



The Artificial Intelligence Dilemma in Education: A “Partner” in Developing Analytical Thinking or a “Crutch”?

Eğitimin Yapay Zekâ İkilemi: Analitik Düşüncenin Gelişiminde Bir “Ortak” mı, Yoksa Bir “Koltuk Değneği” mi?

Serkan COŞKUN*

Abstract

Artificial intelligence (AI) has rapidly become embedded in both everyday life and scientific practice, raising new questions for education rather than offering straightforward solutions. The present study investigates the blurred role attributed to AI in educational settings, asking whether it is conceptualized as a partner that supports the development of analytical thinking or as a crutch that undermines it. To this end, a two-stage qualitative meta-synthesis was conducted on a corpus of 74 sources, comprising 72 peer-reviewed journal articles and two UNESCO reports published between 2019 and 2025. In the first stage, Leximancer software was employed to generate an inductive conceptual map of the corpus (meta-explication). In the second stage, themes derived from this map were subjected to in-depth interpretive content analysis (meta-synthesis). The results indicate that AI is predominantly framed in context-dependent, “mixed” terms: the literature oscillates between pedagogical opportunities such as personalization and efficiency, and systemic risks related to bias, inequality, and the offloading of cognitive effort. AI tends to be described as a partner when it is embedded in inclusive, feedback-rich, and teacher-mediated designs, and as a crutch when gaps in governance and unregulated implementation prevail. Overall, the study shows that the outcomes of AI integration in education are shaped less by the technology’s intrinsic capabilities than by the pedagogical, ethical, and governance arrangements that regulate its use.

Keywords: Artificial intelligence, educational technology, analytical thinking, digital divide, educational inequality, critical pedagogy, cognitive offloading.

Öz

Yapay zekâ (YZ), gündelik yaşam pratiklerinden bilimsel üretime kadar pek çok alana hızla yerleşmiş; eğitim için doğrudan çözümler sunmaktan çok, yeni sorular ortaya çıkarmıştır. Bu çalışma, YZ’nin eğitim bağlamında kendisine atfedilen ikircikli rolü incelemekte ve YZ’nin analitik düşüncenin gelişimini destekleyen bir “ortak” mı, yoksa onu zayıflatan bir “koltuk değneği” mi olarak kavramsallaştırıldığını sorgulamaktadır. Bu amaçla, 2019–2025 yılları arasında yayımlanmış 72 hakemli makale ve iki UNESCO raporundan oluşan toplam 74 kaynağı içeren bir külliyat üzerinde iki aşamalı nitel bir meta-sentez yürütülmüştür. İlk aşamada, külliyatın tümevarımsal bir kavramsal haritası Leximancer yazılımı kullanılarak oluşturulmuştur (meta-açıklama). İkinci aşamada ise bu haritadan türeyen temalar,

* Research Assistant, Hacettepe University, Faculty of Letters, Sociology. Email: :serkancoskun@hacettepe.edu.tr, ORCID:0000-0001-5792-3568



yorumlayıcı içerik analizi yoluyla ayrıntılı biçimde incelenmiştir (meta-sentez). Bulgular, YZ’nin eğitimdeki rolünün literatürde ağırlıklı olarak bağlama duyarlı, “karma” bir yapı içinde ele alındığını göstermektedir; tartışmalar, kişiselleştirme ve verimlilik gibi pedagojik fırsatlarla yanlılık, eşitsizlik ve bilişsel yük aktarımı gibi sistemsel riskler arasında gidip gelen bir eksenle konumlanmaktadır. YZ, kapsayıcı, geri bildirimle dayalı ve öğretmen aracılı tasarımlara yerleştiğinde “ortak” olarak tanımlanma eğilimindeyken; yönetim boşluklarının, zayıf denetim mekanizmalarının ve denetimsiz uyarlamaların öne çıktığı bağlamlarda “koltuk değneği” niteliği kazanmaktadır. Genel olarak çalışma, eğitimde YZ entegrasyonunun sonuçlarının, teknolojinin içsel kapasitesinden çok, kullanımını düzenleyen pedagojik, etik ve yönetsimsel düzenekler tarafından şekillendiğini ortaya koymaktadır.

Anahtar sözcükler: Yapay zekâ, eğitim teknolojisi, analitik düşünce, dijital uçurum, eğitimde eşitsizlik, eleştirel pedagoji, bilişsel yük aktarımı.

Introduction

Hans Freyer, drawing an analogy to the Industrial Revolution, highlights how humanity's inventions create powerful “reverberations” that fundamentally reconfigure the social fabric (Freyer, 2014). The current diffusion of Artificial Intelligence (AI) should be read as a comparable wave placed within this broader historical arc. Rather than simply adding a new layer of tools, AI systems are reshaping everyday routines, decision-making processes from health to finance.

In education, this transformative dynamic is particularly visible. Generative AI (GenAI) and related intelligent systems are widely described as having the capacity to reconfigure the architecture of learning (Liu et al., 2024). At the center of this capacity lies the promise of personalization. Through adaptive learning environments and learning analytics, content, pacing, and difficulty levels can be tuned to individual learner profiles (Mahmoud & Sørensen, 2024; Jiao, 2024). Continuous feedback loops make it possible to track performance in real time and to identify patterns of strength and difficulty (Sajja et al., 2024). At the same time, AI-based tools are being used to lower access barriers by providing support for students with disabilities and by mitigating geographic and infrastructural constraints (Ramaiah et al., 2025; Eden et al., 2024; Egunjobi & Adeyeye, 2024). Taken together, these developments position AI as a potential “partner” that can support, enrich and, at least in principle, democratise learning opportunities.

The rapid and uneven spread of AI, however, also generates serious ethical and pedagogical concerns. A central theme in recent studies is the risk that heavy reliance on AI tools will encourage cognitive offloading and, in doing so, gradually erode higher-order skills such as critical thinking, problem-solving and creativity (Isiaku et al., 2024; Nadim & Di Fuccio, 2025; Habib et al., 2024; Kostas et al., 2025; Lee et al., 2025). Ubiquitous access to instant, AI-generated solutions may make study tasks appear easier, yet a growing body of work suggests that it simultaneously weakens students’ inclination to engage in slow, close reading or to construct arguments grounded in evidence (Zhou et al., 2024). Malik et al. (2025) link such usage patterns to declining academic integrity and weakening learning motivation, which sharpen these concerns further. When these tendencies become habitual, AI ceases to be portrayed chiefly as a learning “partner” and is recast instead as a “crutch” that progressively undermines learners’ intellectual growth.

This divergence in possible trajectories reflects a deeper, unresolved tension in how AI’s role in education is conceptualized (Noroozi et al., 2024). Identical technological systems can be linked to markedly different outcomes depending on the pedagogical design choices, ethical safeguards and structural conditions within which they are embedded. The present study takes this blurred topic as its starting point and is organized around a guiding question. *Under which pedagogical, ethical and structural arrangements can AI support the development of analytical thinking as a “partner”, which conditions does it instead tend to become a “crutch”?*

Current patterns of global connectivity underscore the urgency of this question. Recent estimates indicate that approximately 5.5 billion people—around 68% of the world’s population—are online, while some 2.6 billion remain offline (ITU, 2024). Any attempt to embed AI within education is therefore mediated by the digital divide (ITU, 2024). For certain groups, the key constraint is the absence of basic access; for others, the challenge is almost inverted, taking the form of largely unregulated or unsupervised exposure to powerful AI tools (OECD, 2023a).

Even where connectivity and infrastructure are relatively secure, the rollout of AI systems continues to pose ethical and design-related questions (UNESCO, 2022, 2025). Against this backdrop, the contribution of the present article is to examine how the partner–crutch dilemma can be addressed through governance, ethical regulation and instructional design. Methodologically, the analysis proceeds via a two-stage qualitative meta-synthesis: an inductive conceptual mapping with Leximancer is followed by an interpretive content analysis of the emergent themes, making it possible to analyse AI’s educational integration through the interconnected lenses of opportunity, risk and inequality. As AI becomes increasingly embedded in educational systems, such a systematic interrogation of both its promises and its pitfalls gains particular urgency.

Method

The study adopted a two-stage qualitative meta-synthesis to examine how artificial intelligence (AI) is framed in the education literature through the “partner–crutch” dialectic. Rather than aggregating effect sizes in the manner of a classical quantitative meta-analysis, the design combined an automated, corpus-level mapping of concepts with an interpretive synthesis of arguments and findings.

The sequence was structured around the “what–how–why” logic. An exploratory meta-explication in the first stage was used to map the thematic structure of the corpus, and a subsequent meta-synthesis in the second stage elaborated and interpreted the themes identified.

Stage One – Meta-explication

The first stage aimed to identify the underlying conceptual structures and latent thematic clusters in the AI-and-education literature. To minimize direct researcher intervention and support a data-driven approach, the text-mining and conceptual-mapping software Leximancer was employed. The full texts of the selected sources were imported and analysed without prior manual coding or pre-defined categories. This procedure served the identification of dominant discourses, the relational networks among frequently co-occurring concepts, and the main axes of debate within the corpus.

