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Editorial – Volume 27, Issue 2
Themed Issue: AI in Education and Online Learning (K-12 and Higher Education)

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Welcome to our themed issue on artificial intelligence (AI) in education and online learning (K-12 and higher education). As you know, the use of AI has dominated academic discussions around the globe. While AI touches on an incredibly wide range of topics, as educators we are primarily interested how it applies and can enhance teaching and learning, including Generative AI (GenAI) and Artificial Intelligence in Education (AIEd).

Before launching into this issue's content, the IRRODL editors wanted to alert you that the journal is refining its review process for literature review articles to address both the increasing use of AI in research and the need for more robust scholarly contributions. Moving forward, we will only accept, for review, well-constructed, methodologically rigorous, critical literature reviews that make substantive, original contributions to the open and distributed learning (ODL) field.

We are also reconsidering the type of research we prioritize, including whether to focus more on primary data, secondary data, or a balance of both. As part of this shift, submissions—especially literature reviews—will be carefully screened and not all papers will be automatically sent to reviewers. Instead, selected submissions will first be discussed at the editorial level to ensure they meet the journal's high standards and that it aligns with our mission to advance the ODL field. Submissions should demonstrate how their findings, framework, or analysis contribute meaningfully to the advancement of theory, practice, or policy in the ODL field.

Overall, these changes are intended to improve the quality, relevance, and impact of the research we publish in an evolving academic landscape.

So, onto our brilliant contributions within this special issue.

In our first research article, entitled "A case study of the Your Educational Path digital education ecosystem in crisis contexts: AI, mental health, and equity in Ukraine," **Koshevets** examines the development and nationwide rollout of digital system during the COVID-19 pandemic and ongoing war. The study finds that it achieved large-scale adoption and may serve as a model for other resilient and equitable education in crisis settings.

Sung and **Gunpinar** in their paper "Bringing artificial intelligence literacy into online education: Machine-learning integration through geometry in K–12 teacher professional development" make complex algorithms understandable without advanced technology resulting in increased AI self-efficacy, conceptual math understanding, and positive attitudes toward AI, including valuing the accessibility of teaching AI.

In the next article, "Enhancing human-generative artificial intelligence online collaboration outcomes: The pivotal function of symbiotic role design," **Cheng**, **Liu**, **Xu**, **Zhao**, **Qiao**, and **Zhang** examine how clearly defined roles for humans and generative AI, based on symbiosis theory, can improve online collaborative learning. This quasi-experimental study finds that structured human–AI role design enhances knowledge construction.

Öncü, **Gevher**, **Erdoğdu**, and **Koçdar** then present "Exploring the potential of generative ai for academic support in open and distance learning: A case study of learner experiences," which finds that students valued GenAI for fast, accurate academic support and improved self-assessment in structured tasks, despite issues like occasional hallucinations and device limitations, and suggests strong potential for wider institutional adoption in large-scale online education.

Sağ and **Kayabaş** highlight guided use in "AI as a pedagogical scaffold: Enhancing English as a foreign language argumentative writing and critical thinking in a distributed learning environment." This study examines how generative AI, integrated into a blended learning environment, supports first-year EFL students in developing argumentative writing and critical thinking skills. It suggests that AI enhances idea generation, organization, and learner engagement, while also raising concerns about reliability and overreliance.

In our *Field Notes* section, we welcome two contributions. First, **Anderson** in "The Answerthis.io AI app looks at my Interaction Equivalency Theory" describes how the Answerthis.io AI app is used to generate a concise overview of Interaction Equivalency Theory and demonstrates its usefulness for understanding key ideas in distance education research.

In our second *Field Note* entitled, "Artificial intelligence and communities of inquiry: Reimagining educational experiences," **Stenbom** and **Garrison** argue that integrating generative AI into education should be guided by the Community of Inquiry framework and its concept of shared metacognition to ensure AI enhances, rather than undermines, collaborative, reflective, and human-centered learning.

We are presented with three *Book Reviews* in this issue. In the first review, **Wigati** and **Hartono** examine *Artificial Intelligence and Education in the Global South: A Systems Perspective*, authored by Fernando Reimers, Zainab Azim, Maria-Renée Palomo, & Callysta Thony. This book argues that K–12 education systems, especially in the Global South, must adopt a holistic, equity-focused approach to integrating AI. Next **Pickering** reviews two books by co-authors James Hutson and Daniel Plate. First, *The Case Against Disclosure* warns that forcing exhaustive AI-use transparency misunderstands the creative process and supports bureaucratic documentation. In the next book, *Mind, Machine, and Will* argues that in the age of AI, agency and responsibility should be understood not as products of individual free will but as socially grounded practices.

Finally in our *Literature Review* section **Boulhrir, Ghreir**, **Hamash**, and **Robert** provide us with an analysis of 21 studies (2020–2025) in "Artificial intelligence in education: Mapping adaptive learning and learning analytics in K–12 online, virtual, and distance learning." It highlights inconsistent definitions of AI, a dominance of quantitative methods, and calls for clearer frameworks, more context-sensitive research, and stronger integration of teacher expertise to ensure equitable and effective use of AI.

This special issue contains a wealth of valuable content on AI and offers insight into how educational practices may develop in the future. As a disruptive force, creative and responsible use will no doubt be a key actor in the continuing story of developing and providing quality learning experiences. We hope this issue will spark reflection and inspire.

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A Case Study of the Your Educational Path Digital Education Ecosystem in Crisis Contexts: AI, Mental Health, and Equity in Ukraine

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Abstract

This study investigated the development and implementation of the YEP (Your Educational Path) system, an educational technology ecosystem, developed by Tatl Technology, and deployed across Ukraine during the COVID-19 pandemic and ongoing war. Using a qualitative case study approach, this research drew on official government data from a learning management system pilot program (2019–2023), usage analytics (2019–2024), and documentation from public-private stakeholders. The analysis evaluates the YEP ecosystem through four dimensions: functionality, scalability, policy alignment, and crisis resilience. Key findings included rapid adoption across 2,193 schools, engagement of over 1.8 million users, and integration of AI-driven diagnostics and mental health support tools by the end of 2023. These findings have contributed to global discourse on education in emergencies and suggested a replicable model for resilient digital schooling in conflict-affected contexts.

Keywords: adaptive learning, Ukraine, crisis education, mental health, educational technology

Introduction: Education in Crisis

Ukraine's education system has experienced unprecedented disruption due to the crises of the COVID-19 pandemic and the full-scale Russian invasion. As of mid-2025, over 6.4 million learners have experienced educational instability, with more than 3,400 schools damaged and over 350 completely destroyed (Public Broadcasting Service News, 2024; United Nations Educational, Cultural and Scientific Organization [UNESCO], 2025). The destruction in cities like Kharkiv, where 64 schools were destroyed and 587 schools were damaged, underscores the urgent need for robust, flexible educational infrastructure.

YEP ecosystem is a modular, cloud-based digital education infrastructure designed to support K–12 public education (Grades 1–12) in Ukraine. It consists of five integrated components: (a) a national learning management system (LMS) used for instructional delivery and school administration; (b) an on-demand tutoring and mentorship platform; (c) a centralized booking system for extracurricular and enrichment activities; (d) an integrated mental health monitoring and communication module; and (e) a diagnostics engine powered by artificial intelligence (AI) that supports adaptive learning and early risk detection. Together, these components form a unified digital environment for students, teachers, parents, and administrators.

The system is accessible via Web browsers on desktop and laptop computers as well as mobile devices (e.g., tablets, smartphones). It was designed with a mobile-first and low-bandwidth approach to accommodate unstable connectivity during emergencies. The platform supports asynchronous and synchronous learning, integrates with national education databases, and complies with national data protection and information security requirements.

Anticipating the need for systemic digital transformation, Tatl Technology began developing a comprehensive digital platform for school administration and learning management in 2019. The Ministry of Education and Science of Ukraine formalized its deployment through a national-level experiment known as Єдина школа (Yedyna School), outlined in Order №895 and conducted from 2019 to 2023. This initiative became the base for what would become Your Educational Path (YEP), an expanded educational ecosystem designed to ensure continuity, equity, and personalized learning even in times of crisis. The LMS experiment, which began with pilot implementation in just four schools, rapidly expanded due to its demonstrated effectiveness, eventually involving over 2,193 educational institutions and reaching more than 1.8 million users by its conclusion in 2023. The platform not only digitized administrative functions but also introduced critical modules for distance learning, analytics, and parental engagement. These tools proved essential for supporting students who had fled the country during the war, allowing them to continue their Ukrainian education from abroad, and for those who remained in Ukraine and required additional emotional and academic support due to ongoing trauma and instability. Another pressing challenge Ukrainian students face today is the constant interruption of classes due to air raids and missile attacks. In such a disrupted environment, traditional instruction is often inconsistent and delayed, leading to declining academic performance. At the same time, national exams like the NMT (National Multi-Subject Test) remain high stakes benchmarks that students must prepare for regardless of circumstances. In this context, YEP became not only relevant but essential.

The tutoring platform component of the ecosystem, for example, has provided students with flexible, on-demand tutoring sessions that can be accessed safely from any location and at any time. It ensured continuity of preparation for key assessments, even when school schedules were affected by emergency events. These personalized academic interventions helped bridge learning gaps and maintain student motivation in uncertain times.

In addition to technological progress, YEP reflects a pedagogical shift toward student-centered, data-informed, and crisis-resilient education. According to reports submitted to the Ministry, YEP reduced teacher workload by up to 40%, improved data transparency, and supported the development of digital competencies among educators, with over 25,000 teachers certified through targeted training programs (Order No. 895, Ukrainian Ministry of Education and Science). Building on this institutional and technical foundation, Tatl Technology expanded its vision into a broader ecosystem to include a tutoring platform for tutoring and mentorship, a platform for extracurricular activity booking, integrated mental health support tools, and an AI-powered diagnostics engine for personalized learning assessment. In contrast to fragmented digital solutions, YEP was designed as an integrated infrastructure, offering a unified experience for students, educators, parents, and administrators.

This paper presents a qualitative case study of the design, implementation, and early outcomes of this ecosystem, contributing to scholarship on online and distributed learning, emergency remote education, and digitally enabled education systems in crisis contexts.

Literature Review

K–12 Distance and Online Learning Prior to the COVID-19 Pandemic

Research on online and distance learning in K–12 education has a long and established history, well before the COVID-19 pandemic. Early scholarship examined virtual schools, cyber charter schools, and blended learning environments, focusing on instructional design, learner engagement, teacher roles, and student outcomes (Barbour & Reeves, 2009; Cavanaugh et al., 2009). This body of literature has emphasized that effective online learning is not merely a matter of technology access, but of pedagogical design, institutional support, and sustained teacher-student interaction.

Studies have consistently highlighted the importance of teacher presence, structured learning pathways, timely feedback, and parental involvement in K–12 online settings (Borup et al., 2014; Rice, 2006). Unlike higher education, K–12 distance learning places additional demands on schools to provide monitoring and communication structures that compensate for learners' developmental needs. These concerns are particularly relevant when evaluating national-scale learning management systems intended to support compulsory education.

Prior research has also identified equity concerns in K–12 online learning, including disparities in access to devices, connectivity, and adult supervision at home (Barbour, 2018). As a result, scholars have argued that successful K–12 online learning systems must be integrated at the institutional level, rather than relying on isolated tools or individual teacher initiatives. This literature has provided a critical foundation for understanding how centralized digital infrastructure can support continuity and accountability in public education systems.

Emergency Remote Learning and Crisis-Induced Digital Education

While online learning has a long scholarly tradition, the concept of emergency remote learning emerged prominently during the COVID-19 pandemic. Hodges et al. (2020) distinguished emergency remote learning from planned online education, defining it as a temporary shift of instructional delivery to alternate modes due to crisis circumstances. Unlike purposefully designed online learning, emergency remote learning has been characterized by rapid deployment, limited preparation time, and constrained institutional capacity.

A growing body of research has documented the challenges faced by K–12 systems during pandemic-induced school closures, including uneven teacher readiness, reduced student engagement, increased parental burden, and significant learning loss, particularly among vulnerable populations (Trust & Whalen, 2020; UNESCO, 2020). Studies across multiple national contexts have demonstrated that systems with pre-existing digital infrastructure and coordinated policy responses were better positioned to mitigate disruption (Bozkurt & Sharma, 2020).

Emergency remote learning scholarship has also highlighted the importance of flexibility, asynchronous access, and centralized coordination in crisis contexts. Researchers noted that fragmented digital solutions often exacerbated inequities, whereas integrated systems provided consistency and continuity during prolonged disruptions (Bozkurt & Sharma, 2020). This literature has underscored the relevance of examining large-scale, government-aligned digital ecosystems that extend beyond short-term emergency responses.

Mental Health, Equity, and Trauma-Informed Educational Design

Increasingly, recent scholarship has emphasized that educational responses to crisis must address not only academic continuity but also learners' psychosocial well-being. Trauma-informed educational design prioritizes emotional safety, predictability, agency, and supportive relationships, particularly for learners affected by displacement, violence, or prolonged instability (Darling-Hammond et al., 2019).

Research in school psychology and public health has demonstrated that exposure to chronic stress and trauma significantly affects cognitive functioning, attention, and motivation, with long-term implications for educational outcomes (Perfect et al., 2016). Consequently, scholars have argued that digital education systems deployed in crisis contexts should incorporate mechanisms for monitoring student well-being and facilitating early support, while avoiding surveillance or stigmatization (World Health Organization, 2021).

Equity-oriented approaches to crisis education have further stressed the need for inclusive design, multilingual access, and caregiver engagement, particularly for displaced and refugee learners (UNESCO, 2022). Digital platforms that integrate mental health awareness alongside academic tools have been increasingly viewed as essential components of resilient education systems. However, the literature has also cautioned that such systems must operate within clear ethical boundaries, emphasizing aggregation, prevention, and referral rather than diagnosis or automated decision-making.

AI Integration and Adaptive Learning Models

AI has become a prominent feature of contemporary educational technology, particularly in adaptive learning systems that personalize content, pacing, and feedback. Research has suggested that AI-supported adaptive learning can improve learner engagement and support differentiated instruction, especially in large-scale digital environments (Katonane Gyönyörű, 2024; Multidisciplinary Digital Publishing Institute [MDPI], 2023).

At the same time, scholars have raised concerns about algorithmic bias, transparency, and the appropriateness of AI-driven decision-making in high-stakes educational contexts (Williamson & Eynon, 2020). These concerns have been amplified in crisis and emergency settings, where learners may already be vulnerable due to trauma, displacement, or disrupted schooling. As a result, recent literature has emphasized that AI in education should augment—not replace—human judgment, particularly in areas related to student well-being and risk identification.

Within emergency education contexts, AI has shown potential for identifying learning gaps, monitoring engagement patterns, and supporting educators with early-warning indicators (HolonIQ, 2021). However, there have been few empirical case studies of AI integration at the national scale, particularly under active crisis conditions. This gap highlights the importance of examining real-world implementations that combine AI diagnostics with institutional oversight and ethical safeguards.

Public-Private Partnerships and National Digital Education Infrastructure

The development and deployment of large-scale digital education systems often depend on coordinated public-private partnerships. Research has indicated that such partnerships can accelerate innovation, enhance technical capacity, and improve sustainability when aligned with national policy objectives and regulatory frameworks (Patrinos et al., 2022). Comparative studies of national education platforms, such as Estonia's eKool, illustrated how long-term government commitment and interoperability standards contribute to resilient digital infrastructure (Lust et al., 2020).

In crisis contexts, public-private collaboration becomes even more critical, as governments must respond rapidly while ensuring equity, security, and continuity. Scholars have argued that digitally sovereign, nationally governed platforms offer advantages over fragmented commercial solutions, particularly in maintaining data protection, accountability, and system-wide coordination (Lim & Wang, 2021).

Despite growing interest in digital public infrastructure for education, there has been a lack of empirical research on integrated, multi-component systems deployed during prolonged emergencies, especially in active conflict settings. This gap in the literature underscores the need for detailed case studies that examine not only technological features but also governance, scalability, and resilience.

Summary and Research Gap

The reviewed literature demonstrated that while K–12 online learning and emergency remote education have been extensively studied, there has been limited research on nationally coordinated, integrated digital ecosystems that combine instructional delivery, learner support, mental health awareness, and AI-assisted diagnostics under crisis conditions. Existing scholarship has tended to focus on isolated tools, short-term responses, or post-crisis evaluations.

This study addressed this gap by examining a comprehensive digital education ecosystem implemented at a national scale during pandemic and wartime conditions. By situating the case within established online learning, emergency education, mental health, and AI scholarship, the study contributed to a deeper understanding of how digital public infrastructure can support educational resilience, equity, and continuity in extreme contexts.

Methodology

This study used a qualitative case study methodology, focusing on the design and initial deployment of YEP digital ecosystem in Ukraine between 2019 and 2024. Data were collected from multiple sources to ensure a comprehensive analysis.

- Platform Data: We analyzed information from YEP system resources. This included LMS usage logs (e.g., counts of assignments viewed, grades entered, parent logins) shared via reports to the Ministry of Education and Science of Ukraine (MoES). All data were anonymized and processed in compliance with General Data Protection Regulation aligned standards. Given the non-invasive, administrative nature of the data and the absence of direct interaction with human subjects, no research ethics board approval was required.

- Interviews/Testimonials: While formal interviews were beyond the scope of this conversion, we referenced published testimonials and statements from users and officials.

- International Perspectives: To situate YEP in a global context, we included external analysis on digital education and mental health. UNESCO reports and press releases provided data on the extent of Ukraine's educational disruption (e.g., the percentage of students in remote learning, teacher training initiatives) and emphasized the importance of psychosocial support in schools.

Key policy documents referenced in this study were publicly available through official Ministry of Education and Science of Ukraine publications, including Order No. 895 and associated program summaries (MoES, 2024). Additional descriptive statistics were drawn from publicly released UNESCO situation reports (UNESCO, 2025) and related announcements. Where internal platform metrics were referenced, they were reported in aggregated form as summarized in documentation submitted to MoES and were not released as raw logs due to privacy and security constraints.

Case Description and System Implementation

System Overview and Architecture

YEP ecosystem is a modular, cloud-based digital education infrastructure designed to support K–12 public education in Ukraine. The system was developed as a unified environment integrating instructional delivery, school administration, learner support, and well-being monitoring into a single platform. Rather than functioning as a standalone learning management system, it operates as a multi-component ecosystem intended to maintain educational continuity during large-scale disruptions such as pandemics and war.

The ecosystem consists of five core components, namely (a) a national learning management system (LMS); (b) an on-demand tutoring and mentorship platform; (c) a centralized booking platform for extracurricular and enrichment activities; (d) an integrated mental health monitoring and communication module; and (e) an AI-powered diagnostics engine supporting adaptive learning and early risk identification.

The platform is accessible via standard Web browsers on desktop and laptop computers, as well as on tablets and smartphones. It supports major browsers (e.g., Chrome, Safari, Firefox, Edge) and does not require proprietary software installation. A mobile-first design and low-bandwidth optimization were implemented to ensure usability under unstable connectivity conditions common during emergency situations.

The system was developed as a new platform, informed by prior research and best practices in online learning systems, but not built upon the codebase of existing open-source LMS platforms. The ecosystem is proprietary and operated through a public-private partnership with the Ministry of Education and Science of Ukraine.

Core LMS Functionality

The LMS serves as the foundational infrastructure of the ecosystem. It centralizes core school operations, including electronic gradebooks, attendance tracking, assignment distribution, curriculum planning, internal communication, and parental notifications. These functions were designed to replace paper-based workflows and fragmented digital tools, allowing schools to operate within a single, secure environment.

The development of the LMS began in 2019, driven by Koshevets' vision to digitize Ukraine's education sector before a crisis struck. The system was initially piloted in just four schools, which served as real-world testing for features like centralized grading, remote attendance, and digital communication with parents. These early implementations quickly demonstrated measurable benefits in teacher efficiency and data accuracy, which led the MoES of Ukraine to take notice.

In 2020, as the COVID-19 pandemic accelerated the demand for distance learning tools, the Ministry launched a nationwide digital education experiment. The LMS was selected as the platform of choice for this initiative. The selection was based on the platform's early results, intuitive interface, and ability to integrate seamlessly with national education data systems such as AICEN (Automated Information Computer Educational Network). The experiment aimed to test the feasibility of full-cycle digital transformation across diverse school environments, including urban, rural, and war-affected regions. The goals of the experiment were ambitious: to reduce administrative load on teachers, ensure uninterrupted education during emergencies, and introduce a data-driven approach to pedagogy and management. The LMS met and exceeded these expectations. It introduced modules for real-time analytics, online lesson delivery, and parental engagement that were previously absent from Ukraine's public education infrastructure.

Validated through this national experiment, the platform was eventually rolled out across 2,193 schools by the end of 2023. As shown in Figure 1, the number of schools using the LMS increased from 4 in 2019 to over 2,500 by 2024, reflecting rapid national adoption. Over 2.3 million users, including 91,580 teachers, 1,221,949 students, and 944,162 parents, actively engaged with the system. Figure 2 illustrates the exponential growth in user engagement, with over 3 million combined users expected by the end of 2025. The success of the platform was due to a combination of technological functionality and the ability to automate traditional manual workflows, leading to an estimated 40% reduction in educator administrative burden. The LMS became a digital tool that has been a part of a structural reform, building the base for a more resilient, transparent, and adaptive education system.

Figure 1

Growth in the Number of Schools Participating in the LMS (2019–2024)

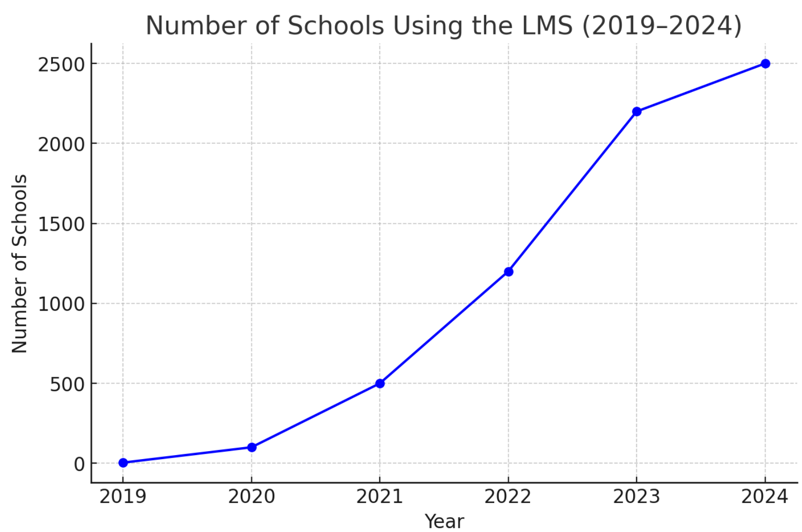
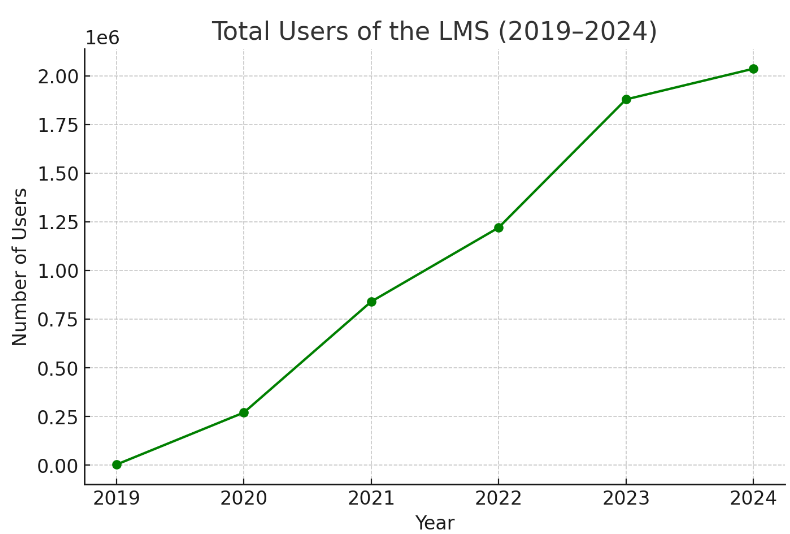


Figure 2

Total Number of Active Users (Students, Teachers, Parents) on the LMS (2019–2024)



Key innovations included a chat communication system among all participants in the educational process, real-time performance dashboards for principals, and modules to support digital attendance, analytics, and integration with national systems like AICEN. The LMS has proven indispensable during air-raid disruptions and remote learning periods, enabling seamless asynchronous and synchronous educational experiences. During the conceptual and diagnostic phases (2019–2021), teachers from pilot schools in Kyiv co-designed features and tested usability. Their feedback influenced improvements to functionality, such as adaptive scheduling, modular grading schemes, and support for special education workflows. As a result of its iterative development, the LMS was able to reflect the administrative needs of schools and evolving pedagogical strategies. Teachers could set differentiated learning goals, automate feedback cycles, and use in-platform communication tools to better engage with parents and students. The introduction of student e-diaries, combined with real-time alerts and visual progress dashboards, transformed how families participated in their children's education. Equally important was the platform's emphasis on compliance, data protection, and national integration. The LMS received certification under the country's comprehensive system of information security; it met national data privacy laws and ensured that student information was securely handled. It also received a formal recommendation from the MoES, making it one of the few platforms approved for use in schools across all regions.

In order to ensure equitable implementation, Tatl Technology equipped participating schools with the necessary hardware, distributing over 120 tablets and 15 laptops during the pilot, and developed digital safety protocols. As the war escalated, the platform's value became even more evident, as it enabled education to continue for internally displaced students and children living under occupation through digital-only formats. Perhaps most importantly, the LMS helped lay the groundwork for Ukraine's broader digital education strategy. Its integration into Kyiv's education policy, along with the ability to plug into national systems like AICEN, made it more than just an ordinary LMS—it became the administrative brain of the Ukrainian school system during the crisis. As new modules for AI testing, mental health tracking, and individualized plans were added, the LMS evolved into the nucleus of the full YEP ecosystem, setting a global example for tech-enabled resilience in public education.

Instructional features supported both synchronous and asynchronous learning. Teachers (a) created and distributed assignments, (b) provided feedback, and (c) tracked student progress through dashboards that aggregated academic and engagement data. Parents and caregivers accessed student performance updates, schedules, and communications through dedicated interfaces, supporting transparency and involvement in the learning process.

The Tutoring Platform: Personalized Academic Support and Global Mentorship

The tutoring platform was the on-demand academic mentorship and tutoring arm of YEP. It connected students with qualified tutors worldwide, offering services across academic subjects, creative disciplines, and test preparation. The platform operated on a hybrid model, combining certified educators and AI-curated learning materials, to ensure each student received support tailored to their pace and level. This personalization was particularly valuable for displaced learners or those who had fallen behind due to conflict-related interruptions to their schooling. Sessions were conducted via secure video, supported by interactive tools such as shared whiteboards, quizzes, and annotated documents. The tutoring platform also logged engagement and outcomes, providing parents and teachers with insights into progress and areas for further attention. What set the tutoring platform apart was its commitment to accessibility and flexibility. Similar hybrid models that combined real-time interaction and personalized diagnostics have shown high effectiveness in comparative contexts (Lust et al., 2020). Students were able to book sessions on demand or schedule recurring lessons, making it easier for those in temporary housing or living under threat of displacement to maintain continuity in their education. The platform also offered group study options, peer learning communities, and multilingual support to ensure inclusivity for Ukraine's diverse student population.

Moreover, the tutoring platform played a significant role in preparing students for national and international standardized testing. It offered structured prep paths for Ukrainian National Multi-Subject Test exams (or their replacements), as well as support for global benchmarks, like the Scholastic Assessment Test, International English Language Testing System, and International Baccalaureate programs. With AI assistance, the platform adjusted difficulty levels in real time and offered custom test simulations based on each learner's historical performance.

From a policy perspective, the tutoring platform complemented the MoES push toward individualized learning and equitable access. While the LMS provided system-wide infrastructure, the tutoring platform addressed the micro-level needs of students, filling learning gaps, reigniting curiosity, and providing mentorship at a time when schools were overburdened and teachers stretched thin. As Ukraine continues to lead innovation in crisis-driven educational technology, the tutoring platform stands as a scalable, exportable model of how tutoring can be democratized through technology.

Booking Platform for Physical and Social Development

Recognizing that quality education goes beyond academics, the booking platform for extra curriculum activities filled the critical gap of extracurricular engagement in the YEP ecosystem. It served as a centralized platform for discovering and booking extracurricular activities, ranging from sports and arts to mental wellness and life skills programs. During these crises, many students were isolated from physical enrichment opportunities. The platform allowed parents and caregivers to browse verified programs in their area or online, filtered by age, interests, time, and location. It promoted a balanced lifestyle by integrating extracurricular and academic schedules in the LMS dashboard. The platform also collected participation data that educators used to monitor student well-being and suggest suitable non-academic development pathways. It supported inclusion for children with disabilities and adapted to the unique needs of displaced families.

The booking platform was particularly important in the context of prolonged instability, where school closures and sheltering-in-place limited children's access to socialization and movement. Through partnerships with local clubs, youth centers, and online activity providers, the platform offered opportunities for children to continue developing critical social-emotional and physical competencies, even in virtual or hybrid formats. Incorporating the platform into the YEP ecosystem also reflected a deeper pedagogical commitment to whole-child development. Research has consistently shown that extracurricular engagement improves academic outcomes, resilience, and long-term life satisfaction. For children affected by trauma, these programs offered recreation and rehabilitation through movement, expression, structure, and peer connection.

From a system-level perspective, the platform supported municipal education departments by providing dashboards that tracked participation rates and identified underserved student groups. Such data informed funding decisions, staffing needs, and community engagement strategies. Schools can also use it to recommend enrichment pathways based on academic performance or emotional health indicators flagged elsewhere in the YEP system. Furthermore, the platform was designed with accessibility and safety in mind. Every program listed on the platform underwent a basic verification check; families rated and reviewed their experiences to ensure transparency. For internally displaced people, the system highlighted mobile-friendly or remote-access activities and included geolocation filters to adapt to shifting environments.

Looking ahead, the booking platform aims to expand its reach by integrating third-party providers such as non-governmental organizations, regional arts councils, and international organizations that support youth development. Plans are underway to incorporate gamified participation tracking, allowing students to earn digital badges for milestones like consistent attendance or skill mastery, adding motivation and a sense of achievement to non-academic growth.

Mental Health Tools: Monitoring, Communication, and Early Detection

Mental health has become a growing concern for students in Ukraine, especially due to the psychological toll of war and displacement. The YEP ecosystem addressed this need through the integrated combination of AgileBrain and a mental health module, which enabled early detection and intervention for students showing signs of emotional distress.

AgileBrain is an AI-powered diagnostic and adaptive learning engine embedded within the broader YEP educational ecosystem. It functions as a continuous cognitive and behavioral analytics layer that collects and analyzes multidimensional learning data, including engagement patterns, task completion time, response accuracy, interaction frequency, and learning trajectory dynamics. Rather than serving solely as a performance-tracking tool, AgileBrain operates as an early-warning system that identifies deviations from a student's established academic and behavioral baseline.

Using pattern recognition and predictive analytics, the system detects subtle shifts in concentration, consistency, or motivation that may indicate cognitive overload, stress exposure, or emerging emotional difficulties. These signals are not treated as standalone indicators but are triangulated with contextual data (e.g., attendance patterns, changes in participation, and academic variability). When risk thresholds are reached, the system triggers automated alerts for educators and parents, enabling timely pedagogical adjustment or referral to psychological support services.

Importantly, AgileBrain does not replace human judgment. Instead, it augments teacher and counselor decision-making by providing structured, data-informed insights. In crisis contexts, such as prolonged school disruption or exposure to conflict-related stress, this form of proactive monitoring is particularly significant, as trauma-related cognitive symptoms often manifest first through changes in learning behavior (Perfect et al., 2016). By embedding cognitive diagnostics within the instructional workflow, the system integrates academic resilience and mental health monitoring into a unified educational response framework.

The mental health module was developed with trauma-informed design principles in mind. Questions and feedback prompts were adapted to be non-triggering, age-appropriate, and culturally relevant. For younger students, the module used visual cues such as emoji-based check-ins, while older students wrote journal-style reflections or submitted audio recordings. This flexibility encouraged honesty and emotional literacy while lowering the barrier to expression. Importantly, teachers and administrators were trained to interpret the data with sensitivity. Color-coded dashboards alerted staff to urgent cases while preserving student anonymity. Patterns such as chronic disengagement, anxiety spikes before tests, or signs of isolation triggered early outreach. The system did not diagnose but flagged potential issues, making it a tool for prevention and support, not surveillance. This combination offered daily mood check-ins, anonymous feedback options, and AI-assisted flagging for crisis indicators. Aggregated data allowed schools to identify at-risk groups and allocate mental health resources proactively to maintain the psychological state of the group. It also supported group wellness activities and classroom-level interventions, helping to normalize discussions about mental health and reduce stigma.

Challenges remained, particularly in rural or under-resourced areas where professional psychological services were limited. However, YEP digital-first approach helped bridge that gap by offering scalable tools that did not depend on physical presence. Partnerships with NGOs and mobile counseling units are being explored to expand reach and responsiveness in underserved regions.

Beyond individual impact, the data collected through the module offered valuable macro-level insights. Regional education departments monitored mental health trends across districts, using anonymous data, evaluating the effectiveness of interventions, and informing policy. By embedding mental health into the digital fabric of the school experience, YEP not only supported students coping with immediate trauma but also helped build a base for a more emotionally resilient generation.

AI Monitoring and Diagnostics

An AI-powered diagnostics engine was central to YEP ability to personalize learning. This tool continuously analyzed academic performance, behavior patterns, attendance, and emotional indicators to tailor student learning paths in real time. The system supported a variety of question formats, multimedia inputs, and performance metrics, making it both robust and adaptable across disciplines. Integrated into both the LMS and the tutoring platform, the diagnostics engine empowered data-informed teaching and intervention strategies. The architecture of the engine was designed to be modular and scalable, supporting real-time assessments and asynchronous learning alike. Teachers created or imported assignments into the system, which automatically tagged and categorized questions by skill type, difficulty, and subject alignment. As students engaged, the engine evaluated not only accuracy but time-on-task, attempt frequency, and even emotional signals (such as stress indicators gathered through integrated mental health tools).

This constant feedback loop allowed for the creation of adaptive learning paths, where a student's progression was no longer linear but dynamically adjusted. For instance, if a learner demonstrated gaps in foundational math concepts, the system recommended a shift to remedial modules within the tutoring platform before returning to grade-level content. This minimized frustration and maximized engagement, especially for students returning after prolonged interruptions or displacement.

The diagnostics engine also played a critical role in ensuring educational equity. Recent studies have supported the transformative potential of AI-based adaptive learning systems in promoting equity and tailoring instruction to individual student needs (Katonane Gyönyörű, 2024; MDPI, 2023). The engine flagged disparities in performance across regions, genders, and socioeconomic backgrounds, providing policymakers with real-time dashboards on achievement gaps. Schools with limited staff benefited from AI-driven alerts that brought attention to students who may otherwise have fallen through the cracks, including those with undiagnosed learning difficulties or emotional barriers to learning.

Privacy and ethical data use were foundational to this engine's operation. The system complied with Ukraine's national data protection laws and integrated with certified secure cloud storage systems. Students and parents retained access to their own learning analytics. Looking forward, the AI engine is being trained to identify non-academic factors that impact learning outcomes, such as poor sleep patterns, device-sharing at home, or signs of social withdrawal. By correlating learning outcomes with broader behavioral and environmental data, the AI-powered diagnostics engine could evolve into a student success tool for assessment, prediction, and prevention.

Results

City-Level Integration and National Adoption

Administrative reports submitted to MoES documented the progressive scaling of YEP LMS from pilot implementation in 2019 to nationwide adoption in 2024. The initial pilot phase (2019–2020) involved four public schools in Kyiv. By the end of 2021, 67.5% of Kyiv's public schools had adopted the LMS, following municipal regulations mandating electronic gradebooks and digital administrative workflows (MoES, 2021).

Subsequent regional adoption occurred through formal agreements between local education authorities and platform developers. By December 2023, MoES reports indicated that 2,193 educational institutions across multiple regions, including Kyiv, Dnipro, Ternopil, and Ivano-Frankivsk, were actively using the system. Platform usage analytics for 2024 showed further expansion to 2,507 institutions nationwide.

As of the fourth quarter of 2024, administrative system logs indicated active engagement by approximately 2.3 million users, including 91,580 teachers, 1,221,949 students, and 944,162 parents or caregivers. These figures reflected accounts with at least one authenticated login during the reporting period. Growth trends derived from annual reports demonstrated a steady increase in institutional participation and user engagement across successive academic years.

Platform Use and Operational Outcomes

System-generated administrative reports indicated substantial use of core LMS functions, including digital gradebooks, attendance tracking, assignment distribution, and parent-teacher communication tools. Between 2021 and 2023, participating schools reported a cumulative total of over 180 million grade entries, 240 million attendance records, and 95 million parent notifications transmitted through the platform.

Feedback collected through structured administrative surveys and internal MoES evaluations suggested that digitization of routine school processes contributed to measurable reductions in administrative workload. Across pilot and early-adopter schools, reported reductions in teacher time spent on administrative tasks ranged from 30% to 40%, particularly in grading, attendance reporting, and preparing documentation. These estimates were based on self-reported workload comparisons submitted to MoES during the 2019 to 2023 experimental phase.

Training and Capacity Building

Administrative records indicated that educator training was a central component of system implementation. Between 2020 and 2024, more than 25,000 teachers completed certified training modules in digital pedagogy, platform operation, and data-informed instructional practices. Training completion rates exceeded 85% among schools participating in the national experiment.

Helpdesk logs and technical support records showed a decline in reported platform-related issues over time, with support requests decreasing by approximately 28% between the first and third years of adoption. This trend corresponded with increased system familiarity and expanded onboarding resources.

Digital Equity and Accessibility Measures

MoES and municipal reports documented targeted equity measures accompanying platform rollout. During the pilot phase, participating schools received 120 tablets and 15 laptops in total to support instructional continuity. During the wartime expansion phase (2022–2024), additional hardware allocations prioritized frontline and rural regions. Platform analytics indicated consistent access across desktop and mobile devices, with approximately 46% of user logins occurring via smartphones or tablets during periods of displacement or emergency remote learning.

