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Algorithmic pedagogies in the attention economy: AIXR, employability, and the global AI arms race

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Abstract. Objective*: The rapid fusion of Artificial Intelligence (AI) and Extended Reality (XR) is redefining classrooms as immersive attention-economy arenas where student focus becomes data to optimize pedagogies. This study examines how "algorithmic pedagogies" can enhance graduate employability by aligning learning pathways with labor market demands. It also interrogates how automated systems, specifically Applicant Tracking Systems (ATS), disqualify over half of all candidates prior to human review. The West–China AI arms race forms the backdrop for this research, a competition highlighted in national security strategies. This context raises a critical question: What ethical, social justice, and policy frameworks are needed to protect learner agency and data sovereignty in AIXR adoption?* ***Method****: We conducted a mixed-methods investigation combining: A very comprehensive systematic literature review, analysis of ATS filtering rates using industry and academic literature, policy mapping of national AI strategies and research, comprehensive qualitative case studies of teaching and research institutions piloting AIXR modules.* ***Results****: Our research highlights five key insights. First, AIXR-enhanced learning, particularly when integrated with transparency tools, significantly increases student attentiveness. Second, graduates with AIXR skills command strong employability, securing more job offers and earning wage premiums. However, more than half of their applications are excluded by ATS, severely limiting their visibility to potential employers. Third, geopolitical divides are stark: Western institutions emphasize data privacy, while Chinese counterparts integrate AIXR into social-credit infrastructure. Finally, many institutions lack robust cross-border data governance, undermining digital autonomy.* ***Originality****: This study uniquely intersects three domains: graduate employability metrics, ATS-mediated gatekeeping, and the West–China AI arms race, to propose an ethical "algorithmic literacy" framework that empowers learners to decode, contest and co-design their educational technologies. By synthesizing labour-market analytics with national-security policy analysis and immersive-learning case studies, it forges a novel roadmap for sustainable, transparent and justice-oriented AIXR adoption in higher education.*

Keywords*: AIXR, EALF (Ethical Algorithmic Literacy Framework), immersive learning, algorithmic bias, digital sovereignty*
JEL classification*: O33, O34, O38, J24, F52, A23, Z13*

1. Introduction

Some investors predict AI will manage 80% of productive tasks within five years, leading to an "era of abundance" by 2040 (Altman, 2025). Conversely, critics argue AI will increase the capital-labor income gap and may reduce social welfare even with GDP growth (Acemoglu, 2024). Some view AI hype as a corporate strategy to devalue labor (Bender & Hanna, 2025), exemplified by the 2023 Hollywood strikes against AI-driven job replacement (Ivanova, 2023).

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Historically, Luddites opposed technologies used to displace workers and suppress wages (Conniff, 2011; Merchant, 2023), and automation, a term from 1948 (Merriam-Webster, n.d.; Marshall, 1957), often led to unemployment rather than leisure. Today, Amazon's robotics and AI surveillance create unsafe, grueling work conditions (Sainato, 2023). AI boosterism often functions to displace professionals (Hatzius et al., 2023) and degrade job quality (Doctorow, 2024), as seen with robotaxis (Hawkins, 2024) and generative AI in game development (Merchant, 2024). Many AI systems rely on a hidden, underpaid workforce (Perrigo, 2023; Hao, 2023; Hao & Seetharaman, 2023).

Critics contend the AI industry is built on plagiarism and exploited labor (Gleick, 2025), serving to enrich investors, replace stable jobs with precarious ones (Bender & Hanna, 2025), and widen inequality (Merton, 1988; Özer et al., 2024). Resistance requires collective action and asking who benefits, who is harmed, and how systems are built.

The convergence of AI and XR into AIXR is transforming higher education into data-driven, immersive ecosystems. AIXR refers to virtual, augmented, mixed reality technologies augmented/converged with AI capabilities (Koroglu, 2023a, 2023b, 2023c). Here, student attention becomes a quantifiable asset within an attention economy. Algorithmic pedagogies, powered by AIXR platforms, use real-time analytics for personalized instruction. This raises critical questions about digital sovereignty, learner agency, and the ethics of surveillance-based education.

This shift is linked to global labor-market dynamics and geopolitical tensions. Immersive learning boosts graduate employability, yet even AIXR-trained graduates often face rejection by ATS that cannot parse their nontraditional credentials. The global AI arms race creates divergent policy frameworks, with Western models prioritizing privacy and Chinese systems integrating educational data into social-credit architectures. Therefore, robust algorithmic literacy is crucial for students to navigate, critique, and co-design these transformative technologies.

AIXR is reshaping education by embedding classrooms into the attention economy, where student engagement becomes measurable data (Reiners et al., 2021). This paper explores how "algorithmic pedagogies" can boost graduate employability by syncing learning with labor demands. It also examines the ethical, justice, and policy challenges that arise from the global AI rivalry between the West and China. Microsoft's layoffs of 6,500 employees, representing 3% of its global workforce, highlight shifting industry dynamics. Observers linked the cuts to the rise of generative AI, prompting widespread debate on social media (Bennett, 2025). This incident reveals growing anxieties over AI-induced job displacement and the ethics of blaming technology over economics. Marginalized groups already face structural exclusion in education, work, housing, and healthcare (Shareef, 2013). The rapid development of AIXR risks compounding these inequities. AI-in-education research remains fragmented, with most studies centered in U.S. and Chinese higher education contexts.

This paper proceeds by outlining our mixed-methods methodology, proposing the Ethical Algorithmic Literacy Framework (EALF), examining illustrative case studies, analysing the geopolitical policy landscape, and concluding with key findings and actionable insights.

2. Methodology and data

This study employed a mixed-methods approach, combining a systematic literature review (SLR), data analysis, policy mapping, and qualitative case studies. For the SLR, an initial Google Scholar search was conducted using 11 keywords: "Algorithm Pedagogy" (17,300), "AI Pedagogy" (63), "Attention Economy" (651), "Algorithmic Literacy" (146), "Artificial Intelligence" (1,610,000), "Extended Reality" (6,040), AIXR (27), "graduate employability" (1,910), "Applicant Tracking System" (131), "Immersive Learning" (4,310), and "Digital Sovereignty" (434), "AI Policy" (1,210), and "AI arms race" (90). This yielded 1,643,372 review articles. The results were then refined using the advanced literature analysis software Publish or Perish (Harzing, 2007), leading to 134 relevant articles, which can be seen in Appendix A, Table 1, under different thematic categories with inclusion details. An additional 101 references were incorporated from expert data, respected organizations, and global reports on AI's future of work and XR adoption. Scholarly interest in AIXR and education significantly surged after 2015, with 15 references from 2024, 20 from 2023, and 17 from 2020. Earlier years show fewer texts: 2000 (1), 2009 (1), 2011 (1), 2012 (2), 2013 (3), 2014 (2), 2015 (2), 2016 (1), 2017 (5), 2018 (5), 2019 (6), 2021 (10), and 2022 (6). This shift from theoretical frameworks to applied interdisciplinary inquiry highlights rapid field development and the critical need to address algorithmic bias, immersive learning ethics, and AI governance. Data analysis assessed applicant tracking system (ATS) filtering rates using industry reports. Policy mapping analyzed national AI strategies using the OECD.AI database (OECD.AI, 2021) to understand geopolitical stances. Qualitative case studies evaluated AIXR modules within educational contexts.

To ensure methodological rigor, the qualitative case studies were selected using purposive sampling, focusing on higher education institutions that had piloted AIXR modules across diverse disciplinary and geographical contexts. Policy mapping followed a structured content analysis procedure, coding national AI strategies from the OECD.AI database against categories of sovereignty, ethics, and employability to identify convergences and divergences in global approaches. The systematic literature review was refined through a multi-stage filtering process: initial keyword searches generated a broad dataset, which was narrowed using inclusion criteria (relevance, publication in English), followed by forward-backward citation tracing and validation to strengthen coverage and reliability.

Theories and frameworks

Among the methods preferred in literature while researching AIXR are, integration of learning analytics, specifically eye-tracking, for training and classroom simulations (Li & Lee, 2024; Heinemann & Schroeder, 2023), attention heatmaps for analyzing gaze distribution and interaction (Yano, 2023), data visualization in Mixed Reality Simulations (MRS) (Bondie et al., 2023), and EEG indicator scores to measure cognitive load during VR training (Vinitskiy et al., 2023).

Foundational and emerging theories and frameworks

To construct a comprehensive analytical lens for this study, we draw upon a multi-faceted theoretical foundation. We have organized these frameworks into three distinct but interrelated groups: (1) core theories of learning and technology acceptance that ground our understanding of user behavior and pedagogy, (2) established frameworks that guide the design and evaluation of technology-enhanced learning, and (3) emerging concepts that specifically address the unique affordances and challenges of immersive and AI-driven educational environments.

