AI in Education: Charting a 30-Year Course Toward Personalized and Autonomous Learning

Ancuta Margondai, Anna Crofton, Alex Alonso

I. Introduction

In the early 1990s, classrooms were still dominated by chalkboards and overhead projectors. A teacher stood at the front, delivering the same lesson to every student regardless of ability, interest, or learning pace. Fast forward to today, and the educational landscape is nearly unrecognizable: students now interact with AI-powered tutors, receive real-time personalized feedback, and even engage in conversations with chatbots capable of understanding their emotional state. What was once a static, one-size-fits-all environment has evolved into a dynamic, data-driven ecosystem where artificial intelligence (AI) plays a central role in shaping students' learning. Understanding how we moved from static instruction to emotionally responsive AI systems require a closer look at the evolving technologies, theories, and design philosophies that guided each era.

Artificial intelligence in education refers to using computer systems that mimic human cognitive processes, such as learning, reasoning, and problem-solving, to enhance teaching and learning outcomes (Luckin et al., 2016; Holmes et al., 2019). This includes various technologies, from rule-based intelligent tutoring systems and adaptive learning platforms to modern generative AI tools that engage students in human-like dialogue. As AI technologies have matured, their applications have expanded beyond content delivery to encompass real-time assessment, predictive analytics, emotion detection, and personalized intervention.

This paper presents a trend analysis and conceptual review of the historical evolution of AI in education over the past three decades, highlighting key technological milestones, pedagogical shifts, and emerging ethical challenges. Divided into three major phases, 1990 to 2001, 2002 to 2012, and 2013 to 2024, it maps how advancements in AI have transformed educational practices from static automation to deeply personalized and increasingly autonomous learning environments.

Over the past 30 years, AI in education has progressed from rule-based automation to data-driven personalization and finally to emotionally intelligent, co-agentic learning environments. This transformation has redefined the student experience, shifting education away from standardized content delivery toward adaptive, emotionally aware, and learner-centered engagement. As we continue to explore the capabilities and limitations of AI in the classroom, understanding this progression offers critical insight into not only where we are, but where we are headed.

II. Background

Artificial Intelligence (AI) has transformed education, reshaping how knowledge is delivered, assessed, and internalized (Holmes, Bialik, & Fadel, 2019; UNESCO, 2021). At its core, AI in education involves using intelligent systems designed to perform tasks that traditionally require human cognition, such as recognizing patterns, adapting to learner needs, and providing feedback to enhance learning experiences (Luckin et al., 2016). These systems aim to automate administrative or instructional processes and foster deeper, more personalized engagement between learners and educational content.

Early educational technologies focused primarily on delivering static content or automating grading, but AI introduced a paradigm shift toward dynamic, data-informed instruction (Baker & Inventado, 2014; Zawacki-Richter et al., 2019). AI-powered tools can now analyze student behaviors, detect misconceptions in real time, and recommend tailored learning pathways (Holmes et al., 2019). For instance, adaptive learning systems like Carnegie Learning and intelligent tutoring systems such as AutoTutor are designed to respond to students' inputs with individualized feedback and scaffolding, mimicking human tutors' support (Graesser et al., 2005).

The proliferation of digital learning platforms has generated vast datasets on learner behavior, enabling the rise of data-driven models that continually refine instruction based on real-time input. This shift toward intelligent systems is rooted in broader advances in computer science and cognitive psychology (Kaplan & Haenlein, 2019). AI applications in education initially drew heavily from symbolic AI and rule-based models, mirroring the decision-making logic of expert human teachers (Woolf, 2009). Over time, however, these models gave way to machine learning and neural network approaches capable of identifying patterns in large datasets and refining their recommendations without explicit programming (Baker & Inventado, 2014).