Low-bandwidth access modes and multilingual interface options were activated across all participating institutions. Administrative monitoring reports noted continued system usage during air-raid interruptions, shelter-in-place conditions, and temporary relocation, with asynchronous access accounting for approximately 62% of total instructional activity during high-disruption periods.

Engagement and Persistence Indicators

While long-term learning outcomes were beyond the scope of this study, engagement indicators derived from administrative data suggested sustained participation during crisis conditions. Schools participating continuously for at least two academic years reported higher assignment submission rates and more frequent parent logins compared to first-year adopters. Internal MoES summaries estimate a 15% to 20% improvement in student academic persistence, defined as continued participation in instructional activities during emergency disruptions, among schools using the platform compared to pre-deployment baselines.

Discussion

This study examined the development and early outcomes of a nationally coordinated digital education ecosystem implemented during pandemic and wartime conditions. The findings highlighted several themes relevant to scholarship on crisis education, online learning, and digital public infrastructure.

Integration as a System-Level Response to Crisis

Unlike many emergency education responses that have relied on fragmented tools or temporary solutions, the YEP ecosystem represented an integrated, system-level approach. By consolidating instructional delivery, administration, tutoring, extracurricular engagement, mental health awareness, and AI-supported diagnostics within a single platform, the ecosystem addressed multiple dimensions of educational continuity simultaneously.

This integration aligned with prior research emphasizing the importance of institutional coherence, governance, and sustained support in K–12 online learning environments. Rather than positioning technology as a standalone intervention, the ecosystem functioned as an infrastructural layer embedded within public education systems.

Personalization, Equity, and Human Oversight

The platform's use of analytics and AI-supported diagnostics has illustrated how personalization can be operationalized at scale without fully automating educational decision-making. In line with existing literature, AI tools in this ecosystem functioned primarily as decision-support mechanisms, augmenting educator judgment rather than replacing it.

Equity considerations were central to this design. Mobile-first access, asynchronous learning options, and integrated tutoring services addressed disparities related to geography, displacement, and school interruption. Importantly, personalization was framed as a means to inclusion, supporting learners who might otherwise disengage due to academic gaps or psychosocial stress.

Mental Health Integration in Digital Schooling

The inclusion of mental health monitoring tools reflected growing recognition that academic continuity alone is insufficient in crisis contexts. The system's trauma-informed design, emphasis on aggregation rather than diagnosis, and reliance on human interpretation aligned with ethical guidance in both education and public health literature.

While the platform did not replace professional psychological services, it provided early signals that informed preventative interventions and resource allocation. This approach contributed to emerging models of digitally supported well-being in schools, particularly where access to in-person services is constrained.

Public-Private Partnership and Governance

The case also illustrated the role of public-private collaboration in rapidly deploying national digital infrastructure. Government oversight, regulatory alignment, and data governance structures enabled system-wide adoption, while private-sector development capacity supported technical scalability and iterative improvement. This balance is critical in crisis contexts, where speed, accountability, and sovereignty must coexist.

Conclusion

This study examined the development and implementation of the YEP digital education ecosystem as a nationally coordinated response to prolonged educational disruption caused by the COVID-19 pandemic and the ongoing war in Ukraine. Drawing on administrative data, platform analytics, and policy documentation, the case illustrates how a centralized, modular digital infrastructure can support continuity of schooling, administrative stability, and learner support under conditions of extreme uncertainty.

The findings suggest that the ecosystem's integrated design, combining a national learning management system, tutoring services, extracurricular coordination, mental health monitoring, and AI-supported diagnostics, enabled rapid scaling and sustained use across diverse educational contexts, including regions affected by displacement, infrastructure damage, and intermittent connectivity. Unlike fragmented or short-term emergency solutions, the platform functioned as a structural component of public education governance, supporting both instructional delivery and system-level coordination during wartime conditions.

Beyond maintaining access to instruction, the ecosystem demonstrates how digital education infrastructure can address broader dimensions of educational resilience. The integration of mental health awareness tools and adaptive learning diagnostics reflects an emerging shift toward whole-child, data-informed approaches to crisis education. These features were implemented within a framework of institutional oversight, regulatory compliance, and ethical safeguards, reinforcing the role of human judgment and professional responsibility in high-stakes educational environments.

From a policy perspective, the case highlights the role of structured public–private partnerships in enabling rapid innovation while preserving national control, data sovereignty, and alignment with public education objectives. Ukraine's experience suggests that when such partnerships operate within clearly defined regulatory frameworks and are supported by large-scale educator training, they can contribute to both emergency response and longer-term system modernization, even during active conflict.

At the same time, several limitations warrant consideration. While the findings indicate substantial adoption and operational integration, the present study does not assess long-term academic achievement outcomes or psychological impacts at the individual student level. The reliance on administrative and platform-generated data limits causal inference regarding learning gains or mental health effects. In addition, the use of AI-supported diagnostic tools introduces potential concerns related to algorithmic bias, data interpretation, and contextual variability across regions and demographic groups. These considerations underscore the importance of ongoing ethical review and methodological transparency in crisis-driven digital innovation.

Future research should therefore employ longitudinal and comparative designs to evaluate sustained academic performance, student well-being, and equity implications over time. Cross-national comparisons and mixed-methods approaches could further illuminate how similar digital infrastructures function across different governance systems and crisis contexts. Additionally, further investigation is needed to examine the validity, reliability, and fairness of AI-assisted diagnostic mechanisms in educational environments characterized by instability and trauma exposure.

Overall, the YEP case contributes to the growing literature on education in emergencies by documenting a rare example of a nationally coordinated, integrated digital education ecosystem implemented during an active war. It offers empirical insight into how digital public infrastructure can function not only as a temporary substitute for schooling, but as a stabilizing and adaptive foundation for public education under conditions of prolonged crisis.

Limitations and Future Research

While this case study provides an in-depth examination of a nationally scaled digital education ecosystem implemented during pandemic and wartime conditions, several limitations should be acknowledged. First, the emergency context precluded the use of randomized control groups or longitudinal experimental designs. Second, platform analytics capture adoption and engagement patterns but do not yet allow for causal inference regarding long-term academic or psychosocial outcomes. Third, the study does not include systematic comparison with non-participating schools or alternative digital platforms.

Future research should incorporate quasi-experimental and longitudinal methods to assess learning outcomes, well-being indicators, and equity impacts over time. Comparative studies across crisis-affected contexts, including post-war and post-displacement settings, would further clarify the transferability and limitations of the model.

Author Contributions

The author has professional involvement in the development and scaling of the ecosystem described in this case study. This dual role is acknowledged as a potential source of bias and was addressed through reliance on external institutional documentation (e.g., MoES reports and UNESCO publications) and descriptive reporting of aggregated metrics. Generative AI tools were used only for language editing and clarity (e.g., grammar, concision) and were not used for data analysis, statistical computation, or generation of findings, interpretations, or references. The author remains responsible for the content, analysis, and integrity of the manuscript.

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Bringing Artificial Intelligence Literacy Into Online Education: Machine-Learning Integration Through Geometry in K–12 Teacher Professional Development

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Abstract

This study examined an online professional development program integrating artificial intelligence (AI) literacy into mathematics instruction through unplugged, explainable machine-learning activities. Ten K–12 educators created explainable feature matrices to classify geometric shapes, making machine-learning algorithms visible and accessible without requiring complex software or technological tools. The intervention used ontological principles to bridge familiar mathematical concepts with algorithmic processes. Findings demonstrated positive changes across all constructs, with participants' AI self-efficacy increasing from below-moderate to above-moderate levels. Sentiment analysis revealed dramatic shifts from negative to positive perceptions of AI in education, with 30% of participants initially using negative descriptors versus 0% post intervention. Thematic analysis revealed three key outcomes: (a) AI concepts became explainable and learnable, (b) participants gained enhanced understanding of classification processes, and (c) participants valued the practical applicability of unplugged approaches. The study demonstrates that effective AI literacy education can be delivered through conceptual understanding rather than technological implementation, providing an accessible pathway for K–12 AI integration regardless of resource constraints.

Keywords: AI literacy, explainable machine learning, geometry, online delivery, teacher professional development

Introduction

Recent developments in artificial intelligence (AI) have led to significant discussion in K–12 education (Aydin & Yurdugül, 2024; Grover, 2024; UNESCO, 2022; Wang & Cheng, 2021). For example, recognizing AI technology as a new subject area for K–12 schools, UNESCO (2022) identified three main areas based on an analysis of government-endorsed AI curricula across 11 countries: (a) AI foundations (algorithm/programming, data literacy, contextual problem-solving); (b) ethics and social impact of AI; and (c) understanding, using, and developing AI. UNESCO also emphasized the need for combining AI curricula with relevant subject matter, mathematical principles, coding, and algorithm (Aydin & Yurdugül, 2024). Similarly, Grover (2024) suggested efforts be made to integrate AI learning with other subjects and that curricula be co-designed by researchers and teachers.

Building teacher capacity in AI education is important given the crucial role experienced teachers play in the Computer Science for All movement—an effort to make high-quality computer science education accessible for all learners (Grover, 2024). Moreover, machine learning (ML) and computational thinking without computers is important since it is part of AI's core algorithm technologies at the K–12 level (Aydin & Yurdugül, 2024; Grover, 2024; UNESCO, 2022).

Both researchers and teachers agree that it is necessary to prepare students for a future where AI is widely used (Casal-Otero et al., 2023). However, traditional approaches to AI education often require sophisticated technological tools and access to AI-integrated software that may require in-person monitoring and support. Further, these software programs or technological tools are not accessible in all educational settings, particularly in open and distributed learning contexts where educators serve geographically dispersed populations with varying resources.

Online professional development (PD) offers a promising solution for addressing these challenges at scale (Borko et al., 2009; Bragg et al., 2021). However, while a recent systematic review examining the use of AI in online learning and education (Dogan et al., 2023) revealed how to use AI technologies for online learning, it did not find a theme related to how to deliver AI literacy in open, distance, and e-learning (ODL) contexts. Moreover, recent studies on preparing teachers with AI literacy did not discuss online PD for ODL contexts but only examined what online AI tools can be used for PD (Ding et al., 2024; Kohnke et al., 2025; Younis, 2024).

This study addressed the challenge of building conceptual AI understanding while preserving the human interaction and immediate support essential to effective ODL environments (Amin et al., 2025). Specifically, we introduced online PD that could effectively deliver AI literacy by fostering engagement and embedding practical learning activities found to be effective online PD design elements (Bragg et al., 2021). To promote engagement among teacher learners attending online PD and encourage application of AI literacy in a familiar context, the intervention was designed based on a mathematics subject—2D geometric shapes. In short, we explored how an unplugged approach to teaching explainable ML concepts through geometry can make AI literacy accessible in diverse ODL contexts, thereby addressing the "double digital divide"—educators lacking both technology infrastructure and foundational AI literacy (Walter, 2024).

Literature Review

Integration of AI Literacy in K–12 Education

AI and ML refer to systems that mimic cognitive functions that human intelligence can perform based on large sets of data (Soori et al., 2023). AI is broader than ML, enabling a machine or system to sense, reason, act, or adapt like a human. ML is an algorithm that teaches computers how to learn from data to solve a problem (Martins & Gresse Von Wangenheim, 2023). As such, ML is a type of computational process that is an extension of programming, computational thinking, and coding (Mills et al., 2024).

Several domains of AI are discussed in K–12 AI literacy education to prepare students to apply AI in living, learning, and working in a digital world (Ng et al., 2021, 2023; Steinbauer et al., 2021), including (a) understanding AI (grasping how AI systems work); (b) using AI (applying AI tools and systems); (c) evaluating AI (assessing AI outputs and decisions) and creating with AI (developing AI solutions and applications); and (d) the ethics of AI (considering fairness, bias, and societal implications of AI systems; Ng et al., 2021).

Each of these components requires a different pedagogical approach to be applicable in K–12 settings. Discussing AI literacy in K–12 contexts, Wang and Lester (2023) identified critical needs for effective AI PD and AI integration within existing curriculum. Moreover, Abdennour et al. (2025) highlighted the need to foster AI literacy among non-technical learners, including hands-on, unplugged ways of delivering AI literacy to all learners regardless of their background knowledge in computer science or AI. Further, a systematic review study by Tan and Tang (2025) noted that in largely focusing on students, research in K–12 AI literacy has left a gap in understanding how teachers acquire and apply AI literacy in classrooms. Indeed, Tan and Tang (2025) found that teachers are not prepared to teach AI-related concepts and that PD opportunities remain limited.

To bridge these gaps, this study introduced pedagogical approaches that are useful for integrating AI literacy, mainly ML, in familiar subjects such as mathematics while addressing multiple domains of AI that it is important for K–12 educators to understand, apply, and evaluate to promote knowledge of AI technology and foster informed decision-making, including ethical use of AI (Lee et al., 2021; Ng et al., 2021).

AI Use in Mathematics Education

Research of AI use in mathematics has focused on applying AI tools or AI learning environments to improve student performance (Hwang & Tu, 2021; Richard et al., 2022), such as using AI to improve teaching strategies (Lee & Yeo, 2022) or teaching AI literacy to help ensure students' future career success (Ng et al., 2021). However, many did not integrate fundamental AI algorithms and ML into subject matter that does not require the direct teaching of AI literacy or use of AI tools. Further, many studies discussed AI tools such as intelligent tutoring software (Lee & Yeo, 2022), personalized learning (Hwang & Tu, 2021), problem-solving assistance (Richard et al., 2022), and automated grading (Vittorini et al., 2021), all of which require the use of AI software as a tool, rather than promoting understanding of how an AI algorithm is developed.

AI and ML, the key algorithms of AI technologies, are often considered "black boxes" because the algorithm is not visible, making it difficult to understand and interpret how it arrived at a given decision or prediction (Ng et al., 2021; Samek & Müller, 2019; Tiddi & Schlobach, 2022). Therefore, more learning opportunities are needed to teach K–12 teachers not merely to use AI tools but also to present more concrete and hands-on activities to help them understand the underlying AI procedures and ML within a familiar context such as mathematics. The intervention presented in this paper specifically addressed the challenges by designing online accessible and interactive activities.

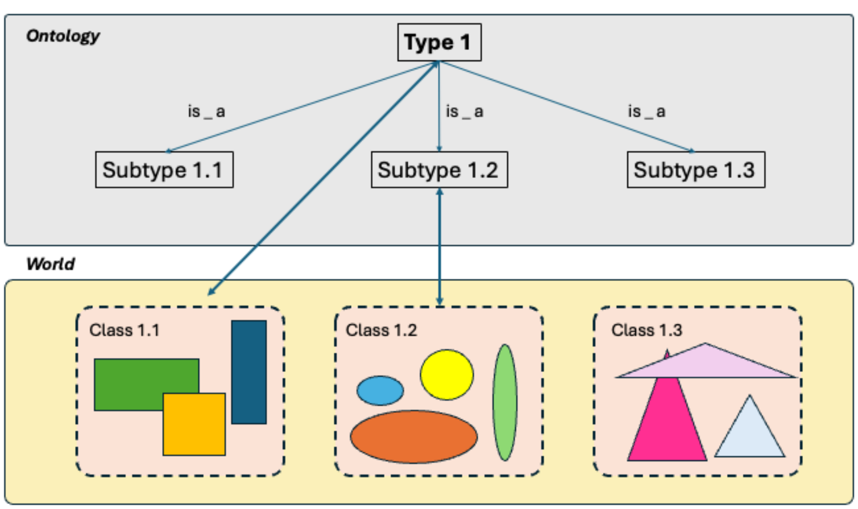
Conceptual Framework: Explainable ML and Ontological Representation

AI's opacity in decision-making has limited its wider adoption (Tiddi & Schlobach, 2022), which has led to challenges in teaching AI concepts to novice learners. This key challenge can be addressed by adopting explainable ML (XML), which focuses on making algorithmic machinery understandable and explainable (Belle & Papantonis, 2021). Transparency is a major element of explainability; it includes three dimensions: (a) *simulatability*: the ability to be simulated by a user; (b) *decomposability*: the ability to break a model into its subparts and explain them; and (c) *algorithmic transparency*: understanding the procedure the model goes through to generate decisions/outputs (Belle & Papantonis, 2021).

Similar to Lee et al.'s (2023) study, which applied XML to predict manufacturing defects by analyzing geometric features, our investigation infused the XML process into a geometry lesson to show how ML enables AI, thereby delivering ML concepts through an explainable and visible approach. Specifically, our online lesson was designed to support K–12 educators and all novices by making XML visible based on ontology concepts (Schulz & Stenzhorn, 2007). Ontologies provide semantic hierarchies, which demonstrate domain entity organization. We found similar applications in representing knowledge hierarchies of geometric shapes as presented in Figure 1.

Figure 1

The Relationship Between Types in Ontologies and Classes of World Entities



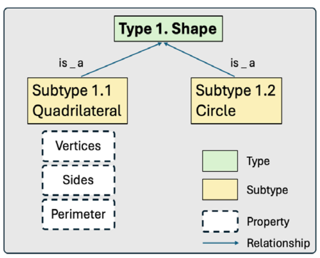
Note. Adapted from "The Ten Theses on Clinical Ontologies," by S. Schulz and H. Stenzhorn, in L. Bos and B. Blobel (Eds.), *Medical and Care Compunetics 4* (p. 271), 2007, IOS Press (https://books.google.ca/books/about/Medical_and_Care_Compunetics_4.html?id=3AfvAgAAQBAJ&redir_esc=y). Copyright 2007 by the authors and IOS Press. Adapted with permission.

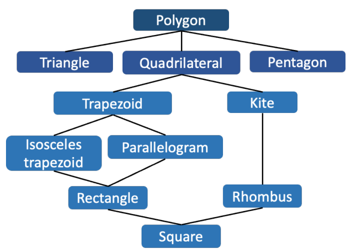
This ontological representation can be transformed into an explainable feature matrix that identifies the key features of each entity, class, and type. That is, the explainable feature matrix employs fundamental ontological principles to practice XML when analyzing geometric shapes, as presented in Table 1.

Table 1

Examples of a Simple Ontology, Hierarchical Classification, and the Explainable Feature Matrix Using Geometric Shapes as a Concept

Example of a simple ontology[1]	Example of a hierarchical classification	Example of an explainable feature matrix





	Simple closed curve with line segments	3 sides	All 3 sides of different length	At least 1 pair of parallel lines
Polygon	Y			
Quadrilateral	Y			
Trapezoid	Y			Y
Isosceles trapezoid	Y			Y
Parallelogram	Y			Y

An ontology is a set of type (concept), subtype, its properties, and the relationships between them	Hierarchical classification is a system of grouping things according to a hierarchy, or levels and orders (Michigan State University, n.d.).	The feature matrix provides selected features to classify given entities (e.g., geometric shapes) that inform relationships between entities.

Note. Adapted from "A Model-Driven Approach for Specifying Semantic Web Services," by J. T. E. Timm and G. C. Gannod, in C. K. Chang and L.-J. Zhang (Chairs), *Proceedings 2005 IEEE International Conference on Web Services* (pp. 313–320), 2005, IEEE (https://doi.org/10.1109/ICWS.2005.9). Copyright 2005 IEEE. Adapted with permission.

A common way to visualize ontology is to use a semantic network or taxonomic hierarchy of its concepts (Ng et al., 2021; Timm & Gannod, 2005). A *semantic network* is used to "express logical sentences as graphical node-and-link diagrams" (Grimm, 2009, p. 112). *Taxonomic order* refers to the main classification principle of ontologies. As such, taxonomies "relate types with their superordinate types" and are generally named using "is_a" formatting (Schulz & Stenzhorn, 2007, p. 270).

We chose the term *explainable feature matrix* to refer to the creation of a table that displays selected features for classifying, comparing, and differentiating a given entity—in this case, geometric shapes. Ultimately, when the matrix is converted to codes via programming, the computer can read it and identify any given shape by checking the features specified in the matrix.

Explainable Feature Matrix and Supervised Learning Models

Of the three ML techniques—supervised, unsupervised, and reinforced learning—our approach focused on supervised learning models. These models predict outcomes based on trained data sets by learning relationships between features and labels (Jordan & Mitchell, 2015).

By viewing the explainable feature matrix as an algorithmic model that AI can use to identify shapes, learners mimic AI's thinking by developing an explainable feature matrix—a visible ML algorithm for classifying and identifying 2D geometric shapes. This process mirrors supervised ML by requiring pattern detection, feature analysis, abstraction, evaluation, and debugging—core computational thinking skills (Grover & Pea, 2013). In short, students experience ML algorithms firsthand, shifting their perspective to understand how AI differentiates shapes through feature recognition.

The Design of an AI-Integrated Geometry Intervention

By grounding complex AI concepts in familiar mathematical content, our methodology provides a pathway for developing AI literacy for novice learners without the geographical barriers that often prevent implementation due to a lack of access to PD. Table 2 shows how AI literacy domains discussed in Ng et al. (2021) were addressed in the study.

Table 2

AI Literacy Addressed in the Study Design

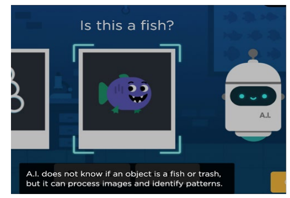
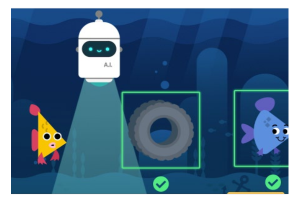
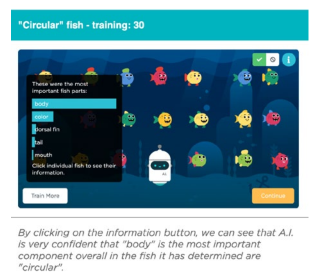
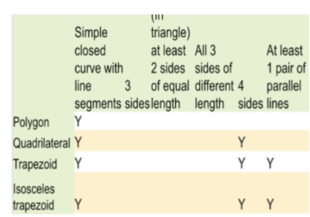
AI literacy domain	Definitions based on previous approaches (Ng et al., 2021)	Current study
Know & understand	Know the basic AI function and how to use AI-driven tools	Understand how AI algorithm functions by identifying patterns and features in hands-on activity
Use & apply	Use and apply AI in different contexts with an understanding of AI concepts	Apply concepts of AI in the learning concept of geometric shapes
Evaluate & create	Evaluate, appraise, create, and build AI	Create a visible feature matrix to identify features/patterns for categorizing geometric shapes, and evaluate the algorithm
Ethics	Considerations regarding ethics, including fairness, social impact, privacy, etc.	Through role-play, evaluate feature matrix algorithms to see how algorithms and selected features affect results

The essence of the lesson is to create explainable feature matrices that make ML algorithms visible and accessible. Table 3 shows the lesson flow organized around the four core AI literacy domains (Ng et al., 2021) along with implementation strategies that can be delivered via conferencing software (i.e., Zoom).

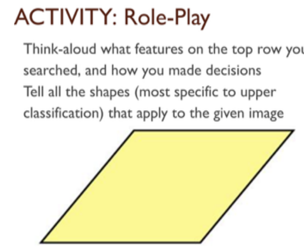
Each domain builds upon the previous one, progressing from basic AI comprehension to practical application, creative development, and, eventually, critical evaluation of algorithmic decision-making processes.

Table 3

Flow of a Lesson Integrating ML in Geometric Shapes Content Around AI Literacy Domains

AI literacy domain	Lesson activity	Teacher facilitation strategies	Tools and materials	Sample image
Know & understand	AI training simulation: Code.org's sorting game to understand how AI learns patterns and makes decisions	Teacher shares screen with Code.org; facilitates learners' responses synchronously through sorting game	Code.org activity	
	Feature identification: Introduction to ML concepts through fish/trash sorting, explaining AI feature-based classification	Teacher presents fish/trash features identified in sorting game; explains algorithmic logic	Slides showing diverse fish/trash shapes; videos showing data training	
Use & apply	Geometric shape analysis: Hands-on activity applying AI classification to geometric shapes, identifying features	Learners receive individual handout links; work on activity sheets while teacher guides feature identification	Google Slides with activity sheets (distributed via individual links; completed independently)	
Evaluate & create	Feature matrix creation: Development of explainable feature matrices for shape classification, creating visible ML algorithm	Teacher demonstrates feature classification with yes/no matrix; students develop feature matrix using specified shapes	Slides for classification; blank table template; sample matrix with 2-3 features	

	Simple closed curve with line segments	3 sides	(in triangle) at least 2 sides of equal length	All 3 sides of different length	4 sides	At least 1 pair of parallel lines
Polygon	Y					
Quadrilateral	Y				Y	
Trapezoid	Y				Y	Y
Isosceles trapezoid	Y				Y	Y

AI literacy domain	Lesson activity	Teacher facilitation strategies	Tools and materials	Sample image
Ethics	Algorithm testing & evaluation: Role-playing activities where participants test algorithms and examine how feature selection affects outcomes, discussing algorithmic decision-making implications	Teacher presents new shapes; students identify shapes using feature matrices; class discusses feature effects and potential algorithmic biases	Whole-class activity with sequential shape slides; reflection prompts about algorithmic fairness	

Note. ML = machine learning. The first three sample images included in the Know & Understand and Use & Apply domain activities are from *AI for Oceans*, by Code.org, 2026 (https://studio.code.org/courses/oceans). Copyright 2026 by Code.org. Reprinted with permission.

Given the increasing demand for AI literacy education in K–12 and the unique advantages of online delivery for reaching diverse populations, we aimed to answer the following research questions by examining before- and after-intervention surveys, open-ended responses, and reflections.

RQ 1. To what extent did the online PD intervention impact participants' AI-related self-efficacy, perceptions, and intentions to integrate AI in their teaching practice?

RQ 2. How did participants' conceptualizations of AI in education evolve following the intervention, as revealed through pre-post word association analysis?

RQ 3. What themes emerged from participants' reflections about their learning experiences with explainable feature matrices and online AI literacy PD?

Method

Participants

Potential participants were invited via email and during online PD sessions hosted by a university located in a northeastern state in the United States. Information about the study was provided along with a consent form; access to a Qualtrics survey was granted based on agreement to participate (IRB# 2023-032). Participation was voluntary, and all data were anonymous. The final sample comprised eight in-service and two preservice teachers (nine females, one male).

Five participants identified as White, four Hispanic, and one as African American. Educational backgrounds included four with master's degrees, four with bachelor's degrees, and two preservice teachers. Eight teachers taught at public schools (six elementary, one middle, one secondary). Two worked as a paraprofessional and substitute teacher, respectively. Experience levels varied (three novice teachers, two with less than 5 years teaching, five with more than 10 years teaching). All participants completed the entire online PD.

Measures

Our qualitative design allowed in-depth examination of participants' learning experiences with descriptive statistics gleaned from surveys. Data included a survey, open-ended responses, and reflection.

Survey

An online survey included items related to demographic information, familiarity with AI, and perceptions related to AI use in education (Appendix A). Three items targeted frequency of using AI tools, duration of use, and familiarity with various AI tools.

Self-efficacy in using AI and integrating AI in teaching was surveyed using seven items adapted from Kiili et al. (2016). Three items involved teachers' self-efficacy toward AI use (Cronbach's α = .86); four items involved self-efficacy toward integrating AI in teaching (Cronbach's α = .93).

Participants' perceived ease of using AI and perceived value of AI-integrated tasks were also measured. The six items related to perceived ease of AI use were adapted from Davis (1989, p. 340; Cronbach's α = .94), who developed scales predicting intention and actual use based on perceived ease of use. We substituted AI for Chart-Master and edited phrases for novice learners based on Doll et al. (1998, p. 846). Reliability showed great consistency (Cronbach's α = .93).

The three items related to perceived value of AI-integrated tasks were adapted from Liu et al. (2022, p. 5; Cronbach's α = .88); we changed wording from "value of AI systems" to "value of integrating AI concepts in content areas" (Cronbach's α = .83). Three items about participants' behavioral intention to use AI in teaching were also from Liu et al. (2022; Cronbach's α = .91). Finally, the XML was measured using three items developed by Shin (2021, p. 9; Cronbach's α = .769) with acceptable reliability (Cronbach's α = .74).

Open-Ended Questions

Measures used before and after the PD session included random words and explanations of AI recommendation systems. For recording random words, a 30-second time limit was set to catch respondents' initial perceptions about AI use in education. A second question asked how social media advertising or product recommendation algorithms work. Finally, five reflection questions asked participants about (a) what they learned regarding AI, (b) what they learned regarding geometry, (c) lesson features affecting their learning, (d) how the PD differed from other geometry lessons, and (e) recommendations for changes. These post-reflection questions were analyzed using thematic analysis (Clarke & Braun, 2017).

Data Analysis

Descriptive statistics reported the mean, median, and standard deviation of the quantitative variables. Given the limited sample size, we analyzed descriptive values to detect pattern differences before and after the PD using visual representations.

For the qualitative data analysis of the open-ended responses and reflection questions, we used thematic analysis, adapting the steps outlined by Braun and Clarke (2006). First, we familiarized ourselves with the data through multiple readings to identify relevant statements and then independently identified keywords within statements, coding them as larger categories. Then we developed the themes based on the categorized themes.

For random words collected pre- and post-intervention, we conducted a qualitative sentiment analysis to examine changes in students' emotional expressions about their teacher's communication before and after the PD. Two researchers independently coded each random word response into four categories: positive emotions, negative emotions, factual information, or no response. This manual coding approach was selected because it allows for nuanced interpretation of brief, context-specific responses and is appropriate for smaller data sets (Feldman & Ungar, 2012; Zhou & Ye, 2023). The coding for sentiment categories met 100% agreement between the two researchers. The random words also underwent thematic analysis (Braun & Clarke, 2006) to identify themes based on the lexical meaning. Once themes were finalized, we reviewed the statements to confirm appropriate theme assignment. The process concluded when we reached 100% agreement on codes and themes.

Findings

Frequency of AI Use and Level of Familiarity

Participants rated their AI tool use and familiarity using a 5-point Likert scale (5 = *daily* to 1 = *not at all*). Four teachers (three in-service, one preservice) reported no AI tool use. Three used AI less than once monthly, two indicated monthly use (less than biweekly), and one reported weekly use. No participants reported daily use.

With 5.0 representing highest familiarity, the mean familiarity with AI tools fell below moderate (N = 10, M = 2.10, SD = 0.60). For everyday AI tools such as chatbots, product recommendations, Google Maps, and smart devices, familiarity was slightly higher (N = 10, M = 2.38, SD = 0.79). However, familiarity with educational AI tools (intelligent tutoring, personalized learning platforms, automated grading, learning aids for students with special needs) was lower (N = 10, M = 1.75, SD = 0.47), falling between *not familiar* and *slightly familiar*. The findings confirm that the PD was provided to participants who were novices regarding educational AI, ML algorithms, and ML classroom integration.

Self-Efficacy, Perception, Intention, and AI Explainability

The descriptive analysis of construct averages showed positive changes across all measured constructs related to AI integration in education (see appendices B and C). Self-efficacy improvements were substantial across both domains. Participants' general self-efficacy toward AI use increased from below-moderate (M = 3.13, SD = 1.037) to above-moderate levels (M = 3.71, SD = 0.603). Similarly, self-efficacy specifically related to integrating AI in teaching showed meaningful gains, rising from M = 3.31 (SD = 0.594) to M = 3.66 (SD = 0.597). The overall self-efficacy composite score increased from M = 3.23 to M = 3.68, indicating that participants moved from *uncertain* to *confident* in their AI-related capabilities.

Perceived ease of using AI increased from $M = 3.21$ ($SD = 0.756$) to $M = 3.54$ ($SD = 0.533$); perceived value of AI-integrated tasks changed from $M = 3.26$ ($SD = 1.006$) to $M = 3.71$ ($SD = 0.416$), showing a 13.8% improvement. Overall, perceptions increased from $M = 3.17$ to $M = 3.60$, suggesting participants developed more positive attitudes toward AI integration following the intervention.

Both behavioral intentions and understanding of AI explainability increased. Participants' intention to use AI in teaching increased from $M = 3.29$ ($SD = 0.722$) to $M = 3.63$ ($SD = 0.702$), indicating greater commitment to implementation. Additionally, participants' understanding of AI explainability increased from $M = 3.00$ ($SD = 0.504$) to $M = 3.37$ ($SD = 0.806$), the median rising from 3.00 to 3.50. The descriptive statistics showed consistent upward trends in all measures.

Open-Ended Responses

Pre and Post Random Words

Qualitative analysis of random words describing AI use in education during a 30-second time limit revealed profound shifts across multiple dimensions (Table 4). The sentiment analysis showed that participants tended to describe AI with a mixture or curiosity and apprehension before the PD, using words such as *intriguing* and *futuristic*. The terms from before PD also reflected uncertainty and concern. Following the PD, responses shifted noticeably toward more positive and enthusiastic descriptions including the words such as *fascinating*, *creative* and *fun*. The negative words that appeared before the PD, such as *scary*, *complex*, and *overwhelming*, were no longer stated after the PD.

A particularly notable change involved participants' understanding of AI applications. Before the PD, none of the responses referenced AI in terms of categorization or classification. However, after the PD, five stated application-focused terminology, including *categorize, classify,* and *sorting*.

Creative and enjoyable aspects of AI emerged as new themes post-intervention. Words related to creativity (e.g., *creative, creating*) appeared in the responses of four participants; fun associations also appeared in the responses of four participants.

Among the seven participants with matched pre-post responses, specific positive changes included: two participants shifting from negative to positive sentiment, one participant's negative word (*cheating*) becoming moderate (*interesting*), and one participant changing from factual information (*technology*) to positive reaction (*creating*).

The factual information category also demonstrated qualitative improvement. Initial responses were limited to basic technological terms, whereas after the PD responses reflected a broader and varied understanding of AI concepts and processes. This shift suggests the online PD successfully moved participants from an apprehensive or superficial understanding toward informed, application-oriented perspectives on AI in education.

Table 4

Qualitative Analysis of Pre and Post Random Words Used to Describe AI

Sentiment analysis	Before PD, *n* (%)	Pre words	After PD, *n* (%)	Post words
Positive emotions	2 (20)	intelligent, intriguing, futuristic	5 (50)	intelligent, fascinating, creative, fun, simple, smart, attractive, curious
Negative emotions	3 (30)	scary, complex, overwhelming, cheating	0 (0)	
Factual information	3 (30)	data, computer, robot, analyze, code, testing, model	4 (40)	robots, recognize, associate, categorize, hierarchy, procedure, order, data, model, classify, programming
No response	2 (20)		1 (10)	
Themes related to application	**Before PD, *n* (%)**	**Pre words**	**After PD, *n* (%)**	**Post words**
Categorization/ Classification	0 (0)		5 (50)	recognize, associate, hierarchy, procedure, order, classify, categorize
Themes related to creative/positivism	**Before PD, *n* (%)**	**Pre words**	**After PD, *n* (%)**	**Post words**
Create variations	0 (0)		4 (40)	creative
Fun references	0 (0)		4 (40)	fun

Note. One participant's response included multiple words.

Level of Understanding About the Algorithm Behind AI Systems

Thematic analysis revealed enhanced understanding of recommendation algorithms after the PD (Table 5). While most participants initially focused solely on similarity-based matching (70%), post-intervention responses showed greater sophistication. Post-intervention, along with similarity-based explanations decreasing to 40%, a new theme emerged, with 30% of participants recognizing that AI systems use "more information from data collected," including collaborative filtering and multiple data sources. Thus, post-intervention explanations were more detailed, suggesting the explainable feature matrix activities improved participants' comprehension of algorithmic decision-making processes.

Table 5

Level of Understanding of AI-Based Recommendation Systems

Theme	Pre *n*	Post *n*	Exemplary Responses
Similarity based on history	7	4	Pre - Suggest similar products - Recently purchased to recommend Post - Past information of things you have bought, and use that information to suggest (...)
More information from data collected	0	3	Post only - (...) It may also use information about what other people who bought that product have bought - Sees key elements in the item

Thematic Analysis of Reflection Questions After the PD Session

Five reflection questions underwent thematic analysis, leading to the themes identified in Table 6. Responses could include one or more themes. We agreed to report themes earning three counts or more; however, themes that earned fewer than three counts are also discussed due to their richness and importance related to the PD session.

Table 6

Themes From Reflection Questions and Selected Codes Used to Derive Themes

Question	Theme	*n*	Exemplary Responses
What did you learn from this lesson about AI? (n = 10)	Made AI explainable & learnable	7	- Great way of explaining AI, simple - Learning about AI is simpler and logical
	Effective classroom use	5	- Great way of learning similarities and differences
	Classification/ categorization	5	- Categorization, AI model creation, benefits students; AL/ML novices can understand, idea for great activity
What did you learn from this lesson about geometry? (n = 8)	Classification and more specific categorization	6	- Learned classification and connections between shapes, classifying features, and hierarchy

Question	Theme	*n*	Exemplary Responses
What activities and lesson features helped or hindered in this lesson? (*n* = 8)	Relationship between shapes	5	- See and understand these connections - Terminology in conjunction with the specific properties of the shapes
	Difficulties in content, technology, and time	4	- Content difficulties - The time frame was difficult to work
	Helpful classification activities	3	- Sorting helped understanding ML - Helped me learn quickly about AI
In what ways was this lesson different from previously experienced geometry lessons? (*n* = 8)	Effective AI integration	3	- Interesting combination between geometry and AI - Use familiar concept to learn completely new concept
	Different approach	3	- Different ways of teaching geometry
What would you like to learn more about or what changes do you want to make to this lesson? (*n* = 7)	Running AI models	3	- How that information (was put) into a computer to help the AI run - Iterating on our models to improve them and make them more accurate
	Other real-world examples of teaching AI	3	- Other real-life examples of teaching AI - Learn more about fun activities the students can compare with the real world

Three themes emerged about what participants learned about AI from the PD: (a) how explainable and learnable AI can be, (b) effective classroom usage, and (c) categorization/classification. Seven participants mentioned AI being "made explainable and learnable." Keywords used by participants included *simple(r)* and *logical*. Half of the participants said they learned how AI can be effectively used in the classroom. For instance, one mentioned using and teaching AI as well as showing students how AI works through everyday examples. Four participants used the words *categorize* or *classification* while one participant said AI is a great way to teach "ordering of shapes through similarities and differences." One participant mentioned AI being interactive, saying, "AI can be creative. It is interactive."

Regarding geometry learning, two themes emerged: (a) classification and more specific categorization, and (b) relationship between shapes. Six participants mentioned learning classification and more specific categorization. Five reported being better able to see and understand the connections between shapes. One participant noted that the geometry lesson could be an "easy tool to teach ML."