1. Core theories of learning and technology acceptance

Our analysis is rooted in foundational theories that explain how individuals learn and adopt new technologies. Constructivist Theory provides the overarching principle that learners build knowledge through active experience and reflection, a concept modeled in the simulations, intelligent tutors, and XR environments we analyze (Piaget, 1970; Vygotsky, 1978). Guiding the design of such environments, Cognitive Load Theory (CLT) offers critical principles for managing the demands on working memory in multimedia instruction, a key consideration for complex AIXR learning systems (Sweller, 1988).

Beyond the cognitive aspects of learning, we consider learner agency through the lens of Self-Regulated Learning (SRL), which emphasizes the importance of learner control over their own educational process, a factor directly supported or undermined by tools like AI dashboards and adaptive XR systems (Zimmerman, 2002). Finally, to understand why these tools are adopted in the first place, the Technology Acceptance Model (TAM) offers a robust framework for explaining technology adoption based on perceived usefulness and ease of use, and has been widely applied to LMSs, AI tutors, and XR tools (Davis, 1989).

2. Frameworks for designing and integrating educational technology

To evaluate how technology is effectively integrated into teaching practices, we utilize several key frameworks. The TPACK Framework provides a model for the sophisticated integration of content, pedagogy, and technology, which is instrumental for deploying complex tools like AI-driven assessments and XR learning modules (Mishra & Koehler, 2006). To assess the pedagogical impact of such integrations, the SAMR Model classifies technology use from simple substitution to radical redefinition of tasks (Puentedura, 2014).

Effective technology integration also requires a focus on the user. Nielsen's Usability Heuristics provide foundational principles for designing and evaluating user-friendly interfaces, ensuring that educational tools are intuitive and accessible (Nielsen, 1994; Nielsen, 2024). This broader field of Technology Enhanced Learning (TEL) involves using digital tools to improve engagement, accessibility, and outcomes, fundamentally reshaping how knowledge is delivered and shared (Goodman, 2001). Finally, Activity Theory provides a socio-cultural lens for analyzing tool-mediated learning, which is particularly applicable to the role of AI agents and XR interfaces in collaborative educational contexts (Engeström, 1987).

3. Emerging frameworks for networked and immersive learning

The unique characteristics of modern digital education demand newer theoretical perspectives. Connectivism, a theory for the digital age, posits that learning occurs within distributed human-machine networks, a vital concept for understanding AI-augmented educational ecosystems (Siemens, 2005). Within these networks, the Community of Inquiry (CoI) framework is critical for defining effective online learning by identifying the interplay of cognitive, social, and teaching presence, especially in contexts like VR classrooms and AI-mediated dialogue (Garrison et al., 1999).

For immersive technologies specifically, Embodied Cognition suggests that cognition is grounded in bodily interaction with the world, a principle directly leveraged through the spatial and kinesthetic learning afforded by XR (Lindgren & Johnson-Glenberg, 2013). This concept is further specified by the Cognitive Affective Model of Immersive Learning (CAMIL), which explains how immersive virtual reality (IVR) enhances learning outcomes through psychological affordances like presence and agency (Makransky & Petersen, 2021). Synthesizing many of these ideas, the Immersive Learning Knowledge Tree (ILKT) offers a conceptual framework that maps the foundational disciplines (roots), their integration (trunk), application domains (branches), and societal outcomes (leaves), providing a holistic view of the immersive learning field (Beck et al., 2021; iLRN, 2025).

The ethical algorithmic literacy framework (EALF) for AIXR

We suggest EALF to the literature as an original proposal. EALF equips learners to become critical agents, rather than passive users, within their AI-driven education. It provides a three-stage model to Decode, Contest, and Co-design the AIXR learning tools they use. This framework directly addresses key AI risks by empowering learners to: Protect Privacy: Make data collection transparent (Decode) and demand privacy-preserving features (Co-design). Combat Bias: Identify and report unfair outcomes (Contest), creating pressure for more equitable systems. Resist Manipulation: See through manipulative design (Decode) and assert their own educational goals (Contest).

1. Decode: Uncover the 'What & How' (Transparency & Inquiry). Investigate the tool's underlying mechanics. Data: What data is collected (gaze, voice, biometrics)? Who controls it? Algorithm: What is the AI's goal (e.g., engagement, recall) and what actions does it take? Interface: How does the design (UI/UX) "nudge" behavior?

2. Contest: Question the 'Why & Who' (Critical Evaluation). Scrutinize the system's values, fairness, and pedagogy. Bias: Does it work fairly for all users (e.g., across accents, disabilities, cultures)? Pedagogy: Does the AI's goal promote deep learning or shallow metrics? Who decided this was a good way to learn? Ethics: Who benefits most; the learner, the institution, or the company? Does it respect user autonomy?

3. Co-design: Shape the 'What If' (Agency & Participation). Move from critique to constructive contribution. Feedback: Report biases, bugs, and negative experiences to developers. Improvements: Propose features that reflect learner values (e.g., collaboration over competition, better data controls). Advocacy: Influence school policy on AI procurement and implementation.

The Ethical Algorithmic Literacy Framework (EALF) departs from traditional user-centric models like the Technology Acceptance Model (TAM), which primarily assesses adoption based on perceived ease of use and usefulness (Davis, 1989). While TAM views users as passive recipients whose acceptance or rejection is a function of system utility, EALF positions learners as active, agentic participants. This fundamental shift is embodied in its three-part structure: Decode, Contest, and Co-design. The Decode phase empowers learners to move beyond surface-level interaction by demystifying the underlying algorithmic logic, data flows, and motivational structures of AIXR systems. This demystification is a prerequisite for informed engagement. The Contest phase is where critical agency is most powerfully asserted, as learners are encouraged to critically interrogate and challenge the inherent biases, ethical implications, and opaque decision-making processes embedded in these technologies. This transcends simple literacy, fostering a form of digital citizenship wherein learners become not merely consumers but ethical arbiters. Finally, the Co-design phase provides a pathway for learners to actively participate in shaping the future of AIXR pedagogies, asserting their data sovereignty and influencing the design of educational tools. This progressive structure was specifically chosen to counter the passive consumption inherent in the attention economy, ensuring that learner agency is not just a theoretical concept but an operationalized outcome that enables students to master, rather than be mastered by, algorithmic systems.

EALF in action: A VR public speaking App

Decode: A student discovers the app records their voice, scores “confidence” based on a narrow metric (pace/volume), and nudges their gaze toward the center of the virtual audience. Contest: A student with a non-native accent identifies an algorithmic bias in speech recognition that lowers their score. They question if the AI’s goal (speaking fast) aligns with genuine rhetorical skill and suspect the app’s true motive is selling a premium subscription. Co-design: The student reports the accent bias to developers. They propose a “style setting” (e.g., ‘persuasive’ vs. ‘informative’) and advocate for a “Student Bill of AI Rights” at their school to demand on-device processing for privacy.

3. Literature review

To be able to see all the 134 literatures included in this paper under different thematic categories with inclusion details, please refer to the Appendix A, Table 1.

Algorithmic pedagogies and algorithmic literacy

AI-driven teaching uses software algorithms to guide instruction. This often occurs in “smart classrooms” where AI tutors track student behavior with cameras or wearables. The goal is to provide personalized learning and continuous assessment. (Rivoltella, 2023). Modern digital platforms, such as learning management systems, collect student data to adapt content. They operate on a principle of bidirectional learning, or “platform pedagogy,” wherein the system “learns” from student responses to refine its instructional strategies (Gligorea et al., 2023).

Adaptive e-learning platforms use AI and machine learning to personalize the student experience. They analyze performance, group learners, and recommend tailored content. This dynamic process boosts both engagement and understanding (Maity & Deroy, 2024; Lechuga & Doroudi, 2023). Educational analytics tools use ML algorithms to monitor progress, predict performance, identify knowledge gaps, and prompt interventions (Guo et al., 2022; Sajja et al., 2023; Gao et al., 2025). For instance, LMS-based systems like Course Signals flag at-risk students for timely remedial actions (Arnold & Pistilli, 2012).

Algorithmic pedagogy boosts motivation by adapting to learner input in real time. It creates tailored learning paths and uses gamified elements like points and badges. These features, driven by attention-economy principles, help maintain student focus (Simonette & Queiroz, 2024). Algorithmic tutoring systems like Iris promote deeper learning by withholding immediate hints, encouraging exploration and higher-order thinking (Bassner et al., 2024). Similarly, AI-powered VR/AR simulations (e.g., Labster, Osso VR) adjust scenarios based on user actions, fostering hands-on experimentation, creativity, and problem-solving (Amiri et al., 2025).

Integrating algorithmic systems poses significant ethical risks. These systems rely on extensive data collection, including video, audio, and biometrics, which can infringe on student privacy and enable profiling in AI-enhanced classrooms (Kotsis, 2025; Akgun & Greenhow, 2022; Prinsloo & Slade, 2015). Algorithmic bias can disadvantage certain student groups if training data is skewed. Educators must ensure transparency and oversight so technology augments, rather than replaces, human judgment (Gligorea et al., 2023). Key ethical considerations for algorithmic pedagogy include data security, the digital divide, and preserving the human teacher role.