Leximancer was operated with the following settings: context window = 2, theme size = high, detail level = high, merge plurals = on, stemming = on, stop list = off, and auto-seeded concepts, with no thesaurus or manual matching applied. These parameters were chosen to maximize thematic resolution and sensitivity to local co-occurrence patterns, while limiting the extent of manual adjustment and thereby reducing the risk of imposing the researcher’s expectations on the data. The resulting concept–theme network, which delineated the core axes of AI, Learning, Digital, and Bias, served as a panoramic map of the field and as the basis for the subsequent interpretive analysis.

Stage Two – Meta-synthesis

The second stage was built directly on the conceptual map produced by Leximancer. In this, the focus shifted from automated mapping to an interpretive synthesis of the arguments, empirical findings and theoretical frameworks represented in the corpus. All selected sources were read in full and manually coded. The coding scheme was informed by, but not mechanically derived from, the Leximancer output. All concepts and themes highlighted on the map served as entry points for structuring the close reading.

At this stage, the analysis moved beyond the “what” question implicitly posed by the software (i.e., which concepts appear central) to address the “how” and “why” questions. How AI is linked to opportunities and risks, and why it is framed as a “partner,” a “crutch” or a context-dependent “mixed” phenomenon in different studies. Each text was coded along three primary thematic dimensions: (1) opportunities associated with AI in education, (2) risks and potential impasses, and (3) an overall assessment of AI’s role as “partner,” “crutch,” or “mixed”. This tripartite lens enabled tracing of how the partner–crutch dialectic is constructed across different contexts and subtopics.

Data Collection and Source Selection Criteria

The analysis is based entirely on secondary sources, namely academic publications and institutional reports. A literature search was conducted in Web of Science and Google Scholar for the period 2019–2025, using the following keyword structure:

("artificial intelligence" OR "generative AI") AND ("education" OR "learning" OR "pedagogy") AND ("critical thinking" OR "cognitive skills" OR "inequality" OR "digital divide" OR "human capital" OR "critical pedagogy" OR "academic integrity" OR "algorithmic bias").

The preliminary queries generated a very large set of results. To maintain both thematic relevance and analytical manageability, the initial search was gradually narrowed. A source was considered eligible only if it engaged directly with the socio-pedagogical dimensions of AI in educational practice, rather than dealing exclusively with technical design or infrastructure. Within this frame, the refined strategy prioritised English-language publications from 2019 to 2025 that addressed at least two of the following sub-themes:

- Personalized learning, adaptive systems, and student engagement
- The relationship between AI and existing educational inequalities, the digital divide, and inclusivity (e.g., students with disabilities, international students, socioeconomically disadvantaged groups)
- Ethical challenges such as algorithmic bias (e.g., gender, race, political views) and data privacy
- The transformation of academic integrity, academic honesty, and assessment methodologies
- Impacts on critical thinking, creativity, and cognitive skills

Applying these criteria produced an initial pool of 185 potentially relevant texts. After detailed screening, 72 journal articles that reflected thematic diversity were retained for analysis. In order to introduce a policy perspective and link academic debates to institutional evaluations, two major UNESCO reports on AI in education (UNESCO, 2022, 2025) were added to this set. The final corpus thus consisted of 74 sources.

Data Analysis Preparation and Process

Data analysis and dataset preparation were carried out in accordance with the research design. At first, the documents that met the inclusion criteria were merged into a single file, which produced a corpus of approximately 698,800 characters. After this, the text was cleaned so that the subsequent analysis would focus on substantive content. In this stage, paratextual and editorial material was removed, including front and back matter (e.g., cover pages and publication details), reference lists, automatic numbering, and captions or labels attached to figures and appendices. With these steps the working corpus was reduced to around 550,016 characters at final. The cleaning protocol was designed to keep the argumentative structure of each text intact, while avoiding unnecessary changes to the original wording. Using the same rules for all documents also helped to limit selective bias in the coding that followed.

The resulting corpus was then examined with Leximancer. In this exploratory phase, the software produced a high-level overview of the material by summarizing word frequencies, charting their distribution across the texts, and identifying recurrent constellations of concepts. From these outputs, a concept–theme map was derived that sketched the main axes along which the discussion in the literature is organized. Four interrelated themes—AI, Learning, Digital and Bias—proved to be particularly salient. These themes subsequently informed both the way in which the Findings section is structured and the focus adopted in the manual analysis. Using the map as a guide, each source was coded by hand along three principal dimensions:

how opportunities are configured, which risks or impasses are highlighted, and where the text situates AI on the partner–crutch continuum. Table 1 provides an illustrative extract from this coding framework, and the full scheme is discussed in more detail in the Findings section.

Table 1. A Sample of the Interpretive Coding Framework

Sources	Risks	Benefits & Opportunities	Partner or Crutch
Resources 1	bias/fairness; inequalities	access & inclusion	Mixed (context-dependent)
Resources 2	hallucinations/reliability; privacy/security	personalization/adaptive learning	Partner
Resources 3	cognitive offloading	access & inclusion	Crutch

After completing the manual coding, a comprehensive codebook covering all 74 sources was compiled. This codebook was then subjected to a secondary analysis using **Voyant Tools**, which was employed to explore the internal structure of the codes through its Cirrus (word cloud), Trends (temporal frequency) and Bubblelines (in-segment distribution) functions. The purpose of this step was to cross-check the interpretive findings with visual–quantitative cues and to identify patterns that might not be immediately visible through reading alone. The codebook, summary tables and raw outputs from Voyant Tools are available from the author upon request.

Limitations

Two limitations of the dataset and design should be acknowledged. First, the corpus consists exclusively of English-language publications and reports. As a result, studies published in other languages, and potentially reflecting different regional or institutional perspectives on AI in education, are not represented. Second, the majority of the included empirical work originates from higher-income contexts and institutions with relatively advanced digital infrastructures. This distribution may influence the balance of opportunities and risks reported in the literature and should be borne in mind when interpreting the findings and their transferability to under-resourced settings.

Findings

The presentation of the results follows the two-stage analytical design outlined in the Method section. In the first step, a Leximancer-based meta-explication was used to produce a conceptual map of the combined corpus ($n \approx 74$), with the aim of identifying the main themes and their points of intersection in the literature. In the second step, an interpretive meta-synthesis drew on this map to classify the studies into “partner”, “crutch” and context-sensitive “mixed” orientations, supported by additional checks using Voyant Tools. A final layer of thematic analysis then examined how these orientations relate to broader patterns of opportunities and risks, in order to describe the conditions under which AI is more often presented as a “partner” and those under which it appears as a “crutch”.

Positioning the Axes of the AI Debate

The first stage of the analysis involved submitting the full texts of all 74 sources ($\approx 550,016$ characters) to Leximancer. This automated meta-explication was designed to minimize direct researcher intervention and to make the internal structure of the literature visible. This provided the dominant themes, the connections between them, and the basic lines of debate. The resulting map showed that discussions cluster around four main themes: AI, Learning, Digital and Bias (Figure 1).

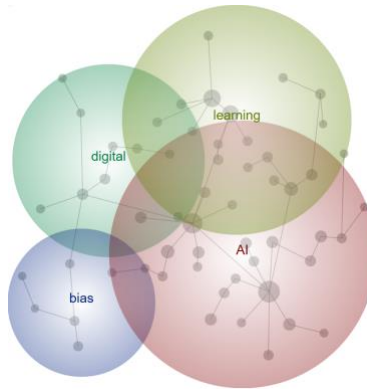


Figure 1. Primary Thematic Axes

Figure 1 represents the position, size and overlap of these four themes. The map can be read as the “skeleton” of the corpus, revealing its central dynamics. As expected, the AI theme sits at the central node of the network, which confirms that the texts are organized around the question of how AI is being integrated into education. The strongest area of overlap is between AI and Learning, indicating that the main preoccupation is with the impact of AI on learning processes. Digital forms a bridge between Learning and Bias and represents the technological and infrastructural context of the discussion, while the close proximity of Bias to AI signals that questions of bias are understood as a key risk in debates on artificial intelligence. To move beyond this broad outline, it is necessary to look at the concepts that underpin each axis. Table 2 provides this detail by listing, for each theme, the most frequently co-occurring concepts and the share of total hits. In effect, each theme can be understood as a cluster of related concepts that together form a distinct line of thought. Examining these clusters clarifies the focal points of the literature and shows how the four themes are interwoven rather than standing apart from one another. The intersectional pattern that emerges from the Leximancer analysis offers a synthetic view of how AI is positioned within contemporary educational research (see Table 2 and Figure 2).