For features that helped or hindered learning, two themes emerged: (a) difficulties in content, technology, and time; and (b) helpful classification activities. One participant mentioned content difficulty, another reported technology challenges; two felt rushed by time constraints. Three participants stated that PD helped them understand ML and AI.

Two themes emerged regarding differences from traditional geometry lessons: (a) effective AI integration and (b) a different approach. Three participants mentioned "effective AI integration." For example, one participant said it was an "interesting combination between geometry and AI." Participants mentioned that the PD used different approaches by applying familiar concepts to learn something new and showing different ways to teach geometry. Finally, regarding suggested PD changes, two themes emerged: (a) running AI models and (b) other real-world examples. Participants wanted to run their created models as an iterative process and see executed models with debugging stages. They also requested more real-world examples and activities for integrating AI.

Discussion

The lesson design was beneficial and promising for online teacher education programs and teacher PD to enhance learning for K–12 students. Specifically, after the online PD, themes related to participants' self-efficacy with AI, self-efficacy about integrating AI in their teaching, perceived ease of using AI, and perceived value of AI-integrated tasks all showed an increase. Although the significance of the results could not be determined due to the small sample size, the improved mean score from pre- to post-AI surveys was supported by the results of qualitative analysis.

First, sentiment analysis using pre and post random words showed dramatic changes from negative to positive views. The words *categorizing, creative*, and *fun* appeared significantly in the post words. These positive shifts suggest that online PD can effectively transform educators' perceptions and build confidence in AI integration. Participants' reflections confirmed their positive perspective changes about AI in education.

The online delivery model proved particularly effective in creating an interactive learning environment where participants could engage with AI concepts through accessible, hands-on activities while maintaining the flexibility and scalability essential for distance learning contexts. The results also showed that the PD addressed AI, its applications and use in education, and increased interest in AI. Specifically, participants mentioned that AI became "learnable" through creating and interacting with the explainable feature matrix which mimics algorithmic decision-making. As one participant stated, the PD showed "effective ways of integrating ML with the geometric concept" and an "easy way to teach machine learning."

Improved understanding and integration intention were associated with elevated interest. Participants requested more classroom-feasible examples, online tools, such as the website Code.org (https://code.org), and ideas for implementing their created matrix in real-world settings. This qualitative finding aligned with survey responses showing mean value changes from before to after PD.

Our ontological approach differs from existing unplugged AI resources and PD programs in its transferability and adaptability across disciplines. Rather than fixed content, we provide a flexible framework centered on identifying features/characteristics, categorizing objects, and creating feature matrix—core processes applicable to any subject area, such as science (biological specimens), language arts (literary genres), social studies (historical events), or other domains. Further, the difficulty level is inherently adjustable: novices work with concrete features (color, size) and simple classifications, while advanced learners identify abstract features (significance, style) and create complex categorizations. This scalability addresses critical ODL challenges (Amin et al., 2025) related to educators having varying resources and prior knowledge. By making ML concepts tangible through familiar content with adjustable complexity, the approach enables equitable AI literacy development without requiring sophisticated technology—essential for diverse online learning environments.

The study also addresses a critical gap in the ODL and AI literacy research. While recent studies have examined online AI tools for teaching, learning, and teacher PD (Ding et al., 2024; Kohnke et al., 2025; Younis, 2024) or how AI technologies support online learning (Dogan et al., 2023), our study demonstrates how to effectively deliver conceptual AI literacy within online PD formats by embedding ML concepts within geometry instruction. The design preserves the real-time interaction and collaborative support identified as critical for effective ODL (Amin et al., 2025), while the geometry-based approach reduces dependence on advanced technological tools, making AI literacy feasible for educators with varying resources. In sum, the PD effectively delivered AI literacy online. The intervention helped participants realize effective ML integration in common subject areas through activities suitable for all K–12 settings.

Conclusion and Limitations

This study demonstrates that online PD can effectively deliver AI literacy training while addressing key ODL challenges. By integrating ML concepts through geometry rather than requiring specialized technology, this approach reduced the persistent accessibility barriers in distance learning (Amin et al., 2025). Generating an explainable feature matrix provided insights into machine-readable formats (Tiddi & Schlobach, 2022) applicable to AI and opportunities for designing activities that make ML explainable and accessible in any classroom setting. The findings inform future instructional ideas that allow a low floor and high ceiling approach (Blake-West & Bers, 2023) in AI education.

However, the small sample size limits reliability and generalizability. A replication study with larger samples can increase statistical power leading to more robust conclusions. Further, time constraints affected the study, with some participants reporting feeling rushed. Future studies can engage a diverse, larger population without time limits. Despite these limitations, the study yielded notable findings on AI use in education, providing future research directions that can be applied in diverse subject areas.

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Appendix A

Table A1

Survey Constructs and Items

Construct	Item	Source
Teachers' self-efficacy in the use of AI	1. I feel confident that I can create meaningful learning experiences for my students with the use of AI. 2. I feel confident that I can motivate my students to be actively involved in their learning with the use of AI. 3. I feel confident that I can develop my teaching with the use of AI.	Kiili et al. (2016), p. 11
Teachers' self-efficacy toward AI integration in their current or future teaching	1. I feel confident that I can integrate AI as a meaningful part of my teaching. 2. I feel confident that I can find new ways to apply AI in my teaching. 3. I feel confident that I can create meaningful learning experiences for my students with AI. 4. I feel confident that I can apply AI to enhance my students' learning.	Kiili et al. (2016), p. 11
Perceived ease of AI use	1. I find AI easy to learn. 2. I find it easy to get AI to do what I want it to do. 3. I find my interaction with AI is clear and understandable. 4. I find AI flexible to interact with. 5. I find AI easy for me to become skillful at using. 6. I find the AI easy to use.	Davis (1989), p. 340
Perceived value of AI integrated task	1. Considering the time and effort spent, I think new ways of integrating AI concepts in the content area are worthwhile. 2. Considering the possible losses, I think the new way of integrating AI concepts in the content area has a positive value. 3. Considering the possible disputes and troubles, I think the new way of integrating AI machine learning concepts in the content area is beneficial to me.	Liu et al. (2022), p. 5
Teachers' behavioral intention to integrate AI in teaching	1. I would like to use the AI systems available for teaching. 2. I would like to use more AI. functions/machine learning for teaching.	Liu et al. (2022), p. 5

Construct	Item	Source
	3. I plan to use the AI systems for more interactive teaching.	
AI explainability	1. I found that AI algorithms are easily understandable. 2. I think AI algorithms are explainable. 3. I can figure out the internal mechanics of a machine learning algorithm.	Shin (2021), p. 9

Appendix B

Table B1

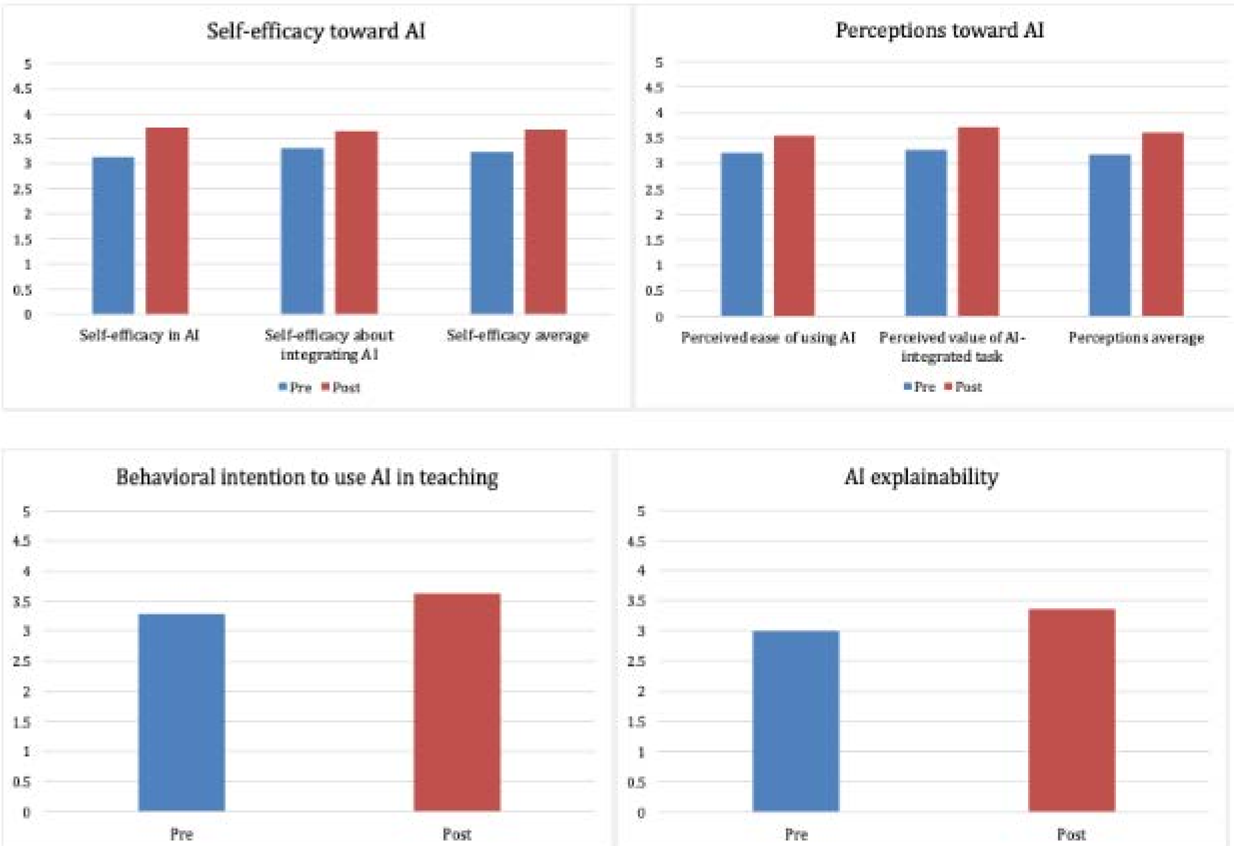
Descriptive Statistics for Each Study Construct

Construct	*M*	*Mdn*	*SD*	*SE*
Self-efficacy				
Self-efficacy in AI pre	3.13	3.33	1.037	0.367
Self-efficacy in AI post	3.71	3.83	0.603	0.213
Self-efficacy about integrating AI pre	3.31	3.00	0.594	0.210
Self-efficacy about integrating AI post	3.66	3.88	0.597	0.211
Self-efficacy average pre	3.23	3.21	0.666	0.235
Self-efficacy average post	3.68	3.79	0.555	0.196
Perceptions				
Perceived ease of using AI pre	3.21	3.33	0.756	0.267
Perceived ease of using AI post	3.54	3.50	0.533	0.188
Perceived value of AI-integrated task pre	3.26	3.33	1.006	0.356
Perceived value of AI integrated task post	3.71	3.67	0.416	0.147
Perceptions average pre	3.17	3.16	0.724	0.256
Perceptions average post	3.60	3.55	0.486	0.172
Behavioral Intention				
Behavioral intention to use AI in teaching pre	3.29	3.17	0.722	0.255
Behavioral intention to use AI in teaching post	3.63	3.67	0.702	0.248
Explainability of AI				
AI explainability pre	3.00	3.00	0.504	0.178
AI explainability post	3.37	3.50	0.806	0.285

Note. Sample size was consistent across constructs. $N = 8$.

Appendix C

Average Pre and Post Values of Study Constructs



Note. In all four charts, the y-axis represents the average value of items for each construct.

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Enhancing Human-Generative Artificial Intelligence Online Collaboration Outcomes: The Pivotal Function of Symbiotic Role Design

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Abstract

While generative artificial intelligence (GAI) has emerged as a vital support tool for collaborative learning, further exploration is required to achieve effective human-machine symbiosis in online collaborative processes. Grounded in symbiosis theory, our study developed a role-based intervention strategy to empower learners and their artificial intelligence (AI) partners through clearly defined responsibilities and collaborative interaction rules. In a quasi-experimental pretest-posttest design involving 58 graduate students, we employed statistical analyses and lag sequential analysis to evaluate the impact of the role intervention on online collaborative learning. The results indicated that the role design (a) significantly enhanced the quality of collaborative knowledge construction, (b) facilitated transitions among higher-order collaborative behaviors, and (c) improved perceived usefulness and ease of use of GAI among learners, although it also led to a moderate increase in collaborative cognitive load. These findings validated the core value of symbiosis theory-based role design for optimizing human-AI collaboration. Our study offered both a theoretical perspective on human-machine co-development and valuable insights for instructors to integrate AI tools and design more effective online collaborative learning activities.

Keywords: human-machine collaboration, human-AI collaboration, symbiosis theory, online collaborative learning, collaborative cognitive load

Introduction

Online collaborative learning has become a prominent instructional approach, enabling learners to connect across time and distance. It relies on interaction and dialogue among learners (de Araujo et al., 2025). Through shared thinking within a team, members exchange information and challenge each other's views, thereby building and deepening their collective knowledge together (Zabolotna et al., 2025). However, dialogue-based collaborative processes are not necessarily effective in online environments. The success of this approach depends on the background knowledge and depth of thought of each team member (Puntambekar et al., 2023). Consequently, overall team performance is often limited by the ceiling effect (Gui et al., 2025), driven by a few high-level members. Furthermore, weak supervision in online collaboration often hinders deeper cognitive processing (Saqr et al., 2024). Therefore, the issue of how to foster high-quality dialogue and overcome superficial collaboration in online collaborative learning remains an important research question.

Generative artificial intelligence (GAI), such as ChatGPT, is a large language model (LLM) with vast knowledge, strong reasoning skills, and the ability to offer multiple perspectives. It provides rich external cognitive resources for collaborative learning (Wei et al., 2025). Through natural language chat, GAI can join the knowledge-building process in real time (Pozdniakov et al., 2025). It helps teams overcome individual knowledge gaps (Hao et al., 2024) and creates a deeper blend of human and machine intelligence. This blend helps group thinking move toward higher-level innovation and reflection (Chen et al., 2023).

Although human-machine collaboration is seen as a key feature of future education, most research has focused on AI-individual learning or single conversational systems (S. Wang et al., 2024). There has been little work on integrating GAI into team collaboration processes or deeper group knowledge construction, particularly in online learning environments (S. Feng, 2025). In practice, GAI has often been limited to information retrieval and answer generation. This has led to two problematic patterns. There may be overreliance on AI, with learners passively accepting its output responses (Zhai et al., 2024) or treating it as a mere tool, ignoring its full potential (Adewale et al., 2024; Mai et al., 2024). Both patterns fail to integrate the strength of human beings and GAI, thereby missing opportunities to create synergy.

Establishing a general framework at the theory level would be necessary for effective human-AI online collaboration. Symbiosis theory offers guiding principles for cultivating a balanced, mutually beneficial relationship between humans and AI. Accordingly, this study introduced a symbiosis-driven role design strategy. We assigned distinct roles to learners and GAI, embedding GAI as an equal intelligent peer within online group discussions. Through empirical analysis of human-AI interaction patterns, the study provided a coherent theoretical framework and practical guidance for effective symbiotic learning environments.

Literature Review

Online Collaborative Learning Supported by GAI

GAI has shown great promise in educational technology, proven to significantly improve learning outcomes (Park & Doo, 2024). As an important social interaction tool, GAI can offer learners viewpoints they had not considered, helping them grow their knowledge and skills (Borge et al., 2024). It can also enhance problem-solving by providing diverse resources (Canonigo, 2024). Even more importantly, GAI can give customized feedback based on each learner's needs and preferences (Shahzad et al., 2025). Due to these capabilities, GAI is considered a new normal in learning (Duranti, 2023), opening new directions for research on its value in online collaborative learning.

Several studies have explored GAI in collaborative settings. For example, Gyasi et al. (2025) examined how the AI feedback assistant affected group knowledge construction. Naik et al. (2025) looked at how LLMs offer personalized reflection during collaborative learning. Zheng et al. (2024) found that AI-driven feedback and feedforward strategies significantly improve the quality of collaborative knowledge building. Although these studies commonly use GAI to support collaboration through feedback or scripted guidance, they largely construed GAI as a tool to assist learners rather than as a participant, adapting and developing within the collaborative process. Moreover, they have not provided a comprehensive evaluation of the various ways learners and GAI can collaborate within groups or of its overall collaborative effectiveness, particularly in online learning environments.

There have also been concerns about using GAI in online collaborative learning. Mena-Guacas et al. (2023) argued that relying too much on AI can weaken deep peer interactions and harm collaboration quality. Li et al. (2024) stressed that human-human and human-machine collaboration each have their own strengths and should be combined thoughtfully. Ji et al. (2025) called for future research to examine the full process of human-machine co-creation in educational settings, especially how knowledge, thinking, and behavior interact when GAI is involved. Therefore, designing effective human-GAI interaction mechanisms that use GAI as a partner while preserving and enhancing learner dialogue and higher-order thinking remains a critical challenge in achieving true human-AI symbiosis.

Human-AI Collaboration

Human-machine collaboration refers to how people and intelligent technologies interact and work together, aiming to use each other's strengths for mutual improvement (Li et al., 2025). The rise of GAI like ChatGPT has expanded this model from simple human-machine interaction to full human-AI collaboration. In such settings, GAI can play roles like teaching assistant (Barrot, 2024) or learning partner (Cress & Kimmerle, 2023), offering expert insights and creative suggestions.

However, most studies have focused on one-on-one human-AI interactions, overlooking group settings with multiple members (Shin et al., 2023). Online collaborative learning relies on social interaction and shared cognition among group members. There is still a lack of systematic, empirical research on how AI helps or hinders these group processes (Lee et al., 2025). This gap limits our understanding of true human-AI symbiotic collaboration.

In practice, human-AI interaction has often exhibited two extreme patterns. The first is commensalism, when technology intrudes too much and suppresses human agency. Learners depend more and more on AI (Zhang et al., 2024). Human input is reduced to data for AI training (Karimova et al., 2025). The second pattern is parasitism, in which technology intervenes too deeply and weakens higher-order human skills (Morales-García et al., 2024). Both patterns fail to leverage the unique strengths of humans and AI.

A solid theoretical framework would weaken or break these negative patterns. Symbiosis theory outlines the key elements of harmonious coexistence and provides clear design principles. By turning these elements into concrete mechanisms, such as role division and interaction boundaries, we can transcend commensal and parasitic modes and build truly synergistic human-machine collaboration. Unlike self-regulated learning, centered on individual regulation (Du, 2025), or cognitive load theory, concerned with task-related cognitive demands (Janssen & Kirschner, 2020), symbiosis theory focuses on how interacting agents co-develop through sustained collaboration (Mackay, 2024). Furthermore, symbiosis theory can be viewed as an extension of distributed cognition theory, applied to cognition distributed across humans and GAI (Hollan et al., 2000). Consequently, we designed a human-GAI collaborative role strategy based on symbiosis theory and evaluated its effectiveness through an experimental pretest-posttest study.

Symbiosis Theory and Role Design Strategy

Symbiosis was originally used to describe how different organisms depend on each other in an ecosystem. In recent years, social scientists have applied this idea to other fields, coining terms like symbiotic learning (C.-L. Wang, 2019) and human-machine symbiosis (Kong et al., 2025). Among symbiotic relationships, mutualism—wherein each partner provides resources or functions the other needs—is the most stable form. It creates a continuous, positive feedback loop (Becks et al., 2025).

Applying human-machine symbiosis to GAI-supported online collaborative learning meant moving beyond the one-way AI-as-tool model. Instead, GAI and learners were treated as equal partners with complementary functions and dynamic interactions (Cress & Kimmerle, 2023; Cukurova, 2025). To turn the principles of mutualism into practical collaboration mechanisms, we used roles as the core mediator, with two main features.

First, using role mapping, we defined clear responsibilities and activity boundaries for both human participants and GAI. This ensured each role complemented the other and maintained a balanced power dynamic throughout the collaboration. The second feature involved interaction rules. We created rules for rotating roles that translated mutual dependence and functional complementarity into concrete, executable scripts. These rules guided when and how each role should step in during the collaboration process.

The following sections outline several role types and their interaction processes based on this framework. We then evaluate how effectively they enabled human-machine mutualism.

Research Questions

Guided by symbiosis theory, we assigned clear roles to both learners and GAI in groups, integrating GAI as an equal intelligent peer in the online discussion. We then examined the effects of this role strategy by assessing knowledge construction, cognitive interaction, and learners' perceptions. Our goal was to improve human-GAI interaction patterns, boost the quality of collaborative knowledge building, and offer a replicable framework for efficient, symbiotic human-GAI collaboration. Our study was guided by the following research questions.

1. How does role design based on symbiosis theory affect knowledge construction in online collaborative learning?

2. How does role design based on symbiosis theory affect cognitive interaction in online collaborative learning?

3. How does role design based on symbiosis theory affect learners' perceptions and experiences of online collaboration?

Method

Participants

We recruited a convenience sample of 59 students (male = 7, female = 52; age M = 22.97 years, SD = 0.93) majoring in educational technology at a public university in China. The study took place in their graduate course *Learning Analytics Methods*, which consisted of eight modules. Our intervention was implemented during the last two modules, each of which required learners to work together on a discussion task. Before the course began, we formed 16 heterogeneous groups, balancing gender and matching students based on their prior course experience and collaboration skills. All participants provided written informed consent and were assured that their course grades would not be affected and that they could withdraw at any time. However, one participant's data was not submitted, meaning our analyses included data from 58 students.

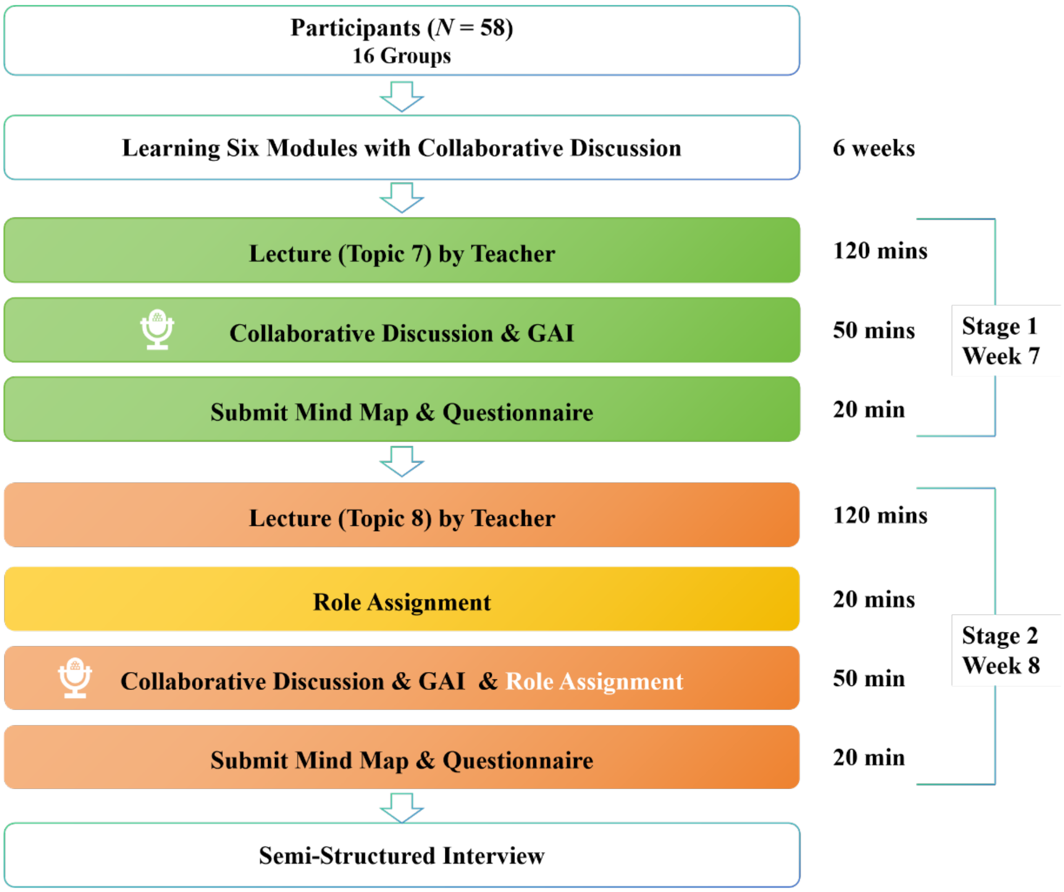
Research Design

The study employed a pretest-posttest experimental design. The procedure is shown in Figure 1. Before the experiment, learners had already completed six weeks of collaborative learning, which ensured they were familiar with their group members and had comparable teamwork experience. The experiment comprised two stages, pre- and post-intervention, with the same procedure for each. The two stages were separated by a one-week interval. In each stage, the instructor first delivered a lecture on the module topic. Next, each group received an open-ended discussion task related to the topic of the lecture. The groups used an online platform (i.e., Tencent Meeting) for verbal collaborative discussions. Afterwards, the groups submitted their mind maps and completed related questionnaires.

The only difference between the two stages was the presence of the role interventions. In stage 1, groups discussed the task without any role assignment, although they could still use the GAI tool (i.e., Yuanbao), an advanced AI assistant developed by DeepSeek. In stage 2, before the discussion, the instructor clearly explained the role assignment and rotation rules. With the support of teaching assistants, participants then completed a 20-minute preparatory discussion to understand and get comfortable with the strategy before moving on to the formal task. However, during formal discussions, the teaching assistants did not intervene; instead, each group collaborated with Yuanbao, which was configured with the role-design strategy. With the participants' consent, both 50-minute discussion stages were recorded via Tencent Meeting. Finally, we conducted follow-up interviews with some participants.

Figure 1

Diagram of Research Process



Role Design

To ensure GAI was effectively embedded in collaborative learning and enabled efficient human-machine collaboration, this study proposed a role intervention strategy based on the theory of symbiosis. The strategy comprised three components: role assignment, role rotation, and GAI role implementation.

First, in role assignment, to ensure functional complementarity between learners and GAI as symbiotic units, we designed three roles—moderator, analyst, and arguer—based on previous studies (Cheng et al., 2014; Q. Feng et al., 2025). Table 1 shows the responsibilities for each role. The moderator was a fixed role, always performed by a learner. Analyst and arguer were flexible roles performed by either learners or GAI.

Table 1

Role Design Based on Symbiosis Theory

Role	Function description	Example prompts
Moderator	Monitor discussion time and guide the group through the process	Let's move on to the next question. Does anyone have different views or anything to add?
Analyst	Raise new questions or ideas based on the discussion topic	My perspective on this is . . . I think that . . .
Arguer	Support or challenge peers' ideas; offer reasoned arguments or alternative viewpoints	I'd like to add . . . I feel there's another angle . . . You might have overlooked . . .

Second, for role rotation, we designed a dynamic mechanism to ensure mutual benefit rather than subordination. This mechanism focused on switching between analyst and arguer roles. First, the analyst proposed an initial argument, then the arguer(s) provided supportive or opposing arguments. Once all group members completed their contributions, the analyst became the arguer, and an arguer became the analyst. This process was repeated until the group reached a consensus. The moderator also took on either the analyst or arguer role as needed. GAI participated as an equal partner. When a human analyst proposed a point, GAI usually acted as the arguer, offering feedback manifested as one group member interacting with the GAI and sharing feedback within the group. If the discussion stalled, GAI switched to the analyst role and introduced a new perspective, while all human members took on the arguer role to debate it together.

Finally, the third phase of role design focused on allocating clear roles to GAI and enabling it to collaborate with learners. We used the Yuanbao GAI tool, and assigned it two roles, namely analyst and arguer, through predefined prompts (see Figure 2). When the system detected that learners needed new ideas, GAI switched to the analyst role and asked open-ended questions or suggested new perspectives. When learners evaluated a viewpoint, GAI switched to the arguer and offered support or counterarguments with reasoning. These role prompts let GAI flexibly change roles based on the discussion flow. Yuanbao's outputs were shared immediately with all group members to support further debate and discussion. These role assignments and rotations were explained by the instructor before the discussion and supported by collaboration scripts during the group work.

Figure 2

GAI Role (YuanBao) Design Interface Description

Note. Interface screenshot from Yuanbao (https://yuanqi.tencent.com).

Instruments and Measures

Our research questions, along with their data sources and analysis methods, are listed in Table 2, followed by detailed explanations for each data source.

Table 2

Research Questions, Data Sources, and Analysis Methods

Research question	Data source	Analysis method
Does role design affect the outcomes of collaborative knowledge construction?	Mind-map artifact scores	Wilcoxon signed-rank test
Does role design affect the development of collaborative interaction process?	Recording from collaborative discussion process	Lag sequential analysis
Does role design impact learners' perceptions of collaboration?	Collaborative cognitive load questionnaire perceived usefulness and ease of use questionnaire Semi-structured interviews	Paired-samples *t*-test Wilcoxon signed-rank test Content analysis

Evaluating Mind-Map Artifacts

We systematically evaluated each group's mind maps before and after the intervention to assess changes in collaborative knowledge construction. Our evaluation used two dimensions, namely structure and content (Veiga et al., 2025). For structure, we measured the number of nodes, hierarchy depth, and branching breadth to quantify the map's organization. For content, we applied the SOLO taxonomy (Leung, 2000) to rate element completeness, complexity of concept relationships, and overall system level on a scale from 1 (pre-structural) to 5 (extended abstract; Lenski et al., 2022). Details are shown in Table 3.

Table 3

Evaluation Criteria for Mind Map Artifacts

Dimension	Indicator	Description
Structural	Number of nodes	Number of nodes in the mind map
	Hierarchy	Hierarchy depth of the mind map
	Branching	Branching breadth of the mind map
Content	Pre-structural	Key topic elements missing; minimal valid information
	Uni-structural	Some elements present; relationships are simple and singular
	Multi-structural	Most elements present; structure is reasonable, but not integrated
	Relational	All elements present; structure complete with diverse connections
	Extended abstract	Elements are comprehensive; structure is systematic and highly complex

Coding Framework for Collaborative Discussion Process

We analyzed the collaboration process using a coding framework based on Gunawardena et al.'s interaction analysis model (Zabolotna et al., 2025) and research on regulated learning (Järvelä & Hadwin, 2013; Zhang et al., 2021). Our framework included four dimensions across 11 specific codes. Details are shown in Table 4.

To ensure coding quality, two team members independently and blindly coded the first group's discussion after becoming thoroughly familiar with the rules. Their interrater agreement was k = 0.73, indicating good reliability. Once this reliability was confirmed, the researchers used the same procedure to code all remaining discussion data.

Table 4

Cognitive Coding Framework for the Online Collaborative Learning Process

Dimension	Indicator	Description	Code
Shared cognition	Questioning	Raising doubts, asking about the topic, or proposing issues to be discussed	Que
	Clarifying	Explaining one's ideas, answering others' questions, or stating viewpoints	Clr
Divergent cognition	Conflicting	Expressing disagreement, presenting views that challenge existing ones	Cft
	Supporting	Directly or indirectly agreeing with others, providing positive feedback	Sup
	Defending	Restating one's position, offering in-depth explanations or evidence	Def
Elevating cognition	Consensus	Reaching a shared understanding or agreement during discussion	Cns

	Evaluating	Judging the relevance or value of ideas presented	Evl
Regulatory cognition	Task understanding	Asking or answering questions about the task's content, purpose, or procedures	TU
	Planning and goal setting	Discussing division of labor, scheduling, and task sequencing	Pla
	Monitoring and reflection	Tracking progress, evaluating timelines, or reflecting on collaboration methods	M/F
Irrelevant	Irrelevant	Utterances or behaviors not related to collaborative cognition	IR

Collaborative Perception Questionnaire

To assess how learners perceived cognitive load during online collaborative discussions, we used the collaborative cognitive load scale by Ouyang et al. (2022). This six-item questionnaire employs a five-point Likert scale and has demonstrated strong reliability and validity (Cronbach's α = 0.833; KMO = 0.806).

We also measured changes in how learners perceived usefulness and ease of use of GAI before and after the intervention. We adapted an eight-item scale from Muñoz-Carril et al. (2021), modifying items to fit our context (e.g., I believe using GAI during discussion activities helps improve online collaborative learning outcomes). Half of the items assessed perceived usefulness, and half assessed perceived ease of use, all on a five-point Likert scale. The adapted scale showed good reliability and validity (Cronbach's α = 0.910 for usefulness and 0.831 for ease of use; KMO = 0.787 and 0.796, respectively).

Interview Design

After the discussion ended, follow-up interviews were conducted with participants from two groups to explore their subjective experiences of the intervention and to help interpret the survey and process data. The interviews were based on one main question. Compared to using GAI directly last week, how did assigning roles affect your group's online collaboration, and how did you feel about it? During each interview, we asked additional questions as needed to clarify and deepen the learners' responses.

Results

Collaborative Knowledge Construction Analysis

We compared pre- and post-intervention mind maps using paired-samples Wilcoxon signed-rank tests (see Table 5). In the structural dimension, there were no significant changes in the number of nodes ($z = 0.944$, $p = 0.345$) or branches ($z = 1.532$, $p = 0.125$), indicating that the role intervention did not alter students' overall coverage of key points or branching logic. However, hierarchy depth decreased significantly ($z = 2.511$, $p = 0.012$), suggesting that, after the intervention, students focused more on core concepts and primary relationships by reducing secondary levels, resulting in a more streamlined map structure. In the content dimension, the overall score increased significantly ($z = 3.771$, $p < 0.001$), demonstrating that role design effectively enhanced the completeness of elements and the logical organization of relationships in the mind maps.

Table 5

Wilcoxon Signed-Rank Test Results for Concept Map Scores

Dimension	Indicator	Pretest *M*	Pretest *SD*	Posttest *M*	Posttest *SD*	*z*	*p*
Structural	Node count	44.35	11.70	40	15.63	0.944	0.345
	Level	4.82	0.64	4.06	0.66	2.511	0.012*
	Branch count	4.00	0.94	3.47	1.01	1.532	0.125
Content	Score	3.65	0.50	4.59	0.51	3.771	0.000*

Note. * $p < 0.05$.

Collaborative Behavior Analysis

We used GSEQ 5.1 to perform lag sequential analysis on the coded discussion data before and after the role intervention. Figures 3 and 4 show the results: each circle represents a cognitive code, and arrows between circles indicate significant transitions (adjusted residual $z > 1.96$). For example, the transition Que → Clr means that a question is often followed by clarification. Node colors represent different encoding dimensions, for example, with blue representing shared cognition.

First, we examined the coding nodes. After the intervention, we observed a new self-transition for the evaluate code, an indication of high-level cognitive activity that did not appear before. This suggested that the role design successfully triggered more advanced thinking during collaboration.

Next, we analyzed the behavior paths. Before the intervention, most groups followed a simple loop centered on questioning, typically moving from task understanding to questioning and then to clarification. This pattern aligned with their pretest mind maps, which were structurally broad but scored lower for content depth. After introducing roles, discussions shifted clearly from shared cognition toward divergent cognition; conflicts among peers sparked a flow from questioning and clarification to defending and supporting ideas. Although the structural metrics of the mind maps did not change significantly, their content became more systematic and innovative, reflecting the added high-level thinking.

Finally, we looked at key path changes. The previously significant path from irrelevant to task understanding disappeared post-intervention, showing that role assignments effectively steered learners away from off-topic remarks back to the task. We also observed an increase in planning and monitoring behaviors, suggesting that the division of roles fostered regulatory cognition, resulting in more structured interaction patterns and stronger self-regulation within online collaborative groups.

Figure 3

Pre-Intervention Behavioral Sequence Transition Diagram

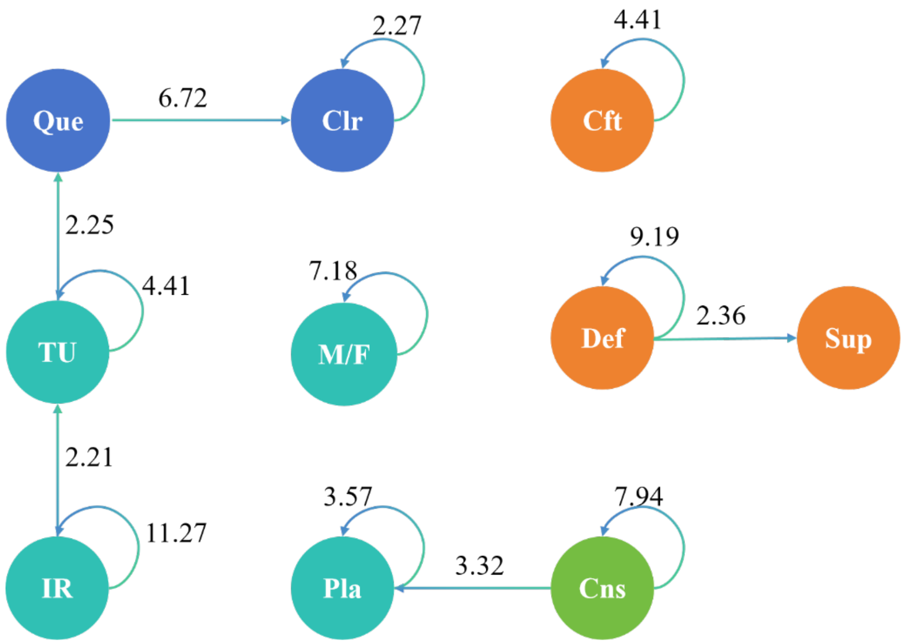
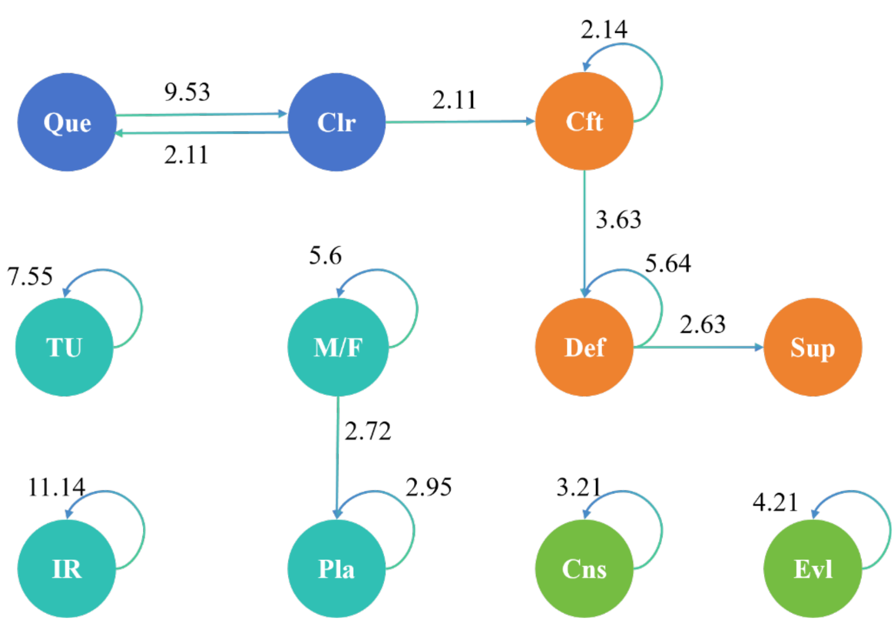


Figure 4

Post-Intervention Behavioral Sequence Transition Diagram



Collaborative Perception Analysis

The collaborative cognitive load data met the assumption of normality (Shapiro-Wilk test, p = 0.084). Therefore, we used a paired-samples t-test to compare perceived cognitive load before and after the intervention (see Table 6). The results showed that posttest cognitive load was significantly higher than pretest load (p = 0.023), indicating that the role-based intervention increased learners' cognitive load during online group collaboration.