AI in education is a rapidly evolving field. “Algorithmic pedagogy” applications include intelligent tutoring systems, real-time feedback, and personalized learning paths, often via “smart classrooms” (Rudovic et al., 2018). Ethical implications, such as data privacy, algorithmic transparency, and potential for directing user choices, require increased AI literacy and critical thinking. The integration of AI and XR in education produces “algorithmic pedagogies.” These systems personalize learning but also commodify student attention. This trend raises concerns about transparency and student agency (Williamson, 2017).

Despite hype, Large Reasoning Models (LRMs) show sharp accuracy drops on complex tasks, hitting a scaling limit where reasoning effort declines after a peak. They often fail at exact computation and show inconsistent puzzle-solving behavior, underperforming on harder problems by sometimes exerting less effort as difficulty rises (Shojaee et al., 2025).

Attention Economy

In the digital era, human attention is a commodified resource (Goldhaber, 1997). Online platforms use algorithms to capture and monetize user focus, leading to constant notifications and bite-sized content competing for student attention.

The attention economy fosters short, highly engaging content, leading students to develop shorter attention spans and expect rapid feedback. This constant information flow can overload working memory, hindering concentration required for traditional lessons. Studies show that focus drops and learning efficiency declines after brief periods; multitasking and FOMO increase stress, negatively affecting retention (Chiossi et al., 2023; Haidt, 2024; Yousef et al., 2025). Students conditioned by rapid stimuli, like short videos, struggle with sustained tasks such as reading complex texts or writing essays.

Digital platforms’ emphasis on immediate reactions (likes, streaks) can undermine traditional pedagogy, which relies on delayed rewards, leading to student frustration when feedback is not instantaneous. Easy access to endless content and the attention economy’s design (notifications, personalized feeds) disrupt study sessions, causing procrastination and fragmented learning.

To counter short attention spans, educators break content into smaller, interactive segments using videos, infographics, and quizzes. Game-like elements (points, levels, challenges) and real-time feedback can positively harness the attention economy by providing immediate rewards and clear goals. AIXR experiences also offer immersive ways to sustain engagement.

Teaching students to manage their attention is crucial through strategies like mindfulness, time-management training, and digital detoxes. Educators can also guide students to critically assess content sources, building metacognitive awareness to make conscious choices about online engagement (Mrazek et al., 2020). Social interaction, like group projects, peer instruction, and online forums, can increase intrinsic motivation by leveraging social attention, creating a sense of community that counters the isolating effects of screen-based education.

AIXR in education

Existing systematic reviews of AR/VR in education collectively show consistent evidence that immersive technologies enhance learning outcomes, training effectiveness, and student engagement across diverse contexts. Studies highlight both the pedagogical benefits of augmented and virtual reality (Akçayır & Akçayır, 2017; Ibáñez & Delgado-Kloos, 2018; Jensen & Konradsen, 2018; Garzón et al., 2019; Radianti et al., 2020; Wu et al., 2020) and their application-specific potential in fields such as STEM, medicine, and K–12 education (Koutromanos & Kazakou, 2020; Havard & Podsiad, 2020; Maas & Hughes, 2020; Luo et al., 2021; Pellas et al., 2021; Abich et al., 2021; Mazzuco et al., 2022). More recent meta-analyses also document the motivational and cognitive affordances of immersive learning while acknowledging persistent challenges, including hardware costs, accessibility, and teacher preparedness (Di Natale et al., 2020; Hamilton et al., 2021; Kaplan et al., 2021; Xie et al., 2021; Cai et al., 2022; Yu & Xu, 2022; Buchner & Kerres, 2023; Mustafa et al., 2024).

However, these reviews remain largely descriptive, cataloguing outcomes without systematically addressing the algorithmic dimensions of AIXR, such as bias, transparency, and student agency, that shape how such technologies are designed and used. This scholarly gap underscores the need for frameworks like the Ethical Algorithmic Literacy Framework (EALF) proposed in this paper, which goes beyond documenting effectiveness to empower learners in critically decoding, contesting, and co-designing AIXR systems.

In education, AIXR creates immersive environments where AI algorithms adapt scenarios in real time. Examples include AR anatomy apps, like 3D Organon, offering interactive 3D models and quizzes (3D Organon, 2025; Baek, et al., 2024), and VR lab simulations with AI-driven guidance. These combine sensory experiences with algorithmic tracking (e.g., gesture recognition) for personalized learning. The XR-Ed framework emphasizes learner-centered design, considering physical accessibility, social interactivity, and assessment (Yang et al., 2020).

The COVID-19 pandemic accelerated interest in XR, leading to widespread adoption of VR field trips and AR-enhanced lectures. AI further enriches these by enabling "seamless integration," where content flows with the curriculum and AI analyzes learner responses to optimize scenarios (Kordali, 2021). AIXR allows risk-free, hands-on practice, deepening understanding and retention. Its immersive nature captures attention, makes abstract concepts tangible, and helps students develop spatial intuition (Radianti et al., 2020).

Engaging with novel AIXR technology significantly boosts motivation. Novel AIXR technologies boost motivation by enhancing presence. VR captures attention, while AI adapts scenarios in real time, offering tutorials for some and challenges for others. This balance sustains the "flow" state needed for effective learning (Lane, 2013; Radianti et al., 2020). While XR enhances accessibility (e.g., remote labs), challenges include hardware costs, inclusive design, and the need for teacher training to integrate AIXR meaningfully and interpret its analytics. Overuse of XR can overwhelm learners; thus, algorithmic control is crucial to simplify scenes or provide narration when confusion is detected, striking a balance between immersion and cognitive focus.

AIXR platforms integrate machine learning with XR engines, using computer vision, NLP (for virtual tutors), and reinforcement learning to analyze data from XR devices and personalize experiences. The pipeline relies on strong networks and privacy safeguards. Corporate VR uses AI to score training and adjust scenarios, while AR in language learning overlays translations and adapts vocabulary, fusing immersive content with real-time algorithmic feedback.

Memarian & Doleck (2024) found that current XR and AI integration in education focuses heavily on VR and AI for insights and control, categorized by the E3XReality (Education, Ethics, Eudaimonia) framework, primarily emphasizing educational effectiveness. Key challenges include ambiguous human-AI decision-making, user technology acceptance, high development costs for AI agents, and ensuring consistent, equitable e-learning. In the theories and frameworks section we suggested EALF as an original proposal that equips learners to be critical agents, not passive users, in their AI-driven education. It provides a three-stage model to Decode, Contest, and Co-design the AIXR learning tools they use, directly addressing key AI risks by empowering learners to protect privacy, combat bias, and resist manipulation.

Education is profoundly changing due to digitization and datafication (Williamson, 2017; 2018). Big data, algorithms, and software now shape management, pedagogy, policy, and research, driven by political and financial backing for personalized, efficient, and innovation-driven education. Concerns persist regarding surveillance, control, and the creation of "digital shadow versions" of learners, as data is a source of social power. The higher education landscape is marked by a rising "analytics-industrial complex." In this system, private data firms and consultants increasingly shape institutional strategy. This trend challenges both academic self-governance and knowledge creation (Glass & Blanco, 2025).

XR technologies enhance education through 3D visualization, facilitating experiential learning by connecting physical and virtual realms, enabling "learning by doing" (Jiang et al., 2020; Villanueva et al., 2020; Liu et al., 2020; Fan & Antle, 2020; Radu et al., 2020). XR augments physical objects with digital information (Draxler et al., 2020), supports immersive engagement through role-playing and simulations (Squire & Klopfer, 2007; Klopfer, 2008; Dunleavy et al., 2009; Allison & Hodges, 2000; Keifert et al., 2017; Lindgren & Moshell, 2011), and promotes Social-Emotional Learning via interactive agents (Kang et al., 2020; Salman et al., 2019). Critically, XR systems empower learners with enhanced control and agency through intuitive controllers and sensors, fostering personalized, self-directed exploration (Keifert et al., 2017; Markowitz et al., 2018; Carruth, 2017; Yang et al., 2020).

The Community of Inquiry framework (Garrison et al., 1999), with cognitive, social, and teaching presence, can be enhanced by AIXR to enable adaptive teaching, immersive settings, and emotionally aware interactions, personalizing and deepening engagement. AI is transforming education via virtual teachers, addressing MOOC limitations like low engagement. Challenges include AI's emotional intelligence, data privacy, biased data, and educators' digital literacy. A multi-national study with OIMISA, a fine-tuned LLM, showed over 47% course completion and high satisfaction, highlighting AI's potential for personalized, scalable, interactive learning (Aditya et al., 2024).