Today, as educational institutions worldwide confront increasing demands for scalable, equitable, and flexible learning environments, AI is no longer a peripheral enhancement; it is becoming integral to rethinking pedagogy itself. Whether embedded in virtual teaching assistants, adaptive quizzes, or emotion-sensitive feedback systems, AI has the potential to redefine the educational experience from one-size-fits-all delivery to personalized, autonomous learning journeys (Luckin et al., 2016; Holmes et al., 2019; UNESCO, 2021).

III. Methodological Approach

This study employs a narrative, multidisciplinary review methodology combined with thematic trend analysis to examine the evolution of artificial intelligence in education from 1990 to 2024. This approach integrates findings across diverse domains and supports identifying recurring themes and meta-trends across historical periods (Thomas & Harden, 2008; Boell & Cecez-Kecmanovic, 2015). It synthesizes scholarly literature, landmark technologies, and educational theory to construct a longitudinal map of how AI has shaped, and been shaped by, shifting paradigms in learning, cognition, and instructional design. Unlike empirical studies that rely on direct experimentation, this paper integrates insights from computer science, learning science, cognitive psychology, and ethics to identify meaningful patterns across decades, reflecting calls for more interdisciplinary approaches in educational AI research (Holmes et al., 2019). The aim is not only to document technological advancements but to interpret their significance within broader educational frameworks and to forecast emerging trajectories for AI-supported learning.

Research Design

To effectively examine the evolution of AI in education, this study employs a structured design composed of three interwoven strategies: historical periodization, thematic synthesis, and trend analysis. These approaches are well suited for research fields that cross disciplinary boundaries and seek to analyze evolving sociotechnical systems (Boell & Cecez-Kecmanovic, 2015; Thomas & Harden, 2008).

First, the study applies a historical periodization strategy by dividing the timeline into three distinct developmental phases: 1990–2001, 2002–2012, and 2013–2024. This chronological framework enables a clearer understanding of how AI capabilities emerged and advanced over time, as well as how these capabilities influenced and were influenced by educational priorities, learning theories, and societal needs in each era. These divisions are not arbitrary; they reflect observable shifts in the technical foundations of AI, from symbolic reasoning systems to statistical machine learning and, most recently, to deep neural networks and generative models (Russell & Norvig, 2010; Goodfellow, Bengio, & Courville, 2016). Each phase also parallels transformations in instructional design, learner autonomy, and expectations for adaptive feedback (Holmes, Bialik, & Fadel, 2019).

Second, the study utilizes thematic synthesis to compare and categorize AI tools based on their pedagogical functions and theoretical alignments. Systems are analyzed across instructional purposes such as assessment, content delivery, real-time feedback, personalization, and emotion recognition. These functions are interpreted using lenses drawn from established learning theories, including constructivism, self-regulated learning, cognitive load theory, and distributed cognition (Zimmerman, 2002; Sweller, Ayres, & Kalyuga, 2011; Hutchins, 1995; Vygotsky, 1978).

Finally, the study applies trend analysis to identify patterns and inflection points both within and across decades. This includes examining shifts in AI's instructional role, the degree of learner support, and the ethical implications of increased system autonomy. From this analysis, broader meta-trends emerge, such as the evolution from automated systems to emotionally intelligent learning partners and from standardized instruction to personalized, real-time learning journeys (Holstein, McLaren, & Aleven, 2020; Woolf et al., 2016). These trends illustrate that AI in education is not simply a technical advancement but a pedagogical transformation that reshapes the relationship between technology, teachers, and learners.

Source Selection Criteria

To ensure the integrity and relevance of the sources included in this study, a set of selection criteria was established to guide the identification and inclusion of literature, tools, and frameworks. Impact and citation frequency played a central role in this process, aligning with best practices in systematic and narrative reviews, which recommend weighting highly cited works to capture influential contributions (Boell & Cecez-Kecmanovic, 2015; Webster & Watson, 2002). Preference was given to peer-reviewed research, educational AI systems that demonstrated effectiveness in classroom settings, and publications frequently cited within the fields of educational technology, learning analytics, and artificial intelligence. This helped prioritize contributions that have had a meaningful influence on both theory and practice.