Table 6

Paired-Samples t-Test Results for Collaborative Cognitive Load

Dimension	Pretest *M*	Pretest *SD*	Posttest *M*	Posttest *SD*	*t*	*p*	Cohen's *d*
Collaborative cognitive load	4.02	0.50	4.19	0.44	-2.332	0.023*	0.306

Note. *p < 0.05.

We compared learners' pre- and post-intervention perceived usefulness and ease of use using Wilcoxon signed-rank tests (see Table 7). The mean perceived usefulness rose from 4.16 to 4.31 (z = 1.809, p = 0.070), showing an upward trend that did not reach statistical significance. In contrast, mean perceived ease of use increased significantly from 4.02 to 4.28 (z = 2.885, p = 0.004). This suggested that after the intervention, learners not only appreciated the tool's functionality but also found it noticeably easier to operate.

Table 7

Wilcoxon Signed-Rank Test Results for Perceived Usefulness and Ease of Use

Dimension	Pretest *M*	Pretest *SD*	Posttest *M*	Posttest *SD*	*z*	*p*
Perceived usefulness	4.16	0.51	4.31	0.49	1.809	0.07
Perceived ease of use	4.02	0.52	4.28	0.54	2.885	0.004*

Note. *p < 0.05.

Discussion

Collaborative Knowledge Construction

The findings of this study demonstrated that role intervention based on symbiosis theory markedly enhanced collaborative knowledge construction. Specifically, restructuring the structure of mind maps enhanced the logical coherence of content, thereby elevating the expressive quality of collaborative outcomes. This indicated that role design prompted groups to shift from simply completing tasks to engaging in more in-depth knowledge construction (Zhu et al., 2023). In line with Gyasi et al. (2025), our results confirmed that embedding AI partners into online group work can support deeper knowledge construction.

Moreover, the results of collaborative knowledge construction corroborated the changes in cognitive behavior; in post-intervention discussions, high-level codes (e.g., evaluation) and transitions such as conflict → defense increased substantially. This indicated that clear role assignments provided learners with guided pathways for reflection and integration (P. Wang et al., 2024) and enabled them to actively process and deepen incoming AI-generated input. As a result, cognitive flows became more efficient, and human and machine intelligences complemented each other more effectively.

In summary, this study empirically validated the pivotal role of structured human-AI role designs in promoting knowledge construction and offered concrete guidance for future role and interaction designs in human-AI symbiotic systems. Furthermore, this strategy can be applied across disciplines and could help teams with varying levels of collaborative ability and knowledge to achieve better collaborative outcomes.

Collaborative Process

The results indicated that role design based on symbiosis theory significantly optimized online collaborative behaviors. By assigning clear roles to learners and AI partners, we observed more frequent sequences of higher-order cognitive actions, such as evaluation, during online discussions. This shift from simple questioning to deeper analysis and critique (Peltoniemi et al., 2025) demonstrated how role allocation energized group thinking.

Lag sequential analysis further revealed a change in cognitive linkage paths. Pre-intervention interactions centered on questioning → clarifying, whereas post-intervention discussions pivoted around conflict → defending. In this new pattern, learners reduced off-topic or repetitive queries, engaging more often in reflection and defense, which indicated that role design encouraged learners to employ metacognitive strategies (Faza & Lestari, 2025). Related research has found that role design fostered more positive interpersonal beliefs and a greater sense of psychological safety among learners (Ching & Hsu, 2016), thereby creating a supportive environment that accounted for the observed behavioral changes. This outcome provided a viable approach for online learning, particularly in asynchronous contexts, by clarifying the division of labor and responsibilities between humans and AI, as well as reducing the risk of superficial interactions associated with weak supervision.

Moreover, these results highlighted the vital role of structured role design in multi-actor human-AI settings, where the strengths of humans and machines are balanced to achieve functional complementarity (Karimova et al., 2025). Learners exercised agency within their assigned roles while AI partners, acting as analysts or arguers, provided timely and diverse insights (Shahzad et al., 2025). This role rotation transcended the limitations of human-only interaction, enabling a one-plus-one-is-greater-than-two synergy among learners and GAI, and ultimately led to increased collaborative participation and enhanced collaborative construction outcomes. These findings provided empirical evidence to support the design of human-AI symbiotic systems that actively shape and renew collaborative cognitive processes.

Collaborative Perception

The results indicated that role-based intervention increased learners' perceived cognitive load. This finding was consistent with previous research (Strauß et al., 2025). Under the role-division mechanism, students had to switch perspectives and deploy different cognitive strategies to fulfill each role, which raised their subjective effort. At the same time, quantitative analyses showed that role design improved learners' perceived usefulness and ease of use of the GAI. In other words, despite the extra mental effort required, students felt that role assignments made the GAI partner's contributions better aligned with their collaborative needs, enhancing the tool's overall return on investment.

This experience emerged clearly in follow-up interviews. As one participant noted, "assigning roles helped us know exactly when to call on the AI instead of relying on its answers from the start." Another said that "the division of labor made the process a bit more complex, but it also made us think more carefully about who should lead each step." These comments suggested that while role design sharpened focus and streamlined discussions, it inevitably added cognitive overhead for planning and switching roles.

Overall, role intervention played a dual role in human-AI symbiotic collaboration. It clarified responsibilities to make interactions more structured and effective, yet it required that learners invest extra cognitive effort to manage role transitions and integrate information. Nevertheless, given the clear improvements in both collaboration outcomes and cognitive depth, the increase in cognitive load appeared both acceptable and worthwhile. It offered learners a clearer collaboration framework and provided empirical guidance for balancing efficiency and mental effort in future human-AI symbiotic systems.

Conclusions and Implications

This study designed human-machine interaction roles for collaborative learning based on symbiosis theory and tested them in authentic online collaborative environments. The findings have important theoretical and practical implications. Theoretically, we introduced a role strategy, using role division to operationalize symbiosis theory in specific human-machine collaboration scenarios, thereby extending its application in online collaborative environments. Practically, our study provides teachers with practical guidance on effectively integrating GAI into online collaborative learning and designing efficient online learning activities. Assigning roles and responsibilities can motivate learners and prevent blind reliance on AI, while making full use of AI's supportive functions to encourage more in-depth discussion. Our research expands upon the practical exploration of GAI within online collaborative learning contexts. Future work can refine the role-switching process to balance collaboration efficiency with cognitive load, creating a more effective and sustainable human-machine symbiotic collaboration model.

Limitations and Future Directions

This study had several limitations. First, despite efforts to control for prior collaboration experience, the pretest-posttest design may have introduced practice effects, and the limited sample size and single cultural context may have limited the generalizability of the results. Future research should conduct comparative experiments across disciplines and cultural contexts to examine how symbiotic human-GAI collaboration varies across settings, thereby testing the robustness of our findings and broadening their applicability. Second, embedding GAI through role assignments improved knowledge construction but also increased learners' cognitive load. Future research could explore multimodal interactions to lower role-switching costs and make collaboration more seamless. Finally, this study examined human-AI collaboration involving only a single GAI. Future research could explore human-machine interaction and collaborative design in multi-agent cooperative scenarios.

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Exploring the Potential of Generative AI for Academic Support in Open and Distance Learning: A Case Study of Learner Experiences

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Abstract

This exploratory case study provides an in-depth analysis of the potential of generative artificial intelligence (GenAI) to enhance academic support in open and distance learning (ODL) systems. The study examined learner experiences with a GenAI-based academic support application in an online web publishing course over a semester, focusing on two phases: free use and structured use. Data were collected through semi-structured interviews and dialogue transcripts from 10 distance learners. Findings highlighted both continuity and transformation in learner practices. In both phases, GenAI was valued for time-saving and accurate responses aligned with course materials. Structured tasks in phase 2 encouraged more purposeful engagement, including systematic self-assessment and information verification. Despite technical challenges such as device incompatibility and occasional hallucinations, learners expressed motivation, satisfaction, and a demand for institutional integration. The results, while preliminary, suggest that GenAI-based academic support holds strong potential for broader implementation in large-scale open universities, offering a pathway to balancing quality, access, and cost in addressing the enduring challenges of mass higher education.

Keywords: generative AI, academic support, open and distance learning, learner experiences

Introduction

Open and distance learning (ODL) has expanded significantly worldwide, serving millions of learners who require flexible access to education. While ODL provides opportunities for inclusivity and lifelong learning, it also presents persistent challenges in providing timely, personalized, and scalable academic support (Mejeh & Rehm, 2024). In large-scale open universities, where hundreds of thousands of learners are enrolled, limited opportunities for direct interaction with instructors often contribute to transactional distance and feelings of isolation (Moore & Kearsley, 2012). Learners frequently express the need for on-demand, interactive assistance that goes beyond prepared course materials and limited synchronous sessions. Beyond Moore and Kearsley's (2012) foundational work, transactional distance persists as a critical and evolving challenge in modern ODL environments. Recent literature has confirmed that bridging this psychological gap remains essential for fostering learner engagement (Gökoğlu et al., 2024) and effectively integrating generative artificial intelligence (GenAI) technologies (Karataş & Yüce, 2024).

Recent advances in GenAI have raised the possibility of addressing these challenges by providing learners with continuous, responsive, and adaptive academic support (Rincon-Flores et al., 2024). Tools such as ChatGPT can simulate conversational interaction, supply explanations, and scaffold learning processes. However, despite the growing enthusiasm surrounding GenAI in education, empirical research on its role in academic support within ODL contexts remains limited, particularly in large-scale open universities. Most existing studies have examined the technical features of GenAI or its experimental classroom applications (Li et al., 2025), leaving a gap in understanding its potential for academic support and its role in shaping learners' experiences in ODL environments.

This study contributes to filling that gap by exploring how a GenAI-based academic support application was experienced by learners in a web publishing course at a large-scale open university in Türkiye. The research was preliminary and exploratory in nature, involving a small group of volunteer learners, and the findings are therefore context-specific rather than generalizable. By examining how learners interacted with GenAI over the course of one semester, this study offers preliminary insights into both its potential and its limitations as a tool for academic support in ODL.

Literature Review

Recent years have witnessed a rapid growth in studies examining GenAI and chatbot-based support in higher education. Research has indicated that AI-driven systems have been implemented to address learner and staff needs, demonstrating both opportunities and limitations (Arun et al., 2019; Choque-Diaz et al., 2018; Hien et al., 2018; Murad et al., 2019). Collectively, these studies have emphasized the necessity of evaluating technological advancements through both pedagogical and ethical lenses.

For instance, Lappalainen and Narayanan (2023) developed *Aisha*, a ChatGPT-API-based chatbot designed to provide library services outside of working hours. Their findings demonstrated that GenAI could offer fast and effective support to learners and faculty alike. Similarly, Hmoud et al. (2024) explored the use of ChatGPT in higher education and found that it enhanced motivation and improved learners' communication experiences. Comparable studies have highlighted ChatGPT's potential as an alternative to traditional chatbot systems in libraries and academic support units.

The ODL literature has further suggested that GenAI can mitigate transactional distance and enhance social presence. Kandemir and Kılıç Çakmak (2024) showed that reduced dialogue in online course design leads to decreased academic achievement, while Gökoğlu et al. (2024) demonstrated complex relationships among social presence, transactional distance, and learner engagement. These findings suggest that GenAI-enabled support systems—by offering continuous and responsive dialogue—could help reduce psychological distance and strengthen engagement. Such benefits would be particularly critical in mega-scale open universities, where high student–teacher ratios make it challenging to sustain personalized interaction.

Möller et al. (2024) tested the AI-powered teaching assistant Syntea (https://www.iu.org/digital-tools/syntea/) with hundreds of distance learning students across more than 40 courses at the IU International University of Applied Sciences. Their analysis provided the first evidence that GenAI can substantially increase the speed of learning, showing that the use of Syntea reduced study time by about 27% on average in the third month after its release. In parallel, studies focusing on feedback have further highlighted GenAI's potential. Zhan et al. (2025) illustrated how GenAI can automate feedback loops, thereby increasing learner participation. Similarly, Bhullar et al. (2024) identified that GenAI applications in higher education primarily focus on learner engagement and individualized guidance. Park and Doo (2024) similarly reported that, across the blended learning studies they reviewed, AI applications were used mainly in the online asynchronous individual learning component, with limited attention to AI-supported designs that connect online activities with classroom-based offline learning.

Beyond service-oriented use cases, empirical studies have increasingly documented the domain-specific learning affordances of GenAI. In AI-assisted language learning, ChatGPT-supported writing activities have been associated with improvements in EFL students' academic writing performance and motivation (Song & Song, 2023). In skills-oriented contexts, access to ChatGPT has been linked to better adherence to coding standards and lower code complexity in novice programmers' submissions, as indicated by static code analysis metrics (Haindl & Weinberger, 2024). Experimental evidence has also suggested that ChatGPT can enhance university students' creative problem-solving outputs in terms of quality-related indicators (Urban et al., 2024). At a broader institutional level, early higher education scholarship has cautioned that AI may reshape teaching roles and influence core practices of content delivery, control, and assessment, with implications for governance (Popenici & Kerr, 2017). Finally, reliability remains a persistent concern: analyses of "AI hallucination" have demonstrated that distorted information in AI-generated content can negatively affect users and therefore requires systematic identification and management when GenAI is deployed in educational settings (Sun et al., 2024).

Ethical concerns constitute another important theme in the emerging GenAI literature. Davar et al. (2025) drew attention to privacy risks and the danger of uncontrolled reliance, while also highlighting the potential of AI chatbots to provide personalized support at scale. Kasneci et al. (2023) emphasized risks related to the opacity of large language models and pointed to the dangers of biased outputs. Strzelecki (2023) showed that learners' trust, perceived fairness, and ethical judgements strongly shape their acceptance of GenAI tools. In large-scale ODL systems, these issues are exacerbated by the volume and sensitivity of learner data and by structural power asymmetries between institutions and students, making questions of data protection, transparency, and accountability particularly salient. From a critical perspective, Wieczorek (2025) warned that AI will not democratize education by default, as existing inequalities may be reproduced or intensified in the absence of institutional safeguards. Overall, these debates indicate that GenAI-based academic support in ODL should be embedded within robust ethical frameworks that explicitly address privacy, bias, overreliance, and transparency, rather than being treated as a neutral technological add-on.

A holistic pedagogical lens is therefore essential for conceptualizing academic support as an integrated process that spans instructional design, learner agency, and inclusive participation. From a pedagogical perspective, Shoufan (2023) noted that learners often struggle with prompt engineering, underscoring the need for explicit *prompt pedagogy* in instructional design. Furthermore, Koçdar et al. (2024) emphasized the necessity of universal design principles to ensure accessibility for learners with disabilities.

Overall, while prior studies provide valuable insights into the role of GenAI in higher education, most have examined general use cases or service-oriented applications. Few have investigated how GenAI-based academic support systems, trained for specific courses or contexts, affect learner experiences in ODL environments (Möller et al., 2024). This gap is especially significant in mega-scale open universities, where delivering scalable yet personalized academic support remains one of the greatest challenges. This study addresses that gap by exploring the potential and challenges of implementing GenAI as a transformative academic support mechanism for open and distance learners.

Conceptual and Theoretical Framework

This study was grounded in a synthesis of established theories that illuminate how GenAI can influence learning in ODL contexts: transactional distance, social presence, Bloom's taxonomy, and Deweyan reflection. Together, these theories are unified under the Community of Inquiry (CoI) framework (Garrison et al., 1999), which integrates teaching, social, and cognitive presence.

Transactional Distance and Social Presence

Moore's (1989) theory of transactional distance highlighted the psychological and communication gaps that arise in distance education, often due to reduced dialogue and rigid structures. GenAI, by offering 24/7 availability and responsive interaction, has the potential to mitigate this gap by creating new forms of dialogue. Complementing this, social presence theory (Gunawardena & Zittle, 1997; Rourke et al., 1999) emphasizes the learner's ability to perceive others as *real* in online environments. GenAI systems, by embedding empathetic and reflective responses, can intentionally foster social presence and help reduce feelings of isolation.

Bloom's Taxonomy

Bloom's taxonomy (Bloom, 1956; Anderson & Krathwohl, 2001) classified cognitive processes from recall to creation. GenAI can accelerate lower-level tasks, such as recalling and summarizing, while also requiring learners to engage in new forms of higher-order thinking. Skills such as prompt design, critical evaluation of outputs, and ethical judgment (Gonsalves, 2024) are increasingly integral to analysis and evaluation. In creation, GenAI may facilitate AI–human collaboration (Lubbe et al., 2025), reframing how learners achieve creative outcomes.

Deweyan Reflection

Dewey (1933) emphasized learning as a process of reflective thinking and experiential engagement. GenAI can support this process by generating ideas or alternative perspectives, but risks arise if learners rely on it uncritically (Wieczorek, 2025). When used in structured activities such as reflective journaling or feedback loops, GenAI can stimulate critical thinking and deeper learning (Demir & Özdemir, 2025; Mandai et al., 2024). This is particularly relevant in ODL contexts, where learners may lack continuous instructor support.

Synthesized Framework

Within the CoI model, GenAI can enhance teaching presence through structured guidance, strengthen social presence through dialogue, and deepen cognitive presence by encouraging reflection and higher-order inquiry. GenAI can extend academic support without replacing the indispensable role of human educators (Bozkurt, 2024).

Research Aim

The main purpose of this study was to examine the usability of GenAI applications in academic support services for learners in ODL and to explore how such applications transform the learner experience. In line with this purpose, the study addressed the following research question:

> How do learners experience and perceive the use of a GenAI-based academic support application across two modes of use—free use and structured use—within an ODL context?

Methodology

Research Design

This study employed a qualitative case study design to explore learners' experiences with a GenAI-based academic support system. A holistic single-case design was adopted (Yin, 2009), with the aim not to produce generalizable results but to generate preliminary insights into how GenAI might enhance academic support in large-scale ODL contexts. As one of the widely used qualitative research methods, the case study approach is particularly suited to in-depth exploration of complex educational phenomena (Creswell & Creswell, 2021).

Course Context

The research was conducted in the online course, Web Publishing, part of the online Web Design and Coding Associate Degree Program at a large-scale open university in Türkiye. This course was deliberately selected because learners have often reported difficulties in mastering both technical and conceptual components, and instructors have frequently received requests for additional guidance. The course therefore provided an appropriate context to examine how GenAI-based support could supplement limited instructor availability and offer just-in-time assistance.

The self-paced course had 4,768 registered learners. Course participants were provided with a range of online learning materials through the learning management system, including videos, textbooks in multiple formats, audio resources, self-assessment activities, quizzes, interactive exercises, and infographics. In addition to these asynchronous resources, the course also offered a 1-hour synchronous session each week, during which a content expert from the academic staff delivered lectures and responded to learners' questions. Participation in both the asynchronous materials and the live sessions was optional. As a result, approximately 30 learners attended the synchronous sessions each week, while others had the opportunity to watch the recorded sessions later.

Beyond these regular learning opportunities, a dedicated GPT-based application—named Academic Support and powered by OpenAI's ChatGPT-4o model—was developed specifically for this study. The relevant course textbook and associated learning materials were introduced into the Academic Support application. Subsequently, the necessary directives were defined and then provided to the application, which allowed the AI-based application to be trained under the guidance of academic and technical experts. This initiative was undertaken to enable an AI-based virtual assistant, capable of providing responses grounded in the specific course textbook and materials, to support learners, effectively serving as an extension of the instructor.

Participants

Since the aim of this study was to conduct an in-depth exploration of learners' experiences over the course of one semester, it was deliberately designed with a small group of participants. The study was introduced during the first synchronous session of the semester by the course instructor, and 10 distance learners volunteered to participate. Ethical approval was obtained from the university's Ethical Approval Committee, and all participants provided informed consent through a volunteer participation form, which outlined the study's purpose, procedures, and data confidentiality measures. During the semester, two participants withdrew from the study, leaving eight learners who completed the process. This attrition reduced the diversity of perspectives and is acknowledged as a limitation of the research.

The participants represented a range of ages, from early twenties to over forty, and were nearly balanced in terms of gender. Their enrollment years spanned from 2017 to 2023, with most entering in the past 2 years. To preserve anonymity, participants were systematically coded (e.g., L1, L2), and all findings and direct quotations are presented using these codes.

Data Collection

Data were collected through (a) semi-structured interviews conducted twice with each learner (after the midterm exam and at the end of the semester), and (b) transcripts of learners' written dialogues with the GenAI-based academic support application during weekly and individual tasks. The interviews elicited learners' perceptions of satisfaction, motivation, teaching presence, and challenges they encountered.

Data Analysis

Thematic analysis was employed to interpret the data. An initial coding framework was developed based on the research questions and conceptual framework, and additional codes emerged inductively during analysis. To enhance reliability, two researchers independently coded a subset of data (Saldaña, 2021). Disagreements were resolved through discussion until consensus was reached, and the coding scheme was refined accordingly. The finalized framework was then applied to the full dataset.

Findings

The findings are presented as exploratory and context-specific, reflecting the experiences of a small group of distance learners in one course. Four major themes emerged from the analysis: (a) motivation and engagement, (b) confidence and reassurance, (c) self-assessment and reflection, and (d) challenges and risks. Differences between phase 1 (free use) and phase 2 (structured tasks) are highlighted. It is important to note that the same learners participated in both phase 1 (free use) and phase 2 (structured use); therefore, the differences observed between the two phases reflect changes in the same individuals' practices rather than differences between separate groups.

Themes

Motivation and Engagement

Learners consistently described the GenAI-based application as motivating. In phase 1, when learners used the tool freely, many engaged with it sporadically. In phase 2, structured tasks prompted more regular use, which learners associated with increased motivation. As one participant explained, "When I had weekly tasks, I felt encouraged to interact. It motivated me to study more." The system also provided quick summaries and explanations, which most learners described as "shortcuts" that saved time and encouraged further study.

Learner comments illustrating this theme included the following statements: "It definitely saved time; I would keep using it and recommend it to others," and "Because it was fast and always there, I felt more willing to sit down and study with it."

Confidence and Reassurance

The application played a strong role in reassuring learners about their exam preparation. Learners emphasized that the tool's alignment with course materials and expert-designed prompts made them feel secure. One learner noted, "Because it used the same textbook as the course, I trusted the answers. It gave me confidence before the exam." This sense of reassurance was more pronounced in phase 2, when structured prompts guided learners through unit-based review.

In relation to this theme, learners explicitly voiced their trust in the system, for example, stating, "I feel like it follows the textbook, so I feel much safer when I study with it," and "I know I am talking to an application, but that actually makes me feel in a safer space than when I ask a person."

Self-Assessment and Reflection

The system also supported self-assessment and reflection. Learners reported that they were able to identify gaps in their knowledge and clarify misconceptions. One participant commented, "I realized what I didn't know when I saw the explanations." The unit-based activities in phase 2 were particularly effective in prompting reflective learning, helping learners evaluate their progress systematically.

Learner accounts further underscored this reflective dimension, for instance: "I realized how little I actually knew and could see exactly where my gaps were," and "When the place of the words changed in a question I already knew, I suddenly couldn't answer it, and that made me see my weaknesses much more clearly."

Challenges and Risks

Despite these benefits, learners also reported challenges. Some expressed frustration with occasional incorrect or incomplete answers, particularly when uploading files or asking complex questions. A participant observed, "Sometimes it gave an answer that didn't match the book. That was confusing." Others admitted difficulty in knowing how to use the system effectively without structured prompts. This finding underscores the risk of overreliance and highlights the importance of task design and instructor guidance.

Learners' descriptions of these challenges included remarks such as, "In the riddle game it marked my answer as wrong even though I was sure it was correct," and "I couldn't use voice interaction through the academic version of the tool, and that sometimes broke my concentration and study flow."

Comparative Patterns Between Phase 1 and Phase 2

When the midterm and end-of-term interviews were considered together, patterns of both continuity and transformation emerged between the free-use phase and the structured-use phase. In both phases, the central elements of teaching–learning presence were framed around time saving and the expectation of accurate answers based on the textbook. However, in phase 2, the systematic design of unit-based tests made the learning experience more targeted and purposeful.

In terms of motivation and belonging, chat-based interaction triggered self-regulation in both phases, but after the structured activities, learners demonstrated a clearer recognition of their shortcomings and a stronger willingness to study. While overall satisfaction appeared sustainable, learners in phase 2 increasingly emphasized the need for seamless one-click integration of the Academic Support application into the institutional e-Campus platform where course materials are hosted. This demand shifted the conversation toward institutional-level scalability.

Technical barriers, such as tablet–mobile incompatibility and connectivity issues, recurred across both phases. Yet, in phase 2, the number of incorrect or hallucinatory responses decreased, suggesting that example-focused prompts partially alleviated these challenges. Regarding activity preferences, the app features Test Me and Where Do I Stand? were consistently described as indispensable. In phase 2, learners also expressed more concrete demands for question-marking options and greater conceptual variety.

Development expectations in both phases centered on visually enriched interfaces, flashcards, and proactive notifications. In the structured phase, learners further highlighted the need for data-driven improvements such as statistical feedback and personalized task schedules. Collectively, these comparative findings indicate that while a GenAI-supported academic support system retains its time-efficient and motivating qualities, it also holds potential for advancement in technical flexibility and data-driven personalization.

Evolution of Learners' Perceptions from Phase 1 to Phase 2

The analysis of both phases illustrates the functional evolution of learners' perceptions of GenAI. In phase 1, learners associated the tool primarily with fast answers and teacher-like support, as reflected in their use of terms such as "teacher," "prompt," and "answer." By phase 2, the vocabulary shifted toward information, question, feedback, and learning, highlighting a stronger emphasis on information verification and self-assessment. By the end of the semester, these dual functions converged into a holistic view of GenAI as an academic support ecosystem.

The prominence of terms such as "activity," "feature," "support," "useful," and "content" demonstrates that learners began to view GenAI not only as a question-answering tool but also as a multilayered learning partner capable of offering customizable activities, useful features, and rich content. The consistent responses of students across both phases underscore that the learner remained central, while the prominence of the terms "explanation" and "feedback" indicates that GenAI supported conceptual clarity and reinforced self-regulated learning cycles through instant feedback.

In sum, while core functions such as answering questions and supporting learning persisted, learners' use of GenAI evolved from perceiving it as a fast-answering virtual teacher in phase 1 to adopting it as a personalized exam coach and learning assessment partner in phase 2. This shift reflects a qualitative deepening of interaction, where GenAI was increasingly positioned as both a digital teacher that strengthens cognitive presence and a formative assessment tool that promotes reflective, self-regulated learning.

Discussion

This study conducted an in-depth exploration of learners' experiences with a GenAI-based academic support application in an ODL context. The findings should be interpreted as preliminary and context-specific, given the small sample size and short duration of the research. Nevertheless, they offer important insights into the opportunities and challenges of using GenAI for academic support in open universities.

The results highlight the potential of GenAI to reduce transactional distance (Moore, 1989) by providing continuous, responsive dialogue that learners described as similar to interacting with a teacher or peer. This aligns with the Community of Inquiry (CoI) model (Garrison et al., 1999), in which teaching and social presences are critical for learner engagement. The learners' perception of the tool as a 24/7 accessible teacher illustrates how GenAI can strengthen teaching presence by delivering just-in-time explanations, while also reinforcing social presence by simulating supportive dialogue. These findings are consistent with prior studies that report positive effects of AI tools on learners' sense of belonging and motivation (Popenici & Kerr, 2017; Urban et al., 2024).

From a broader perspective, these patterns also speak to how GenAI can be positioned within the learner-support ecology of large-scale open universities. Rather than operating solely as a generic productivity tool, the application in this study functioned as an additional support layer embedded in existing course structures and advising processes, which resonates with Li et al.'s (2025) call to redesign open and distance education through "digital bridges" that augment, rather than replace, human support.

Another key contribution of the study is the comparative analysis of phase 1 and phase 2. In phase 1, when learners used the system freely, engagement was sporadic and benefits varied widely. In contrast, in phase 2, structured weekly tasks acted as pedagogical triggers, resulting in more consistent use, deeper reflection, and greater confidence. This shift highlights that the educational value of GenAI is not inherent to the technology itself but depends on how it is embedded in instructional design. Structured prompts, scaffolding, and instructor oversight help transform GenAI from a convenience tool into a meaningful learning aid. This supports recent arguments that prompt pedagogy and carefully designed AI integration are necessary for sustainable impact (Gonsalves, 2024).

Furthermore, the contrast between phases 1 and 2 and the associated learning gains is consistent with recent work on AI-driven tutoring, adaptive support, and GenAI-enhanced feedback. Möller et al. (2024) showed that an AI-powered tutoring system for distance learners could reduce study time while maintaining progress, and Mejeh and Rehm (2024), together with Rincon-Flores et al. (2024), demonstrated how adaptive support systems can personalize learning processes in online settings. Zhan et al. (2025) likewise conceptualized GenAI as an enabler of more-continuous feedback engagement. The present study contributes a qualitative ODL perspective to this body of work by illustrating how structured GenAI activities can channel learners' time-saving strategies into more sustained, reflective, and feedback-oriented engagement, even though issues such as hallucinations and overreliance remain salient.

At the cognitive level, learners reported that the system helped them identify gaps in their understanding and prepare more effectively for exams. In this sense, GenAI functioned as both a cognitive shortcut for lower-level tasks (e.g., summarizing) and a catalyst for higher-order reflection, in line with Bloom's taxonomy (Anderson & Krathwohl, 2001). This finding resonates with research suggesting that GenAI can enhance learning performance by supporting both efficiency and depth (Haindl & Weinberger, 2024; Song & Song, 2023). At the same time, risks were observed: some learners became uncertain when confronted with inaccurate responses, and others struggled to use the tool effectively without structured guidance. These risks echo concerns in the literature about hallucinations, overreliance, and integration challenges (Hmoud et al., 2024; Sun et al., 2024).

From a motivational perspective, the tool appeared to satisfy key elements of self-determination theory (Ryan & Deci, 2000). Learners described how the application enhanced their sense of competence ("I realized what I didn't know"), provided autonomy through flexible access, and fostered relatedness by simulating a supportive peer or tutor. These experiences suggest that GenAI can play a role in sustaining learner motivation, particularly in large-scale ODL systems where human support is limited. However, the motivational benefits are fragile and can be undermined by technical problems or unclear task design, which may discourage use over time.

Finally, the findings contribute to the growing discussion about the role of educators in the age of GenAI. The study illustrates how, rather than replacing instructors, GenAI can extend their presence and free them to focus on higher-level pedagogical tasks. Learners valued the system precisely because it was aligned with course materials and developed under expert supervision, which gave it credibility. This reinforces the idea that GenAI works best as part of a human–AI partnership, where the technology provides scalable support while educators design, monitor, and refine its use.

Limitations

This study has some limitations. First, it was conducted with a very small number of volunteer learners (n = 10) in a single course at one large-scale open university. The findings are therefore exploratory and context-specific rather than generalizable. Second, participant attrition during the semester, from ten to eight learners, reduced the diversity of perspectives and may have influenced the richness of the data. Third, the research was limited to one semester, which restricted the ability to observe the longer-term effects of GenAI-based support on persistence, performance, or engagement. Fourth, the study relied on self-reported data from interviews and learner–AI dialogue transcripts, which, while valuable, may be subject to bias. Fifth, technical limitations of the GenAI tool, such as occasional inaccuracies or file-upload problems, were reported by learners and may have shaped their experiences.

Sixth, although the interview data provided insights into how the eight participating learners used the GenAI-based Academic Support system, the study did not systematically track the types of questions directed to academic staff by the larger course cohort. Anecdotal observations suggest that learners tended to use the AI tool for concept clarification, content verification, and practice questions, whereas questions posed to instructors during synchronous sessions focused more on assessment expectations or technical issues. However, this distinction was not examined in a structured manner and therefore remains an important area for future research. Systematically mapping the kinds of queries addressed to GenAI versus those directed to human instructors would help clarify which aspects of academic support can be effectively augmented by AI and which require sustained human involvement, thereby providing a more nuanced understanding of how GenAI might free instructor time for higher-level pedagogical responsibilities.

Finally, the study did not include an analysis of exam scores or a comparison between the sampled participants and the wider cohort. This was a deliberate methodological decision. As an exploratory and preliminary qualitative case study with a small volunteer sample, the aim was not to measure learning outcomes, but to gain an in-depth understanding of learners' experiences, interactions, and perceptions while using the GenAI-based Academic Support application. Given the small sample size and the self-selected nature of participation, quantitative comparisons such as exam score analysis would not yield meaningful or generalizable results. Future research with larger samples and experimental or quasi-experimental designs may explore whether GenAI-based academic support influences exam performance or other measurable learning outcomes.

Despite these limitations, the study provides important preliminary insights into the role of GenAI as an academic support tool in ODL and highlights directions for further research with larger, more diverse samples and longer observation periods.

Conclusion

This exploratory case study indicates that GenAI-based applications have the potential to extend academic support for distance learners in large-scale ODL systems. By reducing transactional distance, enhancing teaching and social presence, and supporting reflective engagement, such tools can help address one of the most persistent challenges of open universities: providing timely and personalized academic support at scale.

Interpreting the findings in light of broader institutional challenges faced by open universities, particularly those described by Daniel (2004), provides additional insight. Daniel (2004) identified the eternal triangle of education as access, quality, and cost, emphasizing the inherent tensions in balancing these three dimensions. The results of this study suggest that GenAI applications may help reconfigure this triangle in favour of open universities. First, by offering scalable, on-demand assistance aligned with course materials, GenAI can enhance the quality of learner support without proportionally increasing faculty workload. Second, the 24/7 accessibility of such systems broadens access for learners who combine study with work or family responsibilities. Third, while the initial development and integration of GenAI tools requires investment, over time they may help reduce costs by automating routine support tasks and allowing educators to focus on higher-level pedagogical responsibilities such as designing meaningful learning activities, interpreting learning analytics to support at-risk learners, facilitating deep inquiry, mentoring students, and making curriculum-level pedagogical decisions. Thus, carefully designed GenAI applications could enable open universities to address Daniel's (2004) challenge of simultaneously increasing access, improving quality, and reducing costs.

At the same time, the study emphasizes that GenAI is best understood as a supportive tool rather than a substitute for educators. Its effectiveness depends on careful task design, alignment with course materials, and continuous instructor oversight. Challenges such as hallucinations, technical limitations, and risks of overreliance highlight the need for cautious and critical integration.

As a preliminary investigation with a small number of learners, this study offers context-specific insights rather than generalizable conclusions. Future research should involve larger samples across multiple courses and institutions to examine the scalability and sustainability of GenAI-based academic support in ODL. Ultimately, the findings suggest that when combined with pedagogical frameworks such as the Community of Inquiry and supported by reflective learning design, GenAI as a tool that helps educators and learners transform challenges into opportunities and enrich their learning experience (Bozkurt, 2024). Crucially, the successful integration of AI in education demands that institutions not only train purpose-specific models but also invest in continuous AI literacy and prompt engineering training for learners and employees to guarantee responsible and ethical engagement with these technologies.

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AI as a Pedagogical Scaffold: Enhancing English as a Foreign Language Argumentative Writing and Critical Thinking in a Distributed Learning Environment

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Abstract

This study investigated the impact of generative artificial intelligence (GenAI) supported by blended instruction on the argumentative writing skills of first-year students in an English as a foreign language (EFL) teacher education program in a state university in Türkiye. The study was designed as a qualitative case study supported by quantitative data. The study involved nine English language teaching students who initially received traditional academic writing instruction. They completed a pre-test. They participated in a 4-week online writing course integrating GenAI tools within a blended learning environment. Data were collected through pre- and post-tests as well as semi-structured interviews and analyzed using thematic analysis. Findings indicate that GenAI contributed to key stages of the writing process, particularly in idea generation, text organization, argument development, and critical thinking. Participants reported increased confidence and engagement, benefiting from immediate, personalized feedback and flexible learning opportunities. However, concerns regarding reliability and overdependence also emerged. The study suggests that with proper teacher guidance, GenAI can function as a pedagogical scaffold in blended academic writing instruction, supporting learners' higher-order thinking and autonomy. These insights contribute to understanding how emerging AI technologies can be effectively integrated into EFL contexts to enhance complex writing skills.

Keywords: generative artificial intelligence, blended learning, argumentative writing, critical thinking, English as a foreign language, academic writing instruction, open and distance learning

Introduction

The rapid advancement of generative artificial intelligence (GenAI) technologies has created new opportunities and challenges in language education. Large language models such as ChatGPT are transforming teaching and learning practices by providing personalized, flexible, and interactive learning experiences for students (Holmes et al., 2019; Luckin et al., 2016). These kinds of technologies facilitate rapid access to linguistic input and give instant feedback, adaptive support, and personalized learning pathways, transforming how students engage with complex skills such as academic writing (Kasneci et al., 2023). These innovations are particularly significant for English as a foreign language (EFL) learners who often struggle with generating new ideas, text organization, argument development, and revision when delivering extended written discourse (Hyland, 2003; Weigle, 2002). While traditional approaches to writing instruction may not provide timely or individualized guidance (Lee & Tajino, 2008), GenAI tools can potentially scaffold learners' higher-order thinking and reduce cognitive load. Also, GenAI tools can scaffold EFL students.