Table 2. Sub-Parameter Structures and Sizes of Themes

Thema	Hit	(%)	Sub-axes forming the themes
AI	13.810	53.4	education, learning, students, tools, technology, integration, systems, ethical, generative, impact
Learning	8.646	33.5	students, education, AI, support, cognitive, performance, skills, teaching
Digital	2.301	8.9	access, rights, school, technology, students, skills, development
Bias	1.084	4.2	algorithms, ethical, gender, political, groups, training

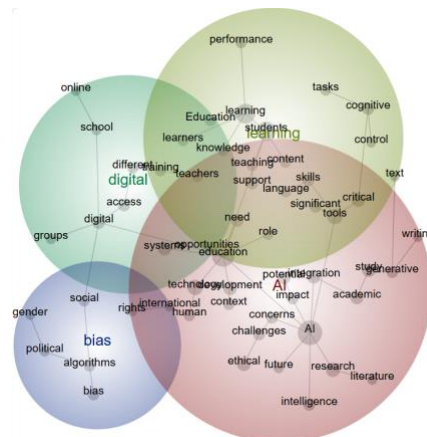


Figure 2. Axes Including Nodes

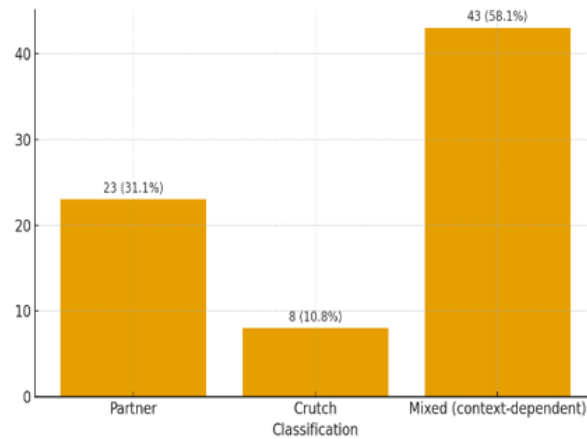


Figure 4. AI-in-Education Classification

The coding does not support a simple either–or distinction in how AI is portrayed. A clear majority of the sources (58.1%; $n = 43$) present its impact as context-dependent and “mixed”. Studies that primarily describe AI as a “partner” constitute 31.1% of the corpus ($n = 23$), whereas those that frame it mainly as a “crutch” make up 10.8% ($n = 8$). The word cloud in Figure 3 mirrors this pattern. “Mixed” is the most pronounced term, “partner” appears as a secondary pivotal point and “crutch” forms a smaller but visible warning cluster. Terms located near the center of the cloud—governance, risk, policy, transparency—indicate that the debate is organized less around a straightforward technological comparison and more around the management of opportunities and risks.

In this context, the words “partner” and “crutch” essentially represent the central organising axis of the discourse. Regarding the partnership, the studies emphasize the role of AI in improving the learning process through personalized feedback and well-structured, collaborative learning environments (Aggarwal, 2023; Airaj, 2024; Jane et al., 2024; Triberti et al., 2024; Yu et al., 2024). These, in turn, are supported by studies that investigate AI’s role in facilitating and empowering teaching and learning (Adeleye et al., 2024; Jiao, 2024; Wang et al., 2023). Besides that, the studies find evidence that AI is being increasingly and flexibly utilised for the purpose of widening educational access and providing tailored support to students with special educational needs (Ramaiah et al., 2025; Shivani et al., 2024). According to these roles, AI is portrayed as a supplementary partner that changes the learning architecture, thus raising the prospects for cognitive outcomes (performance, skills, metacognitive awareness) as well as process indicators (engagement, persistence).

The “crutch” dimension is shaped by a different set of concerns, most of which relate to governance. Studies in this cluster draw attention to issues of access, ethics, policy, transparency, safeguards and bias (Afzal et al., 2023; Baker & Hawn, 2022; Valerio, 2024; Wang et al., 2024; Veras, 2024; Oyelere, 2025). Access and inequality form a core focus (Afzal et al., 2023; Ma et al., 2019; Cheshmehzangi et al., 2023), and are followed by worries about academic integrity and the reliability of AI outputs (Song, 2024; Michel-Villarreal et al., 2023; Costa et al., 2024). Algorithmic bias is described as a mechanism that can both deepen existing inequalities and undermine academic integrity (Baker & Hawn, 2022; Gaskins, 2023). A further strand of work concentrates on cognitive offloading and the externalisation of skills, identifying these processes as additional contributors to the “crutch” effect (Nadim & Di Fuccio, 2025; Jose et al., 2025). The segmented, inter-textual coding confirms that these “partner” and “crutch” framings are not isolated, but recur across different contexts and types of study.

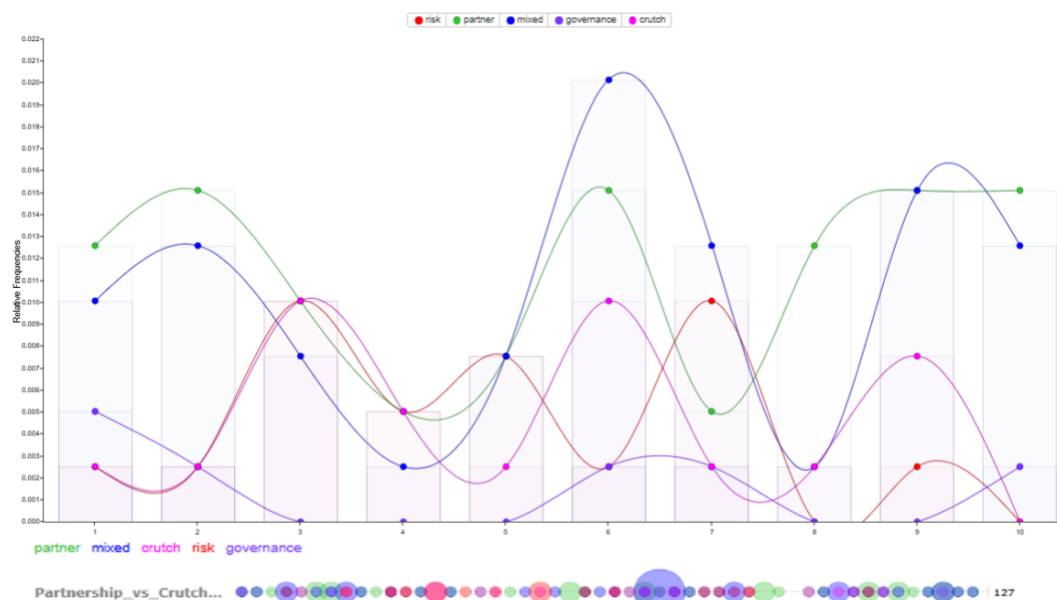


Figure 5. Trend Graph

The secondary analysis with Voyant Tools shows how primary dimensions appear across sequential text segments (Figure 5). Figure 5 demonstrates that the curves and bubble patterns represent three main cut points or phases in the debate. According to the first segment, the discussion is framed mainly as a simple opposition. AI is grounded either as a clear “partner” or as a clear “crutch.” As the corpus moves into the middle segments, the “mixed” label (blue) increases sharply and becomes the dominant pattern. This pattern clearly shows a growing awareness that AI is complex and highly context-dependent. During the same stage, the lines for “risk” (red) and “governance” (purple) also rise. This means questions of regulation and oversight increasingly dominate the discussion. In the final segments, it is most strikingly shown that the sides neutralize each other. Differently, the terms “partner” and “crutch” are still present, but they no longer act as the main organising poles. Instead, “governance” reaches a second peak, which suggests that the debate now centers on how AI should be governed. Thus, these trends indicate a transparent move away from a polarized view and toward a more consensual position. This consensual picture, however, is only possible if the partnership is accompanied by governance arrangements that take risks seriously.

In this context, the coding structure points beyond a simple choice between optimistic and pessimistic evaluations of AI. The findings suggest that the role of AI in education cannot be reduced to a “yes” or “no” verdict. Instead, the central issue becomes the design of the conditions under which AI can operate as a partner and those under which it tends to become a crutch. The remainder of the article takes this insight as a point of departure and examines the “partner” and “crutch” themes in greater detail, with a view to identifying the pedagogical, ethical and governance arrangements that tilt the balance toward one or the other.

Why Partner

The meta-synthesis makes it possible to describe more precisely the circumstances in which AI is treated as a “partner”. In the corpus, partnership is not linked to a single functionality or tool; rather, it is associated with a combination of affordances. When personalized support, responsive feedback and broadened access are brought together, AI is portrayed as part of a wider ecosystem that can reconfigure learning processes.

educational vision (Eden et al., 2024; Adeleye et al., 2024; Ramaiah et al., 2025; Shivani et al., 2024; UNESCO, 2025; Wang et al., 2023).