Additionally, the study embraced a multidisciplinary perspective to reflect the complex and intersectional nature of AI in education, a strategy increasingly recommended in contemporary educational research (Luckin et al., 2016; Holmes, Bialik, & Fadel, 2019). Foundational works were drawn from education scholars such as Zimmerman and Vygotsky, computer scientists like Russell and Norvig and Goodfellow et al., and cognitive psychologists including Anderson and Sweller. Ethical and sociotechnical literature was also incorporated to ensure that the review addressed not only what AI systems can do but also what they ought to do in learning environments (Beauchamp & Childress, 2013; Kizilcec & Lee, 2020).

The selection also prioritized technological milestones, AI systems and models that represented breakthroughs in technical functionality, pedagogical integration, or instructional influence. This included systems like SHERLOCK, AutoTutor, and Cognitive Tutors in earlier decades, as well as Knewton, the GPT series, and emotion-aware platforms like those used by Squirrel AI in more recent years. These exemplars were selected based not only on their novelty but also on their sustained impact on instructional design and learner experience (Graesser et al., 2005; Pane et al., 2014).

Lastly, temporal significance was carefully considered to ensure that each historical era included in the study was represented by both its most influential advancements and its emerging critiques. This mirrors historiographic practices in educational technology research that emphasize the importance of including critical discourse and counter-narratives to fully contextualize technological shifts (Selwyn, 2016). This approach enabled a balanced comparison across decades. It allowed the analysis to capture not just the progression of AI technologies but also the shifting educational, cognitive, and ethical landscapes that have accompanied their development.

Analytical Lenses

This study applies four distinct yet interconnected analytical lenses, pedagogical, functional, relational, and ethical, to support a comprehensive and multidimensional analysis. This pluralistic lens approach is well suited to examining complex sociotechnical systems like AI in education, where learning, behavior, and systems design converge (Luckin et al., 2016; Holmes et al., 2019).

The pedagogical lens evaluates how AI systems align with established educational theories. Each system or tool is interpreted in relation to frameworks such as constructivism, which emphasizes active learner engagement and knowledge construction (Vygotsky, 1978); self-regulated learning, which highlights metacognitive control and learner agency (Zimmerman, 2002); cognitive load theory, which informs optimal instructional pacing and content complexity (Sweller, Ayres, & Kalyuga, 2011); and distributed cognition, which explores how thinking is extended through tools and environments (Hutchins, 1995). These theories serve as foundations for assessing not just what AI systems do but how they support, or potentially disrupt, meaningful learning.

The functional lens examines the evolving instructional roles of AI systems across time. Systems are analyzed in terms of core functions such as tutoring, grading, feedback generation, dialogic engagement, and learner motivation. This lens highlights how AI has transitioned from static automation to interactive, adaptive, and proactive support, a trend seen in intelligent tutoring systems (Graesser et al., 2005) and more recent generative models (Holstein, McLaren, & Aleven, 2020).

The relational lens focuses on the shifting nature of interaction between human learners and AI systems. Earlier conceptions of AI emphasized it as a passive, rule-based tool; however, newer systems increasingly function as learning companions, mentors, or co-agents capable of simulating social and emotional support (Woolf et al., 2016; D'Mello & Graesser, 2012). This shift illustrates how AI has begun to occupy relational roles traditionally reserved for human educators, raising questions about affect, trust, and learner identity.

Lastly, the ethical lens surfaces tensions between AI's benefits and the risks it may pose within educational environments. Concerns include algorithmic bias, student surveillance, opaque decision-making, and erosion of learner autonomy, issues that have become especially salient as emotion-aware systems and generative AI grow more embedded in classroom tools (Kizilcec & Lee, 2020; Beauchamp & Childress, 2013). Applying this lens ensures that technological innovation is weighed against the need for equity, transparency, and ethical accountability in AI-enhanced learning.