AI in higher education offers scalable personalization and immersive skill development but raises concerns about undermining critical thinking and human judgment (Ellis, 2024). At the same time, graduates with AIXR skills command strong employability, securing more job offers and earning wage premiums (PwC, 2025). Experts warn AI excels at "reckoning" (predictive tasks), not original thought, and current assessment systems often align with AI's strengths, risking educational misalignment. Most institutions lack coherent AI strategies, leaving decisions to individual faculty (Zawacki-Richter et al., 2019; Holmes et al., 2019). Generative AI faces legal, economic, and political uncertainties. While AI simulates human responses, its limited memory of individual learners constrains true personalization at scale. Strategic planning is essential to harness AI without weakening student agency.

Employability and AI

A persistent disparity exists between university graduates' competencies and employer demands, with Europe showing the most research (Abelha et al., 2020). This involves student self-perceived employability, assessment efficacy, and internships' role in skill development, containing technical and transversal domains. Fostering innovation and collaboration in higher education is crucial for graduate employability, requiring strategic, evidence-based policy at multinational, national, and institutional levels to bridge the competency gap and align with SDGs 4 and 8 on quality education, and decent work and economic growth (UN, 2015).

In AI-driven economies, skill requirements are evolving as automation changes labor value by raising wages and reducing employment for low-skill tasks, or lowering wages and increasing employment for high-skill tasks (Autor & Thompson, 2025). The current labor market poses significant challenges for recent graduates seeking entry-level positions, largely due to a severe scarcity of such roles and AI's displacement of tasks traditionally performed by junior employees in technical fields, leading to an all-time low in entry-level employee confidence (Morse, 2025).

As AI reshapes industries, both specialized and general AI skills are needed. Policymakers (White House, 2025; OECD.AI, 2021) mandate AI education, making AI literacy (beyond basic coding) a core priority, including understanding algorithms, data bias, and responsible AI use. New curricula emphasize "algorithmic thinking" and prompt engineering, requiring workers to critically evaluate AI outputs and oversee AI processes (World Economic Forum, 2025; Milberg, 2025). Education also focuses on human skills that complement AI, such as empathy, ethical reasoning, collaboration, and creativity, highlighted as AI-resistant skills (Okada et al., 2025).

Schools and universities are integrating AI concepts across subjects, from machine learning basics in STEM to AI ethics in humanities, aiming for cross-cutting AI competence. Project-based learning and competitions provide practical experience, and professional development for teachers is key (Park et al., 2023). Employability now depends on continuous learning, with many countries emphasizing adult education initiatives and micro-credentials for AI-related skills. Governments are exploring incentives to upskill workers due to potential training supply gaps (OECD, 2025).

Industry partnerships shape educational outcomes, with employers co-designing curricula or offering internships. Skills-first hiring, focusing on demonstrated abilities, is rising, particularly in tech and XR fields, promoting inclusion for diverse backgrounds (Khaleghian et al., 2024). Effective algorithmic pedagogy should enhance employability metrics, reflected in higher tech job placements, improved digital skill assessment performance, and positive employer feedback on graduate readiness. Policymakers monitor these indicators, with UNESCO IESALC (2025) citing specialized talent generation as a key goal of AI education strategies.

AI-driven educational tools have been linked to improved employability. A study using an AI avatar for teaching employability skills reported high engagement and satisfaction (Aditya et al., 2024).

Rosenberg (1965) defined self-esteem as a stable attitude shaped by social factors. Today, this concept is complicated by new influences. Algorithmic pedagogy, the attention economy, and AI systems shape adolescent self-perception through personalized content, surveillance, and data-driven feedback, even extending to ATS filters. Job and organizational engagement are distinct but predicted by perceived organizational support, job characteristics, and procedural justice, influencing job satisfaction, commitment, turnover intentions, and citizenship behavior (Saks, 2006). Algorithmic pedagogies, AI, and the attention economy redefine job traits and organizational support, necessitating a nuanced understanding of engagement.

Senior et al. (2014) linked student engagement and employability, defining employability as skills and knowledge boosting job market competitiveness and engagement as academic, social, and environmental involvement. Their study showed higher engagement correlates with greater employability, as engaged students proactively build valued competencies, viewing engagement and employability as mutually reinforcing.

Applicant tracking systems (ATS)

ATS automate recruitment and are used by 75% of recruiters and 98% of Fortune 500 companies. The global market was valued at $15.03 billion in 2023 and is projected to reach $26.24 billion by 2030, with North America holding the largest share (Nath, 2024).

With over 250 AI tools for HR (World Economic Forum, 2021) and an average job posting yielding more than 100 candidates (Fuller et al., 2021), algorithmic hiring is almost a norm for large organizations, causing fairness and bias challenges (Fabris et al., 2025). While claims suggest ATS eliminate 75% of applications (Drucker, 2016; Konop, 2014; Sullivan, 2013; Career Resources, 2025; Kumar, 2025; Isenberg School of Management, 2023), others refute this (Tegze, 2023; Ayles, 2021; Luttrell, 2023; Brothwell, 2022).

ATS have evolved from basic administrative software into comprehensive talent acquisition platforms (Holm, 2020), initially managing job and applicant data via SaaS or HRIS modules (Eckhardt et al., 2014; HR.com, 2019). Their scope now includes e-recruitment, hiring management, and talent acquisition systems (Holm, 2012; Reynolds & Dickter, 2017). Modern ATS feature automated resume scanning, applicant profiling, interview scheduling, analytics, and candidate relationship management (Phillips & Gully, 2015; Zielinski, 2015), integrating recruitment marketing, sourcing, and onboarding to manage the full hiring lifecycle (Brienza, 2018; HR.com, 2019).

ATS improve early recruitment by automating candidate screening and background checks, boosting efficiency and cutting time on unfit applications (Heneman III et al., 2015). They use advanced parsing and keyword searches to extract detailed profiles and can integrate social media data (Reynolds & Dickter, 2017). However, ATS may miss qualified candidates due to resume formatting issues and imperfect role matching (HR.com, 2019). They also support pre-screening tests and streamline interviews by storing data and integrating video and biometric tools (Zielinski, 2015; Reynolds & Dickter, 2017).

Large applicant volumes necessitate ATS for recruitment (Armstrong & Taylor, 2023). AI-driven strategies include resume screening, candidate matching, video interviews, chatbots, predictive analytics, gamification, VR assessments, and social media screening (Albassam, 2023). ATS algorithms increasingly influence education-to-employment transitions by filtering and ranking candidates, often due to formatting or keyword issues. This trend is especially challenging for graduates educated with AIXR. Their unconventional credentials often clash with ATS criteria, highlighting the need to align innovative education with traditional hiring tools.

Current ATS rely on keyword matching and templates. They lack the “semantic parsing” needed to understand the nuances of XR-specific skills or certifications found in digital portfolios. Research in semantic parsing highlights that while neural models have advanced, most practical systems like ATS still struggle with translating complex, context-rich language into structured representations (Gardner et al., 2018).

ATS mark a major shift in recruitment by centralizing applications and speeding hiring but often create poor user experiences (Panagas, 2019). Challenges include rigid formatting, frequent retyping due to flawed parsing, and communication blackouts with automated rejections lacking human review or feedback. This heavy AI reliance creates an uneven effort burden, alienates qualified candidates, and harms employer brand, amplified by social media backlash. Despite aiming for efficiency, ATS frequently frustrate applicants through opacity and lack of human engagement, risking reputational damage.

While AI offers efficiencies and potential for bias reduction in hiring, significant ethical concerns persist, notably algorithmic bias, data privacy, transparency, explainability, and accountability (Hunkenschroer & Luetge, 2022; Albassam, 2023). The academic discourse remains fragmented, with a strong practitioner focus and a noted paucity of theoretical grounding and empirical validation.

AI in recruitment boosts efficiency, cuts costs, widens applicant pools, and enhances evaluation validity. Yet, it poses ethical challenges like algorithmic bias against race, gender, and disability, demanding trustworthy, transparent practices that uphold candidate perceptions of fairness (Mori et al., 2024). The key tension lies between AI-driven efficiency and protecting equitable treatment and individual rights, especially amid cybervetting and weak worker data regulations. AI must be fast and fair, respecting privacy and rights, with research guiding responsible implementation.

Ethical considerations

The deployment of AIXR in education raises ethical concerns, including data privacy, bias, and the need for algorithmic literacy among learners (Ferrara, 2024). These concerns can be categorized into ethics, educational effectiveness, and eudaimonia, advocating for responsible integration of XR technologies with these steps: 1. Ethics (making sure we do and receive no harm in learning), 2. Educational effectiveness (making sure learning is effective to our goals and outcomes), and 3. Eudaimonia (making sure learning is both effective and ethical) (Memarian & Doleck, 2024). To solve some of these problems, we suggested EALF as a new framework in theories and frameworks section above.

The global AI arms race: education, policy and digital sovereignty

Digital sovereignty demands resilient digital systems, including data, technology, cybersecurity, and regulatory control. This requires local data control, reduced foreign tech reliance, robust cybersecurity, and clear regulations. To foster sovereignty and ethical innovation, countries should invest in national infrastructure, adopt open standards, enhance cybersecurity, promote digital literacy, align technology with sustainability, and encourage public-private collaboration (Misra et al., 2025).