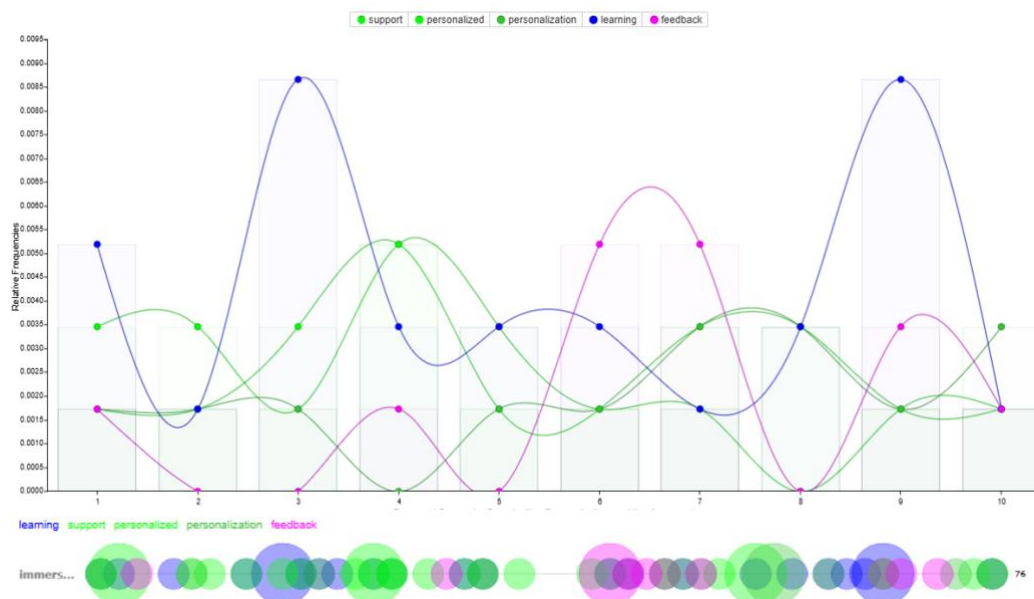


Figure 8. Trend Graph

The distribution of the “partnership” storyline across the ten text segments is visualized in Figure 8. In segments 1 and 4 of the corpus, the word "learning" is often used together with "personalized", which is one of the main themes indicated by the differentiated support at this stage. In the middle segments (5, 7), words related to the notion of feedback become more prominent; the references to real-time and adaptive responses explain the ways through which such a supportive arrangement is expected to work in practice. In the last segments (8, 10), "learning" is once more identified as a major anchor, indicating that the flow of the discourse is mainly geared towards the learning outcomes rather than the technological refinement as an end in itself.

On the basis of these patterns, the “partner” role can be conceptualized as a cyclical configuration of interrelated functions. First, AI-based systems register traces of learner activity—for example interaction logs, error patterns and time-on-task measures. Second, these traces are assembled into diagnostic or predictive learner profiles (Zhang et al., 2021; Mahafdah, 2024; Mahmoud & Sørensen, 2024). Third, the derived profiles are used to steer adaptations in content, pacing, task difficulty and scaffolding (Jiao, 2024; Yu et al., 2024). Fourth, learners receive formative input in the form of hints, explanations, worked examples and prompts designed to support reflection (Sajja et al., 2024). Fifth, teachers remain active mediators of this process, drawing on the generated information for pedagogical decision-making, ethical oversight and the construction or revision of assessment rubrics (Triberti et al., 2024; Kurtz, 2024). The underlying rationale is augmentative rather than substitutive: professional judgement and transparent, interpretable system behavior are treated as prerequisites for sustaining both pedagogical quality and trust (Airaj, 2024).

Reported effects within this strand of work cluster around three domains. A first group of studies documents gains in learning effectiveness, including improvements in performance—especially in writing (Costa et al., 2024), problem-solving and applied skills—linked to more appropriate management of cognitive load (Gkintoni et al., 2025; Chandrasekera et al., 2025), error-contingent hints and goal-oriented feedback (Jane et al., 2024). A second group emphasizes efficiency and scalability, pointing to shorter assessment and feedback cycles, enhanced capacity for monitoring and targeted intervention in large cohorts, and greater feasibility of support in high-enrolment contexts (Kostas et al., 2025; Tanveer et al., 2020; Wang et al., 2023; Tariq, 2025).

The studies in the third group place the access and inclusion dimensions at the center of discussion. As models advance, they provide opportunities to work in multiple languages and across different literacy modes. This provides tangible support for students, especially those with disabilities. Transcription services, speech-to-text, sign-recognition tools, and alternative presentation methods have emerged as inclusive strategies (Ramaiah et al., 2025; Shivani et al., 2024). However, these developed tools require certain prerequisites. If the working environment has low-resource conditions, with scarce bandwidth, devices, and human support, it creates additional barriers for specific groups (Adeleye et al., 2024). Therefore, access and inclusion act together for partnership in AI.

For AI to keep this “partner” role, the corpus points to several conditions rather than a single key factor. One main claim is that teaching should be organized around formative assessment. In this way, AI-generated feedback can feed back into ongoing learning instead of appearing only at the end of a course. A second theme concerns adaptive systems, whose decision rules should stay transparent and open to human review, so that teachers can interpret, correct or override automated suggestions when needed (Taherdoost & Madanchian, 2023). Authors also argue that accessibility and inclusion should be treated as starting points in design, not as extra features added later (Bulathwela et al., 2024). In parallel, they call for the handling of educational data to be limited to clearly stated teaching aims and to take place under strong security safeguards (Jeyaraman et al., 2023; UNESCO, 2022). Finally, several contributions underline the need for regular scrutiny of AI tools for unfair treatment and discriminatory patterns, treating fairness and bias checks as an ongoing responsibility rather than a one-off compliance exercise (Baker & Hawn, 2022; Grote & Keeling, 2022). Within the literature, these elements are framed as protective barriers against a drift from “partner” to “crutch”—for instance through excessive cognitive offloading or the reinforcement of existing inequalities—and are closely aligned with broader calls for human-in-the-loop forms of governance (Kurtz, 2024; Mahmoud & Sørensen, 2024).

Yet, no pedagogical reform can succeed if it ignores the material conditions of learning. The literature mostly positions AI in education as a personalized, data-informed and feedback-centered learning partner. When framed in this way and embedded in strong ethical and pedagogical governance, AI is expected not only to raise efficiency but also to improve learning quality and broaden participation. Designing for “partnership” thus appears, within the corpus, as the most coherent way of mobilising AI’s mixed potential in favor of educational goals.

Why Crutch

The risk-focused coding allows for a complementary reading, in which AI appears not as a partner but as a “crutch”. This section investigates the conditions under which that framing becomes dominant. The analysis draws on four visual outputs derived from the 74-source corpus: a bar chart of risk categories, a word cloud, curves of conceptual frequency and a word distribution map. Together, these visualizations outline the main contours of the “crutch” paradigm.



Figure 9. Why Crutch?

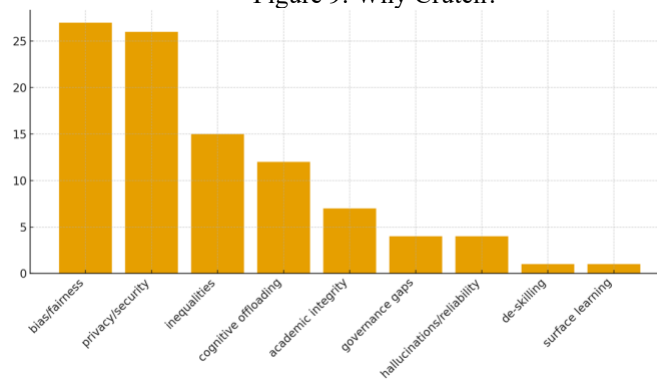


Figure 10. Categories of AI's Grounding Risks

The distribution of the risk codes points first to a triad of central concerns: bias and fairness, privacy and security, and various forms of inequality (Baker & Hawn, 2022; Gaskins, 2023; Grote & Keeling, 2022; UNESCO, 2022, 2025; Farahani & Ghasemi, 2024; Ghimire, 2025; Lee et al., 2025). Cognitive offloading and academic integrity issues follow closely, while governance gaps, hallucinations and reliability, de-skilling and surface learning appear as less frequent but still significant “long-tail” risks (Gkintoni et al., 2025; Gerlich, 2025; Jose et al., 2025; Zhou et al., 2024; Chen et al., 2024; Ateeq et al., 2024; Evangelista, 2025; Triberti et al., 2024; Monib, 2024). This pattern indicates that the “crutch” effect is not only described as a matter of individual learner behavior; it is also linked to structural issues such as data governance and social inequality (UNESCO, 2025; Peters, 2022; Baker & Hawn, 2022; Farahani & Ghasemi, 2024).