Trend Mapping Process

To conduct the trend analysis, this study followed a structured four-phase mapping process designed to surface both micro-level changes and macro-level paradigm shifts in the use of AI in education. The first phase involved the identification of landmark technologies and foundational scholarly works within each of the three defined eras. Sources were selected through a review of peer-reviewed journals, conference proceedings, and digital libraries such as IEEE Xplore, JSTOR, Google Scholar, and ERIC, with attention given to academic influence and real-world application.

In the second phase, these systems and sources were categorized based on instructional function, theoretical alignment, and underlying AI architecture. Categories included rule-based logic systems (e.g., SHERLOCK), statistically adaptive platforms (e.g., ALEKS, Knewton), and neural or generative models (e.g., GPT-series). Each system was also classified by its pedagogical intent, such as assessment, content delivery, learner motivation, or emotional support, allowing for a layered interpretation of how AI's instructional role evolved over time.

The third phase focused on the synthesis of within-era themes and comparative analysis across time periods. Special attention was given to how key concepts, such as personalization, feedback, and learner modeling, were operationalized differently depending on technological capabilities and instructional philosophy. This step made it possible to track how seemingly similar goals were implemented with radically different design logic and theoretical foundations.

Finally, the fourth phase involved the projection of meta-trends that describe broader paradigm shifts in the field. These include transitions from reactive systems to proactive learning companions, from basic performance monitoring to emotion-sensitive and relational AI, and from discrete-task tools to holistic, ecosystem-level educational technologies. This mapping process enables the paper to move beyond descriptive summaries and toward a more integrated, future-facing analysis of AI's educational trajectory.

This structured synthesis allows for both vertical depth (deep exploration of individual decades) and horizontal breadth (cross-era comparisons that show the trajectory of AI's evolution in education).

Limitations of the Approach

While the methodological framework employed in this study enables a rich, theory-informed synthesis, several limitations must be acknowledged. First, there is a degree of scope bias, as the study draws primarily from English-language sources and focuses predominantly on AI technologies developed and deployed in Western contexts. As a result, culturally specific innovations, particularly those emerging from East Asian, Latin American, or African educational systems, may be underrepresented despite their growing global relevance. This issue is common in education and technology research, where the dominant discourse tends to reflect global North perspectives (Selwyn, 2016; Tikly, 2019).

Second, selection subjectivity is inherent in identifying key systems, models, and theoretical contributions. Although selections were grounded in citation impact, cross-disciplinary influence, and historical significance, they ultimately reflect the researcher's academic lens. Other scholars, especially from different disciplinary traditions or regions, might emphasize alternative developments or prioritize different educational goals (Webster & Watson, 2002; Boell & Cecez-Kecmanovic, 2015).

Third, this study does not involve empirical testing or experimental validation of AI systems. Instead, it functions as a conceptual review and historical analysis, synthesizing existing findings, educational theory, and case examples to uncover long-term trends. While such an approach enables breadth and pattern recognition, it cannot substitute for empirical evaluation of system effectiveness, learner outcomes, or contextual fit (Grant & Booth, 2009).

Despite these limitations, the strength of this approach lies in its ability to situate the development of AI in education within a coherent, longitudinal narrative supported by theoretical and pedagogical frameworks. This methodology offers a strategic, reflective overview of how AI has evolved and how it might be ethically and effectively integrated into future learning environments (Holmes, Bialik, & Fadel, 2019).