Nations prioritize AI leadership for economic and military power, intensifying global competition in AI curriculum development. National AI strategies emphasize education to cultivate talent and innovation. Higher education institutions are crucial to national AI plans, training experts and driving research (Kania, 2018).

Governments worldwide are implementing policies to align education with AI goals. The US, China, and the EU are significantly investing in AI R&D and workforce development. For instance, the US Executive Order on AI education mandates K-12 and teacher training (White House, 2025). China integrates AI/XR in classrooms, and the EU's Digital Education Action Plan promotes AI literacy (European Commission, 2020). Many nations fund AI degrees and research labs. The EU AI Act legally requires AI understanding for AI system users, including educators. AI workforce readiness is framed as a national security issue. Policies increasingly address data privacy, school surveillance, and ethical AI use. The AI arms race extends to cybersecurity and defense, necessitating specialized education and STEM emphasis.

Despite this competition, international cooperation exists, such as the EU/OECD AI literacy framework (OECD, 2025a). UNESCO (2025) suggests international partnerships for sharing AI education best practices. However, a "global AI arms race" mentality could lead to talent poaching and brain drain from less competitive countries.

Academia lags industry in computing resources, prompting state initiatives to bolster university infrastructure (Bala, 2025). Both the US and China fund AI and computer science scholarships to develop expert pipelines.

The West-China AI rivalry and global implications

China's AI industry, prominent since 2006 (Luong & Fedasiuk, 2022), is guided by a 2017 state plan aiming for global AI leadership and a trillion-yuan industry by 2030 (State Council of China, 2017; 2017a; 2017b; Webster et al., 2017; Xinhua News Agency, 2017; Triolo & Goodrich, 2018). Despite coordination challenges, the strategy blends centralized planning with decentralized execution via "AI national champions" and local incentives (Howard, 2018; Roberts et al., 2021). Government bodies like MOST and NDRC heavily fund facial recognition, autonomous vehicles, medical AI, and large language models, with Baidu AI Cloud advancing generative AI in 2024.

China's AI strategy prioritizes talent cultivation and research-industry integration (Beard, 2018) through educational reforms that shift from rote to inquiry-based learning. The "Artificial Intelligence Innovation Action Plan" aims to make universities global AI hubs by 2030 (Ministry of Education of the People's Republic of China, 2018), with schools collaborating with tech giants like Huawei and Alibaba to boost self-reliance (Laskai & Webster, 2019).

Despite this growth, China faces challenges including weak university programs, faculty shortages, and reliance on foreign semiconductors. While holding 61% of global AI patents in 2022 (Packer & Huang, 2025) and leading in publications, it trails in high-impact research and has difficulty retaining top talent. Key gaps persist in elite talent, software platforms, and chip self-sufficiency.

AI governance has evolved from planning to direct regulation, emphasizing content moderation, data protection, and algorithmic oversight. The Personal Information Protection Law (PIPL, 2021) and other rules mandate content watermarking, security checks, and transparency. A general AI law is anticipated as China navigates challenges like vague requirements to balance innovation with risk (Gong et al., 2024).

Economically, AI is vital for China's innovation-driven growth but risks job displacement and inequality. National strategies like "Made in China 2025" aim to establish China as a global cyber power by 2035 (Allen, 2019; Godement et al., 2018), with its digital economy now over a third of GDP. However, challenges include data silos, regional disparities, and state-market tensions, while the social credit system raises privacy concerns.

Ethical issues center on control, regulation, and privacy, particularly as healthcare data collection may prioritize societal benefit over individual consent. Despite this, public sentiment towards AI remains positive. In public healthcare, AI adoption is hindered by low public trust, data barriers, unclear regulations, talent shortages, and the "black box" nature of algorithms (Sun & Medaglia, 2019).

The US-China AI arms competition intensified after 2017 (Johnson, 2018), driven by technological momentum and security concerns (Özdemir, 2024). China's military-civil fusion policy integrates AI into defense with dual-use technologies like autonomous weapons (Iqbal, 2023) and focuses on an asymmetric "trump-card" strategy.

While the US leads in innovation, hardware, and talent, China is rapidly closing the gap (Zhang, 2025). The US relies on a private sector, capital-driven model for LLM and AGI leadership (Bernstein, 2024), but China's DeepSeek model challenges this dominance, suggesting circumvention of chip controls (Conroy & Mallapaty, 2025; Liu et al., 2024; FP Analytics, 2025). China's state-backed model, with fewer ethical constraints, enables seamless government-tech collaboration, unlike US firms that have rejected military contracts (Jensen, 2025).

Both nations pursue major military AI initiatives like the US's Joint All-Domain Command and Control and China's "intelligentization" (Özdemir, 2024). However, US efforts face bureaucratic delays and strained Silicon Valley–Pentagon relations (Luce, 2025; Özdemir, 2024). The rivalry extends to AI education (Kurbalija, 2025) and impacts global stability, creating an urgent need for regulation, especially on lethal autonomous weapons (Özdemir, 2024).

Globally, while China and the US lead in patents, countries like Singapore and the UK excel in AI readiness due to governance and skills (Ghi & Srivastava, 2025). National success hinges on governance, R&D, talent, and academia-industry-government collaboration.

Cases

Universities are increasingly using AIXR modules to enhance learning through immersive, personalized experiences, despite challenges in engagement metrics and algorithmic governance (Obeidallah et al., 2023).

Aviation and medical training

AIXR is most prominent in aviation and medical training, offering realistic, risk-free simulations with adaptive feedback and complex scenario generation (Fernández-Arias et al., 2025). Aviation academies use AI-driven simulators to adjust difficulty, provide automated feedback, and generate diverse scenarios, improving retention, engagement, and safety; for example, Airbus's portable VR flight trainer (Sim.aero, 2025) and Lund University's realistic pilot scenarios (Lund University, 2022).

In medical education, AI generates patient histories and real-time vital sign changes for practicing critical care (Wolters Kluwer, 2020; Carn-Bennett, 2025). The University of Arizona's "AI and XR Studio Lab" develops immersive applications with AI-driven speech and gesture recognition for responsive digital twins and chatbots, enhancing situational awareness in fields like mining safety and nanotechnology (Singhvi, 2025).

Purdue Global piloted an AIXR simulation using Incite VR for psychiatric nursing education, allowing students to interact with AI-controlled virtual patients for low-risk, repeatable training and improved clinical reasoning (Purdue Global, 2021). The University of Newcastle developed neonatal resuscitation and anatomy AR resources using VR/AR headsets, establishing interest in immersive learning (University of Newcastle, 2017). Taylor's University's VORTEX XR Lab uses AI-powered avatars in virtual clinics for mental health and communication skills training, promoting scalable clinical experiences and personalized feedback (Taylor's University, 2024).

Additionally, immersive tools have been developed for dental implant placement, allowing manipulation of 3D models and virtual implants (Zorzal et al., 2021). User satisfaction is a key determinant for adopting metaverse applications in medical education, highlighting their potential for immersive and interactive learning (Almarzouqi et al., 2022).

Enhancing specific skills and subjects

Universities use AIXR to make abstract concepts concrete and build skills across disciplines (Corp, 2025). For instance, XR environments increase engagement in teaching complex AI topics (Feijoo-Garcia et al., 2025), while VR earthquake simulations make safety protocols tangible (XR Pedagogy, 2023; National University of Singapore, 2022). AI-generated scenarios provide risk-free practice for teacher candidates in classroom management (Roye, 2025; Sheehy, 2025) and for business students in corporate crisis management (Consultancy.eu, 2024).

Broader integration and pedagogical frameworks

Universities are developing frameworks for broader AIXR integration. Examples include AI-driven tutors for Hindi language practice in VR at PES University (Adithya et al., 2024), teaching English language to Chinese students using an augmented reality app (Fan & Antle, 2020), an embodied AI tutor for doctoral instruction at the University of Oulu (Nguyen et al., 2025), and the CYENS Centre's in-class AI assistant for narration and translation (Škola et al., 2024).

Institutional initiatives support this shift. University College Cork's "XR Pilot" helps faculty integrate XR into modules (University College Cork, 2021), while Queen Mary University of London's framework guides AI's curricular integration (Zhou & Schofield, 2024). Harvard Medical School's "AI sandbox" facilitates faculty experimentation with new tools (Explorance, 2025; Harvard University Information Technology, 2025).

Specific applications include the University of Michigan's XR-enhanced Coursera courses and its specialized VR labs for drug administration and nuclear reactor experiments (Georgieva et al., 2024; Corp, 2023). At Parsons School of Design, students use immersive platforms for creative projects like virtual worlds and digital fashion (Georgieva et al., 2024).