At the same time, integrating GenAI into formal instruction raises important pedagogical and ethical considerations. Overreliance on AI-generated content can lead to superficial learning, academic integrity concerns, and decreased critical engagement with texts (Tlili et al., 2023; Zhai & Wibowo, 2023). Teachers, thus, play a crucial role in mentoring AI use to ensure that students critically evaluate, adapt, and improve outputs rather than copy them (Ertmer & Ottenbreit-Leftwich, 2010). In blended learning environments, where face-to-face and online instruction are combined, GenAI can be positioned as a dynamic support, offering immediate feedback and personalized recommendations while instructors facilitate reflective and interactive learning (Bozkurt & Sharma, 2020; Graham, 2013).

Argumentative writing represents one of the most cognitively demanding genres in academic contexts, requiring learners to construct logical claims, provide evidence, and address counterarguments (Nussbaum, 2008; Wingate, 2012). Despite the growing interest in digital writing tools, empirical research exploring how GenAI influences students' experiences and development of argumentative writing skills remains limited (Sun, 2023). Understanding this integration is particularly critical in higher education programs preparing future English teachers, who will themselves mediate technology-integrated writing instruction.

To fill this gap, the study investigated the impact of GenAI-supported blended instruction on first-year English language teaching (ELT) students' argumentative writing skills. Especially, it explored students' perceptions, experiences, and skill development when guided to use GenAI critically and reflectively during a structured 4-week online writing program. By examining both qualitative and quantitative outcomes, this research contributes to understanding how AI-integrated pedagogy can support complex writing and critical thinking in EFL contexts while preserving academic standards and learner autonomy.

Literature Review

Theoretical Framework

This study adopted the Community of Inquiry framework (Garrison, Anderson, & Archer, 2000), widely recognized as the foundational model for blended and flipped learning environments. The Community of Inquiry framework posits that deep and meaningful learning occurs through the interaction of three core elements or *presences*: cognitive, social, and teaching. However, given the integration of generative AI, this study proposed an AI-enhanced Community of Inquiry perspective.

In this adapted framework, the role of teaching presence, traditionally held solely by the instructor, is distributed between the human teacher and the GenAI agents. While the human instructor designs the flipped learning pathway and facilitates high-level discourse, GenAI tools assume the role of intelligent agents that provide immediate feedback, error correction, and structural guidance. Concurrently, cognitive presence is amplified as students engage in dialectic interactions with AI to trigger exploration, integration, and resolution phases of critical thinking. This framework allows for analyzing how the synergy between human guidance and AI support orchestrates the development of argumentative writing skills within a distributed learning environment.

GenAI in Language Education

GenAI has recently gained importance as a transformative tool for second language writing instruction. Large language models such as ChatGPT can assist learners by generating ideas, refining vocabulary and syntax, and providing immediate feedback (Godwin-Jones, 2022; Law, 2024). Research has highlighted GenAI's capacity to analyze learner profiles, offer adaptive ways to support learners, and support pedagogical decision-making (Holmes et al., 2019; Hu et al., 2025). It can also foster linguistic awareness by encouraging self-directed correction and metacognitive engagement (Kasneci et al., 2023). As GenAI provides personalized feedback, creates rapid content, and reduces teacher workload (Bozkurt, 2023), challenges remain regarding fair access, ethical use, and information reliability. In EFL contexts, GenAI is reported to support content development and text cohesion, helping students overcome cognitive barriers during drafting and revision (Guo et al., 2022; Xu & Jumaat, 2025). Nevertheless, researchers have cautioned against uncritical adoption, pointing to potential factual inaccuracies, overreliance, and reduced critical engagement (Tlili et al., 2023). These concerns emphasize the importance of teacher mentoring and explicit instruction in prompting and evaluating AI-generated output.

Blended Learning and AI-Supported Writing Instruction

Digitalization has advanced blended learning, integrating face-to-face and online elements to combine flexibility with structured support (Graham, 2013). Its rapid adoption during the COVID-19 pandemic highlighted the need for teachers' digital competence and pedagogical design to prevent poor usage of technology (Bozkurt & Sharma, 2020; Ertmer & Ottenbreit-Leftwich, 2010; Hattie, 2012). Learners must self-direct, while instructors guide inquiry and critical thinking (Anderson, 2008).

On the other hand, flipped learning extends this shift by moving content exploration outside class and dedicating class time to collaboration and problem solving, strengthening deep understanding and 21st-century skills (Demirer & Aydın, 2017; Sun et al., 2023).

Blended learning, which integrates digital and face-to-face formats, is recognized for its flexibility, learner autonomy, and capacity to deliver timely, personalized feedback (Bozkurt & Sharma, 2020; Graham, 2013). Integrating GenAI into such environments creates new affordances for writing pedagogy. AI-driven tools can support brainstorming, outline generation, and revision cycles, while teachers provide higher-order feedback and maintain academic integrity (Han et al., 2023; Park & Doo, 2024). In writing instruction, studies show that AI-supported blended tasks can improve coherence and structure of argument by enabling immediate, personalized scaffolding (Guo et al., 2023; Suh et al., 2025). However, the degree of benefit depends on structured guidance, as unguided AI use may result in poor text generation and diminished reasoning.

Argumentative Writing in EFL Contexts

Argumentative writing is among the most demanding genres for EFL learners due to its cognitive and rhetorical complexity: students must formulate clear claims, provide evidence, and anticipate counterarguments (Qin, 2013; Wingate, 2012). Traditional writing instruction often lacks individualized, timely feedback, limiting opportunities for repeated correction and critical thought (Hyland, 2003; Lee & Tajino, 2008). Emerging evidence suggests that, when critically integrated, GenAI can foster argument quality, text coherence, and metacognitive awareness in EFL writing (Sun, 2023; Wang, 2024). However, the current research base is fragmented and has rarely focused on the experiences of ELT students, a group that will influence future AI-mentored pedagogy.

Research Gap

Despite increasing interest in AI-supported academic writing, there remains a lack of empirical work exploring how GenAI-enhanced blended instruction shapes both skill development and perceptions among ELT students. This study sought to fill this gap by examining the impact of GenAI-supported blended learning on ELT students' argumentative writing performance and their views on AI as a pedagogical scaffold. This study also assessed how digital applications supported by GenAI contribute to key stages of writing, such as idea generation, organization, developing strong arguments, and critical thinking. Accordingly, this paper sought answers to the following research questions:

1. How do EFL students perceive the role of GenAI as a pedagogical scaffold in their writing process?
2. How do participants experience the integration of GenAI tools within a blended learning environment?
3. In what ways does GenAI-supported instruction influence students' development of argumentative writing skills?

Research Methods

This study employed a single holistic case study design (Yin, 2018) to provide an in-depth understanding of how GenAI-integrated blended instruction influences the argumentative writing processes, skill development, and perceptions of EFL learners within a real-life context. The case was defined as the first-year ELT writing cohort using GenAI tools within a blended learning environment over a 4-week period. This approach was selected to allow for a comprehensive examination of the bounded system, focusing on participants' lived experiences and the pedagogical implications of the intervention. While the research was fundamentally qualitative, descriptive data from pre- and post-writing assessments were used to triangulate findings and provide evidence of performance changes, thereby enhancing the trustworthiness of the study.

Participants

Participants were nine first-year students enrolled in the English Language Teaching (ELT) program at a state university in Türkiye. All participants had previously completed an academic writing course using traditional instruction methods. They voluntarily joined a 4-week GenAI-supported blended writing instruction, particularly designed for this study. The instruction was delivered via a learning management system (LMS) complemented by synchronous online sessions (Zoom), allowing participants to access instructional materials, submit assignments, and interact with AI tools while receiving real-time teacher support. The participants' ages ranged from 18 to 23. Regarding gender distribution, the group included both female and male participants, with a majority being female. An examination of the participants' birthplaces revealed that each student came from a different city.

Procedure and Materials

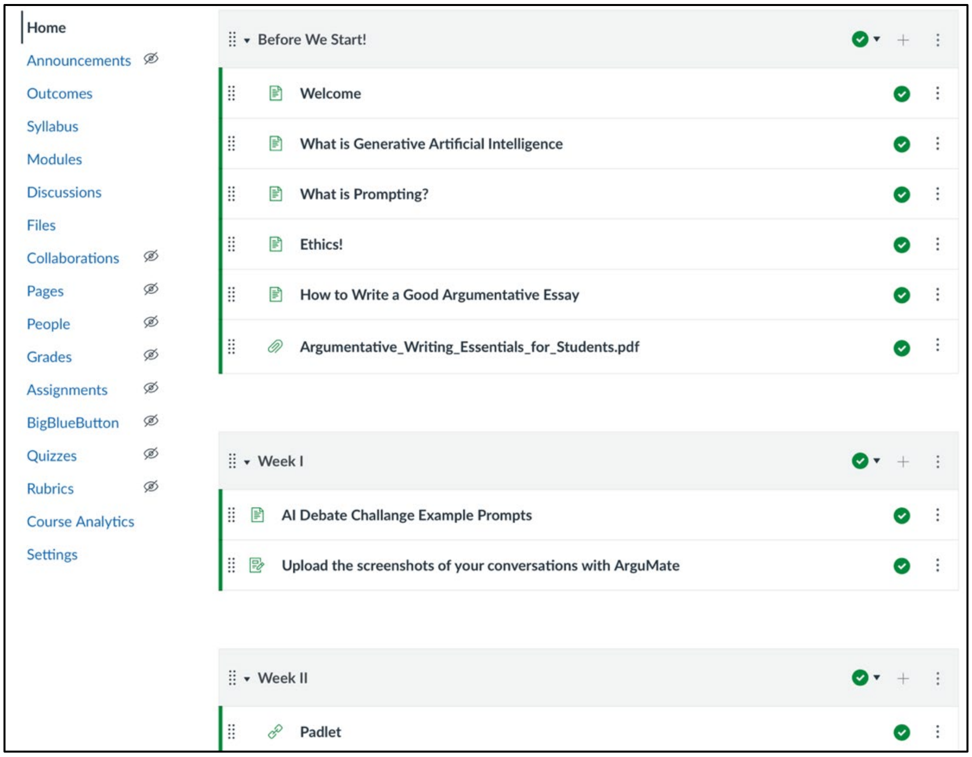
The instructional procedures were grounded in a flipped learning model (Bergmann & Sams, 2012), used here as a specific modality of blended learning. This design necessitated a distinct division of labor between AI and human agents: students first engaged with GenAI tools (e.g., Argumate, Quillbot) and instructional content asynchronously via the Canvas LMS to generate initial ideas and drafts. Subsequently, synchronous Zoom sessions were dedicated to human scaffolding, where the instructor guided critical reflection, peer discussion, and the evaluation of AI-generated outputs, ensuring a transition from passive reception to active reasoning.

The weekly procedure was designed to progressively build participants' argumentative writing skills.

Before the lessons, short reading texts and informative videos on what GenAI is, what prompting is, ethics, and writing a good argumentative essay were presented to the participants. The LMS was used to present these texts and videos. Figure 1 shows a screen from the learning management system (Canvas) used to deliver instructional materials.

Figure 1

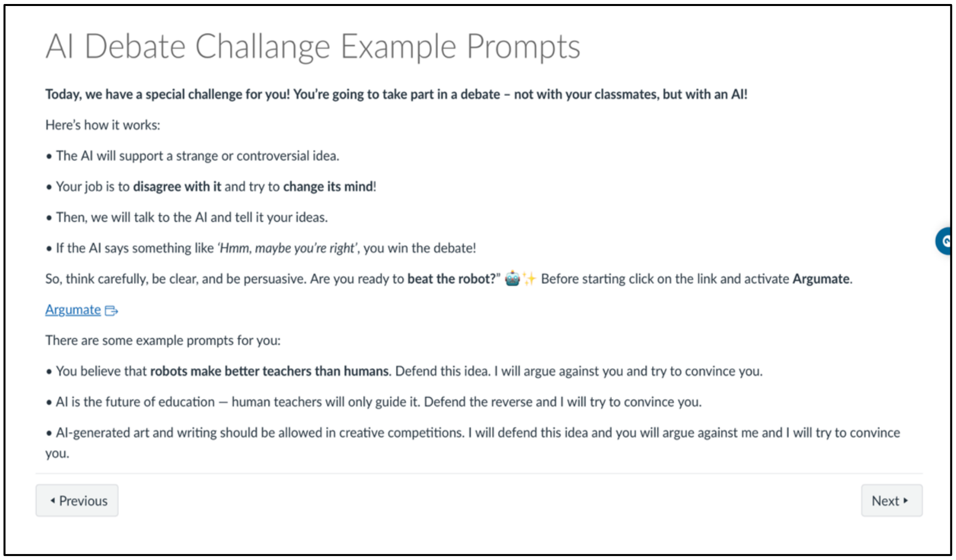
Screenshot Showing Introductory Course Materials Offered on the Learning Management System



In the first week, activities generating arguments and counterarguments against AI were conducted. Participants used the platform Argumate (https://argu-mate.com/), a GenAI system specifically designed for debate. While producing counterarguments to participants' claims, it also provided feedback on their sentences, to engage in debates with an AI agent, aiming to develop critical thinking and the students' ability to form counterarguments. For the activity, three topic and example prompts were presented. Subsequently, participants were asked to debate with the AI agent on the topic they chose. The screenshot in Figure 2 shows the instructions students were given to complete the activity and the three topics they could choose from.

Figure 2

Screenshot of Student Instructions for the Argumate Activity



AI Debate Challange Example Prompts

Today, we have a special challenge for you! You're going to take part in a debate – not with your classmates, but with an AI!

Here's how it works:

• The AI will support a strange or controversial idea.

• Your job is to **disagree with it** and try to **change its mind**!

• Then, we will talk to the AI and tell it your ideas.

• If the AI says something like *'Hmm, maybe you're right'*, you win the debate!

So, think carefully, be clear, and be persuasive. Are you ready to **beat the robot?"** 🤖✨ Before starting click on the link and activate **Argumate**.

Argumate

There are some example prompts for you:

• You believe that **robots make better teachers than humans**. Defend this idea. I will argue against you and try to convince you.

• AI is the future of education — human teachers will only guide it. Defend the reverse and I will try to convince you.

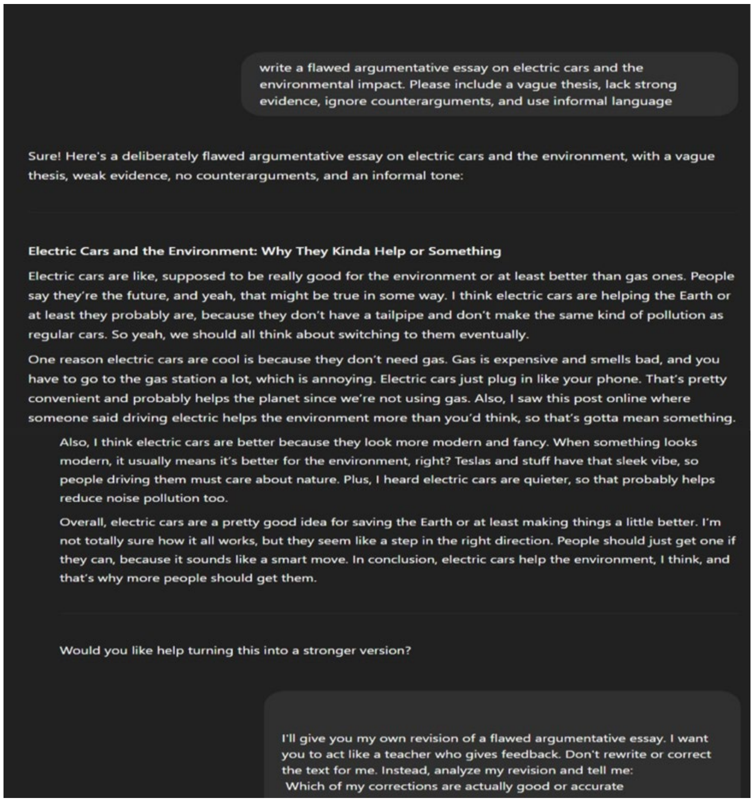
• AI-generated art and writing should be allowed in creative competitions. I will defend this idea and you will argue against me and I will try to convince you.

◂ Previous   Next ▸

An example from one interaction is shown in Figure 3. When this example is analyzed, it can be seen how participants debated with the AI and how the AI responded.

Figure 3

Screenshot of One Partial Argumate Debate From This Study



During the second week, participants created essay outlines on Padlet (https://padlet.com/) based on their Argumate discussions and used the GenAI tool QuillBot (https://quillbot.com/) to refine their drafts and receive feedback on structure and language. Figure 4 presents an example of the various essay outlines created on Padlet.

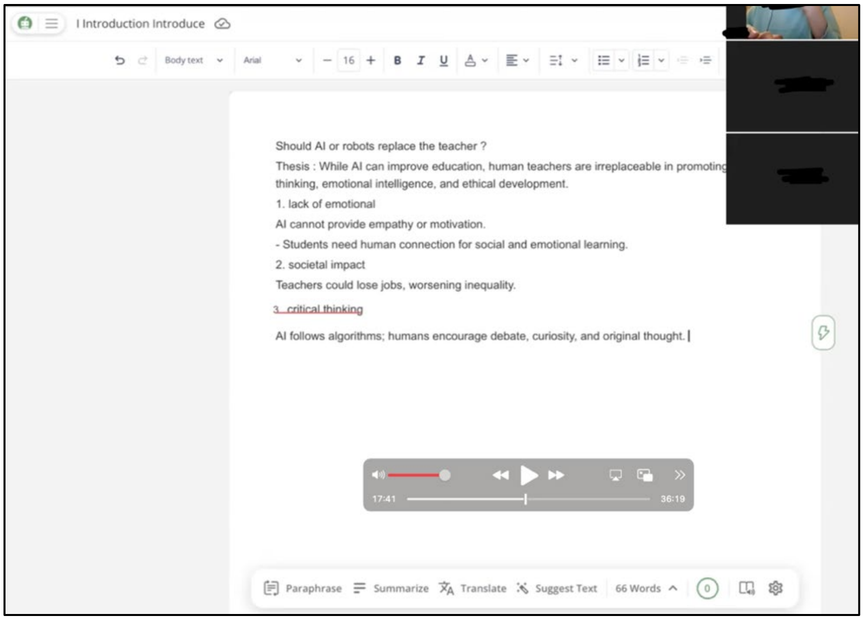
Figure 4

Screenshot of Sample Essay Outlines Created on Padlet

After creating the outlines, these drafts were discussed. Based on the outlines, participants wrote their own argumentative essays on the Quillbot platform, where the writing and feedback processes were carried out. During the process, the GenAI tool corrected participants' grammar mistakes and provided alternative ideas by giving feedback. After completing the process, participants engaged in an online discussion on the LMS, reviewing their experiences, what they wrote, and how the GenAI tool provided feedback. Figure 5 illustrates one participant's work completed in Quillbot.

Figure 5

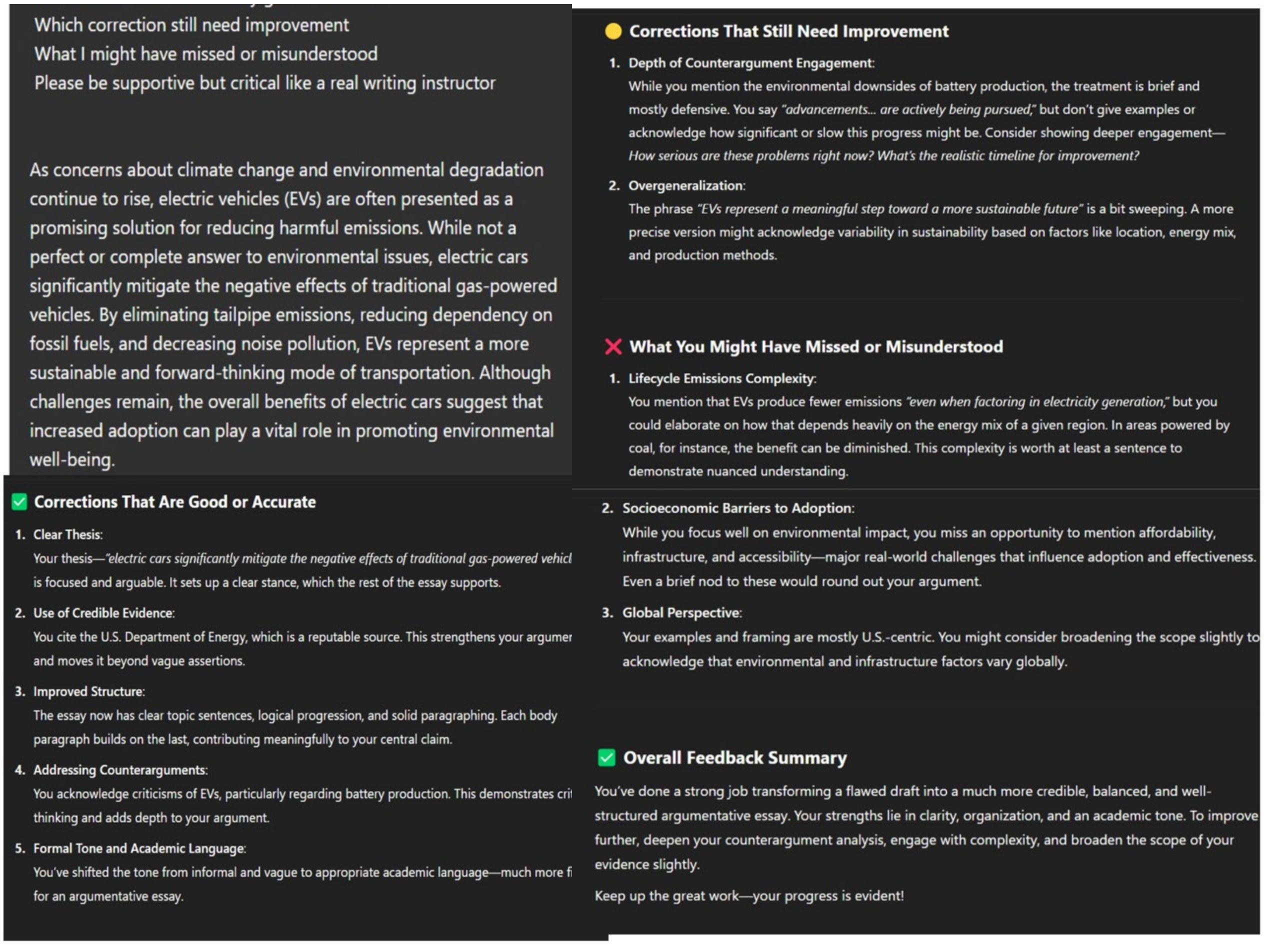
Screenshot of a Quillbot Activity



The third week focused on enhancing critical evaluation skills. Participants prompted ChatGPT(Version 4o) to generate a flawed argumentative essay and were then tasked with identifying and correcting its weaknesses. Afterward, participants were expected to give feedback to ChatGPT and provide alternative sentence suggestions. In response to participants' feedback and correction, ChatGPT gave the participants feedback as a mentor teacher. Figure 6 presents an example of one participant's work from this activity.

Figure 6

Screenshot Example of the Flawed Argumentative Essay Activity



In the final week, a worksheet was provided on Google Docs, and an in-class discussion was carried out on a flawed sample essay embedded in the worksheet. After discussing, participants answered questions about the flawed essay, and they revised a poorly written sample essay, using AI for information-gathering as needed. In this way, they made the flawed essay more coherent and effective. Their final versions were checked on the platform Grammarly (https://www.grammarly.com/) for grammatical accuracy and then discussed in class.

Data Collection

Different data sources were used. These included pre- and post-writing test assessments, semi-structured interviews, and participants' drafts from the argumentative writing activity. First of all, a pre-writing test was applied to participants who had already taken the academic writing instruction. During the blended learning sessions, participants then took the GenAI integrated lessons, which lasted four weeks. Then, the participants took the post-writing test. Pre- and post-writing tests required participants to produce argumentative essays on comparable topics. They were scored using an analytic rubric based on the

International English Language Testing System (IELTS) writing exam, focusing on organization, argument strength, language accuracy, and coherence. In addition, results were evaluated by two field experts. The results of the tests were compared, and the mean score was calculated. Lastly, semi-structured interviews were conducted individually to explore participants' perceptions of GenAI's usefulness, limitations, and other implications (see Appendix for sample interview responses).

Data Analysis

The qualitative data obtained from semi-structured interviews and reflective journals were analyzed using Braun and Clarke's (2006) six-phase framework for thematic analysis. MAXQDA software (Version 24.9.1; https://www.maxqda.com) was used to facilitate the transcription, coding, and data management processes. This recursive analysis involved: (a) familiarizing ourselves with the data through repeated reading; (b) generating initial codes; (c) searching for themes; (d) reviewing themes against the dataset; (e) defining and naming themes; and (f) producing the final report. To ensure trustworthiness, two of us independently coded the data, and discrepancies were resolved through negotiation until consensus was reached.

Regarding the quantitative component, descriptive statistics were calculated for the pre- and post-test argumentative writing scores. In line with the single-case study design, these quantitative results were not used for statistical generalization but served as a method of data triangulation. They provided objective descriptive evidence to corroborate participants' subjective perceptions of their skill development.

Ethical Considerations

This study was conducted in accordance with institutional and international ethical research standards. Ethical approval was obtained from the Ethics Committee of Anadolu University prior to data collection. All participants were informed about the purpose, scope, and voluntary nature of the study. Written consent was obtained from each participant, and anonymity and confidentiality were strictly maintained throughout the research process. Participants were assured their data would be used solely for academic purposes and that they could withdraw from the study at any stage without consequence.

Results

The research aimed to examine whether GenAI tools make a difference in the writing skills of first-year ELT participants, to understand how GenAI contributes to improving their argumentative writing skills and how it can be used to support the language learning process. The research findings are categorized under three main themes: (a) participants' perceptions of the GenAI-supported writing process, (b) participants' experiences of using GenAI in argumentative essay writing, and (c) the perceived role of GenAI in the language learning process. Thematic analysis revealed that participants most frequently emphasized the supportive and facilitative aspects of GenAI in the writing process. Key themes included feedback, vocabulary development, self-paced learning, and learner-centered approaches. Overall, participants expressed predominantly positive attitudes, noting that GenAI made writing easier and more efficient. However, a few participants expressed concerns about potential overreliance and the risk of reduced effort or laziness.

Theme 1: Participants' Perceptions of the GenAI-Integrated Writing Process

The analysis of semi-structured interviews and pre- and post-writing test results revealed participants' perceptions of the GenAI-integrated writing process under five main themes: positive aspects, first impressions, expectations, negative aspects, and prejudices. Overall, participants displayed a positive attitude toward GenAI, emphasizing its supportive role in providing immediate feedback, correcting errors, and generating ideas.

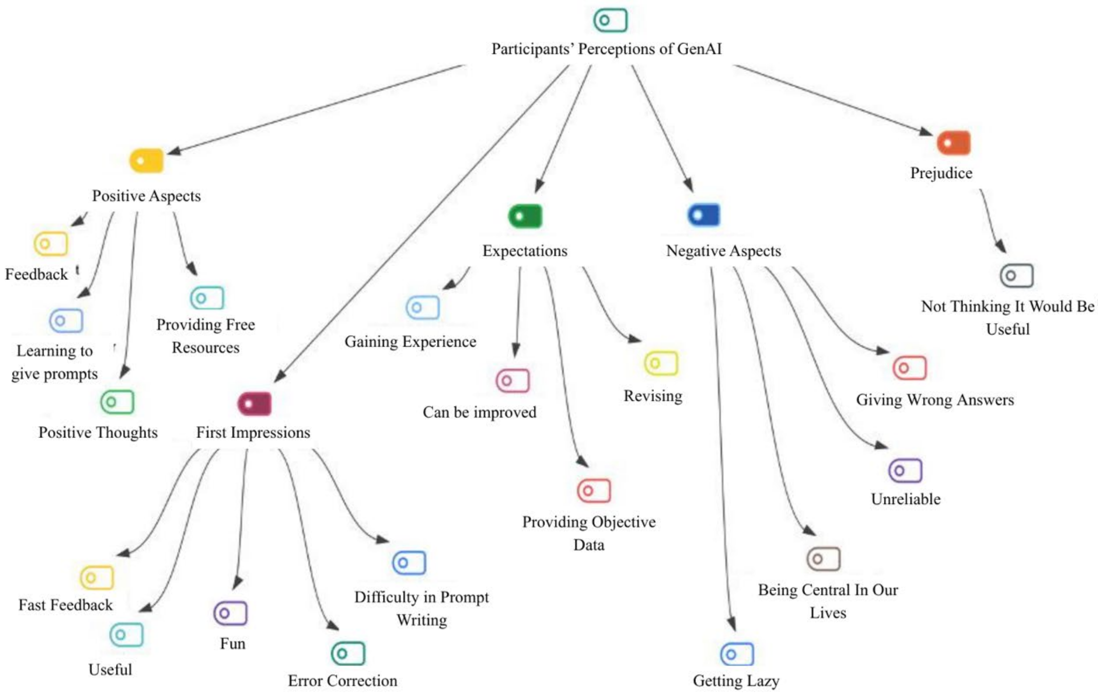
Many participants found GenAI particularly useful for improving their writing through detailed, objective, and fast feedback. Participant 4 highlighted, "After writing a text, I send it to AI and ask it to correct my mistakes. This helps me learn from them." Similarly, participant 9 reported that tools such as Grammarly improved their confidence and made them more aware of their errors. Several participants also appreciated the accessibility of AI-based learning resources. Participant 8 mentioned that AI could generate customized materials and provide recommendations when learning other languages, saving time and cost.

Participants acknowledged the importance of effective prompting for meaningful interaction with AI. While some initially struggled with it, they later found that mastering prompts enhanced their productivity and understanding. Early experiences were often marked by excitement and surprise, which evolved into greater confidence and enjoyment as they became familiar with the tools.

Despite overall positive attitudes, a few participants expressed concerns about overreliance on AI, potential inaccuracies, and reduced effort. Some also reflected on AI's increasing presence in daily life as a possible disadvantage. Interestingly, several participants who were initially skeptical later reported finding GenAI highly beneficial after direct experience. Figure 7 shows a thematic analysis of participants' perceptions of GenAI.

Figure 7

Thematic Map of Participants' Perceptions of Generative Artificial Intelligence



In conclusion, participants viewed generative AI as a facilitative, motivating, and pedagogically valuable support tool that enhanced both their confidence and engagement in the writing process.

Theme 2: Participants' Experiences With GenAI

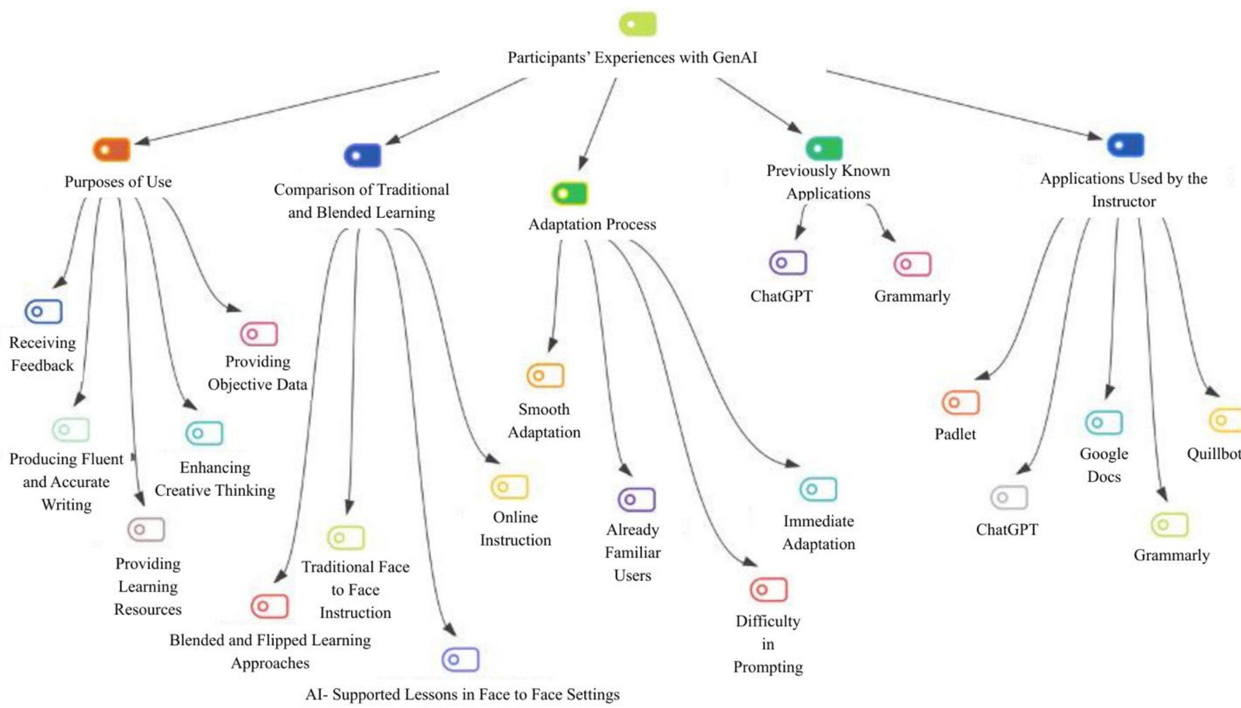
The analysis of semi-structured interviews, pre- and post-writing tests, and classroom data revealed five main themes related to participants' experiences with GenAI: (a) purposes of use, (b) comparison with traditional/blended learning and learning-environment preferences, (c) adaptation process, (d) previously known tools, and (e) AI tools used by the instructor. The thematic analysis produced 20 codes in total.

Participants reported using GenAI tools for diverse purposes, most commonly to receive feedback, generate ideas, facilitate the writing process, and access resources. Participant 9 noted, "I wasn't very confident, but after using tools like Grammarly, my confidence returned, and I started paying more attention to my mistakes." Participant 4 stated that AI feedback helped identify errors, while Participant 1 emphasized AI's contribution to creativity: "I usually struggle to find ideas.... Its examples helped me generate better ones." Others described writing more fluent and academic texts through vocabulary enrichment and grammar correction. Many participants perceived GenAI feedback as faster, more objective, and less time-consuming than traditional methods. They also highlighted the advantages of blended and flipped-learning models, where AI tools complemented classroom instruction. Several found these combinations more effective than conventional teaching, describing AI as explanatory and responsive. Most participants adapted quickly to

GenAI, particularly those already familiar with digital tools. A few initially struggled with prompting, but improved with teacher support and preparatory materials. Participants also recognized their prior exposure to applications such as ChatGPT, Grammarly, QuillBot, Google Docs, and Padlet, noting that these tools served distinct pedagogical purposes. Guided classroom use of these platforms enhanced writing structure, collaboration, and confidence. As Participant 9 remarked, "Padlet helped me see my peers' ideas, which expanded my perspective," while Participant 3 shared, "QuillBot made my writing more academic and refined my sentences." The map of participants' experiences with GenAI-supported instructions is illustrated in Figure 8.

Figure 8

A Map of Participants' Experiences with GenAI-Supported Instruction



To conclude, participants viewed GenAI as an efficient, supportive, and versatile resource that enriched their writing and blended-learning experiences.

Theme 3: The Role of GenAI in the Language Learning Process

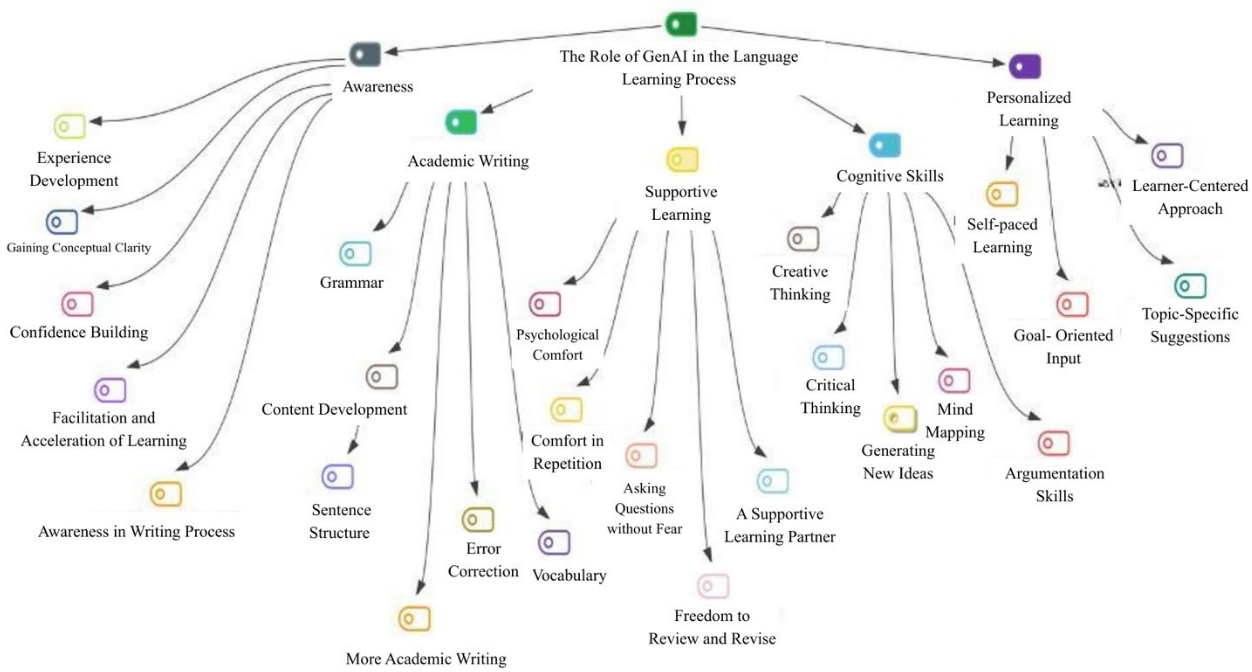
The analysis of semi-structured interviews, pre- and post-writing tests, and classroom data revealed five main themes based on the role of GenAI in the language learning process: (a) awareness, (b) academic writing, (c) supportive learning, (d) cognitive skills, and (e) personalized learning. Across these themes, 25 codes were identified, illustrating the multifaceted contributions of GenAI to participants' language learning development. Participants reported that using GenAI increased their awareness of their own learning processes, helping them gain confidence, develop self-regulation, and recognize their mistakes more effectively. Participant 4 reflected, "As I gained experience using it, I became more confident, especially in academic writing." Similarly, participant 3 noted, "I wasn't confident before, and my writing scores were low, but after writing essays with AI and checking them, my sentence structures improved, and my grades increased."