The word cloud situates these risks within a broader conceptual field. The cluster around “gap”, “access” and “digital divide” signals that unequal opportunities and infrastructural disparities are treated as key problems. Another cluster—centered on privacy, data, security and use—highlights data governance as a central axis of concern. The pairing of bias and algorithmic further points to questions of algorithmic justice (Afzal et al., 2023; Ma et al., 2019; Cheshmehzangi et al., 2023; Bentley et al., 2024; UNESCO, 2025; Baker & Hawn, 2022; Leavy et al., 2020; Peters, 2022). On the cognitive plane, terms such as critical thinking, literacy and offloading underscore the worry that extensive delegation of tasks to AI may weaken

habits of deep reading and evidence-based reasoning (Gkintoni et al., 2025; Klimova & Pikhart, 2025; Jose et al., 2025; Zhou et al., 2024; Gerlich, 2025). In this way, the “crutch” effect is portrayed as arising from the interaction of systemic (access, justice, privacy) and cognitive (offloading, superficiality) risks.

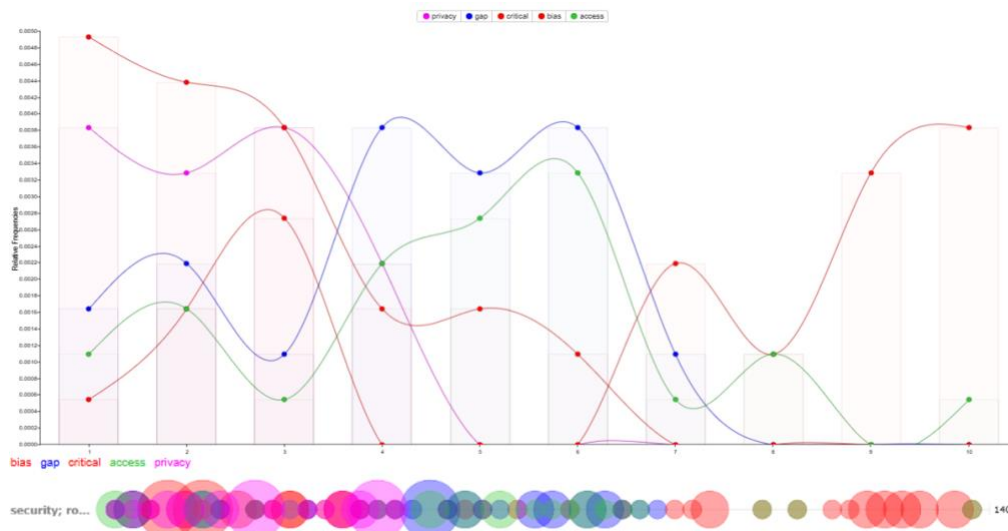


Figure 11. Trend Graph

The trend graph adds a temporal and argumentative dimension to this picture. The curve for “critical” (critical thinking) shows two marked peaks, one at the beginning of the segmented corpus (segment 1) and another toward the end (segments 9–10). The risk discussion thus opens and closes with concerns about the erosion of critical skills. In the earlier segments, privacy (pink) and access (green) are more prominent, suggesting that the argument initially builds on well-established, concrete issues. The “gap” theme (blue) peaks in the middle segments (4 and 6), which confirms that the digital divide is treated as a core problem. The overall narrative can be read as placing the loss of critical thinking at both the starting point and the final warning of the risk-oriented discourse.

Across the corpus, AI is described as a “crutch” when two threshold conditions coincide. The first is structural. Weaknesses in justice and privacy safeguards, compounded by biased datasets, are said to institutionalise algorithmic discrimination (Baker & Hawn, 2022; Grote & Keeling, 2022; Leavy et al., 2020; Thomas, 2024). When these conditions are combined with deficits in infrastructure and access—which deepen the digital divide (Afzal et al., 2023; Ma et al., 2019; Cheshmehzangi et al., 2023; Veras, 2024)—and with the absence of clear principles of transparency and accountability (Jeyaraman et al., 2023; Taherdoost & Madanchian, 2023; UNESCO, 2022), AI systems tend to reinforce existing inequalities rather than redistribute opportunities (Farahani & Ghasemi, 2024).

The second condition is cognitive substitution. Where AI use is driven primarily by demands for speed and ease of production, learners are encouraged to offload thinking to the system. This is reported to undermine critical thinking, deep processing and academic integrity, turning AI into a tool that “thinks for” the learner (Gerlich, 2025; Jose et al., 2025; Nadim & Di Fuccio, 2025). AI “thinks for the learner”; risk is just one dimension, but there are also less frequently mentioned risks such as hallucinations (Cárdenas, 2023), reliability problems, deskilling, or surface learning. These dimensions have to be taken into consideration, especially to avoid the crutch role of AI.

The results reveal that the “crutch” role becomes substantial under specific conditions. AI can directly turn into a “crutch” when systemic vulnerabilities in justice and privacy intersect with the learning designs lacking cognitive support (Bentley et al., 2024; UNESCO, 2025). This bifurcation, as stated before, coincides with the “mixed” character of AI. This mixed nature of discussions shows that AI can be a partner when sufficient governance and grounded pedagogical principles are in place”. Otherwise, it devolves into a crutch when these supports are weak (Ateeq et al., 2024; Wang et al., 2024). Research also confirms the

importance of regular bias audits (Peters, 2022), adequate privacy protections (Valerio, 2024), and policies that promote access equity (Oyelere, 2025). Governance should be understood in this sense, bringing together ethics, policy, transparency, and oversight. These acts will determine whether AI emerges as a partner or a crutch.

Discussion

The analysis presented in this article has examined how artificial intelligence (AI) is positioned in educational debates when framed explicitly through the “partner–crutch” dilemma in relation to analytical thinking. The two-stage design—combining Leximancer-based meta-explication with an interpretive meta-synthesis—shows that this dilemma cannot be settled with a straightforward “yes” or “no.” Across the corpus, AI is associated at once with supportive and disruptive consequences, and the direction of its influence is largely determined by human agency: how systems are designed, the constraints under which they operate and the pedagogical purposes they are meant to serve. AI is therefore not intrinsically a “partner” or a “crutch”; it becomes one or the other within particular socio-technical arrangements. The central challenge that emerges from the findings is to configure AI in ways that reduce, rather than intensify, existing inequalities (Bulathwela et al., 2024; Mao, 2025).

The results further indicate that any attempt to treat AI as a partner presupposes a robust governance infrastructure. International organisations consistently emphasize that realizing the benefits of AI requires investments in people and institutional capacity alongside technological development (OECD, 2023b; UNESCO, 2023, 2025). Empirical work documents capacities such as personalization, gains in learning efficiency and more inclusive forms of support as key advantages (Mahmoud & Sørensen, 2024; Jiao, 2024; Jane et al., 2024; Yu et al., 2024; Sajja et al., 2024). Meanwhile, the OECD notes that generative AI brings up “fundamental questions” about whether it is a tool that enhances human skills or a substitute for them and lists cognitive offloading as a primary concern (OECD, 2023b). These assessments align with our study, which, among other things, considers cognitive offloading the key mechanism that explains the “crutch” approach. UNESCO’s emphasis on human rights, equity, and quality as the three main principles of AI governance (UNESCO, 2022, 2023, 2025) is quite in line with the findings of the meta-synthesis. Scholars generally agree upon governance, policy, and transparency as those factors that mediate the double-faced nature of opportunity and risk (UNESCO, 2022, 2023, 2025). Together, these sets of arguments suggest that AI has greatly complicated the educational environment and, hence, the need for multi-layered, context-sensitive governance mechanisms (Ghimire, 2025; Stone, 2025).

At every turn, the challenge of establishing robust governance frameworks is met with glaring disparities in access and readiness. To some extent, current digital divide statistics serve as a revealing indicator in this regard. For example, in 2023, nearly half (47%) of higher education institutions in high-income countries reported using at least one AI-based tool, whereas the figure in low-income countries was only 8% (Li et al., 2025). Besides this gap between the two groups of institutions, there is the reality that, in 2024, about 2.6 billion people were estimated to be living offline globally (ITU, 2024). Under such conditions, the introduction of AI into education is likely to mirror and potentially amplify existing structural inequalities rather than counteract them. This pattern resonates with the present study’s finding that inequality, access constraints and the digital divide are central systemic drivers of the “crutch” framing. Across the corpus, AI’s educational effects are therefore characterized as mixed and highly contingent: whether it operates as a levelling resource or as an additional axis of stratification depends on infrastructural capacity, the preparedness of teachers and the wider cultural–institutional setting.

The findings also imply that, for AI to operate as a constructive partner, educational systems themselves need to adapt. Conventional pedagogies and assessment models sit uneasily alongside the affordances of generative technologies. Routine assignments and rote-based tests can now be completed with considerable AI assistance, undermining their capacity to measure learning or to stimulate critical thought (OECD, 2023b; Lubbe et al., 2025). Maintaining heavy reliance on such tasks risks unintentionally encouraging the “crutch” dynamic. Within the analysed literature, cognitive offloading and surface-level learning emerge as key components of this risk. A reorientation of assessment practices is therefore

necessary, away from product-focused, memorisation-heavy formats and towards project-based, process-oriented and collaborative tasks that privilege creativity, problem-solving and critical analysis. Under such conditions, AI can be repositioned from an answer-producing device to a thinking partner that supports questioning, exploration and the gradual refinement of ideas. Central to this reorientation is the “human-in-the-loop” principle, which keeps educators and learners actively involved in designing, supervising and interpreting AI-supported processes.