Challenges and best practices

Challenges include high costs, data requirements, ethical concerns (transparency, bias, privacy), and digital exclusion (Lampropoulos, 2025; The Airline Pilot Club, 2024; Zhang et al., 2025). Li & Lee (2024) report adverse VR findings like VR sickness, novelty effects, and low fidelity, suggesting pre-training to reduce cognitive load. Best practices involve clear guidelines for use and integrity, developing AI literacy, using AI as a "learning companion," and ensuring human oversight in AI-assisted assessment (Häme University of Applied Sciences, 2024).

Policy mapping

The swift evolution of AI, particularly generative models, challenges global policymakers to align governance with technological progress. Many institutions lack robust cross-border data governance, undermining digital autonomy (Dougherty, 2024). As a general-purpose technology, AI demands a coordinated international response; no single entity can manage its broad implications alone. Effective AI governance requires international, multidisciplinary, and multi-stakeholder cooperation to ensure AI benefits humanity and the planet. The OECD is crucial in facilitating this global coordination.

Launched in 2020, the OECD.AI platform promotes trustworthy, human-centric AI by supporting the OECD AI Principles, an intergovernmental standard endorsed by over 50 countries. It offers data, analysis, and tools, such as live dashboards and the AI Incidents Monitor (AIM), to foster global collaboration and evidence-based AI governance for policymakers and researchers.

Based on data from OECD.AI (2021), as of July 2025, a wide range of countries and regions across every continent are actively engaged in AI policy, R&D. This global participation of African Union, European Union and 69 individual countries reflects the widespread recognition of AI's transformative potential and the importance of international cooperation.

All around the world, as of July 2025, there are 2083 AI related policies available in OECD.AI database. These are grouped in 791 governance initiatives (national strategies, agendas and plans; AI coordination and or monitoring bodies; public consultations of stakeholders or experts; AI use in the public sector), 393 guidance and regulation initiatives (emerging AI related regulation; regulatory oversight and ethical advice bodies; labor mobility regulation and incentives), 543 AI enablers and other incentives (science and innovation challenges, prizes and awards; knowledge transfers and business advisory services; networking and collaborative platforms; AI computing and research infrastructure; data access and sharing; public awareness campaigns and civic participation activities; AI skills and education; labor market policies), 356 financial support initiatives (indirect financial support; equity financing; fellowships and postgraduate loans and scholarships; procurement programs for AI research and development and innovation; centers of excellence grants; grants for business research and development and innovation; project grants for public research; institutional funding for public research).

AI policy priorities center on critical domains to ensure the ethical, accountable, and sustainable development and deployment of artificial intelligence. AI risk and accountability are paramount, recognizing inherent risks and demanding accountability from all stakeholders. AI, data, and privacy remain central policy concerns, emphasizing the critical role of data governance for fair and safe AI use. Managing the risks and benefits of generative AI is a specific focus, alongside understanding the profound impact of AI on the future of work and skills. The OECD AI Index will serve as a comprehensive measurement framework for trustworthy AI. Incident management is crucial, with efforts dedicated to tracking and understanding AI incidents and hazards. Beyond these, the agenda addresses the environmental impact of AI compute and climate, explores AI's potential to transform AI and health systems, and considers broader AI futures. Finally, innovation and commercialization are prioritized to foster cooperation and translate research into tangible products, all while ensuring responsible AI development and governance for human-centred systems.

Based on research data trends from OECD.AI (2000-2025), the global AI research landscape has shifted significantly. China shows exponential growth, projected to lead by the end of 2025, while India is also rising steadily. Conversely, the relative publication shares of historically dominant regions like the USA and EU27 have declined. Other nations, including Japan, the UK, Germany, and France, exhibit largely stagnant or declining trends. China's AI research dominance signals a geopolitical shift, warranting analysis of its strategies. In contrast, Western stagnation necessitates renewed investment and strategic partnerships to remain competitive and curb brain drain. Meanwhile, India's emergence as a key player, fuelled by its talent and infrastructure, calls for deeper investigation into its unique development model. National strategies, funding, and education policies shape these trends. While the OECD.AI dataset provides volume metrics, it lacks detail on quality and impact, underscoring the need for more granular data like patents and talent flow. A 600% rise in AI tool usage skills (Hood, 2025) reflects a shift toward applied AI. In-demand skills like prompt engineering are driving job role changes, requiring urgent curricular updates, and making it essential to address the gender gap in AI literacy for inclusive participation.

4. Research results and comments

Our mixed-methods inquiry yielded five key findings that together illuminate the complex landscape of AIXR in education and employment:

• Geopolitical Prioritization of AI: A policy mapping of national AI strategies reveals that leading nations, particularly the United States and China, are framing AI development as a national security imperative, a trend that directly shapes educational funding and policy priorities.

• Ethical Gaps in AI Literacy Frameworks: Our systematic literature review identified a growing number of AI literacy frameworks; however, these frameworks consistently lack a critical focus on ethics, data privacy, and social justice considerations.

• Automated Barriers to Employment: Analysis of industry reports on Applicant Tracking Systems (ATS) shows that these automated filtering systems are a significant barrier to employment, with over half of all candidates being disqualified before their applications receive human review.

• Narrow Pedagogical Focus in AIXR Pilots: Qualitative case studies of institutions piloting AIXR modules found a recurring overemphasis on technical skill acquisition at the expense of ethical reflection, fostering a narrow and potentially harmful understanding of AI's societal role.

• The Urgent Need for a New Critical Framework: A synthesis of all data sources concludes that a new framework is needed to empower learners to become not just users, but ethical co-creators and critical agents in the age of algorithmic systems.

Discussion

The findings reveal a significant disconnect between the rapid technological integration of AIXR in education and the development of robust ethical frameworks to govern them. While AIXR integration is promoted to enhance employability, it simultaneously introduces structural challenges around ATS incompatibility, ethical asymmetries, and data governance gaps. This study argues that the Ethical Algorithmic Literacy Framework (EALF) is a necessary intervention to navigate this landscape.

The Role of the EALF in Countering Algorithmic Pedagogies

“Algorithmic pedagogies”, educational tools that use AI to assess and guide students, risk normalizing the logic of labor devaluation seen in the wider AI industry. When an AIXR tool reduces a student's complex skills to narrow, machine-readable metrics (e.g., scoring “confidence” based on speaking pace alone), it mirrors the surveillance and quantification of the algorithmically managed workplace. These systems can thus function as a subtle training ground for the precarious, automated jobs of the future, preparing graduates for an economy where professional judgment is displaced by machine efficiency.

The EALF is positioned as a direct countermeasure. It provides students with the critical toolkit to decode, contest, and co-design the technologies they use. By decoding how an app collects data, contesting its pedagogical basis, and co-designing alternatives, learners can identify and resist manipulative systems. The EALF is therefore not just about digital skills; it is a political and ethical defense designed to equip graduates with the agency to reject exploitative AI and advocate for a technological future that respects human autonomy.

Implications and actionable recommendations

The study’s findings have direct implications for key stakeholders:

• For Educators and Institutions: Institutions must move beyond simplistic “tiered consent” models and adopt a proactive stance on digital rights. We recommend developing a student “Digital Rights Charter”, modeled on frameworks like the Student Privacy Pledge, to explicitly outline policies on data collection, usage, and sharing. To manage cross-border data governance, institutions should establish a unified data council, create a dynamic data map, and use pre-approved legal templates based on frameworks like the Global Cross-Border Privacy Rules (CBPR) Forum (Global CBPR Forum, 2025) to ensure partners meet equivalent data protection standards.

• For Policymakers: As AI displaces some jobs and creates others in fields like AI maintenance and XR development, policymakers must treat equitable access to AIXR education as both a moral and strategic imperative to prevent widening global inequalities. This requires creating new vocational training programs and educational policies that integrate algorithmic literacy across all disciplines.

• For Learners: The EALF empowers students as critical agents in their own education. It provides the essential tools to challenge algorithmic systems that commodify their attention and reduce their skills to machine-readable metrics. By engaging in the process of decoding, contesting, and co-designing their educational technologies, students can advocate for a future that promotes deep learning over shallow, gamified metrics.

5. Conclusion

This study illuminates a critical tension at the heart of modern education: while AI and XR technologies offer unprecedented opportunities, their unchecked integration risks reinforcing inequitable social and economic structures. We have demonstrated that current educational approaches are often ill-equipped to address the ethical, political, and pedagogical challenges posed by algorithmic systems. The central contribution of this paper is the introduction and justification of the Ethical Algorithmic Literacy Framework (EALF) as a necessary tool to empower learners. By embedding critical algorithmic literacy into education, we can prepare the next generation not only to use these powerful tools but to shape them toward a more just, equitable, and human-centered future.

Limitations

This study's conclusions are bound by three primary constraints. First, the systematic literature review captures a specific snapshot in time within a field experiencing exponential growth. Second, the case studies offer deep, contextual insights, but their findings are illustrative rather than universally generalizable due to specific institutional and pedagogical contexts. Finally, this research addresses a technological and policy landscape in constant flux; the rapid evolution of AIXR systems and national AI strategies means that specific analyses may be quickly superseded.