In addition, participants acknowledged that effective prompting enhanced their ability to communicate with AI tools, developing critical digital literacy. As participant 1 explained, "When it didn't give the answers I wanted, I realized the issue was in my prompts." In addition, AI's guidance helped clarify conceptual ambiguities, allowing participants to enter lessons more prepared and engaged. As participant 8 stated, "Thanks to the materials shared before class, we came in already knowing unfamiliar concepts."

Participants emphasized GenAI's significant contributions to academic writing, including improved grammatical accuracy, vocabulary range, organization, and idea development. They reported noticeable progress between their pre- and post-writing performances, particularly in grammar and lexical resource areas. A thematic map that shows the role of GenAI in the language learning process has been given in Figure 9.

Figure 9

The Role of GenAI in the Language Learning Process



To summarize, findings indicate that GenAI served as an effective learning partner, promoting greater awareness, linguistic competence, and motivation. It not only enhanced participants' writing performance but also fostered a more autonomous, reflective, and cognitively engaging learning experience.

Discussion

The findings of this study indicate that participants perceived GenAI tools as supportive, guiding, and motivating resources for academic writing. They valued GenAI for providing rapid, objective feedback, identifying errors, and assisting in text organization, findings consistent with Sun (2023), who emphasized ChatGPT's ability to support learners in idea generation, structure building, and academic language use.

A major contribution of this study lies in demonstrating how GenAI reduces writing anxiety and enhances confidence. Participants reported feeling less judged and more willing to experiment with ideas when interacting with AI than in traditional classrooms. This observation aligns with Barrot (2023), who found that ChatGPT fosters emotional support and engagement by reducing fear of making mistakes. When integrated into a pedagogically structured course, GenAI can thus create a psychologically safe learning environment that encourages active participation.

The results also show that participants personalized their interaction with GenAI to meet individual needs, consulting it before, during, and after writing for idea generation, language refinement, and revision. This reflects learner agency and autonomy, supporting previous work by Barrot (2023) and Erdem-Aydın et al. (2025), who highlighted GenAI's potential to enable personalized, learner-centered instruction. Especially in large or remote classes, GenAI can act as a valuable partner for educators to support individualized learning.

Another important finding concerns the development of critical thinking. In debate-based tasks using the Argumate tool, participants produced counterarguments, questioned AI responses, and reconstructed ideas, shifting from passive reception to active reasoning. This finding also responds to calls in the literature, highlighting the need for pedagogically grounded AI applications in higher education (Zawacki-Richter et al., 2019).

Participants also reported noticeable improvement in academic writing competence, particularly in grammar, vocabulary range, organization, and tone. They described GenAI as a virtual tutor and collaborator that supports scaffold planning, drafting, and revision, echoing Chan & Lee (2023) and Dwivedi et al. (2023), who found that AI-assisted writing enhances textual quality and efficiency in higher education.

Despite these benefits, participants expressed concerns about ethical issues, misinformation, and overreliance, confirming previous warnings by Erdem-Aydın et al. (2025). Some questioned the accuracy of AI outputs, indicating emerging critical awareness and the need for explicit guidance in evaluating AI-generated content.

Overall, the findings show that GenAI functions not only as a writing tool but as a pedagogical and cognitive scaffold that enhances awareness, reflection, and self-regulation. Interpreted through the lens of the AI-enhanced Community of Inquiry framework, these results illustrate a distributed teaching presence. While GenAI assumed the role of providing hard scaffolding through immediate, structural feedback and error correction, the human instructor maintained the critical soft scaffolding by fostering emotional support and guiding complex discourse. This supports Kasneci et al. (2023), who described GenAI as an interactive system designed to facilitate learning through engagement. When supported by teacher guidance, participants reported greater efficiency and ethical awareness—consistent with Bozkurt (2023) and Erdem-Aydın et al. (2025), who emphasized the effectiveness of blended, teacher-mediated AI integration.

The results demonstrate how GenAI can serve as an innovative tool for learner support, aligning with the theme "Innovations in GenAI for learner support." Specifically, the study illustrates how generative AI tools such as Argumate and QuillBot can be effectively integrated into blended learning environments to enhance engagement and learning outcomes. By enabling participants to receive immediate and personalized feedback through GenAI applications, the study also resonates with the special issue's theme of "Personalization and Feedback." Moreover, the findings highlight that GenAI is not merely a technical tool but a pedagogically meaningful system that reduces learners' fear of making mistakes and fosters psychological comfort by allowing them to learn through their own experiences. Finally, the 4-week blended course designed for this research provides a practical model for integrating GenAI applications into distributed learning environments, offering both pedagogical and methodological insights for future implementation.

Conclusion

This study examined the impact of GenAI-supported blended instruction on first-year English as a foreign language (EFL) participants' argumentative writing skills and perceptions. The integration of GenAI tools within a structured blended learning module led to measurable improvements in writing quality, particularly in organization and argument strength, while fostering participants' confidence and metacognitive engagement. Qualitative findings showed that participants valued personalized support, immediate non-judgmental feedback, and opportunities to critically evaluate AI-generated suggestions. At the same time, concerns regarding reliability, accuracy, and the risk of overreliance highlight the need for careful pedagogical framing.

These results contribute to the growing body of research on AI integration in higher education, especially in teacher education contexts where future educators are learning how to incorporate emerging technologies responsibly. The findings indicate that teacher mediation, explicit AI literacy training, and guided prompt engineering are key to harnessing GenAI's benefits while mitigating potential drawbacks. Blended learning offers a flexible space for such integration, balancing digital affordances with interactive human guidance.

Several limitations should be acknowledged. The study involved a small sample size and was conducted within a single institutional context, limiting the generalizability of results. In addition, the relatively short instruction period may have influenced the depth of skill transfer. Future research could adopt larger, more diverse samples and longitudinal designs to explore sustained development of writing competence and evolving perceptions of AI use. Investigating how pre-service teachers later integrate GenAI into their own instructional practice also warrants attention.

Despite these limitations, the study provides empirical evidence that thoughtfully designed AI-supported blended learning can strengthen complex writing skills and foster critical digital literacy in EFL education. The findings inform both classroom practice and policy, offering guidance for institutions and teacher educators aiming to integrate GenAI tools in ways that enhance learning while maintaining academic integrity and intellectual autonomy.

Implications

The findings of this study carry several pedagogical and institutional implications for the integration of GenAI in language education, especially within open and distance learning contexts. First, the results emphasize that GenAI tools can serve as adaptive and confidence-building companions for learners, supporting not only linguistic development but also emotional engagement and self-efficacy. This suggests that language educators should incorporate GenAI strategically to enhance learner autonomy, reduce writing anxiety, and foster critical reflection.

Second, the study highlights the importance of teacher mediation. Participants reported the most productive outcomes when GenAI was used under guided supervision with structured prompts and preparatory materials. This underscores the need for professional development programs that equip educators with competencies in prompt design, ethical AI use, and data interpretation. Institutions should therefore focus on capacity-building frameworks that enable teachers to integrate AI meaningfully rather than mechanically.

Third, the results reveal that GenAI can help address the personalization gap in large-scale and distance education settings. By offering individualized feedback, differentiated scaffolding, and context-sensitive learning support, AI systems can complement human instruction and provide equitable access to academic writing support.

Finally, future research should explore policy frameworks and ethical guidelines that balance innovation with responsibility. Ensuring transparency, fairness, and academic integrity will be crucial for sustaining trust in AI-mediated learning environments. When embedded within pedagogically sound and ethically aware systems, GenAI has the potential to transform writing instruction into a more inclusive, reflective, and learner-centered process.

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Declaration of Generative AI and AI-assisted Technologies in the Writing Process

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Appendix

Sample Interview Responses

Note: The interview responses provided below were originally conducted in Turkish via audio recordings. The spoken responses were transcribed and subsequently translated into English by the authors with the assistance of AI translation tools. Minor grammatical and structural adjustments were made during the translation process to ensure clarity and readability for an English-speaking audience, which accounts for their organized and structured appearance.

General Experience and First Impressions

1. What was your experience using generative AI? What were your first impressions?

> "I found the experience both fun and interesting. We had to use an AI tool for argumentative writing and debate. It was very impressive to interact with a tool that could recall information instantly, unlike humans. It helped me learn to express my thoughts more clearly, so the AI could also respond with counterarguments. At first, I didn't think it would be very useful because I already had practice writing essays for IELTS and had attended writing courses. But now, I see that it is truly very useful. I gained new perspectives on how to build structure, create an outline, and generate ideas effectively."

2. What were the first challenges or positive aspects?

> "The biggest challenge was writing prompts. Initially, I hadn't realized how important detailed prompts were. I was using vague phrases like 'Write about this.' Now, when I provide context, for example, 'I am a first-year English language teaching student, and I am writing an argumentative essay on this topic,' I get much more relevant and high-quality responses. I had used it for school projects before, but not seriously. I usually got help from Google. However, thanks to this course, I learned to use AI tools more purposefully."

3. How long did it take to get used to it?

> "It didn't take me long to get used to it because I had used it a little before. But in this course, I learned to use it more systematically."

4. How confident were you before using these tools? Did your perception change?

> "I was already confident. I was one of the best students at my school, and I was getting good grades at university too. Still, AI made my writing more structured and professional."

5. Which was more beneficial: traditional methods or AI-supported writing?

> "AI-supported writing was more beneficial because it explained *why* it used a certain structure. Traditional methods are based more on inference and experience. In contrast, AI can provide explanations according to your level. You can even ask it to simplify the topic."

Contribution to Writing Skills and Academic Development

6. How did AI tools contribute to your English writing skills?

> "It improved my grammar, vocabulary, and academic writing. My academic vocabulary was particularly lacking. Seeing how AI writes formally gave me the opportunity to learn these expressions and apply them in my own writing."

7. Did the suggestions from AI make your writing more fluent or accurate?

> "Yes, my writing became more fluent and accurate. I improved my paragraphs with the suggestions from the AI. I used a more academic and clearer language."

8. Which was more effective: traditional or AI-supported activities?

> "Both are valuable. Traditional activities provide interaction with the teacher and friends, which is important. But AI gives faster and more detailed feedback. The most effective is the combination of the two, the blended model."

9. Do you think AI feedback was effective?

> "Yes, it contributed a lot. I especially improved in structuring and planning my paragraphs. I used to write more intuitively before. Now, I can create a plan like a mind map before writing."

10. Was there a decrease in your writing mistakes?

> "Yes, there was a decrease. I am more conscious about punctuation, transition words, and sentence structures now. My writing has become clearer and more organized."

Future Use and Awareness Level

11. Would you consider using these tools in the future?

> "Yes, I would. It is much more comfortable to proceed with AI, especially when I hesitate to ask questions. It allows me to learn at my own pace."

12. Do you believe regular use could lead to lasting improvement?

> "Yes, I do. AI provides opportunities for repetition and offers continuous feedback, which supports improvement."

13. Did AI tools speed up or facilitate your writing process?

> "Yes. Thanks to AI, I can plan and create my texts faster. It clarifies what I am going to write in advance."

14. Are you able to write in a more organized way now?

"Definitely. The structures became more distinct. The way AI demonstrated paragraph organization, idea flow, and transitions was very useful."

15. What is the most important thing you learned about AI?

"AI is very effective not just for writing, but also for supporting the learning process. It doesn't just show you *what* it wrote, but also explains *why* it wrote it that way. This makes it easier to understand and learn the language."

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The Answerthis.io AI App Looks at My Interaction Equivalency Theory

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Abstract

This field note provides an example of the use of an education/researcher artificial intelligence program to provide an overview of the Interaction Equivalency Theory. This theory was first presented as an example in Anderson, T. (2003), "Getting the mix right again: An updated and theoretical rationale for interaction", in the *International Review of Research in Open and Distributed Learning, 4*(2). The AI tool provides a useful synopsis and overview of the value of this theory for distance education students and researchers.

Keywords: EQuiv, interaction equivalency, student-student interaction, student-teacher interaction, student-content interaction

The Answerthis.io AI App Looks at My Interaction Equivalency Theory

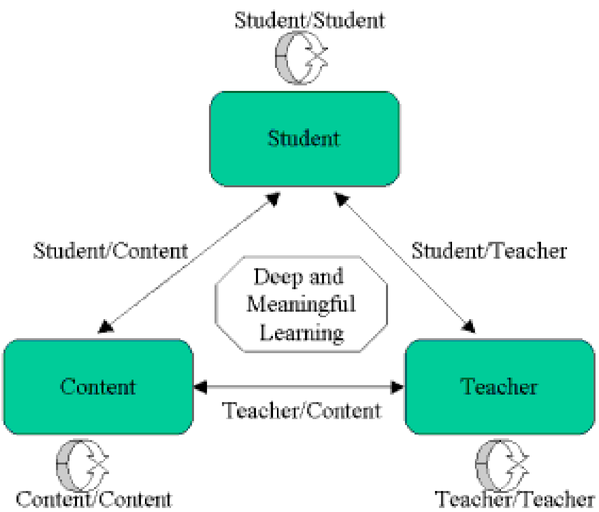
This "note from the field" is not a scholarly work. However, I hope it serves as a useful, illustrative example of new ways that researchers, teachers, and students can dig into the research literature. Open access journals, such as IRRODL, make freely available years of scholarly work directly related to challenges and opportunities in distance education practice and research. However, scouring, summarizing, and making that knowledge accessible is time-consuming and challenging. Using AI tools makes this knowledge much more accessible. However, AI brings its own bias and selection lens, is prone to error, and thus its results require critical review.

I'm not immune from the relentless hype (and warnings from multiple perspectives) about general AI, AI-enhanced browsers, and AI customized for specific applications. Thus, I couldn't resist spending a few minutes checking out an AI app—Answerthis.io, specifically aimed at researchers and students (https://answerthis.io/).

Not being overly modest (to say the least), I decided to ask a question about an article I published over 20 years ago: "Getting the Mix Right Again: An Updated and Theoretical Rationale for Interaction, published in 2003 in *The International Review of Research in Open and Distributed Learning, 4*(2). Figure 1 is an illustration from the article showing the types of interactions supported in formal educational contexts. The basic idea of the article was that interaction of one type can be substituted for one of the other types of interaction, without major impairment of the learning experience.

Figure 1

Modes of Interaction in Distance Education From Anderson and Garrison (1998)



Note. From "Getting the Mix Right Again: An Updated and Theoretical Rationale for Interaction," by T. Anderson, 2003, *The International Review of Research in Open and Distributed Learning*, *4*(2), p. 3 (https://doi.org/10.19173/irrodl.v4i2.149). CC BY 4.0.

The paper achieved modest success with 1,850 citations (Google Scholar, March 2026). This was a bit surprising as I wasn't sure there really was a learning equivalency between student/content interaction, student/teacher interaction, and student/student interaction. Moreover, I wasn't sure how this "theory" could be empirically validated or disproved. However, over the years, a number of researchers (aided in no small part by my Japanese colleague Terumi Miyazoke (https://miyazoe.info/) have used it, and it seems to have been useful—perhaps most noticeably for financially pressed distance education administrators trying to create affordable (and thus accessible) learning opportunities.

I asked the Answerthis.io app: "What is useful about Anderson's interaction equivalency theory?"

The AI tool examined 93 papers in a minute or two and came back with more indicators of usefulness than I could have come up with. The resulting (completely unedited) AI answer is as follows:

> "**Anderson's Interaction Equivalency Theory"** (also known as the Interaction Equivalency Theorem, or EQuiv) is a significant conceptual framework in online and distance education. At its core, it states that "deep and meaningful learning is supported as long as one of three forms of interaction (student-teacher, student-student, student-content) is at a high level; the other two may be offered at minimal levels or even eliminated without degrading the educational experience." The theory recognizes that sustaining all forms of interaction at maximum levels may not always be feasible due to constraints such as time, resources, and institutional scale, especially in online or blended environments.

Key Benefits and Usefulness of Anderson's Theory

1. **Flexible Course Design and Resource Allocation:**

   EQuiv allows educational designers and institutions to focus resources and instructional efforts where they are most impactful. If strong interaction can be established in one domain (e.g., through rich content or peer collaboration), then the other types may be comparatively minimized without a loss in learning quality. For instance, in very large courses where teacher-student interactions are limited, enhanced student-content or student-student interactions can compensate, enabling scalability without compromising outcomes.

2. **Personalization and Adaptation:**

   The theory provides a rationale to adapt interaction according to the specific needs and circumstances of different learner groups, such as non-traditional or part-time students who may not engage frequently with instructors but can benefit from alternative interaction forms.

3. **Practical Framework for Blended and Online Learning:**

   It offers educators a guide to make informed decisions on which instructional tools or approaches to use, justifying, for instance, the use of Learning Management Systems (LMS) to enhance interaction and accessibility, allowing for key educational goals (like participation and learning engagement) to be met even if instructor interaction is limited.

4. **Supports Student Satisfaction and Achievement:**

   Empirical and conceptual studies support the application of EQuiv in raising learner satisfaction, reducing attrition risk in distance education settings, and increasing course completion rates, particularly when strong "interaction presence" is maintained in at least one channel.

5. **Guides Risk Identification and Intervention:**

   The theory isn't just for course designers—it can be used by institutions to develop risk profiles of students potentially at risk of dropping out, enabling targeted interventions where interaction is lacking.

6. **Extends Beyond Structured Courses:**

   Although EQuiv originated in distance and online learning, it has potential applications in other higher education contexts, such as the master-apprentice model in doctoral education. By compensating for limited supervisor (S2T) interaction with enhanced content or peer interactions, EQuiv addresses issues of isolation and supports deeper learning.

7. **Efficient Use of Learning Technologies:**

   By focusing on maximizing one type of interaction, it provides a rationale for the use of asynchronous content, peer forums, or automated feedback systems—tools essential for scaling and accessibility in digital education.

8. **Framework for Ongoing Research and Development:**

   The theory has stimulated further research into interaction dynamics, informing both empirical investigations and theoretical development around how different forms of interaction contribute to learning, motivation, and retention in virtual environments.

9. **Facilitates Deep and Meaningful Learning:**

   The focus on ensuring at least one robust interaction provides conceptual and empirical support for deep cognitive engagement, even when all three modes are not maximally present. This is crucial for the design of effective massive open online courses (MOOCs) and large-scale distance education, where teacher-student contact is inherently limited.

10. **Guides Implementation of New Educational Models:**

    EQuiv justifies the structural design decisions in "flipped classrooms," blended courses, and synchronous/asynchronous online programs, providing a theoretical foundation for deliberate reduction or enhancement of interaction modes based on course goals, audience, and technological affordances.

In summary, Anderson's Interaction Equivalency Theory is useful because it offers a flexible, evidence-based, and scalable framework for online, blended, and distance education. By clarifying how and where to invest instructional resources, it enables educators and institutions to optimize learning outcomes, enhance satisfaction, reduce attrition, and adapt to diverse learner needs across multiple educational contexts.

My Takeaways

- The tool does a credible job of summarizing ways that other scholars have used the theory. It looks to be both accurate and thorough.
- In a couple of minutes, AI was able to scour the literature and find applications of the theory, made by others, that I had not heard of nor could have imagined today, much less than when I originally wrote the paper.
- It shows that assigning tasks such as this as an assessment activity in a senior undergraduate or graduate course hardly seems worthwhile, given the time and effort taken by a teacher for assessment. I have had graduate students create blog and wiki entries on major ideas and short literature reviews in distance education in the past, but given these new tools, such an exercise may still be useful for student learning but has little practical value for assessment. I can, however, imagine assessments in which the student is challenged to provide examples from their own context in which these ten "uses" are instantiated.
- For a busy scholar (or student) trying to get up to speed on ideas from the literature that they may have missed or be unfamiliar with, or if they are in need of a refresher, the tool can be remarkably efficient and effective.
- The tool may inspire new and novel educational innovations as these uses are put into practice, or inspire new research questions.

- The tool doesn't yet have much of a revenue model—it was free for this example—but no doubt that will come.

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Artificial Intelligence and Communities of Inquiry: Reimagining Educational Experiences

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Abstract

Generative artificial intelligence (AI) is transforming education, creating opportunities for personalization, efficiency, and engagement while also raising concerns about misinformation, overreliance, and the erosion of critical thinking. To navigate these tensions, this article argues for the necessity of a coherent theoretical framework to guide the educational adoption of AI. Drawing on the Community of Inquiry (CoI) framework and its construct of shared metacognition, we outline how collaborative inquiry can integrate AI in ways that preserve human agency and sustain deep and meaningful learning.

We examine the potential for AI to assume multiple roles within a community of inquiry—supporting instructional design, guiding learners as an independent resource, assisting instructors through analytics, participating in discussions, and sustaining dialogical partnerships with students. While these roles highlight the capacity of AI to enrich learning communities, they also underscore risks of passivity, diminished authenticity, and overdependence if reflective inquiry is bypassed.

We argue that shared metacognition—collective monitoring and management of thinking—offers a responsible pathway for educators and learners to engage critically with AI-generated outputs, ensuring that technology strengthens rather than supplants collaborative inquiry. In conclusion, we contend that AI can contribute to worthwhile educational experiences only when framed within a coherent conceptual perspective that emphasizes skeptical engagement, collaborative reflection, and the preservation of human purpose. In this regard, the CoI framework has considerable potential to provide understanding and guidance in the adoption of AI tools.

Keywords: artificial intelligence (AI), the Community of Inquiry (CoI) framework, shared metacognition, critical thinking, collaborative inquiry

Introduction

The development of artificial intelligence (AI) reflects a history marked by milestones that have reshaped how humans interact with technology. Early AI applications took the form of rule-based expert systems (Buchanan, 2005; Haenlein & Kaplan, 2019), designed to mimic decision-making in areas such as medical diagnosis, financial advice, and manufacturing (Waterman, 1986). The subsequent rise of machine learning marked a major breakthrough, enabling computers to learn from data, improve over time, and make predictions. This transformed sectors from health care to finance through applications such as predictive modeling and algorithmic trading (Jordan & Mitchell, 2015).

In recent years, AI has moved to the forefront of technological innovation through its ability to simulate human thinking. This is especially evident with the advent of generative AI, a leap from the deterministic and narrow applications of earlier systems (Corbeil & Corbeil, 2025). Generative AI refers to technology that creates content—whether it be text, images, audio, or video—that can be indistinguishable from human output. Its most visible form currently—chat-based interaction tools—has captured the imagination of the tech world and sparked broad interest across sectors. Among these, education stands out as a field poised for transformation, with many considering generative AI as a paradigm shift (Bond et al., 2024). This conviction arises from AI's potential to reshape traditional educational models, refining the boundaries of learning, teaching, and scholarly inquiry (Bozkurt & Sharma, 2023). Through personalized learning, enhanced interaction, and augmented teaching, AI stands at the threshold of reimagining education (Zawacki-Richter et al., 2019). Yet, as AI inevitably transforms education, we must preserve the core elements of a worthwhile educational experience (Selwyn, 2022).

To move beyond ad hoc adoption of AI technologies, we must recognize the unique characteristics of AI alongside the essentials of a worthwhile educational experience. The transformative potential of generative AI in education calls for a coherent understanding of the complexities, inherent potential, and risks of adopting such a powerful technology in an educational learning environment. A sound theoretical perspective offers the necessary structure and perspective to integrate AI's potential while mitigating its challenges. This article responds to that challenge by examining the characteristics of generative AI from an educational perspective and proposing a theoretical framework to guide educators in its responsible adoption. In doing so, we seek a vision and rationale for integrating generative AI in ways that sustain meaningful education. Although the analysis in this article is situated in higher education, we deliberately formulate the conceptual claims to have relevance beyond this context, extending to other forms and levels of learning.

The basic assumption underlying this discussion is that the adoption of AI requires critical thinking and discourse, entailing careful interrogation of information and reasoned dialogue (Rios et al., 2025; Sitepu et al., 2025). We argue that critical thinking and collaborative inquiry are essential for leveraging AI's strengths while mitigating the risks of overreliance on this powerful technology. While AI excels at filtering and organizing vast amounts of information, it also raises concerns about the erosion of critical thinking and dialogue. The risk lies in accepting AI outputs uncritically, bypassing the metacognitive process of analysis and reflective inquiry.

A Theoretical Framework

Considering the transformative potential of AI from an educational perspective requires examining the frameworks guiding our understanding and design of effective learning environments. Theoretical frameworks that explicitly inform the educational adoption of AI technologies are notably absent. Among the theoretical approaches used to study teaching and learning in digital contexts, the Community of Inquiry (CoI) framework has been particularly influential and holds potential for understanding and guiding AI-related educational initiatives. The CoI framework was developed to analyze and design learning processes in collaborative-constructivist learning environments (Cleveland-Innes et al., 2024; Garrison, 2017). Garrison et al. (2000, 2001) conceptualized it as a theoretical construct to describe and support learning within, though not limited to, digital environments grounded in the theoretical perspectives of Dewey (1933), Peirce (1955), and Lipman (2003). Since its inception, the CoI framework has garnered widespread use, discussion, and examination (Bozkurt & Zawacki-Richter, 2021).

Three interrelated elements are central to the CoI framework: Teaching, Social, and Cognitive Presence. Teaching Presence “originates from the multidimensional roles and responsibilities of a teacher in collaborative and constructivist learning environments” (Stenbom & Cleveland-Innes, 2024, p. 8). Social Presence is the degree to which students and teachers “feel socially and emotionally connected with others in an online environment” (Swan, 2020, p. 80). Cognitive Presence is the core thinking and meaning-making element when participants engage in individual and cooperative practical inquiry (Garrison, 2015). The CoI framework is grounded in the principles of a worthwhile educational experience that promotes critical reflection and discourse. It was never considered to be unique to online learning. Therefore, we argue that the CoI framework has great potential to guide educators in understanding, designing, and implementing collaborative learning that effectively leverages AI tools to support deep and meaningful learning.

The introduction of AI, and specifically generative AI, into a community of inquiry offers a new lens through which to view and enhance CoI presences. AI’s capabilities for personalized learning, dynamic content generation, and interactive engagement have significant potential to enrich communities of inquiry (Anderson et al., 2025). Exploring this integration requires understanding how AI can complement and extend learning communities within educational contexts. Considering this, recent research highlights the need for “theoretical and conceptual frameworks for understanding and evaluating AI” (Namaziandost & Rezai, 2024, p. ii) in online learning. In this context, Nasr et al. (2025) applied the Cognitive Presence (practical inquiry) construct to examine how generative AI influences critical thinking across its phases. Nasr et al. (2025) demonstrated the value of a theoretical lens—specifically the Cognitive Presence construct—showing that learner co-participation with AI can effectively support critical inquiry and thinking.

At its core, the CoI theoretical framework is a process model, representing the dynamic of collaborative inquiry grounded in personal reflection and critical discourse. In this way, educators can foster deep and meaningful educational experiences and outcomes. From a community of inquiry perspective, we suggest that AI should be understood not as a neutral tool operating outside the learning process, but rather as a sociotechnical actor whose functions intersect with Teaching, Social, and Cognitive Presence in different ways. AI tools may support instructional design, facilitation, and direction (Teaching Presence); influence psychological safety, belonging, and affective/emotional engagement (Social Presence); and support learners’ inquiry processes (Cognitive Presence) (Stenbom et al., 2026). In this article, we do not assume a single role for AI; rather, we propose that AI is capable of assuming multiple roles within a community of inquiry, depending on how it is designed, positioned, and engaged within the learning environment. We elaborate on these roles later in the article.

As we will see, the educational challenge of AI lies in maintaining academic integrity to ensure that learners actively construct personal meaning and shared knowledge. This is crucial for learners to critically assess AI-generated results and remain prepared to defend their reasoning. Thus, the CoI framework, with its emphasis on critical discourse, is well-suited to guide the educationally sound adoption of AI. Critical thinking and inquiry remain central to leveraging AI's strengths while mitigating the risk of intellectual passivity that can accompany easy access to AI-generated information. The CoI framework offers both cognitive and methodological grounding for meaningful learning in AI-mediated environments.

Studies have noted that AI research has insufficiently explored issues of critical thinking and collaboration (Bozkurt & Sharma, 2023). Yet AI has the potential to support "collaborative learning by facilitating communication and cooperation among learners, instructors, and resources" (Namaziandost & Rezai, 2024, p. i). With this in mind, we argue that AI can amplify reflective interaction and foster skeptical, critical approaches through collaboration and shared inquiry. This is crucial as true knowledge (deep and meaningful learning) is constructed and confirmed through personal reflection and critical discourse guided by collaborative inquiry dynamics and supported by shared meta-cognitive awareness (Garrison, 2015). This argument also speaks to facilitating insight and creativity in the educational process. Therefore, this conceptual article addresses the research question: *How can a collaborative-constructivist perspective inform our understanding of generative AI in digital learning environments?* To answer this, we begin with a brief overview of the capabilities and limitations of generative AI.

AI Overview

AI refers to the use of computer systems designed to perform tasks that traditionally would require human intelligence, such as problem-solving, pattern recognition, language understanding, and decision-making. In educational settings, AI can take many forms, including adaptive learning platforms, automated assessment tools, intelligent tutoring systems, and conversational agents supporting learners in real time (Bond et al., 2024; Zawacki-Richter et al., 2019). The adoption of AI in education accelerated dramatically with the introduction of generative AI in 2022–2023, marked by the release of tools such as ChatGPT, Copilot, Gemini, and Claude. Since then, the field has continued to evolve rapidly, as AI systems can now create text, images, video, and audio, and new systems appear daily. As Beckman et al. (2025, p. 1) caution, "the rapid pace of technological change with generative artificial intelligence is accelerating much faster than our capacity to understand and regulate it." Although AI is not new, it has become more accessible and user-friendly than ever before.

This rapid development further highlights the importance of clarifying key concepts, especially the distinction between *deep learning* as an AI method and *deep learning* as a pedagogical approach central to the CoI framework. AI deep learning trains algorithmic models on vast datasets (LeCun et al., 2015; Jordan & Mitchell, 2015), while in a community of inquiry, deep learning depends on critical discourse and systematic reflection (Lipman, 2003; Garrison, 2017). AI can reveal connections otherwise overlooked, yet its results are often unverifiable because sources are rarely transparent; AI is only as good as its training data. This calls for reflection and dialogue to assess plausibility and consider alternatives. Generative AI does not itself manage inquiry; in contrast, educational deep learning is a human-centered process of questioning, constructing meaning, and developing metacognitive awareness to guide inquiry. The challenge for educators is to use AI to support, not replace, collaborative inquiry that cultivates imagination and discovery.

AI has considerable potential to execute well-defined or repetitive activities with efficiency and precision. Moreover, generative AI can also support more open-ended and creative processes. In education, AI tools have been shown to support data-driven decision-making, provide adaptive learning guidance, help educators monitor progress, and enable more flexible and personalized pathways (Corbeil & Corbeil, 2025). However, while AI can open new avenues, its value in education depends on how it is used. Without an intentional focus on reflection and discourse, there is a serious risk that learners could become passive recipients of AI-generated information, accepting it without question and forfeiting the cognitive engagement needed for deep learning. In a collaborative-constructivist framework, where meaning emerges through sustained dialogue, reflection, and the testing of ideas, such passivity undermines the very processes that make learning transformative.

Instead, we call for an approach where AI serves as a catalyst for inquiry, prompting learners to consider diverse perspectives, alternative explanations, and new resources that can extend the conversation. It can help to structure complexity, visualize relationships, and provide feedback that encourages deeper questioning. Yet these affordances must be balanced against the danger of using AI as a shortcut that bypasses reasoning, debate, and negotiating meaning. The challenge is to integrate AI in ways that preserve human agency in sense-making, ensuring that technology enriches rather than replaces the collaborative discourse and critical thinking essential to deep learning.

The literature on AI and digital learning is growing rapidly, with many studies highlighting the potential of generative AI to enhance learner engagement. For instance, Kılınç (2023) argues that ChatGPT has the “ability to engage in dynamic, context-aware conversations that can facilitate a more engaging and interactive learning environment, thereby enhancing students’ critical thinking and problem-solving skills” (p. 206). We support this view, yet most people remain vulnerable to confirmation bias. In addition, people are now open to assault from AI misdirection and misinformation (Garrison, 2023). Unchecked, such misinformation risks reinforcing echo chambers that erode critical discourse and weaken learners’ capacity for reflective inquiry. This makes the educator’s role in fostering critical evaluation and open dialogue more essential than ever if AI is to strengthen, rather than diminish, deep learning. For this reason, much work is required to appreciate exactly how best to achieve engaging but critical learning environments that use generative AI technologies. To this end, a sound theoretical framework is essential to explore and assess approaches that use generative AI tools.

Kılınç (2023) clearly outlines the benefits and limitations of generative AI when he states, “Limitations and hazards associated with using ChatGPT in education include the potential for perpetuating biases, producing, and spreading misinformation, positioning itself as the ultimate epistemic authority without sufficient evidence” (p. 207). All of this leads educators to “emphasize the need to harness technology, cultivate a sense of community, and encourage educators to pursue continual professional development” (p. 230). The greatest educational risk of generative AI is reducing learning to the passive consumption of easily digestible content, without the purposeful discourse needed to uncover distortions and hidden assumptions. Educators must not undermine critical reflection and discourse by overvaluing AI’s capacity for information generation and assimilation.

A review of online learning research noted that intelligent tutoring systems have played an important role (Hwang et al., 2022; Jansson et al., 2024). From the perspective of traditional distance education grounded in independent study, intelligent tutoring systems that personalize and support independent study have clear benefits. However, personalization and efficiency cannot replace the collaborative inquiry through which learners challenge claims and assumptions. This concern is evident in another article exploring the boundaries of AI, which states, "generative AI requires enhancing the scope of current educational roles or adopting new ones such as facilitators of learning, curators of learning resources, designers of learning experiences, and assessors of learning" (Bozkurt & Sharma, 2023, p. i). As we move forward in adopting AI technologies, we must address these responsibilities while balancing the advantages of personalization with the need for collaborative inquiry.

Another crucial issue closely linked to AI's growing influence is learning analytics. Considerable overlap exists between AI and learning analytics in supporting cognitive presence within educational communities. A review of AI in online higher education identified performance assessment and prediction as its primary functions and reported positive effects on instructional quality and learning outcomes (Ouyang et al., 2022). This highlights how learning analytics can be used to evaluate learning processes and enhance critical engagement. AI can also strengthen analytic tools that identify metacognitive strategies and guide the monitoring and management of collaborative inquiry.

AI presents enormous challenges to educators. Addressing these challenges requires a coherent theoretical perspective to guide the meaningful integration of AI into education. The theoretical perspective offered here is based on metacognitively informed collaborative inquiry capable of monitoring and managing discourse in real time.

Shared Metacognition

The CoI framework provides a well-established foundation for understanding how meaningful learning experiences are achieved through the interplay of teaching, social, and cognitive presence (Bozkurt & Zawacki-Richter, 2021). Within the framework, the concept of shared metacognition has a distinctive role as an explanatory model for how collaborative inquiry is monitored, regulated, and sustained over time (Garrison, 2015). Shared metacognition captures how learners collectively take responsibility for reflecting on their thinking, evaluating emerging understandings, and managing the direction and quality of inquiry—processes that become particularly critical in AI-rich learning environments.

Metacognition refers to the awareness and regulation of thinking and learning processes. In other words, it is the ability to reflect on what is known, how it is known, and how to adjust approaches to achieve better outcomes. It involves monitoring and controlling cognitive processes and jointly articulating and negotiating thinking with others (Flavell, 1987). Within the CoI framework, shared metacognition captures collective monitoring and regulation of thinking that occurs in a collaborative learning environment (Jansson et al., 2021). This offers a coherent way to harness the potential of AI while managing the inherent risks of such powerful and pervasive technology. Educational experiences in AI-rich contexts require maintaining reflective responsibility and control through metacognitive monitoring and managing of the collaborative inquiry process. In this regard, the Shared Metacognition construct (Garrison & Akyol, 2015a, 2015b) provides a starting point for the discussion of why and how shared metacognition is of relevance as we enter the age of AI.

The theoretical foundation of the shared metacognition construct is grounded in the literature on metacognition with a focus on regulation. The premise is that deep approaches to thinking and learning necessitate that we “communicate, explain, and justify … one’s thinking to self and others” (Flavell, 1987, p. 27). In short, thinking collaboratively “reveals our thought processes and encourages us to think about our thinking” (Garrison, 2015, p. 82). Therefore, regulation of collaborative inquiry depends on participants taking responsibility for monitoring and managing the inquiry process. The shared metacognition construct consists of self- and co-regulation, each of which has monitoring and management functions, embedded in collaborative inquiry. These dynamic dimensions have been validated both structurally and transactionally (Garrison & Akyol, 2015a, 2015b). To be clear, shared metacognition relies on discourse, where critical feedback uncovers errors and misleading outputs produced by AI.

Shared metacognition is critical to understanding and effectively implementing inquiry in a community of learners. Through this process, participants learn to audit and verify AI results. To this end, the Shared Metacognition instrument was developed to empirically assess purposeful regulation of learning in communities of inquiry (Garrison & Akyol, 2015a, 2015b). Martha et al. (2023) used the Shared Metacognition construct and questionnaire to examine how metacognitive support, provided through teaching presence, influences self- and co-regulation in collaborative inquiry. They found significant improvement in both perspectives, supported by quantitative and qualitative data, and concluded that “integrating metacognitive and motivational scaffolds fosters cognitive engagement and manages learner motivation” (p. 582). These findings demonstrate the effectiveness of shared metacognition in regulating collaborative inquiry and its relevance for auditing AI results.

Generative AI will inevitably reshape how educators design deep and meaningful learning experiences. It can support online learning communities by curating resources and generating natural-language responses, yet its opacity and potential for fabricating content pose serious risks. Interactive AI may reduce these risks, but it also tempts educators to surrender academic direction. While AI can inform the regulation of inquiry, excessive reliance threatens to erode critical engagement. The essential challenge is to sustain a questioning attitude toward AI results and resist dependence on its generative power.

To reiterate, we argue that shared metacognition within the CoI framework provides a constructive means to integrate generative AI that can enhance learning while curbing uncritical use of flawed outputs. Shared metacognition lies at the core of understanding, monitoring, and managing collaborative inquiry, ensuring learners retain awareness and responsibility in constructing and validating knowledge. In this way, it offers a foundation for managing AI’s benefits and risks and realizing its transformative educational potential. Educational leaders must model and promote their critical use to achieve meaningful learning outcomes—an essential challenge explored in the next section.