In response to these challenges, many countries and institutions are developing their own policy frameworks. UNESCO’s 2023 guidance and the Global Education Monitoring Report underline that success with AI depends less on “the technology itself than how we choose to govern it, with policy and ethics” (UNESCO, 2023). At the national level, these principles are translated into concrete strategies. One concrete national illustration of this governance orientation is Turkey’s 2025–2029 AI in Education Strategy. The document sets out forty planned measures, including the creation of a dedicated ethics body for AI in education, large-scale professional development initiatives for teachers, revisions of curricula and digital tools to support personalised learning, targeted interventions for learners with disabilities, and substantial investments in the underlying infrastructure (MEB, 2025). Comparable programs in other jurisdictions similarly present transparency, accountability and robust data governance as basic preconditions for the legitimate and safe adoption of AI in schools and higher education (European Commission, 2022; U.S. Department of Education, 2023). A common thread running through these texts is the concern that, in the absence of clearly articulated safeguards, algorithmic systems may generate or intensify bias and undermine privacy, with negative consequences for trust and for learners’ well-being. As a result, enthusiasm for adaptive instructional technologies is increasingly paired with demands for equally adaptive policy architectures. Continuous monitoring, systematic bias audits, explicit rules for academic integrity and active outreach to underserved groups are framed as core elements of a new minimum standard for pedagogy.

The Leximancer results discussed earlier reveal a marked divergence between this policy agenda and the dominant emphases within the research corpus examined in the present study. In the journal articles analysed, the themes labelled “AI” (53.4% of hits) and “Learning” (33.5%) together account for 86.9% of all thematic occurrences. This pattern points to a strong preoccupation with pedagogical affordances such as personalization, performance gains and forms of cognitive support. Within this thematic configuration, the cluster labelled “Digital” – which aggregates issues of access and infrastructure – accounts for 8.9% of all hits, whereas the “Bias” cluster – associated with concerns about algorithmic justice – appears in only 4.2% of cases. When this pattern is compared with policy and governance documents, an almost opposite emphasis emerges: institutional analyses tend to place structural inequalities, bias and protective safeguards at the center of their arguments. The contrast suggests that scholarly debates and institutional decision-making are, at least in part, organized around different constellations of problems. Such divergence is not necessarily negative, but it does reveal governance-related blind spots in the academic literature that may constrain the development of strategies for AI integration that are both realistic and fair. Systematically addressing these gaps is therefore likely to be decisive in shaping how AI is ultimately framed and situated within education systems.

A further consideration concerns the dynamism of the technology itself. The systems that educational policies seek to regulate are not static objects; they evolve rapidly, often moving in step with—or ahead of—regulatory and pedagogical adaptations. Studies show that large language models, with layers of memory–retrieval–reflection–planning, can maintain persistent memory streams, enabling contextual recall and long-term action design, which in turn produces coherent and socially believable behavioral patterns (Park et al., 2023). The “Generative Agents” architecture introduced by Park and colleagues (2023) extends large language models (LLMs) with the ability to store memories, synthesize from past experiences, and plan, allowing an agent to record its experiences, draw high-level inferences from them, and use these inferences to plan future behavior. In the educational context, multi-agent classroom simulations are no longer just a conceptual proposition but an experimentally tested application area. SimClass at NAACL-HLT 2025 was reported to be able to dynamically generate teacher-student and peer-to-peer interactions in two real course conditions, monitored with the Flanders Interaction Analysis and Community of Inquiry frameworks, and to establish autonomous teaching cycles through class roles and a “classroom control

mechanism” (Zhang et al., 2025). Furthermore, inter-agent discussion/collaboration mechanisms significantly improve performance on challenging tasks like mathematical reasoning; for example, a multi-agent method presented at NeurIPS 2024 improved accuracy on the most difficult problems in the MATH dataset from 54.68% to 76.73% (Lei et al., 2024).

In any case, all these opportunities from AI, such as scenario-based learning, scalable formative feedback, and personalized task flows (Córdova-Esparza, 2025), also bring internal dilemmas like planning deviations, inference biases, and instruction-following errors (Du et al., 2023). Therefore, these developments require two interrelated lines of change to realize their potential. One of them is in teaching, and the other is in the institutional structures. The main problem on the pedagogical side is that AI tools enable unprecedented speed in improving basic factual learning capacity. Because concrete, factual things can be easily described and explained, large language models can learn from these outputs. That is why curriculum frameworks need much broader space for assessment formats that follow students’ thinking over time, inviting them to reason, argue, and solve problems with others. Otherwise, isolated exercises, rote tasks, basic informational queries, or questioning without supporting creativity will only serve to make the generation much more AI-dependent.

Therefore, digital literacy needs to be redefined. It should no longer mean simply knowing how to operate software, but being able to use digital tools in a critical and creative way, where students question outputs, compare sources and make informed choices. Classroom environments whether digital or face-to-face, should be organized along these lines. Teachers or educators will then act as designers and ethical gatekeepers of AI-supported activities, rather than functioning only as deliverers of content. Alongside these pedagogical shifts, issues of equality require direct attention. In many systems, gaps in connectivity, devices and institutional support create settings where AI is more accessible to already advantaged learners than to others. When such structural differences are left unaddressed, AI tools tend to mirror existing hierarchies, which means they can widen opportunity gaps instead of closing them.

The studies reviewed here suggest that AI is most likely to function as a genuine learning partner when three basic conditions are met: learners can access the tools, their backgrounds and needs are fairly represented, and their data are protected by clear rules. These conditions need to be built into technical design and policy from the outset, not added later as optional safeguards. A human-centered stance, therefore, does not oppose technological innovation; rather, it demands that innovation be steered in ways that strengthen learners’ agency and gradually reduce the inequalities that shape educational trajectories.

Conflict of interest:	The author declares no potential conflict of interest.
Financial support:	The author received no financial support for the research.
Ethics Board Approval:	The author declares no need for ethics board approval for the research.

References

- Adeleye, O. O., Eden, C. A., & Adeniyi, I. S. (2024). Innovative teaching methodologies in the era of artificial intelligence: A review of inclusive educational practices. *World Journal of Advanced Engineering Technology and Sciences*, 11(2), 69-79. <https://doi.org/10.30574/wjaets.2024.11.2.0091>
- Afzal, A., Khan, S., Daud, S., Ahmad, Z., & Butt, A. (2023). Addressing the digital divide: Access and use of technology in education. *Journal of Social Sciences Review*, 3(2), 883-895.
- Aggarwal, D. (2023). Exploring the scope of artificial intelligence (AI) for lifelong education through personalized and adaptive learning. *Journal of Artificial Intelligence, Machine Learning and Neural Network*, 4(41), 21-26. <https://doi.org/10.55529/jaimlenn.41.21.26>
- Airaj, M. (2024). Ethical artificial intelligence for teaching-learning in higher education. *Education and Information Technologies*, 29(13), 17145-17167. <https://doi.org/10.1007/s10639-024-12545-x>
- Ateeq, A., Alzoraiki, M., Milhem, M., & Ateeq, R. A. (2024). Artificial intelligence in education: implications for academic integrity and the shift toward holistic assessment. *Frontiers in Education* (Vol. 9, p. 1470979). Frontiers Media SA. <https://doi.org/10.3389/feduc.2024.1470979>

- Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, 32(4), 1052-1092. <https://doi.org/10.1007/s40593-021-00285-9>
- Bentley, S. V., Naughtin, C. K., McGrath, M. J., Irons, J. L., & Cooper, P. S. (2024). The digital divide in action: how experiences of digital technology shape future relationships with artificial intelligence. *AI and Ethics*, 4(4), 901-915. <https://doi.org/10.1007/s43681-024-00452-3>
- Bulathwela, S., Pérez-Ortiz, M., Holloway, C., Cukurova, M., & Shawe-Taylor, J. (2024). Artificial intelligence alone will not democratise education: On educational inequality, techno-solutionism and inclusive tools. *Sustainability*, 16(2), 781. <https://doi.org/10.3390/su16020781>
- Cárdenas, J. (2023). Artificial intelligence, research and peer-review: Future scenarios and action strategies. *Revista de Psicología y Educación*, 32(4), a184. <https://doi.org/10.22325/fes/res.2023.184>
- Chandrasekera, T., Hosseini, Z., Perera, U., & Bazhaw Hyscher, A. (2025). Generative artificial intelligence tools for diverse learning styles in design education. *International Journal of Architectural Computing*, 23(2), 358-369. <https://doi.org/10.1177/14780771241287345>
- Chen, Z., Chen, C., Yang, G., He, X., Chi, X., Zeng, Z., & Chen, X. (2024). Research integrity in the era of artificial intelligence: Challenges and responses. *Medicine*, 103(27), e38811. <https://doi.org/10.1097/MD.00000000000038811>
- Cheshmehzangi, A., Zou, T., Su, Z., & Tang, T. (2023). The growing digital divide in education among primary and secondary children during the COVID-19 pandemic: An overview of social exclusion and education equality issues. *Journal of Human Behavior in the Social Environment*, 33(3), 434-449. <https://doi.org/10.1080/10911359.2022.2062515>
- Córdova-Esparza, D.-M. (2025). AI-powered educational agents: Opportunities, innovations, and ethical challenges. *Information*, 16(6), 469. <https://doi.org/10.3390/info16060469>
- Costa, K., Mfolo, L. N., & Ntsobi, M. P. (2024). Challenges, benefits and recommendations for using generative artificial intelligence in academic writing—a case of ChatGPT. *Medicon Engineering Themes*, 7(4), 3-38. <https://doi.org/10.31222/osf.io/7hr5v>
- Damasevicius, R., & Sidekerskiene, T. (2024). AI as a teacher: A new educational dynamic for modern classrooms for personalized learning support. Z. E. Ahmed (Ed.), *AI-Enhanced Teaching Methods* (pp. 1-24). IGI Global.
- Du, Y., Li, S., Torralba, A., Tenenbaum, J. B., & Mordatch, I. (2023). Improving factuality and reasoning in language models through multiagent debate. In *Forty-first International Conference on Machine Learning*.
- Eden, C. A., Adeleye, O. O., & Adeniyi, I. S. (2024). A review of AI-driven pedagogical strategies for equitable access to science education. *Magna Scientia Advanced Research and Reviews*, 10(2), 44-54. <https://doi.org/10.30574/msarr.2024.10.2.0043>
- Egunjobi, D., & Adeyeye, O. J. (2024). Revolutionizing learning: The impact of augmented reality (AR) and artificial intelligence (AI) on education. *International Journal of Research Publication and Reviews*, 5(10), 1157-1170. <https://doi.org/10.55248/gengpi.5.1024.2734>
- European Commission. (2022). *Ethical guidelines on the use of artificial intelligence (AI) and data in teaching and learning for educators*. Publications Office of the European Union. <https://data.europa.eu/doi/10.2766/15375>
- Evangelista, E. D. L. (2025). Ensuring academic integrity in the age of ChatGPT: Rethinking exam design, assessment strategies, and ethical AI policies in higher education. *Contemporary Educational Technology*, 17(1), ep559. <https://doi.org/10.30935/cedtech/15775>
- Farahani, M., & Ghasemi, G. (2024). Artificial intelligence and inequality: Challenges and opportunities. *International Journal of Innovative Education*, 9, 78-99. <https://doi.org/10.32388/7HWUZ2>
- Freyer, H. (2014). *Sanayi çağı*. (B. Akarsu & H. Batuhan, Çev.). Doğu Batı Yayınları.
- Gaskins, N. (2023). Interrogating algorithmic bias: From speculative fiction to liberatory design. *TechTrends*, 67(3), 417-425. <https://doi.org/10.1007/s11528-022-00783-0>
- Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies*, 15(1), 6. <https://doi.org/10.3390/soc15010006>
- Ghimire, A., & Qiu, Y. (2025). Redefining pedagogy with artificial intelligence: How nursing students are shaping the future of learning. *Nurse Education in Practice*, 84, 104330. <https://doi.org/10.1016/j.nepr.2025.104330>
- Gkintoni, E., Antonopoulou, H., Sortwell, A., & Halkiopoulos, C. (2025). Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy. *Brain Sciences*, 15(2), 203. <https://doi.org/10.3390/brainsci15020203>
- Grote, T., & Keeling, G. (2022). On algorithmic fairness in medical practice. *Cambridge Quarterly of Healthcare Ethics*, 31(1), 83-94. <https://doi.org/10.1017/S0963180121000839>
- Shivani., Gupta, M., Gupta, S. B. (2024). A systematic analysis of AI-empowered educational tools developed in India for disabled people. *Information Technologies and Learning Tools*, 100(2), 199. <https://doi.org/10.33407/itlt.v100i2.5501>

- Habib, S., Vogel, T., Anli, X., & Thorne, E. (2024). How does generative artificial intelligence impact student creativity? *Journal of Creativity*, 34(1), 100072. <https://doi.org/10.1016/j.yjoc.2023.100072>
- Isiaku, L., Kwala, A. F., Sambo, K. U., & Isiaku, H. H. (2024). Academic evolution in the age of ChatGPT: An in-depth qualitative exploration of its influence on research, learning, and ethics in higher education. *Journal of University Teaching and Learning Practice*, 21(6), 67-91. <https://doi.org/10.53761/7egat807>
- ITU. (2024). *Facts and figures 2024 – Internet use*. International Telecommunication Union. <https://www.itu.int/itu-d/reports/statistics/2024/11/10/ff24-internet-use/>
- Jane, O. C., Ezeonwumelu, C. G., Barah, C. I., & Jovita, U. N. (2024). Personalized language education in the age of AI: Opportunities and challenges. *Newport International Journal of Research in Education*, 4(1), 39-44. <https://doi.org/10.59298/NIJRE/2024/41139448>
- Jeyaraman, M., Balaji, S., Jeyaraman, N., & Yadav, S. (2023). Unraveling the ethical enigma: Artificial intelligence in healthcare. *Cureus*, 15(8). <https://doi.org/10.7759/cureus.43262>
- Jiao, D. (2024). AI-driven personalization in higher education: Enhancing learning outcomes through adaptive technologies. *Adult and Higher Education*, 6(6), 42-46. <https://doi.org/10.23977/aduhe.2024.060607>
- Jose, B., Cherian, J., Verghis, A. M., Varghise, S. M., S, M., & Joseph, S. (2025). The cognitive paradox of AI in education: Between enhancement and erosion. *Frontiers in Psychology*, 16, 1550621. <https://doi.org/10.3389/fpsyg.2025.1550621>
- Kitsios, F., Kamariotou, M., Syngelakis, A. I., & Talias, M. A. (2023). Recent advances of artificial intelligence in healthcare: a systematic literature review. *Applied Sciences*, 13(13), 7479. <https://doi.org/10.3390/app13137479>
- Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. *Frontiers in Psychology*, 16, 1498132. <https://doi.org/10.3389/fpsyg.2025.1498132>
- Kostas, A., Paraschou, V., Spanos, D., Tzortzoglou, F., & Sofos, A. (2025). AI and ChatGPT in Higher Education: Greek students' perceived practices, benefits, and challenges. *Education Sciences*, 15(5), 605. <https://doi.org/10.3390/educsci15050605>
- Kurtz, G., Amzalag, M., Shaked, N., Zaguri, Y., Kohen-Vacs, D., Gal, E., ... & Barak-Medina, E. (2024). Strategies for integrating generative AI into higher education: Navigating challenges and leveraging opportunities. *Education Sciences*, 14(5), 503. <https://doi.org/10.3390/educsci14050503>
- Leavy, S., Meaney, G., Wade, K., & Greene, D. (2020). Mitigating gender bias in machine learning data sets. *International Workshop on Algorithmic Bias in Search and Recommendation* (pp. 12-26). Springer International Publishing.
- Lee, J., Cimová, T., Foster, E. J., France, D., Krajňáková, L., Moorman, L., ... & Zhang, J. (2025). Transforming geography education: the role of generative AI in curriculum, pedagogy, assessment, and fieldwork. *International Research in Geographical and Environmental Education*, 34(3), 237-253. <https://doi.org/10.1080/10382046.2025.2459780>
- Lei, B., Zhang, Y., Zuo, S., Payani, A., & Ding, C. (2024). MACM: Utilizing a multi-agent system for condition mining in solving complex mathematical problems. *Advances in Neural Information Processing Systems*, 37, 53418–53437. <https://doi.org/10.48550/arXiv.2404.04735>
- Li, Y., Tolosa, L., Rivas-Echeverria, F., & Marquez, R. (2025). Integrating AI in education: Navigating UNESCO global guidelines, emerging trends, and its intersection with sustainable development goals.
- Linkon, A. A., Miah, M. K., Rahman, M. M., & Hasan, M. (2024). Advancements and applications of generative artificial intelligence and large language models on business management: A comprehensive review. *Journal of Computer Science and Technology Studies*, 6(1), 225-232. <https://doi.org/10.32996/jcsts.2024.6.1.26>
- Liu, D. (2024). The impact and prospects of AI-generated content in educational environments. *Transactions on Computer Science and Intelligent Systems Research*, 6, 64-71. <https://doi.org/10.62051/7mewnb62>
- Liu, J., Wang, C., Liu, Z., Gao, M., Xu, Y., Chen, J., & Cheng, Y. (2024). A bibliometric analysis of generative AI in education: Current status and development. *Asia Pacific Journal of Education*, 44(1), 156-175. <https://doi.org/10.1080/02188791.2024.2305170>
- Lubbe, A., Marais, E., & Kruger, D. (2025). Cultivating independent thinkers: The triad of artificial intelligence, Bloom's taxonomy and critical thinking in assessment pedagogy. *Education and Information Technologies*, 1-34. <https://doi.org/10.1007/s10639-025-13476-x>
- Ma, J. K. H., Vachon, T. E., & Cheng, S. (2019). National income, political freedom, and investments in R&D and education: A comparative analysis of the second digital divide among 15-year-old students. *Social Indicators Research*, 144(1), 133-166. <https://doi.org/10.1007/s11205-018-2030-0>
- Mahafdah, R., Bouallegue, S., & Bouallegue, R. (2024). Enhancing e-learning through AI: advanced techniques for optimizing student performance. *PeerJ Computer Science*, 10, e2576. <https://doi.org/10.7717/peerj-cs.2576>
- Mahmoud, C. F., & Sørensen, J. T. (2024). Artificial intelligence in personalized learning with a focus on current developments and future prospects. *Research and Advances in Education*, 3(8), 25-31.