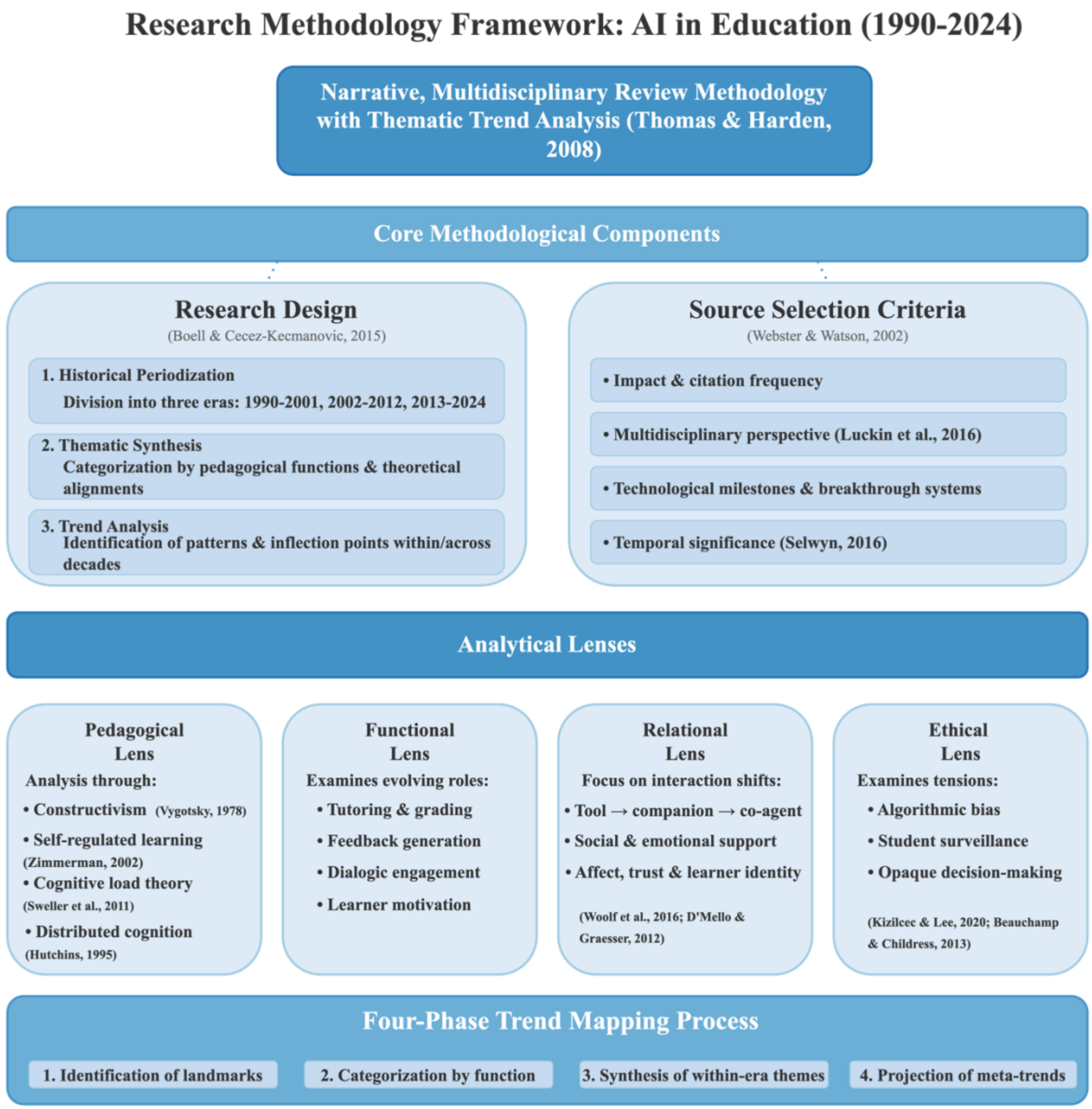

Figure 1: Theoretical Framework: From Automation to Co-Agency in AI-Supported Learning

IV. Theoretical Framework: From Automation to Co-Agency in AI-Supported Learning

The evolving role of artificial intelligence in education over the past three decades is not merely a technological phenomenon, it reflects deeper shifts in how we conceptualize learning, cognition, instruction, and agency. To understand this trajectory, it is essential to situate the development of AI within theoretical paradigms that frame the learner's relationship to knowledge, tools, and their own cognitive development. This framework draws from constructivist learning theory, self-regulated learning, cognitive load theory, and emerging perspectives on human-AI co-agency to analyze how AI's role has transformed from tool to tutor to collaborative partner (Holmes, Bialik, & Fadel, 2019; Luckin et al., 2016).