Practical Implications

Fundamentally, AI adoption requires a mindset that is skeptical and critical yet also open-minded and curious, recognizing its opportunities while remaining attentive to potential challenges. This balanced mindset is essential for navigating AI’s opportunities and risks. In education, it is crucial to understand how generative AI can enrich learning communities while inevitably reshaping the educational experience. Effective implementation, therefore, requires insight into its potential across the design, facilitation, and direction of meaningful learning.

While AI is found in the core capabilities of a range of technologies, the focus here is on how AI can enhance and support collaborative learning. Within a community of inquiry, AI can help monitor and manage teaching, social, and cognitive presence, with learning analytics playing a key role. Its ability to synthesize vast information and engage interactively—as seen in tools such as ChatGPT, Copilot, Gemini, and Claude—offers significant opportunities for collaborative inquiry. Despite risks of misuse (e.g., automated essay generation), generative AI's capacity for sustained dialogue can stimulate deeper questioning and reflection, supporting the goals of the CoI framework (Rospigliosi, 2023). A review of ChatGPT as a tool for supporting inquiry in higher education recently analyzed its role through the lens of the CoI framework (De Silva et al., 2025). The study assessed how ChatGPT fosters social and cognitive presence in online research communities and found that it positively influenced the quality, efficiency, and motivation of student research. Yet it also cautioned that ChatGPT cannot replace human supervision or peer collaboration, emphasizing the need for students to verify the accuracy and reliability of its outputs.

When designing and shaping learning methods in collaborative-constructivist contexts, the first key element is recognizing how AI can enhance learning within such communities. The focus must remain on critical thinking and inquiry—core principles of the CoI framework and shared metacognition—rather than on AI-generated results. Generative AI can be especially valuable in early inquiry phases by helping define problems, clarify solutions, and synthesize existing knowledge to reveal alternative perspectives. Building on these findings, studies have observed practical applications of AI in collaborative inquiry in areas such as writing and reflection. Southworth (2023) noted that focusing on the writing process helps students develop metacognitive and analytical skills, especially when peer feedback and self-evaluation are included. Similarly, Shen and Teng (2024) found that AI-assisted drafting allows learners to focus on substance rather than surface. Such practices reflect Teaching Presence in designing, facilitating, and directing critical engagement with AI-generated content.

The second element would be to use AI for learning analytics. AI supports learning analytics by transforming large, complex learner data into meaningful insights that reveal learning processes, predict risks, and support timely, informed pedagogical decisions (Mamede & Santos, 2025). By enabling pattern detection, personalization, and analysis of both quantitative and qualitative data, AI helps educators and learners move from retrospective reporting to actionable understanding and support (Ouyang et al., 2023; Sajja et al., 2025). AI-driven learning analytics fit naturally with text-based online learning transactions and can serve as a powerful diagnostic resource, revealing the personal and collaborative complexities of a learning community. Previous research shows that AI tools have greatly enhanced the effectiveness of a community of inquiry through analytics. Learning analytics depends on the timely assessment of engagement and performance to ensure the effective progression of collaborative inquiry. AI systems can also be trained on shared metacognitive strategies associated with collaborative inquiry. Finally, when the CoI framework was developed, the authors envisioned automatic coding of the presence for diagnostic purposes. One promising example is Castellanos-Reyes et al. (2025), which leveraged GPT-based large language models to automate the content analysis of Cognitive Presence. Their findings suggest that these models show potential in achieving high accuracy in coding, offering a scalable approach to applying the CoI framework for research and diagnostic purposes.

The CoI framework provides a means to explore how AI systems can be understood as actors within a community of inquiry. In this sense, learning activities may involve both human participants and virtual participants in the form of AI agents. The term AI agent is used to describe an AI-based system that can receive input, respond in context, and act with a certain degree of independence in ways that influence the learning activity. Through this kind of participation, AI agents may function in ways similar to human members of a community of inquiry. Integrating a high-quality AI agent into a community of inquiry would naturally bring several benefits, enriching the educational landscape. Ultimately, AI agents could support human teachers by serving as co-instructors, enhancing the learning experience through personalized and adaptive strategies. While the notion that AI agents could replace human instructors sparks debate, it is essential to focus on how these technologies may augment and support the pivotal aspects of facilitation and direction in the educational process. In synergy with human educators, AI can strengthen key dimensions of Teaching Presence—design, facilitation, and direction—thereby enriching the community of inquiry.

Roles of AI in a Community of Inquiry

As AI becomes increasingly prevalent in education, its integration into communities of inquiry holds significant potential. Building on earlier discussions, this section examines how AI can enrich learning activities guided by the CoI framework's focus on critical thinking and inquiry. We outline five distinct roles AI may assume within a community of inquiry, illustrating practical applications and their implications for educators and learners. These roles are not mutually exclusive and may intersect or coexist within the same learning experience.

- AI support for learning design: AI assists educators in structuring and sequencing content, generating materials, and identifying biases to promote inclusive and effective course designs.
- AI as an independent resource: AI tools serve as on-demand resources, helping students and educators with writing or editing texts, understanding concepts, and generating ideas.
- AI as a support function and guide for instructors: Integrated AI systems monitor student interactions, provide insights on participation, and suggest strategies to enhance teaching effectiveness and student engagement.
- AI agents as members of a community of inquiry: AI entities actively participate as fictional teachers or students in discussions and learning activities, contributing to teaching, social, and cognitive presence within the educational community.
- Human and AI agents creating a relationship of inquiry: AI serves as an engaged partner in individualized learning, offering guidance and fostering critical thinking through a dynamic student-AI relationship.

AI Support for Learning Design

As instructors design courses and learning activities guided by the CoI framework, AI can provide tools for structuring learning activities, sequencing content, and encouraging inclusivity. For instance, AI systems can generate presentation materials and thought-provoking questions or create case studies tailored to specific learning objectives, contributing to the design and organization component of Teaching Presence. By automating repetitive tasks, such as curating resources or mapping learning outcomes, AI allows educators to focus on higher-order planning. Additionally, AI can help design activities that encourage collaboration and reflection, ensuring that inquiry-based learning emphasizes shared metacognition and collaborative inquiry. AI tools can also identify potential barriers in course design, such as cultural or linguistic biases, and suggest adjustments to foster equitable participation.

These design capabilities expand the CoI framework by emphasizing the preparatory work required to establish an effective community.

AI as an Independent Resource

As external resources, AI tools provide students and instructors with flexible, on-demand material. Functioning outside formal learning management systems or communication tools, AI tools such as ChatGPT, Copilot, Gemini, and Claude act as information sources, synthesizers, and supports for critical thinking. Students might use AI to clarify complex concepts or generate counterarguments, which they then bring into learning activities to deepen Cognitive Presence. Specifically, AI can support students across the categories of Cognitive Presence, from generating new ideas during triggering events and exploration, through synthesizing information during integration and evaluating solutions during resolution. These tools empower learners to engage in reflection on their learning processes and their role in group activities. AI can also support group efforts by serving as a shared resource for brainstorming or synthesizing knowledge, fostering collaboration and collective engagement. In short, AI tools offer opportunities to extend learners' capacity to question, analyze, and collaboratively construct meaning—key features of Cognitive Presence within the CoI framework.

AI as a Support Function and Guide for Instructors

When integrated into the educational platform, AI can become an analytical and strategic support for instructors. Drawing on approaches from Learning Analytics, particularly profiling and prediction, AI systems may monitor participants' activity, evaluate community interactions, and provide actionable insights to enhance teaching and social presence while promoting cognitive presence. For example, AI can track participation trends, identify students in need of extra support, and suggest facilitation strategies to foster community and prompt collaborative inquiry. Yet profiling and prediction also carry risks: they may categorize learners in ways that oversimplify complex identities, reinforce stereotypes, or privilege certain perspectives, thereby challenging the inclusivity and openness of collaborative learning (Bond et al., 2024). Moreover, AI can help instructors assess where students are situated within the phases of Cognitive Presence—triggering events, exploration, integration, or resolution—and recommend individualized feedback or interventions tailored to their cognitive development. This role adds nuance to the CoI framework by emphasizing instructors' capacity for data-driven decision-making. Here, the human instructor remains in charge, with the AI acting solely as an adviser providing suggestions for action. Through dynamic feedback loops, AI reduces the cognitive load on educators, allowing them to focus on fostering meaningful interactions. However, ethical considerations arise, particularly regarding transparency and bias in historical data, which may reproduce inequities and undermine inclusivity.

AI Agents as Members of a Community of Inquiry

In this transformative role, AI becomes a semi-autonomous member of a community of inquiry, actively contributing to teaching, social, and cognitive presence. As an instructor, co-instructor, or fictional student, AI agents can engage in discussions, provide real-time scaffolding, and adapt their input based on the group's needs. A well-trained AI agent may be of value in all aspects of Teaching Presence (i.e., designing, facilitating students, and providing directions) and Social Presence (i.e., being affective, prompting open communication, and fostering group cohesion), thereby supporting students' practical inquiry (Cognitive Presence).

In situations where a human and an AI instructor work together, the AI can complement the human instructor's expertise by handling well-defined routine tasks and providing real-time support during discussions. All support functions mentioned above can be integrated into such AI agents, which in this case may act automatically, without requiring human approval. Although communities of inquiry led largely by AI are not ideal, it is reasonable to expect such approaches to emerge, driven by their promise of scalability and efficiency. This raises important questions about the potential impact on the quality of collaborative learning and the preservation of human-centered elements within the community. This role challenges traditional boundaries, positioning AI as a participant agent rather than a supporting tool. While this autonomy enhances scalability and responsiveness, it also raises concerns about authenticity in presence and the risk of dehumanizing collaborative learning. For instance, the social presence created by an AI may lack genuine emotional intelligence, potentially undermining trust and engagement in the community. We therefore call for an integrated approach, where AI manages well-defined and repetitive activities consistently and without fatigue while the human instructor ensures higher-order thinking, integrating perspectives, guiding inquiry, and sustaining the authenticity of collaborative inquiry.

Human and AI Agent Creating a Relationship of Inquiry

This role is grounded in the concept of a partnership between a student and a tutor (Stenbom et al., 2016), reimagined through the substitution of the tutor with an AI counterpart. Unlike the *AI as an Independent Resource for Inquiry* role—where AI is treated as a tool or information source—a relationship of inquiry emerges when interaction becomes sustained and dialogical. Here, the learner engages with an AI tutor not only as a provider of answers but as a partner whose outputs are continually scrutinized, adapted, and guided, reflecting elements of pedagogical trust and mutual shaping.

This type of interaction has been tested for years in the form of conversational agents, virtual tutors, and chatbots. However, with the advent of generative AI and large language models, these systems have become significantly more sophisticated. In a relationship of inquiry, the AI assumes the role of a tutor by contributing to Teaching Presence (designing, guiding, directing, explaining, and scaffolding learning), supporting Social Presence (interacting affectively and openly, and supporting relationship cohesion), and fostering Cognitive Presence (prompting inquiry). This dynamically models a one-to-one version of the *AI Agents as Members of a Community of Inquiry* role rooted in the principles of the CoI framework.

This approach offers several advantages. It provides scalable and consistent tutoring support, making individualized learning more accessible. Learners benefit from real-time guidance tailored to their specific needs, which can help them better understand content and stay motivated. Furthermore, interacting with an AI tutor can foster metacognitive skills and promote self-directed learning by encouraging students to reflect on their understanding and strategies.

At the same time, however, the lack of human intelligence may reduce the authenticity of Social Presence and Teaching Presence. There is also a risk that learners may become overly dependent on AI, potentially missing opportunities to engage in peer collaboration and develop interpersonal skills. Lastly, ethical concerns must be considered, especially regarding how data is used and the potential for AI systems to reinforce biases present in their training data.

Conclusion

This article has examined the question: *How can a collaborative-constructivist perspective inform our understanding of the adoption of generative AI in digital learning environments?* We argued that collaborative inquiry shaped by shared metacognition most effectively facilitates and directs deep and meaningful thinking and learning in the context of generative AI technologies. This speaks directly to the essence of the CoI framework and specifically shared metacognition to encourage critical analysis of AI generative information and facilitating approaches to learning that extend beyond surface meaning. In the final analysis, educators and learners must manage the risks of AI by encouraging skepticism and maintaining control of educational decisions. AI offers clear benefits, such as supporting individualized learning, efficiently handling well-defined problems, and carrying out repetitive tasks without fatigue. Yet, however sophisticated its reasoning capabilities may appear, AI remains soulless. It can construct coherence and simulate meaning, but meaning becomes truly educational when humans engage with, interpret, and integrate these outputs into shared understanding. AI may speed up information assimilation, but educators must slow inquiry to allow for critical reflection and discourse. That is, we need to take the time to reflect and openly share our understanding of generative AI outputs. Thoughtful and constructive use of generative AI necessitates critical thinking and discourse best made possible through shared metacognitive inquiry that reflects collaborative monitoring and management of the learning process.

As the reasoning power of AI grows, the need to question and make sense of AI-generated information may diminish. From a collaborative-constructivist perspective, this risk underscores the importance of educating individuals to resist complacency and of employing AI to enhance critical and collaborative thinking. This highlights the need for a theoretical framework to study and understand AI's integration into educational practice. The increasing power of AI and its potential dominance in generating coherent information raises the role and importance of human critical analysis of information and knowledge structures in terms of the evolution of knowledge. Indeed, we are already in a situation where much of the information we encounter has been at least partially generated by AI. This uncertainty about the origins of information requires us to adopt a critical stance toward everything we engage with, demanding constant reflection, verification, and skeptical inquiry. The argument here is that an educational framework is essential for understanding and implementing AI to generate new insights and construct shared knowledge. Such a conceptual educational framework can be a guide and justification for a purposeful, critical, collaborative inquiry approach where curious skepticism is the central tenet when incorporating AI tools in an educational context.

The key to the successful educational adoption of AI is to understand the challenge of such a potentially impactful technological tool. Every indication is that AI has started to transform educational practices, which makes it imperative that we have a means to make sense of the complex issues. As we start down this transformational road, it becomes imperative to have a coherent perspective of the elements and dynamics that need to be considered. At the same time, we must recognize that the rapid pace of development means our present understanding is provisional. Rather than seeking final answers, the task is to remain open to continuous reflection and refinement, allowing our theoretical and educational perspectives to evolve alongside the technology itself. We must be sure to measure, analyze, and understand the impact of AI in terms of the nature and goals of the learning experience—in other words, to provide it with a soul grounded in human purpose. This is why it is essential to have a meaningful and defensible theoretical framework that can guide us in the application and assessment of AI in achieving deep and meaningful learning experiences. Only then will we understand the potential of AI to shape worthwhile learning experiences.

Declaration of Generative AI Use

During the preparation of this work, the authors used ChatGPT (OpenAI) to support language editing and improve clarity of expression. After using this software, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Book Review: *Artificial Intelligence and Education in the Global South: A Systems Perspective*

Authors: Fernando Reimers, Zainab Azim, Maria-Renée Palomo, and Callysta Thony (Springer, 2026, 198 pages). ISBNs: 978-3-032-11448-8 and 978-3-032-11449-5 (eBook). https://doi.org/10.1007/978-3-032-11449-5

Reviewed by: Agnes Amila Wigati[1] and Deni Puji Hartono[2]
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Introduction

The 2026 book *Artificial Intelligence and Education in the Global South: A Systems Perspective* by Reimers, Azim, Palomo, and Thony addresses the urgent need for K–12 educational systems to adapt to the disruptions caused by artificial intelligence (AI) in the global workforce. The authors define AI as the simulation of human intelligence by machines capable of communication, reasoning, and learning. Published as an open-access resource, this work is designed to be highly accessible, offering vivid descriptions and practical software references, such as ChatGPT, Khanmigo, and various AI-driven data analytics tools. The authors make this complex subject matter tangible for educators and policymakers alike.

The primary focus is on the Global South, as it is home to 90% of the world's population under the age of 18. The transformative potential of AI may have its greatest impact here, provided it is guided by intentionality. Adopting a systems perspective, the authors evaluate AI not as a collection of isolated tools, but as an integrated ecosystem encompassing students, teachers, curricula, policies, institutions, and communities. This approach prioritizes three critical dimensions: fostering AI literacy to equip stakeholders with ethical awareness and the capacity for co-intelligence; enhancing school system effectiveness by leveraging AI to optimize learning opportunities; and ensuring educational relevance through curricula that cultivate uniquely human competencies.

The book provides a rigorous analysis of the "global learning crisis," characterized by the failure of millions of children to master foundational skills, noting that increased school enrolment has not necessarily translated into proficiency in literacy and numeracy. The authors caution that without systemic intervention, existing digital divides and socioeconomic disparities are likely to be exacerbated by the rapid deployment of AI technologies. While employing the term *Global South* as shorthand for resource-constrained regions, the authors demonstrate that this category is far from monolithic. Instead, they provide a compelling variation of initiatives from the heterogeneous regions that comprise the Global South. In doing so, they illustrate how the strategic integration of AI can serve as a catalyst for narrowing, rather than widening, educational gaps.

Crucially, the book positions itself within the current AI discourse by advocating for purposeful engagement. Rather than viewing AI as a tool for passive consumption or as a replacement for human agency, the authors encourage stakeholders to become active, critical users who can harness AI to solve local challenges. However, integrating AI into such an ecosystem requires a clear-eyed understanding of the existing educational landscape. The success of this systems-based approach is deeply contingent upon addressing the pre-existing structural inequalities and the uneven quality of schooling that currently define many regions of the Global South. To critically evaluate its practical applications, this review highlights five essential elements for equitable systemic transformation: curriculum, personalized learning, teacher professional development, governance, and ethics.

Curriculum

The curriculum serves as the foundational blueprint of any educational system. The authors argue that AI's most immediate value lies in its ability to facilitate the creation of localized and culturally relevant materials, which is a critical step in overcoming the learning crisis in linguistically diverse regions. Key initiatives include:

- Local content creation: In Mali, AI was used to produce over 180 children's books in the Bambara language. Similar efforts in Benin and Cameroon involved drafting science textbooks that reflect local cultural contexts.
- Teacher support: In Brazil, AI-powered lesson planning tools have assisted teachers in generating tailored instructional materials.
- National strategies: The book contrasts various national approaches, such as China's mandatory K–12 AI curriculum and Uruguay's flexible framework centered on computational thinking, critical thinking, creativity, ethics, and societal impact.

Personalized Learning

While the curriculum defines what is learned, personalized learning addresses how it is mastered. The book emphasizes AI's capacity to democratize elite-level tutoring for the masses in the Global South. In India, the Mindspark adaptive learning platform adjusts content based on real-time performance. In Nigeria, virtual assistants have shown significant learning outcome gains for girls, potentially narrowing the gender gap. Furthermore, AI enhances inclusivity, as seen in Kenyan projects translating English into Kenyan Sign Language for deaf students. These diverse applications underscore the authors' assertion that AI-driven personalization is not merely a technical upgrade but a strategic imperative for fostering inclusive education and mitigating structural disparities in student success.

Teacher Professional Development

A central thesis of the book is that teachers remain the heart of the educational system. AI is presented as a pedagogical assistant rather than a replacement. It supports teachers through instructional coaching (immediate feedback), simulations (practicing classroom management), and administrative automation (reducing routine burdens to prioritize student interaction). Educational technology cannot succeed without human agency; thus, professional development is the bridge between AI potential and classroom reality.

Governance

At the macro level, the success of the aforementioned three critical dimensions—AI literacy, school system effectiveness, and educational relevance—depends on robust governance. Using a systems approach for analysis, the authors demonstrate how AI can be integrated into the broader educational system. AI enhances governance through data-driven decision-making, optimizing resource allocation, and employing machine learning to predict student dropout. This allows policymakers to move beyond isolated interventions toward systemic risk management across the entire educational landscape.

Ethics

Finally, a robust ethical framework is indispensable to safeguard the integrity of the entire educational ecosystem. Without ethical vigilance, the potential benefits of AI in curriculum design or institutional governance risk being invalidated by algorithmic bias, data privacy breaches, or the erosion of transparency. Another critical challenge that the authors specifically identify is de-skilling, which is the loss of critical human cognitive capacities. They argue that meaningful transformation must arise from system-wide innovations deeply rooted in local cultural and linguistic contexts. Consequently, the book maintains that ethical integration is not merely a regulatory requirement but a strategic imperative to ensure that AI functions as a catalyst for human agency rather than a precursor to new forms of technological dependency.

Conclusion

Ultimately, the book positions AI as a tool to empower the Global South and direct it toward a more equitable and high-quality educational future, provided AI is approached not as a silver bullet but as a deliberately managed ecosystem. The book is a valuable source for educators, researchers, and administrators interested in using AI in the various contexts of the Global South.

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Book Review: Two Books by James Hutson and Daniel Plate: *The Case Against Disclosure* and *Mind, Machine, and Will*

Authors: *The Case Against Disclosure: Defending Creative Autonomy in the Age of AI*, by James Hutson and Daniel Plate (Common Ground Research Network, 2025, 240 pages). ISBNs: 978-1-966214-56-4 (hardback), 978-1-966214-57-1 (paperback), and 978-1-966214-58-8 (eBook).

Authors: *Mind, Machine, and Will: Determinism, Responsibility, and Agency in the Age of AI*, by Daniel Plate and James Hutson (Nova Science, 2025, 231 pages). ISBNs: 979-8-89530-934-6 (hardback) and 979-8-89530-952-0 (eBook).

Reviewed by: Emily Pickering, *Boise State University, USA*

Introduction

From Socrates' condemnation of the written word to today's anxiety over generative artificial intelligence, technological changes have consistently disrupted how humans create, communicate, and claim ownership of ideas. In the two books, *The Case Against Disclosure* and *Mind, Machine, and Will*, James Hutson and Daniel Plate situate contemporary AI debates within this longer intellectual history. They urge readers to reconsider how meaning, authorship, and agency are understood in an age of hybrid human-machine collaboration. To address complexities in their arguments, the authors draw from multidisciplinary theories and practices. Reviewing the books together highlights their shared call to educators, scholars, artists, and policy makers to rethink the AI practices and policies shaping creative and scholarly life.

The Case Against Disclosure

In *The Case Against Disclosure: Defending Creative Autonomy in the Age of AI* (2025), Hutson and Plate argue that in a digital era marked by increasing ease to collectively create works, it is practically untenable for institutions to demand detailed obsessive AI disclosure documents in a misconceived attempt to detail every AI-influenced prompt or revision. This form of disclosure misunderstands the nonlinear nature of creativity. They show how the creative process always resists this bureaucratic control. Exhaustive AI disclosure requirements shift intellectual labour away from genuine intellectual responsibility, substituting it with a new burden of proving authorship. Creativity has never been fully transparent or individually isolated; it is shaped by subconscious influence, collaboration, and cultural inheritance.

A central thread running through the book is the defense of discernment over disclosure. Hutson and Plate do not deny the importance of ethical engagement with AI, but they question whether exhaustive forced procedural AI transparency meaningfully protects authorship. Instead, they argue that authorship hinges on human-intervention judgment, selection, and responsibility during the writing process—even within algorithmic collaboration. Historical examples, from medieval scribal practices to kinetic art and digital media, highlight that co-creative processes and variations in collective ownership of knowledge are longstanding cross-cultural traditions.

Particularly interesting is the authors' critique of institutional fear. They suggest that AI disclosure regimes may serve less to protect creativity and more to preserve control. In educational settings, plagiarism-detection technologies and rigid policies often disadvantage multilingual and neurodiverse writers, reinforcing narrow norms for originality. This critique raises important questions about how emerging AI policies may shape access, participation, and equity across increasingly networked learning environments. In contrast to this rigidity, the authors advocate for encouraging ethical exploration with AI rather than enforcing suspicion. Responsible AI use, they argue, is demonstrated not through exhaustive disclosure but through intentional integration.

Ultimately, *The Case Against Disclosure* defends creative autonomy, not as an isolated practice but as the capacity for people to exercise discernment within evolving technological environments. The authors propose a pragmatic framework to ensure accountability in AI use without impeding creativity. They write that their framework "explicitly preserves methodological privacy and intellectual autonomy, even as it maintains legitimate transparency" (p. 160). The framework offers a pathway to reduce bureaucratic friction by creating space and processes for continual dialogue between institutional administrators and content creators who use AI-driven tools.

Mind, Machine, and Will

The book *Mind, Machine, and Will: Determinism, Responsibility, and Agency in the Age of AI* (2025) advances a bold and philosophically rigorous argument: contemporary debates about artificial intelligence, authorship, and accountability cannot be resolved by defending traditional notions of autonomous free will. Drawing on Wittgensteinian philosophy, contemporary neuroscience, legal theory, and speech act theory, the authors propose a shift from metaphysical individualism toward a practice-based, communal model of agency. Meaning, value, and agency are not grounded in private mental states or in hidden intentions, but in publicly accessible practices. Following Wittgenstein's critique of private language, the authors argue that rule-following and meaning-making are by nature social activities. Agency, in this account, is not a purely metaphysical property but something constituted within communities whose norms and expectations remain open to revision.

This philosophical shift is especially important given the neuroscientific findings that challenge traditional notions of free will. Research demonstrating that decisions arise from complex causal chains—from neural processes to environmental conditions—undermines the idea that actions are fully self-originating. Rather than dissolving responsibility, however, the authors argue that these findings invite a revision of the concept of accountability. Responsibility now is about participation within processes of reason-giving and justification as opposed to autonomous intentions with no cause.

This evolved mindset has significant implications for generative artificial intelligence. As machine-generated content becomes increasingly indistinguishable from human-generated work, questions of authorship and authenticity cannot be addressed by purely metaphysical claims to creativity. Instead, the authors propose a practice-based model in which responsibility attaches to demonstrated competence and public participation. Transparency, in this view, does not require an audit of every neural or algorithmic prompting. Instead, it requires visible assumption of responsibility within shared institutional frameworks.

One of the book's most distinguishing contributions is its portrayal of human-AI hybrid authorship. Rather than framing AI as a feared rival to the human mind, the authors position AI as a collaborator in changing communal practices. Copyright systems grounded in human exceptionalism, they argue, are increasingly inadequate. What deserves recognition is not metaphysical originality but meaningful participation in socially recognized creative practices. At the same time, the authors identify some of the weaknesses of overreliance on AI in the creative process. The limitations of artificial intelligence tools highlight the necessity of continuous human oversight and responsive correction. Ethical resilience depends on constructing institutions that support participation, adaptation, and collective learning.

One of the most provocative moves in *Mind, Machine, and Will* is its challenge to traditional models of blame and responsibility. If no idea is fully self-originating, then legal and ethical systems cannot continue to focus primarily on hidden intention or individual will. Instead, the authors urge a shift toward evaluating how agents—both human and machine—function within shared practices. The authors write that the challenge is "not how to preserve the illusion of individual autonomy, but how to construct public, corrigible practices that are trustworthy in their own right" (p. 89). This may leave readers feeling unsettled at first, yet the authors reassure that pushing past metaphysical nostalgia frees societies to build transparent systems capable of adapting alongside technological change.

Ultimately, this book offers reconstructed ideas of agency, value, and justice in a time of machine intelligence. In doing so, it reframes the AI debate away from panic and prohibition, which are historically commonly attached to technological transformations, and towards institutional redesign. Ethical AI is framed as less about isolating the intention of the agent and more about creating communities of shared responsibility.

Crossover Between the Two Books

Read together, *The Case Against Disclosure* and *Mind, Machine, and Will* offer a layered response to contemporary anxieties about AI, creativity, and accountability. While the former focuses on institutional policy and the practical consequences of excessive AI disclosure mandates, the latter takes a deep dive into the philosophical assumptions upon which the mandates are constructed.

Both works challenge the widespread belief that transparency alone guarantees integrity. In *The Case Against Disclosure*, Hutson and Plate question whether documenting every AI prompt or revision meaningfully preserves authorship. In *Mind, Machine, and Will*, they extend this critique by arguing that accountability has never depended on full transparency of inner processes but on participation in public demonstrations of reason-giving and shared standards.

The books complement one another in important ways. *The Case Against Disclosure* reassures readers that human discernment remains central even in human-AI hybrid creative practices. It defends creative autonomy and warns against institutional overreach. *Mind, Machine, and Will*, however, complicates the very notion of autonomy by questioning whether it has ever been as independent or self-contained as cultural narratives suggest. Rather than abandoning responsibility, the second book reframes it as something publicly enacted within communities and institutions. When read together, the defense of autonomy in the first book is strengthened by the second book's argument that agency is sustained through shared public practices.

Readers primarily concerned with educational policy, publishing standards, or institutional AI guidelines may find *The Case Against Disclosure* most immediately applicable. Those interested in the deeper philosophical questions about free will, moral responsibility, and the future of legal systems in a world saturated with AI will likely find *Mind, Machine, and Will* more engaging. Read together, however, the books provide a more complete understanding of the importance of transparency in creativity as a shared, evolving practice, where content creators are free to adopt or reject AI tools as actors, not passive consumers. Both books are valuable to readers interested in considering what it means for society to use AI.

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Artificial Intelligence in Education: Mapping Adaptive Learning and Learning Analytics in K–12 Online, Virtual, and Distance Learning

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Abstract

This scoping review examines how artificial intelligence (AI) has been conceptualized and applied in adaptive learning and learning analytics in K–12 online and distance education between 2020 and 2025. Following Arksey and O'Malley's framework and reported in accordance with PRISMA-ScR, we analyzed 21 empirical studies to explore thematic patterns, methodological trends, and research gaps. Most studies reported gains for learners in engagement, motivation, and self-regulation. However, reported benefits were unevenly distributed and often favored better-resourced learners, particularly in contexts where teacher mediation and institutional support were modest. AI was explicitly integrated in two-thirds of the studies, yet definitional inconsistencies blurred distinctions between genuine intelligence and automated adaptation. Quantitative designs were predominant, largely focusing on performance outcomes as derived from system logs and test data. While a small but growing number of mixed-methods studies have focused on learner experience and teacher mediation, the field remains constrained by methodological consistency and insufficient clarity regarding AI mechanisms. The findings highlight the importance of clearer conceptual frameworks, research designs that are participatory and context-sensitive, and ethical approaches that center teacher expertise and learner participation. This review argues that the transformative potential of AI for adaptive learning depends less on technological sophistication than on equitable, pedagogically informed integration between human judgment and automated systems.

Keywords: artificial intelligence in education, AIED**,** adaptive learning, personalized learning, artificial intelligence, K–12 online learning, learning analytics, equity, scoping review

Introduction

K–12 education has undergone accelerated digital transformation since 2020, particularly following the COVID-19 pandemic, when emergency remote instruction gave way to sustained online, virtual, and distance arrangements. Early syntheses of this period document large-scale shifts to digital platforms alongside uneven capacity, variable access around the world, and concerns about engagement and equity, which continue to shape online learning ecosystems today (Huck & Zhang, 2021). At the same time, international guidance urges governments and educational technology providers to build safe, inclusive, and evidence-informed digital infrastructures while weighing the opportunities and risks of artificial intelligence (AI) in education (Global Education Monitoring Report Team, 2023). Against this backdrop, it is timely to ask how adaptive learning (AL) and learning analytics (LA) are being investigated and deployed in K–12 online and virtual settings, and with what implications for learners, educators, and systems.

Conceptual and pedagogical work highlights that equity, accessibility, and ethics are not peripheral but central to responsible adoption of AI in education. From a pedagogical perspective, human-centered approaches emphasize that AL and LA should be designed with teachers and learners, being the main stakeholders, in mind, aligned to classroom realities rather than displacing them (Shum et al., 2019). From an equity and governance perspective, international reviews further show that policy capacity, infrastructure, and privacy safeguards vary widely, shaping whether AI-enabled systems reduce or reproduce inequities across contexts (Aguerrebere et al., 2022). At the level of learner development, particularly in elementary grades, Boulhrir and Ait Bouch (2025) argue that developmental appropriateness, teacher mediation, and data protection are flagged as essential conditions for use. Other scholars similarly argue for stronger alignment between adaptive mechanisms and defensible theories of learning (Boulhrir et al., 2026). Although AI systems are often presented as closed loops approximating one-to-one tutoring, their effectiveness depends on explicit connections between learner models, instructional models, and content models (Martin et al., 2020; Wang et al., 2020). Methodologically, measurement choices are especially influential because they shape what learner characteristics are inferred and, in turn, what aspects of instruction are adapted. Theoretically, however, many studies provide limited justification for how particular learner characteristics are linked to specific feedback or institutional pathways (Boulhrir, 2025; Maier & Klotz, 2022; Tretow-Fish & Khalid, 2023).

Several recent reviews provide important foundations for understanding AL, LA, and AI in education, yet they differ in scope and emphasis from the present study. Martin et al. (2020) synthesize AL research across contexts and technologies prior to the widespread normalization of K–12 online schooling, while Rundquist et al. (2024) focus specifically on LA in K–12 mathematics, with attention to teaching and learning impacts within the subject area. More recently, Yim and Su (2025) offer a broad scoping review of AI learning tools across K–12 settings, emphasizing tool types and adoption trends. Building on these syntheses, the present review narrows the analytical lens to AI-enabled AL and LA in K–12 online, virtual, and distance education, with explicit attention to AI mechanisms, methodological patterns, and equity implications.

Accordingly, this scoping review aims to systematically map empirical research on AI-enabled AL and LA in K–12 online, virtual, and distance education published between 2020 and 2025. Specifically, it investigates (a) what research methods have been used, (b) what themes, outcomes, and technological tools are reported, (c) the extent to which AI is explicitly emphasized, and (d) what gaps persist for future inquiry.

It adopts a mechanism-aware lens that distinguishes signals, models, decisions, and targets to clarify how AI is embedded in study designs and system architectures (Romero Alonso et al., 2024; Wang et al., 2020). We expect this contribution to provide a consolidated account of current trends and gaps, generate commensurable claims for researchers, offer mechanism-linked guidance for practitioners, and identify governance priorities for policymakers concerned with equitable and responsible adoption (Global Education Monitoring Report Team, 2023; Yim & Su, 2025). Hence, the article proceeds as follows. The next section details Arksey and O'Malley's (2005) framework, which guided our methods, including sources, eligibility, screening, and charting. The results synthesize patterns by AI mechanism and research design. The discussion considers implications for pedagogy, equity, and responsible data use. The conclusion outlines priorities for future research in AI-enabled K–12 online education.

Conceptual and Theoretical Background

Research on AL and LA in K–12 online education is grounded in three interconnected foundations: system components, pedagogical alignment, and evaluation frameworks. Together, these perspectives explain how AI-enabled personalization is conceptualized and studied and why a focused mapping of the field is warranted.

System Components

A common way among researchers to classify system design is by distinguishing the sources that a system interprets from the targets it adapts. These sources typically include learner knowledge states or preferences inferred by AI models, while targets involve feedback, navigation, or activity selection (Maier & Klotz, 2022; Martin et al., 2020). On the assessment side, item response theory (IRT) models underpin many operational platforms, whereas sequence models such as Bayesian knowledge tracing and deep knowledge tracing are frequently discussed but are less often deployed at scale (Ihichr et al., 2024). In AL, often in conjunction with LA, these architectures aim to approximate one-to-one tutoring by estimating learner state and adjusting instructional sequences, task difficulty, or feedback (Wang et al., 2020). Despite this technical sophistication, many systems are described as closed loops, with limited attention to the pedagogical reasoning that governs when and why specific adaptations occur.

Pedagogical and Equity Lenses

Across the literature, design is treated more as a people-first process than a purely technical activity. Human-centered approaches to LA emphasize that systems must be fit for purpose, usable, and aligned with teacher and student needs rather than simply demonstrating algorithmic novelty (Shum et al., 2019). Effective K–12 online instruction builds on pillars such as organization and design, connectedness, accessibility, individualization, active learning, and real-time assessment (Johnson et al., 2023). For younger learners, such as those at elementary levels, developmental appropriateness and teacher mediation are non-negotiable when AI enters early grades. International perspectives keep reminding us that policy capacity and infrastructure vary widely, raising the possibility that AI systems may reproduce rather than reduce inequities if safeguards are absent. These tensions make coordinated governance and professional learning integral to responsible adoption.

Evaluation Logics

According to recent studies, measurement choices are not neutral; they shape what is inferred and, by extension, what is adapted. While adaptive assessment research documents widespread use of IRT, sequence models and reinforcement-inspired approaches are gaining traction (Ihichr et al., 2024). Studies of personalized feedback show adaptation at the micro-, meso-, and macro-levels, but rationales that connect learner characteristics to specific interventions are often thin (Maier & Klotz, 2022). Evaluations of dashboards and analytics environments typically emphasize usability and perceived value, but very few probe multimodal evidence or the deeper structures of pedagogy in classroom use (Tretow-Fish & Khalid, 2023). Claims about learning in this respect would be stronger if instrumentation, validity evidence, and teacher practices were examined together within authentic K–12 contexts. These conceptual, pedagogical, and evaluative strands imply that research on AI-enabled AL and LA is fragmented, with unresolved tensions around definition, purpose, and impact. These unresolved tensions underscore the value of a scoping review that systematically maps research designs, outcomes, and persistent gaps.

Method

This review followed the five-stage framework proposed by Arksey and O'Malley (2005) and was reported in accordance with the PRISMA extension for scoping reviews (PRISMA-ScR; Hamash et al., 2025; Tricco et al., 2018). The purpose was to map rather than appraise study quality, identifying research trends, methodological approaches, technological tools, and persistent gaps related to AI in AL and LA in K–12 online, virtual, and distance education environments.

Stage 1: Identifying the Research Questions

The review was guided by four research questions:

- RQ1: What research methods have been used in empirical studies of AL and LA in K–12 online, virtual, and distance education published between 2020 and 2025?
- RQ2: What themes, educational outcomes, and technological tools are reported in these studies?
- RQ3: To what extent is AI explicitly emphasized in the analyzed studies?
- RQ4: What gaps persist that future research should address?

Stage 2: Identifying Relevant Studies

Searches were conducted in Scopus and ScienceDirect in August 2025, covering publications from January 1, 2020, to August 31, 2025. To supplement coverage, Google Scholar was searched with targeted title queries, and reference lists of included articles were screened. Search strings combined terms for *population*, *intervention*, and *context*:

- Population: "K-12" OR "primary education" OR "secondary education" OR "elementary school" OR "high school"
- Intervention: "adaptive learning" OR "personalized learning" OR "learning analytics"
- Context: "online learning" OR "virtual learning" OR "distance education" OR "remote learning"

The review was limited to English-language publications due to resource constraints and the language coverage of the selected databases; no geographic restrictions were intentionally applied, although regional representation reflects indexing and publishing patterns within these sources. All search strings were subsequently validated manually by the research team. As detailed in Figure 1, the search yielded 177 records (142 from ScienceDirect, 32 from Scopus, and 3 from Google Scholar).