- Malik, A., Khan, M. L., Hussain, K., Qadir, J., & Tarhini, A. (2025). AI in higher education: Unveiling academicians’ perspectives on teaching, research, and ethics in the age of ChatGPT. *Interactive Learning Environments*, 33(3), 2390-2406. <https://doi.org/10.1080/10494820.2024.2409407>
- Mao, Z., Wang, S., & Yao, H. (2025). The nonlinear relationship between artificial intelligence development and income inequality: the moderating effect of education level. *Aslib Journal of Information Management*. Ahead of print. <https://doi.org/10.1108/AJIM-01-2025-0029>
- Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., & Gerardou, F. S. (2023). Challenges and opportunities of generative AI for higher education as explained by ChatGPT. *Education Sciences*, 13(9), 856. <https://doi.org/10.3390/educsci13090856>
- Monib, W. K., Qazi, A., Apong, R. A., Azizan, M. T., De Silva, L., & Yassin, H. (2024). Generative AI and future education: a review, theoretical validation, and authors’ perspective on challenges and solutions. *PeerJ Computer Science*, 10, e2105. <https://doi.org/10.7717/peerj-cs.2105>
- Nadim, M. A., & Di Fuccio, R. (2025). Unveiling the Potential: Artificial intelligence's negative impact on teaching and research considering ethics in higher education. *European Journal of Education*, 60(1), e12929. <https://doi.org/10.1111/ejed.12929>
- Noroozi, O., Soleimani, S., Farrokhnia, M., & Banihashem, S. K. (2024). Generative AI in education: Pedagogical, theoretical, and methodological perspectives. *International Journal of Technology in Education*, 7(3), 373-385. <https://doi.org/10.46328/ijte.845>
- OECD (2023b). *Opportunities, guidelines and guardrails for effective and equitable use of AI in education*. In *OECD Digital Education Outlook 2023*. OECD Publishing.
- OECD. (2023a). *PISA 2022 results (Volume I): The state of learning and equity in education*. OECD Publishing.
- Oyelere, S. S., & Aruleba, K. (2025). A comparative study of student perceptions on generative AI in programming education across Sub-Saharan Africa. *Computers and Education Open*, 8. <https://doi.org/10.1016/j.cao.2025.100245>
- Park, J. S., O’Brien, J., Cai, C. J., Morris, M. R., Liang, P., & Bernstein, M. S. (2023, October). Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST ’23)* (pp. 1–22). ACM. <https://arxiv.org/abs/2304.03442>
- Peters, U. (2022). Algorithmic political bias in artificial intelligence systems. *Philosophy & Technology*, 35(2), 25. <https://doi.org/10.1007/s13347-022-00512-8>
- Ramaiah, M. S., Nagarajan, S. K. S., Whig, P., & Dutta, P. K. (2025). AI-powered innovations transforming adaptive education for disability support. *Advancing Adaptive Education: Technological Innovations for Disability Support* (pp. 73-100). IGI Global.
- Sajja, R., Sermet, Y., Cikmaz, M., Cwiertyny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, 15(10), 596. <https://doi.org/10.3390/info15100596>
- Song, N. (2024). Higher education crisis: Academic misconduct with generative AI. *Journal of Contingencies and Crisis Management*, 32(1), e12532. <https://doi.org/10.1111/1468-5973.12532>
- Stone, B. W. (2025). Generative AI in higher education: Uncertain students, ambiguous use cases, and mercenary perspectives. *Teaching of Psychology*, 52(3), 347-356. <https://doi.org/10.1177/00986283241305398>
- T.C. Millî Eğitim Bakanlığı (MEB). (2025). *Eğitimde Yapay Zekâ Politika Belgesi ve Eylem Planı (2025–2029)*.
- Taherdoost, H., & Madanchian, M. (2023). AI advancements: Comparison of innovative techniques. *AI*, 5(1), 38-54. <https://doi.org/10.3390/ai5010003>
- Tanveer, M., Hassan, S., & Bhaumik, A. (2020). Academic policy regarding sustainability and artificial intelligence (AI). *Sustainability*, 12(22), 9435. <https://doi.org/10.3390/su12229435>
- Tariq, M. U. (2025). Navigating public administration 5.0: Embracing AI for smarter governance. *Public Governance Practices in the Age of AI* (pp. 167-186). IGI Global.
- Thomas, S. (2024). AI and actors: Ethical challenges, cultural narratives and industry pathways in synthetic media performance. *Emerging Media*, 2(3), 523-546. <https://doi.org/10.1177/27523543241289108>
- Triberti, S., Di Fuccio, R., Scuotto, C., Marsico, E., & Limone, P. (2024). “Better than my professor?” How to develop artificial intelligence tools for higher education. *Frontiers in Artificial Intelligence*, 7, 1329605. <https://doi.org/10.3389/frai.2024.1329605>
- U.S. Department of Education, Office of Educational Technology. (2023). *Artificial intelligence and the future of teaching and learning: Insights and recommendations*. <https://tech.ed.gov/ai/>
- UNESCO. (2022). *Recommendation on the ethics of artificial intelligence*.
- UNESCO. (2023). *Global education monitoring report 2023: Technology in education—A tool on whose terms?* UNESCO.
- UNESCO. (2025). *AI and education: Protecting the rights of learners*.

- Valerio, A. (2024). Anticipating the impact of artificial intelligence in higher education: Student awareness and ethical concerns in Zamboanga City, Philippines. *Cognizance Journal of Multidisciplinary Studies*, 4(6), 10-47760. <https://doi.org/10.47760/cognizance.2024.v04i06.024>
- Veras, M., Dyer, J. O., & Kairy, D. (2024). Artificial intelligence and digital divide in physiotherapy education. *Cureus*, 16(1), e52617. <https://doi.org/10.7759/cureus.52617>
- Wang, N., Wang, X., & Su, Y. S. (2024). Critical analysis of the technological affordances, challenges and future directions of Generative AI in education: a systematic review. *Asia Pacific Journal of Education*, 44(1), 139-155. <https://doi.org/10.1080/02188791.2024.2305156>
- Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the potential impact of artificial intelligence (AI) on international students in higher education: Generative AI, chatbots, analytics, and international student success. *Applied Sciences*, 13(11), 6716. <https://doi.org/10.3390/app13116716>
- Yu, C., & Yao, G. (2024). Enhancing student engagement with ai-driven personalized learning systems. *International Transactions on Education Technology (ITEE)*, 3(1), 1-8. <https://doi.org/10.33050/itee.v3i1.662>
- Zhang, Y., Yun, Y., An, R., Cui, J., Dai, H., & Shang, X. (2021). Educational data mining techniques for student performance prediction: method review and comparison analysis. *Frontiers in Psychology*, 12, 698490. <https://doi.org/10.3389/fpsyg.2021.698490>
- Zhang, Z., Zhang-Li, D., Yu, J., Gong, L., Zhou, J., Hao, Z., Jiang, J., Cao, J., Liu, H., Liu, Z., Hou, L., & Li, J. (2025, April). Simulating classroom education with LLM-empowered agents. In L. Chiruzzo, A. Ritter, & L. Wang (Eds.), *Proceedings of the 2025 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)* (pp. 10364–10379). Association for Computational Linguistics.
- Zhou, X., Zhang, J., & Chan, C. (2024). Unveiling students' experiences and perceptions of artificial intelligence usage in higher education. *Journal of University Teaching and Learning Practice*, 21(6), 126-145. <https://doi.org/10.53761/xzjprb23>