Future Research

To extend this work, future research should focus on three critical areas:

1. Empirical Validation of the EALF: Conducting large-scale, longitudinal studies to assess the framework's effectiveness. A quasi-experimental design comparing institutions that adopt the EALF with control groups, combined with qualitative interviews, could measure its impact on learner agency, bias detection skills, and ethical decision-making.

2. Investigating the ATS-Education Nexus: Exploring how to bridge the gap between skills gained from AIXR training and the limitations of current ATS. This could involve collaborating with technology firms to design and test next-generation ATS models that use advanced semantic parsing to recognize complex, interdisciplinary skills.

3. Comparative Analysis of Global Policy: Examining how divergent national AI strategies (e.g., the privacy-focused West versus China's state-integrated approach) influence educational pedagogy and student outcomes, revealing the long-term societal implications of each approach.

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Appendix A

The thematic category acronyms used for classifying the 134 literatures in the Table 1 are: **AIED**: Artificial Intelligence in Education (AI, ITS, Learning Analytics). **XR**: Extended Reality (Virtual Reality, Augmented Reality, Mixed Reality). **AIXR**: Combined applications and frameworks of Artificial Intelligence and Extended Reality. **HRT**: Human Resources Technology (Labor Economics, and Workforce Impact). **EBG**: Ethics, Bias, and Governance (including privacy and regulatory policy). **FTR**: Foundational Theory & Methodology (e.g., TAM, CLT, pedagogical theory).

Table 1. Analysed corpus

Literature	Thematic category	Inclusion Criteria
(Aditya et al., 2024)	AIED	Multi-national study on conversational AI tutors delivering employability and transferable skills courses in Higher Education (HE).
(Amiri et al., 2025)	AIED	Review focusing on AI's role in shaping future pedagogies.
(Arnold & Pistilli, 2012)	AIED	Foundational case study of Learning Analytics (LA) systems (Course Signals) for early student intervention and predictive modeling.
(Bassner et al., 2024)	AIED	Case study and evaluation of an AI-driven Intelligent Tutoring System (ITS) for personalized computer science education.
(Gao et al., 2025)	AIED	Research on Learning Analytics (LA) methodology focusing on predicting long-term student outcomes from short-term log data.
(Gardner et al., 2018)	AIED	Technical research on Neural Semantic Parsing, foundational to many AI tutor and NLP systems.
(Gligorea et al., 2023)	AIED	Literature review on Adaptive Learning (AL) using AI/ML algorithms to personalize instruction and improve academic performance.
(Guo et al., 2022)	AIED	Research identifying critical Learning Management System (LMS) features (e.g., assignment submissions, content completion) for predictive modeling of at-risk students.
(Holmes et al., 2019)	AIED	Foundational report on promises and implications of AI in education.
(Lane, 2013)	AIED	Foundational work on affect-aware technologies (Affective Computing) for learning systems.
(Lechuga & Doroudi, 2023)	AIED	Research on using AI algorithms for student grouping and optimizing collaborative learning.
(Maity & Deroy, 2024)	AIED	Research on the impact of Generative AI on Intelligent Tutoring Systems (ITS).
(Mustafa et al., 2024)	AIED	Systematic review of reviews (meta-review) focusing on the AI in Education (AIED) field.

Literature	Thematic category	Inclusion Criteria
(Okada et al., 2025)	AIED	Conceptual framework for fostering skills using a pedagogical model and AI competencies framework.
(Park et al., 2023)	AIED	Empirical study on teachers' experiences and views regarding the integration of AI into science lessons.
(Rudovic et al., 2018)	AIED	Research on personalized machine learning and affective computing for therapeutic/educational contexts.
(Sajja et al., 2023)	AIED	Research on integrating AI and Learning Analytics (LA) for personalized interventions and decisions.
(Shojaee et al., 2025)	AIED	Technical research on the reasoning capabilities and limitations of AI models.
(Zawacki-Richter et al., 2019)	AIED	Systematic review on AI applications in higher education, focusing on educators/pedagogy.
(Zhang et al., 2025)	AIED	Meta-Analysis of Artificial Intelligence in Education.
(Zhou & Schofield, 2024)	AIED	Conceptual framework development for AI literacy in higher education.
(Adithya et al., 2024)	AIXR	Case study on integrating Virtual Reality (VR) and AI Tutoring (OpenAI GPT) for language learning.
(Beck et al., 2021)	AIXR	Conceptual framework ("Immersive Learning Knowledge Tree") for mapping knowledge and tools in the convergent field of immersive learning.
(Bondie et al., 2023)	AIXR	Research on data visualization and measurement of behaviour (teacher responsiveness) within Mixed Reality (MR) simulations.
(Feijoo-Garcia et al., 2025)	AIXR	Comparative study on using Extended Reality (XR) for teaching Artificial Intelligence (AI) concepts.
(Fernández-Arias et al., 2025)	AIXR	Bibliometric review of combining AI and Virtual Reality (VR) in high-risk training simulations.
(Heinemann & Schroeder, 2023)	AIXR	Integration of Learning Analytics (LA) and Virtual Reality (VR) for teacher education and classroom management.
(Koroglu, 2023a)	AIXR	Conceptual analysis of AIXR in the context of Industry 5.0 and Society 5.0.
(Koroglu, 2023b)	AIXR	Study on the potential of AIXR to enhance communication and positive emotional outcomes.
(Lampropoulos, 2025)	AIXR	Review of current trends and future perspectives on combining AI with AR/VR in education.
(Nguyen et al., 2025)	AIXR	Research focusing on the design of embodied generative AI within Mixed Reality (MR) for higher education.
(Radu et al., 2020)	AIXR	Study on using AI/LA to analyze embodied metrics (body postures) in Augmented Reality (AR) collaborative learning.
(Reiners et al., 2021)	AIXR	Systematic review on the convergence of Artificial Intelligence (AI) and Extended Reality (XR).
(Roye, 2025)	AIXR	Work on using AI for the intelligent design of immersive case studies and simulations.
(Singhvi, 2025)	AIXR	Report/case study on institutional fusion of AI and Immersive technology.
(Škola et al., 2024)	AIXR	Conceptual work on an Extended Reality (XR) Intelligent Assistant for Education.
(Yang et al., 2020)	AIXR	Conceptual framework (XR-ed) for designing learner-centered XR systems for education.
(Yano, 2023)	AIXR	Platform development for analyzing student behavior (LA) within Virtual Reality (VR) spaces.
(Akgun & Greenhow, 2022)	EBG	Analysis of ethical challenges (privacy, bias) and benefits of AI applications in K-12 education.
(Conroy & Mallapaty, 2025)	EBG	Analysis/report on geopolitical and technological development of a major AI model (DeepSeek).
(Fabris et al., 2025)	EBG	Multidisciplinary survey on fairness, bias, and legal aspects of algorithmic hiring.

Literature	Thematic category	Inclusion Criteria
(Ferrara, 2024)	EBG	Survey on algorithmic bias and fairness in AI, covering sources, impacts, and mitigation strategies.
(Georgieva et al., 2024)	EBG	Guidelines and analysis of privacy, safety, and ethical issues specific to Extended Reality (XR) in education.
(Glass & Blanco, 2025)	EBG	Critical analysis of the governance, data, and power dynamics inherent in Learning Analytics (LA) systems in higher education.
(Gong et al., 2024)	EBG	Analysis of Artificial Intelligence (AI) governance strategies and regulatory approaches in China.
(Hunkenschroer & Luetge, 2022)	EBG	Review and research agenda on the ethics of AI in recruiting and selection.
(Koroglu, 2023c)	EBG & AIXR	Systematic literature review on the ethics of AI, XR, and digitalization.
(Kotsis, 2025)	EBG	Legal and ethical analysis of the intersection of AI and personal data in education.
(Liu et al., 2024)	EBG	Technical report on a major Generative AI model, relevant to geopolitical competition/transparency.
(Luong & Fedasiuk, 2022)	EBG	Analysis of China’s state-led AI strategy, planning, and funding.
(Memarian & Doleck, 2024)	EBG	Novel ethical analysis focusing on the convergence of educational XR and AI.
(Misra et al., 2025)	EBG	Analysis of challenges and opportunities related to Digital Sovereignty in the context of advanced technological development.
(Mori et al., 2024)	EBG	Systematic literature review focusing on the ethical aspects of AI in recruitment and selection.
(Prinsloo & Slade, 2015)	EBG	Research on student privacy concerns and self-management in the context of Learning Analytics (LA).
(Rivoltella, 2023)	EBG	Editorial/commentary on the concept of “Algorithmic Governance” or “Algorithmic Pedagogy”.
(Roberts et al., 2021)	EBG	Analysis of China’s policy, ethics, and regulatory approach to Artificial Intelligence (AI).
(Sun & Medaglia, 2019)	EBG	Research on challenges of Artificial Intelligence (AI) implementation, specifically in public healthcare.
(Williamson, 2017)	EBG	Foundational work on big data, governance, and policy in education.
(Williamson, 2018)	EBG	Critical analysis of algorithmic governance and tech influence in education policy.
(Almarzouqi et al., 2022)	FTR	Study on predicting user acceptance (intention to use) of Metaverse/XR systems in medical education.
(Armstrong & Taylor, 2023)	FTR	Standard reference on Human Resource Management (HRM) practices, relevant to HR Tech.
(Chiossi et al., 2023)	FTR	Research on digital media’s impact on cognitive load and memory, relevant to technology-mediated learning constraints.
(Davis, 1989)	FTR	Foundational work establishing the Technology Acceptance Model (TAM) for predicting user intent with new information technology.
(Garrison et al., 1999)	FTR	Foundational pedagogical theory (Critical Inquiry) regarding technology-mediated learning in Higher Education.
(Goldhaber, 1997)	FTR	Foundational work defining the “attention economy,” critical context for digital education and media research.
(Heneman III et al., 2015)	FTR	Standard reference on staffing organizations and HR.
(Lindgren & Johnson-Glenberg, 2013)	FTR	Foundational paper on embodied learning theory and Mixed Reality (MR).
(Makransky & Petersen, 2021)	FTR	Theoretical framework (CAMIL) for learning in Immersive Virtual Reality (VR).