Stage 3: Study Selection

Screening occurred in two rounds: title/abstract screening, followed by full-text screening and data charting. The inclusion and exclusion criteria are summarized in Table 1.

Table 1

Inclusion and Exclusion Criteria

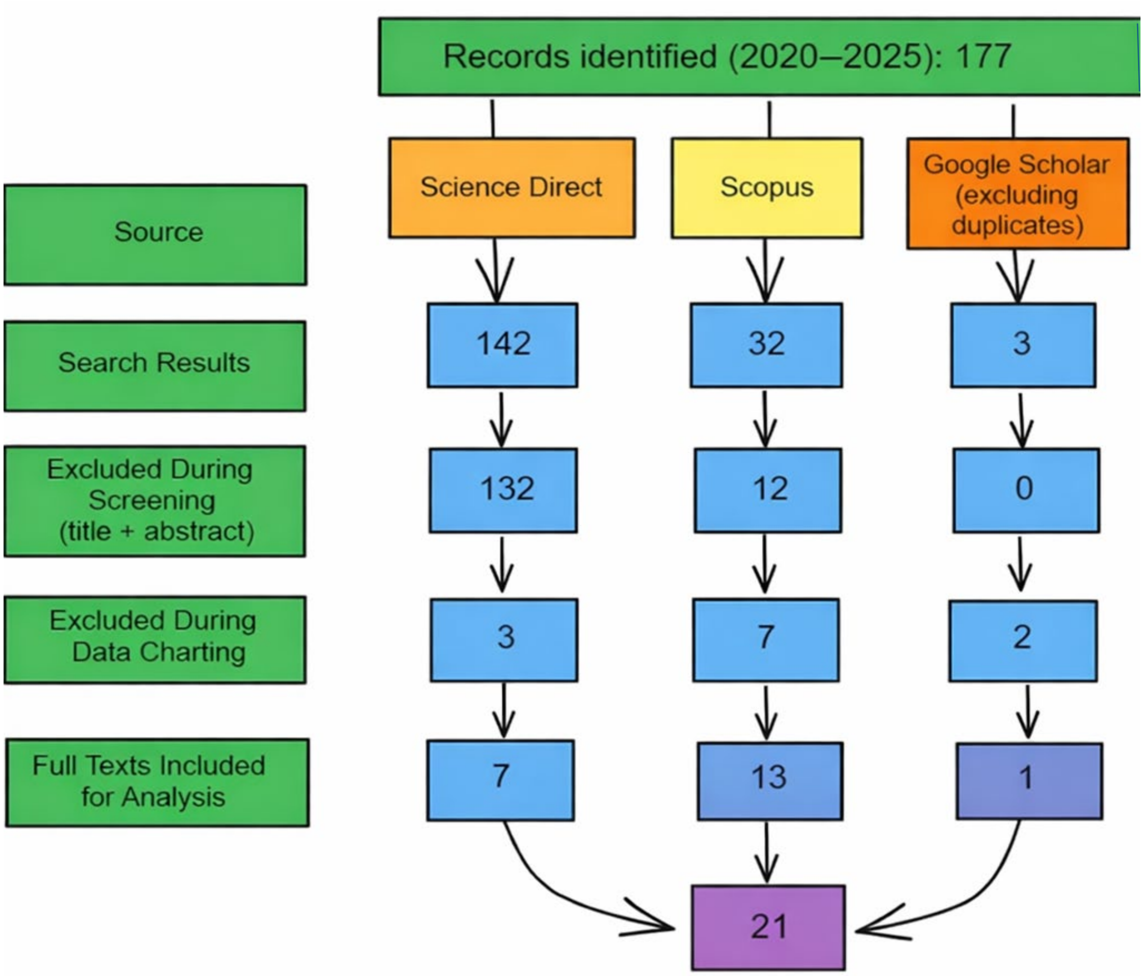
Criterion type	Included	Excluded
Population	K–12 learners (primary, elementary, secondary, high school)	Higher education or adult learners
Intervention	AL and LA as central features	Conceptual/theoretical work without empirical data
Context	Online, virtual, or distance education	Face-to-face or blended if online not primary
Study type	Peer-reviewed empirical studies (quantitative, qualitative, or mixed methods)	Non-peer-reviewed (e.g., book chapters, dissertations)
Language	English	Non-English
Publication years	2020–2025	Outside 2020–2025

Note. AL = adaptive learning; LA = learning analytics.

Studies employing AR/VR environments or neurocognitive measures (e.g., electroencephalogram [EEG] or functional near-infrared spectroscopy [fNIRS]) were included when these tools informed adaptive decision-making, learner modeling, or analytics-driven instructional adjustments within online or virtual K–12 learning contexts. Of the 177 records, 144 were excluded during title/abstract screening. More studies were excluded during data charting for reasons such as wrong population, wrong context, or lack of empirical evidence. The final dataset included 21 studies. The selection process is summarized in the PRISMA flow diagram in Figure 1. Title/abstract and full-text screening, as well as data extraction, were conducted independently by two reviewers. Disagreements regarding study inclusion or data charting were resolved through discussion and consensus. Inter-rater reliability was calculated during screening, yielding a Cohen's kappa of 0.789, indicating substantial agreement.

Figure 1

PRISMA Flow Diagram for Selected Studies



Stage 4: Charting the Data

Data from included studies were extracted into a standardized charting tool using Google Forms (see Appendix for an illustrative sample). Fields included citation, country or region, study design, educational level, platform or tool, learning context, AL/LA focus, data sources, outcomes, findings, reported limitations, and thematic tags. We also coded for AI mechanism type, target of adaptation, and locus of use (teacher- vs. learner-facing).

Stage 5: Collating, Summarizing, and Reporting

The descriptive analysis summarized publication trends, methodological approaches, and technological tools across the included studies. An iterative descriptive–thematic synthesis was then used to group outcomes, AI mechanisms, and pedagogical purposes, identifying recurring patterns and gaps. Given the heterogeneity of study designs and outcome measures, the synthesis focused on mapping trends rather than aggregating effects or making causal claims, consistent with the aims of a scoping review.

Results

Research Methods in Empirical Studies of AL and LA in K–12 Online Education (RQ1)

To answer the first research question, the analysis of study design highlights a relatively dominant reliance on quantitative methods, accounting for more than half of all publications, which suggests that research on AI-enabled adaptivity in K–12 contexts is predominantly based on performance metrics and controlled evaluations, with fewer studies employing exploratory classroom-based approaches. Mixed-methods studies, although fewer in number, show an upward trend in the later years of the review period, which is indicative of a growing interest in combining statistical rigor with contextual depth. However, qualitative research remains limited in terms of use and focuses on learner and teacher perspectives. A detailed landscape of the methodologies is detailed in Table 2.

Table 2

Methodologies Implemented in Publications

Study design	2020	2021	2022	2023	2024	2025	Total
Quantitative	2	0	4	2	2	3	13
Mixed methods	0	0	1	0	1	3	5
Qualitative	0	1	0	1	1	0	3
Total	2	1	5	3	4	6	21

To examine how these approaches were operationalized, Table 3 summarizes the specific research designs used. Descriptive and experimental designs were most common (each 26.1%), followed by quasi-experiments (21.7%). Comparative, design-based, and qualitative components appeared infrequently, each representing less than 10%. The dominance of descriptive and experimental work underscores reliance in the field on conventional empirical approaches; the scarcity of design-based or participatory research is indicative of limited methodological innovation.

Table 3

Research Design

Study type	Count	%
Descriptive	6	26.1
Experimental	6	26.1
Quasi-experimental	5	21.7
Comparative	2	8.7
Qualitative component (surveys, interviews, observations)	1	4.3
Design-based research with evaluation	1	4.3
Quantitative (observational/modeling)	1	4.3
Explanatory sequential approach	1	4.3

Regarding the data sources in the studies, Table 4 shows a strong preference for conventional empirical methods, with descriptive and experimental designs leading. Quasi-experimental approaches also feature notably, but more innovative or participatory methods remain rare in a way that suggests limited methodological diversity in the field.

Table 4

Data Sources

Data source	Count	%
System logs	10	21.7
Assessment scores	10	21.7
Surveys	7	15.2
Interviews	3	6.5
Clickstream data	3	6.5
Observation	2	4.3
Explicit ratings (fun, difficulty)	1	2.2
Simulated student interactions	1	2.2
Public policy documents	1	2.2
Systematic review	1	2.2

Data source	Count	%
Teacher orchestration data	1	2.2
Pilot evaluation responses	1	2.2
fNIRS logs	1	2.2
Pre-/post-tests, standardized scores, attendance logs, and classroom data	1	2.2
Questionnaires	1	2.2
Semi-structured interviews with stakeholders	1	2.2
EEG recordings	1	2.2

Note. fNIRS = functional near-infrared spectroscopy; EEG = electroencephalogram.

Analytical techniques were dominated by descriptive and inferential statistical methods, depicting nearly half of all analyses being either descriptive or inferential. Notably, as Table 5 details, qualitative and computational methods are emerging, but their use remains limited. Relatively less representation is noted for regression and specialized techniques, along with psychometric validation. Conventional statistical approaches are used more frequently than regression-based, qualitative, or advanced computational methods.

Table 5

Data Analysis Methods Reported Across Studies

Category	Methods	No. of mentions	% of occurrences
Descriptive statistics	Frequency counts, means, SD	12	22.6
Inferential statistics	*t*-tests, ANOVA, ANCOVA, Wilcoxon signed-rank, effect size, Shapiro–Wilk	11	20.8
Regression models	Linear regression, logistic regression	4	7.6
Qualitative analysis	Thematic analysis	6	11.3
Advanced computational methods	Machine learning, fuzzy C-means clustering, recommender evaluation metrics, XBI	6	11.3
Psychometrics/Validation	Instrument validation, IRT	2	3.8
Specialized/Other	EEG attention index, simulation modeling, moderation analysis, multilevel models	6	11.3

Note. n = 53 occurrences in 21 studies. XBI = Xie–Beni Index; IRT = item response theory; EEG = electroencephalogram.

Overall, the field reflects a pattern of empirical activity accompanied by methodological narrowness. Methodologically, the dominance of short-term quantitative and experimental designs indicates that evidence on AI-enabled adaptivity in K–12 online education is shaped largely by what platforms can readily measure. Theoretically, this emphasis reflects a narrow conception of learning as performance, rather than as a socially situated and meaning-making process.

Themes, Technological Tools, Educational Outcomes, Opportunities, and Challenges (RQ2)

The analysis of the selected literature reveals a dynamic but uneven landscape of AL technologies in K–12 education (Table 6). In fact, personalization is the most pervasive theme: Systems adapt content, feedback, and pacing to learner profiles, cognitive performance, or engagement patterns. Many studies ground these mechanisms in constructivist or cognitivist principles that promote differentiation and learner autonomy. Teacher orchestration consistently emerges as a mediating factor, with teacher guidance and feedback amplifying gains in motivation and achievement.

Table 6

Adaptive Learning Technologies in K–12 Education

Tool/platform	Description	Citation
ALEKS, DreamBox	Commercial adaptive learning platforms for math and reading	Divanji et al. (2023)
Geniebook	AI-powered platform with real-time analytics and personalized feedback	Sancenon et al. (2022)
NgodingSeru.com	Gamified coding platform with adaptive scaffolding	Maryono et al. (2025)
PSALMS	AI system for automated remediation and concept mapping	Wahyuningsih et al. (2024)
AR pop-up book	AR tool for interactive storytelling	Saif et al. (2021)
Matrix factorization LMS	Personalized recommendation engine for learning content	Lamb et al. (2022)
EEG-based attention monitor	Neuroadaptive system tracking cognitive engagement	Pardamean et al. (2022)

Note. AR = augmented reality; LMS = learning management system; EEG = electroencephalogram.

Technological tools primarily include commercial software, custom AI systems, and immersive environments. Although some platforms such as ALEKS and DreamBox remain common in mathematics and reading, newer systems integrate neurocognitive inputs, fuzzy logic, and real-time analytics. Gamified and augmented reality tools, including Geniebook, NgodingSeru.com, and augmented reality pop-up books, emphasize engagement and multimodal interaction. Together, these technologies reflect growing experimentation with AI-driven adaptivity, alongside limited evaluation in authentic classroom contexts.

Educational outcomes are diverse, as depicted in Table 7; most studies report academic improvement and conceptual understanding, alongside motivational and affective benefits such as increased engagement and enjoyment. Self-regulated learning is a recurring behavioral outcome, with evidence of improved goal setting and reflection. Fewer studies address equity explicitly, though several note benefits for low-performing or marginalized learners when adaptivity is coupled with teacher support, aligning with previous literature on educational technology (Hamash et al., 2025; Hamash & Mohamed, 2021).

Table 7

Educational Outcomes Reported Across Studies

Outcome type	Description	Citations
Academic achievement	Improved test scores and conceptual understanding	S. Yang et al. (2021); Katz et al. (2022)
Motivation and enjoyment	Increased learner satisfaction and engagement	Al-Malki & Meccawy (2022); Y. Yang et al. (2025)
Self-regulated learning	Enhanced goal setting, reflection, and autonomy	Leite et al. (2022); Y. Yang et al. (2025)
Equity and inclusion	Support for low-performing and marginalized learners	Chellanthara Jose et al. (2024); Katz et al. (2022)

Opportunities reported across studies emphasize differentiation, agency, and scalability (Table 8). Adaptive systems enable tailored learning paths informed by diagnostic data and real-time feedback. Gamified and immersive designs strengthen motivation, particularly in STEM (science, technology, engineering, and mathematics) and language subjects. A small number of AI-based platforms (e.g., PSALMS), however, demonstrate automation of remediation, content mapping, and potentially scalable personalization.

Table 8

Opportunities Presented in the Literature

Opportunity	Description	Citation(s)
Differentiated instruction	Tailored learning paths based on diagnostics	Divanji et al. (2023)
Student agency	Empowerment through self-paced and personalized learning	Sancenon et al. (2022); Wahyuningsih et al. (2024)
Gamification	Use of missions, badges, and leaderboards to boost engagement	Maryono et al. (2025); Saif et al. (2021)

Opportunity	Description	Citation(s)
Scalable deployment	LMS and mobile-first platforms enabling broad access	Chellanthara Jose et al., (2024); Lamb et al. (2022)
Real-time adaptivity	Dynamic instructional adjustments based on analytics and neurodata	Pardamean et al. (2022); Kim et al. (2024)

Note. LMS = learning management system.

Despite these benefits, several challenges persist as technical barriers appear (Table 9), including limited infrastructure and device access, while pedagogical constraints stem from weak teacher training and overreliance on gamification. Ethical concerns about data privacy, bias, and real-time monitoring also persist, particularly in neuroadaptive and AI feedback systems. Policy misalignment and insufficient curricular integration further restrict the systemic adoption of adaptive technologies.

Table 9

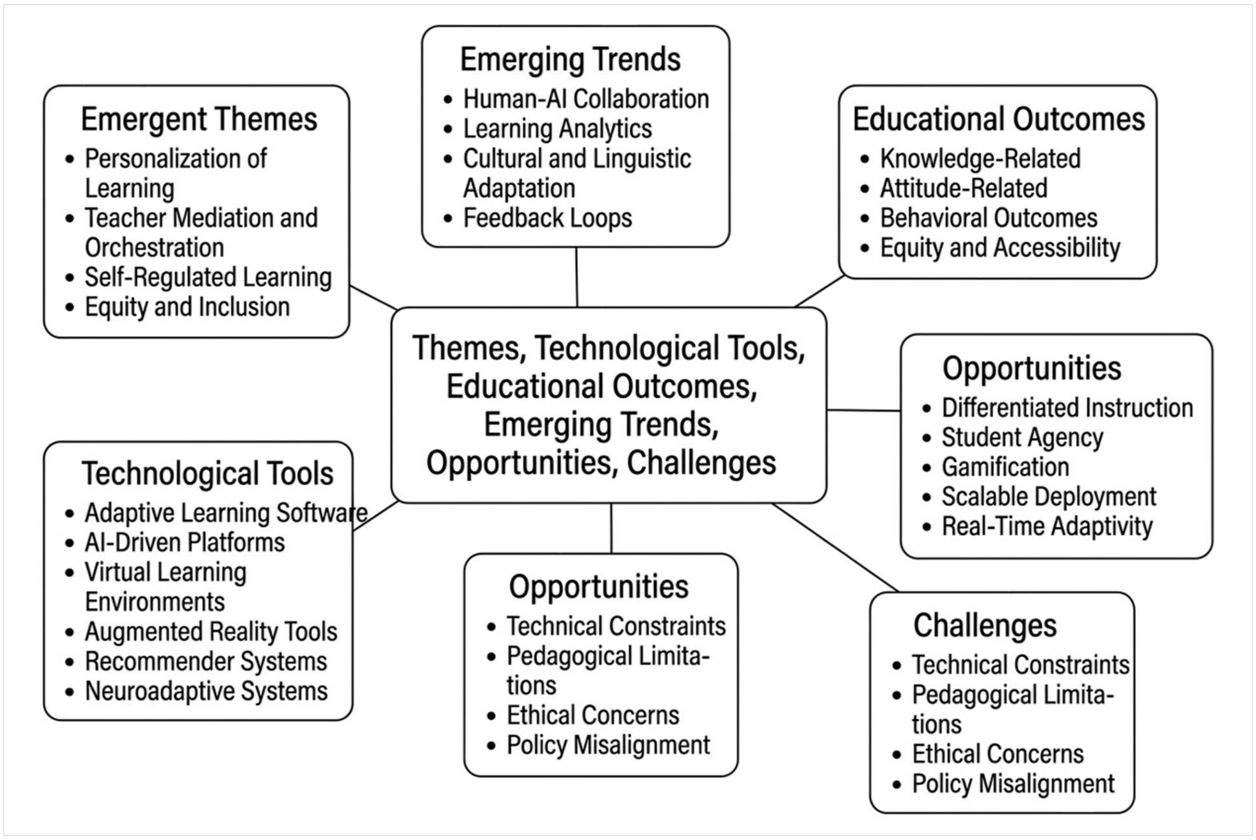
Challenges Presented in the Literature

Challenge type	Description	Citations
Technical constraints	Infrastructure gaps, device limitations, and setup costs	Saif et al. (2021); Pardamean et al. (2022)
Pedagogical limitations	Lack of teacher training and overreliance on gamification	Divanji et al. (2023); Maryono et al. (2025)
Ethical concerns	Privacy, bias, and fairness in adaptive systems	Katz et al. (2022); Kim et al. (2024)
Policy misalignment	Inconsistent curricular integration and lack of formal support	S. Yang et al. (2021); Leite et al. (2022)

Beyond these established themes (also illustrated in Figure 2), several emerging directions highlight the evolving sophistication of adaptive technologies. Studies increasingly frame human–AI collaboration as central in the sense that teacher roles are emphasized in interpreting analytics and refining system recommendations (Katz et al., 2022; Leite et al., 2022). LA integration supports data-informed pedagogy and iterative system improvement (Kim et al., 2024; Lamb et al., 2022). Furthermore, cultural and linguistic adaptation has gained visibility through localized and multilingual design (Al-Malki & Meccawy, 2022; Chellanthara Jose et al., 2024). These trends point to a gradual shift toward inclusivity, transparency, and sustained pedagogical partnership between humans and AI. Hence, both the promise and fragility of AI-driven adaptivity in K–12 education is evident; although technological capacity and engagement outcomes are advancing, long-term success will depend on ethical safeguards, teacher expertise, and the contextual fit of adaptive systems within diverse learning environments.

Figure 2

Thematic Map of Analyzed Literature



To What Extent Is AI Emphasized in the Analyzed Studies? (RQ3)

AI integration in adaptive online learning remains uneven across the reviewed studies. About 67% of studies positioned AI as the primary engine for personalization, using learner modeling, predictive algorithms, and recommender systems and often linked to measurable gains in achievement and engagement. Around 24% treated AI as a secondary feature, embedded in platforms or dashboards, with emphasis on pedagogy rather than algorithmic detail. The remaining 10% relied on non-AI strategies such as gamification or teacher-led differentiation, framing adaptivity as a pedagogical challenge. The strongest trend centers on AI-driven modeling and recommendation systems (e.g., Bidirectional Encoder Representations from Transformers [BERT]-based mapping, reinforcement learning sequencing), which emphasize algorithmic personalization as a performance lever. A few AI-related studies stress continued dependence on human-mediated adaptivity and raise scalability concerns (see Table 10 for detailed coding and examples).

Table 10

AI Emphasis in Included Studies (RQ3)

No.	Study	AI explicitly mentioned?	Primary role of AI	Connection to adaptive/personalized learning
1	Cheah et al. (2025)	Yes	Generative AI for content creation, grading, admin support	Indirect—supports personalization via teacher practices
2	Divanji et al. (2023)	No	Adaptive learning (non-AI)	Adaptive systems adjust content/feedback; not explicitly AI driven
3	Hwang et al. (2020)	Yes	Fuzzy expert system for cognitive/affective modeling	AI dynamically adjusts materials and feedback
4	Chellanthara Jose et al. (2024)	Yes	Adaptive learning + AI feedback/assessment	AI models assess performance and engagement in real time
5	Lamb et al. (2022)	Yes	ML prediction from neurocognitive data	Real-time AI predictions enable adaptive pathways
6	Leite et al. (2022)	No	Adaptive learning (non-AI)	Personalization via SRL patterns and teacher orchestration
7	Li et al. (2025)	Yes	Conversational AI tutor (RICE Algebra bot)	AI adapts responses and scaffolds algebra learning
8	Y. Yang et al. (2025)	No	Self-regulation scaffolds (non-AI)	Personalization is student driven
9	Poly et al. (2025)	Yes	Fuzzy clustering recommender	AI recommends resources based on learning style and accessibility
10	Al-Malki & Meccawy (2022)	No	Gamified recommender (non-AI)	Not connected to AI adaptivity
11	Sancenon et al. (2022)	No	Adaptive recommender (ML implied)	Learner model selects topics/difficulty for worksheets
12	Pardamean et al. (2022)	Yes	Learning style prediction (matrix factorization)	AI recommends materials matching predicted style
13	Saif et al. (2021)	No	AR-based adaptive tools (non-AI)	Adaptive via interaction, not AI

No.	Study	AI explicitly mentioned?	Primary role of AI	Connection to adaptive/personalized learning
14	Palliyalil & Mukherjee (2020)	Yes	AI-driven personalization in Byju's app	AI predicts learning styles and recommends content
15	Wahyuningsih et al. (2024)	Yes	BERT-based concept mapping and path generation	AI generates personalized remedial learning paths
16	Katz et al. (2022)	Yes	AI personalization and recommendation in Algebra Nation	AI tailors content exposure and feedback
17	Bhatt et al. (2024)	Yes	Deep learning recommender	AI recommends activities using implicit/explicit feedback
18	Kim et al. (2024)	No	EEG attention monitoring (AI proposed, not implemented)	AI mentioned only as potential future application
19	Maryono et al. (2025)	No	Adaptive gamified system (non-AI)	Not connected to AI adaptivity
20	Katz et al. (2022)—Simulation study	Yes	AI personalization and recommendation	AI adjusts learning paths based on mastery and engagement
21	Bhatt et al. (2024)—Deep learning recommender systems	Yes	Sequence-aware deep recommender	AI personalizes activity recommendations

Note. AI = artificial intelligence; ML = machine learning; SRL = self-regulated learning; AR = augmented reality; BERT = Bidirectional Encoder Representations from Transformers; EEG = electroencephalogram.

Discussion

Research Methods: Methodological and Theoretical Implications (RQ1)

The dominance of short-term quantitative and experimental designs indicates that evidence of AI-enabled adaptivity in K–12 online education is shaped largely by what platforms can readily measure rather than by sustained classroom inquiry (Yim & Su, 2025). This data pattern privileges performance indicators derived from system logs and tests, limiting insight into instructional practices, learner sensemaking, and longer-term pedagogical effects.

This methodological concentration reflects a deeper theoretical gap in terms of the limited integration of constructivist and sociocultural theories of learning into the design and evaluation of adaptive systems. As a result, the prevalence of experimental and quasi-experimental designs continues to reinforce behaviorist assumptions, framing learning primarily as a quantifiable outcome rather than as a dynamic, socially situated process. Adaptivity, hence, is often framed as a technical optimization of performance metrics rather than as a vehicle for meaning making or interaction. In line with earlier observations by Martin et al. (2020) and Shum et al. (2019), such a focus risks the potential reduction of learning to what can be measured, overlooking affective, social, and contextual dimensions that are essential to authentic pedagogy.

A notable limitation lies in the disconnect between algorithmic modeling and pedagogical theory, as few studies explain how adaptive mechanisms such as sequencing, feedback loops, or learner modeling derive from established learning theories. Adaptivity is often justified by technical feasibility rather than educational reasoning, reinforcing earlier concerns about misalignment among learners and instructional and content models (Wang et al., 2020). This is highlighted and confirmed by the dominance of vendor-driven or platform-specific studies, which frame personalization through available system features instead of pedagogical intent. Algorithmic processes are often described functionally, with emphasis on performance or usability, leaving instructional logic implicit. From a theoretical perspective, such framing risks equating technical optimization with educational value, particularly when evaluations are tightly coupled to proprietary platforms. Hence, clearer theoretical grounding and greater use of qualitative or mixed-methods designs would allow for stronger claims about how AI shapes learning through interaction, reflection, and collaboration.

Pedagogical and Equity Dimensions (RQ2)

From pedagogical and equity perspectives, the findings suggest that adaptive systems without sustained teacher mediation tend to benefit learners who possess strong self-regulation skills and access to institutional support (Rundquist et al., 2024). Studies reporting more equitable outcomes often situate adaptive systems within pedagogical practices where teachers interpret analytics, scaffold learner decision-making, and adjust system use in response to diverse needs. In practice, inclusive design is reflected in how adaptive tools are used within everyday instructional routines. For example, several studies show that LA dashboards are most effective when teachers use them to identify misconceptions or disengagement and then adapt feedback, pacing, or grouping strategies rather than relying on automated recommendations alone.

Adaptive platforms that combine personalized learning paths with scheduled teacher check-ins and guided reflection activities similarly appear better suited to supporting self-regulation and persistence than stand-alone systems. Therefore, professional development, as Boulhrir and Ait Bouch (2025) argue, plays a critical role, equipping teachers to critically engage with adaptive tools, understand their limitations, and align system feedback with curricular goals and learner contexts. In the absence of such support, adaptive technologies risk amplifying existing disparities by privileging learners who are already better positioned, particularly in the absence of sustained teacher mediation of curriculum implementation and adaptation (Aguerrebere et al., 2022; Shum et al., 2019).

Conceptual Ambiguity and AI Definitions (RQ3)

The reviewed studies reveal a persistent inconsistency in how AI is defined and operationalized in K–12 online learning research, which complicates the evaluation of classroom applications. To address this issue, we propose a clearer distinction between AI-enabled adaptivity and rule-based digital personalization. In this review, AI refers to systems that infer latent learner states or patterns from data using computational models that can generalize beyond prespecified rules, such as machine learning, probabilistic modeling, or adaptive inference mechanisms (Holmes et al., 2023; Luckin et al., 2016). By contrast, rule-based systems rely on fixed decision logic, scripted pathways, or manually encoded conditions, even when implemented within digital or adaptive platforms. Conflating these approaches obscures both pedagogical and ethical analysis, as systems that merely automate predefined responses differ fundamentally from those that dynamically model learner behavior. Applying a consistent definition clarifies whether reported effects arise from intelligent adaptation, instructional design choices, or teacher mediation, thereby strengthening the interpretability and comparability of findings across studies.

This inconsistency in definitions indicates important implications for how AI-enabled learning is evaluated and interpreted. When studies describe AI without specifying algorithms, data sources, or decision rules, it becomes impossible to evaluate transparency, ethical integrity, or educational relevance. In some cases, tools branded as "AI-based" offered little evidence of autonomous learning or intelligent modeling, highlighting how marketing language can outpace scholarly precision. Case in point, the lack of shared definitions or reporting standards risks overstating the presence of AI and underestimating the complexity of its pedagogical integration. When algorithms, adaptation logic, and human oversight were clearly described, systems supported improved performance as well as better alignment between teacher intention and machine feedback (Katz et al., 2022; Leite et al., 2022). This is one way transparency can foster trust and positions AI as a collaborator rather than a black box.

Research Gaps and Future Directions (RQ4)

This review contributes theoretically by consolidating system-level, pedagogical, and evaluative lenses into a mechanism-aware account of how AL and LA are currently conceptualized in K–12 online education. Distinguishing signals, models, decisions, and targets clarifies where claims about "AI-enabled" adaptivity are grounded in learning theory and where they remain primarily technical. Methodologically speaking, for instance, it advances the field by mapping dominant designs and data practices while making visible the underuse of longitudinal, mixed, and participatory approaches (Martin et al., 2020; Wang et al., 2020). These contributions collectively reposition AL research away from isolated performance effects and toward questions of pedagogical alignment, teacher mediation, and contextual validity.

Conceptual ambiguity continues to hinder progress, as varying definitions of AI and adaptivity reflect disciplinary fragmentation, with computer science framing it as optimization and education viewing it as differentiation and inclusion. Without common-ground definitions and terminology, it is difficult to compare findings or anchor them in defensible learning theories such as constructivism or self-regulation, especially when research is conducted by specialists from disparate fields who use common terms but attach different meanings to them.

Methodological narrowness also persists; confirming results from previous studies (Rundquist et al., 2024; Yim & Su, 2025), few investigations employ design-based, participatory, or longitudinal methods that could illuminate how adaptivity evolves through human–machine interaction. This may explain why evidence of sustained gains in agency or collaboration is still limited. Notably, studies conducted in Global South and non-English-speaking contexts remain underrepresented in the mapped literature, reflecting broader structural and linguistic asymmetries in K–12 AI and LA research. Aguerrebere et al. (2022) spotlight this imbalance and call for globally inclusive research if AI is to ethically serve equity rather than privilege. Ethical and governance dimensions are equally underdeveloped; few studies explain how privacy, bias, or transparency are addressed, introducing uncertainty about accountability and fairness in online/virtual learning environments. We speculate that this reflects insufficient collaboration between educators, technologists, and ethicists.

This review identifies several implications that clarify priorities for theory, research, and practice in K–12 online and distance learning. At a theoretical level, future work should articulate clearer links between adaptive mechanisms and defensible models of learning. Greater emphasis is needed on longitudinal and classroom-embedded designs that examine how adaptivity operates over time and across diverse learner groups, alongside transparent reporting of algorithmic logic and human oversight. From a practice and policy development perspective, evidence suggests that adaptive systems are most effective when implemented with sustained teacher involvement, professional learning, and governance frameworks that address data use, equity, and accountability. These identified directions indicate that progress in AI-enabled adaptivity will depend on aligning system design and evaluation with explicit pedagogical models, transparent decision logic, and sustained teacher involvement.

Conclusion

This scoping review mapped 21 empirical studies on AI-enabled adaptive learning and learning analytics in K–12 online education published between 2020 and 2025. Synthesizing the identified methodological, conceptual, and equity-related gaps, three key messages emerge: the need for greater methodological diversity, clearer conceptual grounding of AI-enabled adaptivity, and more inclusive, context-sensitive research agendas. Overall, the evidence points to a rapidly expanding but uneven field, marked by technological innovation alongside persistent conceptual and methodological gaps. As adaptive systems continue to improve performance, motivation, and self-regulation, their benefits remain unevenly distributed, with stronger effects observed for students who already have access, resources, and teacher support.

Three overarching insights emerge, beginning with the need for greater methodological diversity and for research that integrates quantitative rigor with qualitative insight to illuminate how adaptive systems interact with pedagogy and context. Second, equity must guide both design and evaluation. Adaptive tools succeed when teachers and learners actively shape their use, ensuring that personalization aligns with human judgment and local realities. Third, conceptual clarity is foundational. Without consistent definitions of what constitutes AI in education, evidence will remain fragmented and difficult to translate into practice or policy.

In response to the identified gaps, future research should adopt transparent, theory-driven, and mixed-methods approaches that explicitly connect AI mechanisms to learning principles, classroom practice, and learner agency. For educators and policymakers, addressing these gaps requires professional learning, data governance, and ethical oversight to ensure that adaptivity serves inclusion rather than automation. As a scoping review, this study was limited to English-language, peer-reviewed publications indexed in Scopus and ScienceDirect (with targeted Google Scholar supplementation) published between 2020 and 2025. The future of AI-enabled online learning in K–12 education depends less on the sophistication of algorithms than on the collective will to embed technology within equitable, pedagogically grounded systems.

Use of AI Tools

AI tools (e.g., Microsoft 365 Copilot) were used during Stage 2 to generate alternative Boolean search strings and streamline phrasing, and for mechanical editing tasks such as truncating charted entries or sentences and correcting grammar throughout the body of the manuscript. DiagramGPT was used to create the PRISMA flow diagram in Figure 1. All substantive coding and interpretive decisions were made by the researchers.

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Appendix

Data Charting Using a Google Forms Instrument (Sample)

Data_Extraction_AI_Adaptive_K-12_IRRODL

32 responses

32 responses

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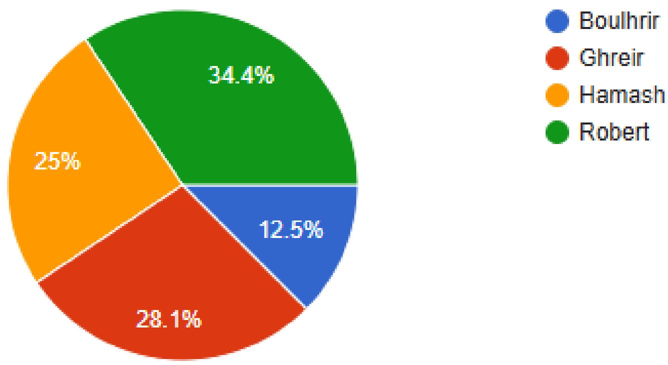

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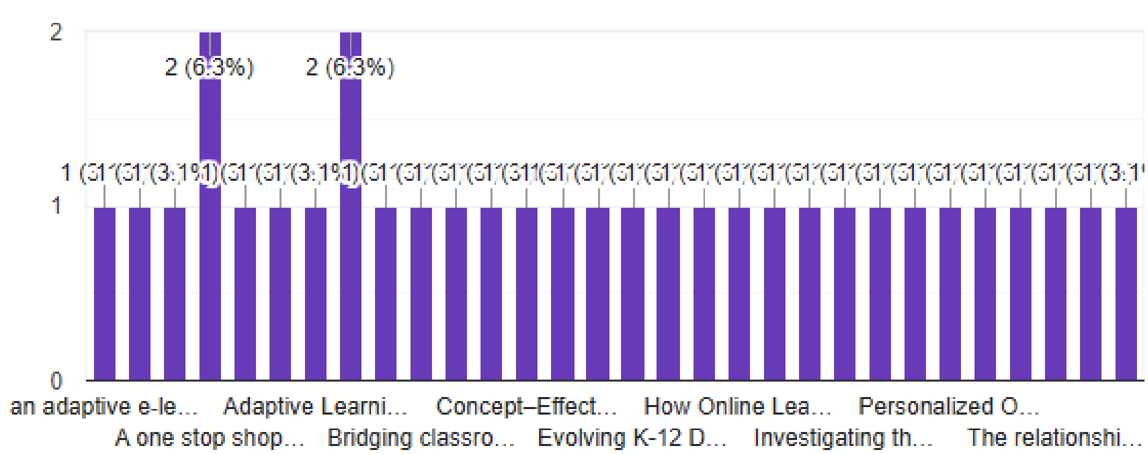

Database

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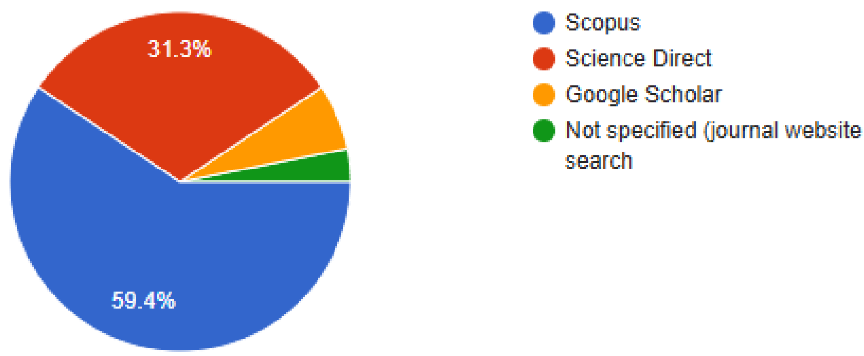

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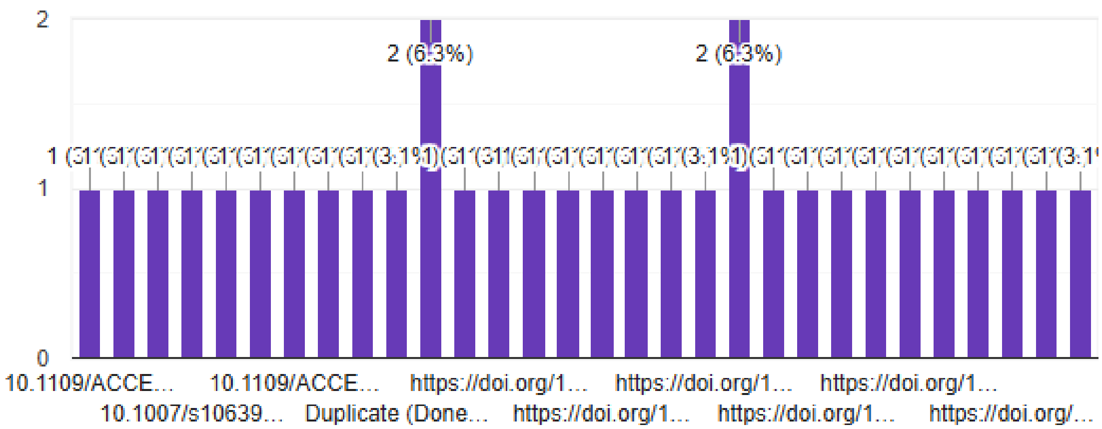

In-text Citation Handle (e.g., *Smith (2021), Smith and Htims (2024), OR Smith et al., 2021*)

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