age. Wolfram Media, Incorporated.

Wu, C.-H., Chien, Y.-C., Chou, M.-T., & Huang, Y.-M. (2025). Integrating computational thinking, game design, and design thinking: a scoping review on trends, applications, and implications for education. Humanities and Social Sciences Communications, 12(1), 163. https://doi.org/10.1057/s41599-025-04502-x

Wu, T.-T., Lee, H.-Y., Chen, P.-H., Lin, C.-J., & Huang, Y.-M. (2025). Integrating peer assessment cycle into ChatGPT for STEM education: A randomised controlled trial on knowledge, skills, and attitudes enhancement. Journal of Computer Assisted Learning, 41(1), e13085. https://doi.org/https://doi.org/10.1111/jcal.13085

Wu, T.-T., Lee, H.-Y., Li, P.-H., Huang, C.-N., & Huang, Y.-M. (2023). Promoting Self-Regulation Progress and Knowledge Construction in Blended Learning via ChatGPT-Based Learning Aid. Journal of Educational Computing Research, 61(8), 1539-1567. https://doi.org/10.1177/07356331231191125

Yang, H. L., & Xiang, J. J. (2024). Mobile Learning and Students’ Academic Achievement: A Second-order Meta-analysis Study. Journal of Educational Computing Research, 62(4), 741-763. https://doi.org/10.1177/07356331241226589

Yang, X., Cheng, P.-Y., Lin, L., Huang, Y. M., & Ren, Y. (2018). Can an Integrated System of Electroencephalography and Virtual Reality Further the Understanding of Relationships Between Attention, Meditation, Flow State, and Creativity? Journal of Educational Computing Research, 57(4), 846-876. https://doi.org/10.1177/0735633118770800

Yeung, W. L., Ng, O., & Zhang, Y. (2024). Young children’s embodied computational thinking developed with touchscreen mathematics applications. Quadrante. https://doi.org/10.48489/quadrante.37071

Yilmaz, R., & Yilmaz, F. G. K. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence*, *4*, 100147. DOI:10.1016/j.caeai.2023.100147

Zhao, S., Pan, Q., Gao, D., Cheng, J. (2022). Integrating internet of things and mixed reality to teach performance-based architectural design: a case study of shading devices. Education and Information Technologies, 27, 9125-9143. https://doi.org/10.1007/s10639-022-10998-6.