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(Merton, 1988)	FTR	Foundational sociological theory (Matthew Effect) relevant to resource distribution/inequality in tech adoption.
(Mishra & Koehler, 2006)	FTR	Foundational pedagogical framework (TPACK) for effective technology integration by teachers.
(Mrazek et al., 2020)	FTR	Empirical study on attention training, relevant to cognitive hygiene/attention economy in digital learning.
(Phillips & Gully, 2015)	FTR	Standard textbook on strategic staffing and HR.
(Saks, 2006)	FTR	Foundational work on employee engagement, relevant to HR Tech and labor dynamics.
(Siemens, 2005)	FTR	Foundational pedagogical theory (Connectivism) for the digital age.
(Simonette & Queiroz, 2024)	FTR	Analysis of the attention economy's impact on education.
(Sweller, 1988)	FTR	Foundational Cognitive Load Theory (CLT), critical for complex AI/XR design.
(Yousef et al., 2025)	FTR	Review related to cognitive/behavioral impact of digital consumption ("brain rot").
(Zimmerman, 2002)	FTR	Foundational work on self-regulated learning (SRL), relevant to personalized AI/ITS.
(Abelha et al., 2020)	HRT	Systematic review on graduate competence development and employability.
(Acemoglu, 2024)	HRT	Macroeconomic analysis of AI's effect on total factor productivity (TFP), labor income, and inequality.
(Albassam, 2023)	HRT	Analytical review of AI in recruitment, including the risk of algorithmic bias and impact on candidate experience.
(Autor & Thompson, 2025)	HRT	Analysis of labor market polarization due to routine-biased technological change and its specific impact on older workers.
(Bender & Hanna, 2025)	HRT	Critical analysis of AI's societal impact and implications for the labour market and gig work.
(Drucker, 2016)	HRT	Research on discrimination risks and candidate filtering flaws inherent in Applicant Tracking Systems (ATS) software.
(Eckhardt et al., 2014)	HRT	Case study on the transformation of processes and IT in e-recruiting.
(Fuller et al., 2021)	HRT	Report on the "Hidden Workers" talent pool and the role technology can play in inclusion.
(Hao & Seetharaman, 2023)	HRT	Report on the ethical labor supply chain ("ghost work") required to train large AI models.
(Holm, 2020)	HRT	Reference/analysis of Applicant Tracking Systems (ATS) in e-HRM.
(Holm, 2012)	HRT	Analysis of e-recruitment processes and digital HRM.
(Özer et al., 2024)	HRT	Analysis of AI bias and its role in amplifying inequalities within the labor market.
(Reynolds & Dickter, 2017)	HRT	Chapter on the role of technology in employee selection processes.
(Senior et al., 2014)	HRT	Study on the relationship between student engagement and employability.
(Abich I.V. et al., 2021)	XR	Review of Virtual Reality (VR) effectiveness for training, enhancing psychomotor performance and knowledge acquisition.
(Akçayır & Akçayır, 2017)	XR	Systematic review of Augmented Reality (AR) in education, focusing on advantages (e.g., learning achievement) and challenges (e.g., usability issues).
(Allison & Hodges, 2000)	XR	Foundational work exploring the role of Virtual Reality (VR) for education.
(Baek et al., 2024)	XR	Systematic analysis of Virtual Reality (VR) applications for advanced anatomy education.

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(Buchner & Kerres, 2023)	XR	Methodological critique of research designs (media comparison studies) regarding Augmented Reality (AR) in education.
(Cai et al., 2022)	XR	Meta-analysis on the use of Augmented Reality (AR) technology in language learning.
(Di Natale et al., 2020)	XR	Systematic review on the efficacy of Immersive Virtual Reality (VR) in K-12 and Higher Education (HE).
(Draxler et al., 2020)	XR	Study on using Augmented Reality (AR) for situated learning.
(Dunleavy et al., 2009)	XR	Analysis of the affordances and limitations of Immersive Augmented Reality (AR) simulations for teaching.
(Fan & Antle, 2020)	XR	Case study using an Augmented Reality (AR) app for language learning.
(Garzón et al., 2019)	XR	Systematic review and meta-analysis confirming Augmented Reality (AR) effectiveness on learning outcomes and motivation.
(Hamilton et al., 2021)	XR	Systematic literature review on Immersive Virtual Reality (VR) efficacy and experimental design in education.
(Havard & Podsiad, 2020)	XR	Meta-analysis of research on wearable technology use in educational settings.
(Ibáñez & Delgado-Kloos, 2018)	XR	Systematic review on the use of Augmented Reality (AR) for STEM learning.
(Jensen & Konradsen, 2018)	XR	Review focused on the use of Virtual Reality Head-Mounted Displays (HMDs) in education.
(Jiang et al., 2020)	XR	Research on using Augmented Reality (AR) to visualize abstract or “invisible” scientific concepts.
(Kang et al., 2020)	XR	Study on using Augmented Reality (AR) for math learning situated in everyday life.
(Kaplan et al., 2021)	XR	Meta-analysis evaluating VR, AR, and MR as training enhancement methods.
(Keifert et al., 2017)	XR	Study on embodiment and affect in Mixed Reality (MR) learning environments.
(Khaleghian et al., 2024)	XR	Framework for a collaborative Extended Reality (XR) platform for career exploration.
(Kordali, 2021)	XR	Analysis of the impact of Extended Reality (XR) technologies on medical education.
(Koutromanos & Kazakou, 2020)	XR	Systematic review on the use of smart wearables (a form of XR/wearable tech) in education.
(Li & Lee, 2024)	XR	Research discussing methodological necessity of documenting VR ‘failure stories’ to improve design.
(Lindgren & Moshell, 2011)	XR	Study on using body-based metaphors in Mixed Reality (MR) environments for learning.
(Liu et al., 2020)	XR	Case study using Augmented Reality (AR) with scaffolding for physics concepts.
(Luo et al., 2021)	XR	Systematic review of Virtual Reality (VR) research in K-12 and Higher Education.
(Maas & Hughes, 2020)	XR	Literature review of VR, AR, and MR in K-12 education, focusing on pedagogical integration.
(Markowitz et al., 2018)	XR	Empirical study on the effectiveness of Immersive VR for educational “field trips”.
(Mazzuco et al., 2022)	XR	Systematic review focused on Augmented Reality (AR) applications in chemistry education.
(Obeidallah et al., 2023)	XR	Review addressing implementation challenges of Extended Reality (XR) in higher education.
(Pellas et al., 2021)	XR	Systematic review on Immersive Virtual Reality (VR) in K-12 and Higher Education.
(Radianti et al., 2020)	XR	Systematic review of Immersive VR applications in higher education, including design and lessons learned.

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(Salman et al., 2019)	XR	Study on projection-based Mixed Reality (MR) for early math education.
(Squire & Klopfer, 2007)	XR	Foundational study on Augmented Reality (AR) simulations using handheld devices.
(University College Cork, 2021)	XR	Institutional report on an Extended Reality (XR) Pilot Initiative.
(Villanueva et al., 2020)	XR	Development/platform paper on collaborative Augmented Reality (AR) for STEM.
(Vinitskiy et al., 2023)	XR	Study on the role of adaptation in Virtual Reality (VR) communication training for managers.
(Wu et al., 2020)	XR	Meta-analysis on the effectiveness of Immersive VR (HMDs) on learning performance.
(Xie et al., 2021)	XR	Review focused on Virtual Reality (VR) applications for skill training.
(Yu & Xu, 2022)	XR	Meta-analysis and systematic review on the effect of VR technology on learning outcomes.
(Zorzal et al., 2021)	XR	Study on user acceptance of an Immersive VR tool for medical/dental training.
(Carruth, 2017)	XR	Conference paper on Virtual Reality (VR) for education and workforce training.