a. Constructivism and Sociocultural Learning Theories

The earliest intelligent tutoring systems were influenced by cognitivist and constructivist principles, particularly those inspired by Piaget and Vygotsky. These frameworks emphasized the learner as an active constructor of knowledge rather than a passive recipient. Systems like AutoTutor and SHERLOCK sought to scaffold knowledge acquisition by adapting content to the learner's zone of proximal development (ZPD), echoing Vygotskian theory (Vygotsky, 1978; Graesser et al., 2005; Lesgold et al., 1992).

As AI evolved, it began incorporating more dialogic and situated learning designs, recognizing that cognition is shaped by interaction, language, and social context. This is evident in emotion-aware tutors who respond to frustration or confusion, simulating not only instructional support but also relational engagement (Woolf et al., 2016; D'Mello & Graesser, 2012). In this view, AI becomes not just a content delivery mechanism but a socio-cognitive agent that shapes the learning environment.

b. Self-Regulated Learning (SRL)

As adaptive platforms matured, AI began supporting not just content mastery but metacognitive and behavioral regulation, the core of self-regulated learning (SRL) theory (Zimmerman, 2002). Modern AI systems track student progress, provide nudges, suggest study breaks, and offer goal-setting tools. This reflects a shift from instructional AI to coaching AI, where systems are designed to teach and empower learners to monitor, plan, and evaluate their own learning (Holstein et al., 2020).

SRL frameworks help explain why AI features like adaptive dashboards, feedback timing, and task sequencing matter, not just because they optimize performance but also because they cultivate learner autonomy and metacognitive awareness (Winne & Hadwin, 1998). AI's alignment with SRL also raises ethical concerns: Does over-scaffolding reduce self-regulation? How do we balance help and independence?

c. Cognitive Load Theory and Personalized Instruction

Cognitive Load Theory (CLT) provides another theoretical anchor, particularly in the design of adaptive content delivery. CLT posits that instructional design should minimize extraneous load, optimize germane load, and manage intrinsic complexity (Sweller, Ayres, & Kalyuga, 2011). AI-driven personalization aligns with CLT by dynamically adjusting task complexity, pacing, and modality based on a learner's performance and history.

For example, platforms like ALEKS and Knewton leveraged data to infer what the learner knew and what level of working memory strain they could manage (Falmagne et al., 2013; Pane et al., 2014). These systems often prioritized bite-sized content, immediate feedback, and concept mastery, reflecting deep compatibility with CLT-informed design.

d. Human-AI Co-Agency and Distributed Cognition

As AI moved from static automation to dynamic interaction, a new theoretical shift became necessary, one that reconceptualized AI as an agent in learning, not just a tool. This aligns with emerging theories of co-agency and distributed cognition (Hutchins, 1995; Bakhtin, 1981; Holstein et al., 2020). In this framework, cognition is not solely within the learner but distributed across people, tools, and environments.

AI systems that engage in dialog reflect on student mood or suggest personalized learning paths to participate in a shared cognitive task. The AI is no longer merely reactive, it is collaborative and capable of shaping outcomes, strategies, and identity formation. This raises key questions: Should AI be granted instructional autonomy? Can it take on relational responsibility like human mentors?

e. Ethical Theories and AI in Learning

No modern framework is complete without addressing AI's moral and philosophical dimensions in education. Drawing from principles and ethics of care, scholars have questioned whether AI respects learner dignity, equity, and privacy (Beauchamp & Childress, 2013; Noddings, 2005). Frameworks such as algorithmic fairness (Kizilcec & Lee, 2020) and explainable AI (XAI) also underscore the importance of transparency, student trust, and accountability in AI decision-making.

Thus, the theoretical lens extends beyond cognitive support to interrogate: What kind of educational relationships are we building? Who benefits from AI-driven personalization, and who might be left behind?

Figure 2 below illustrates the core theoretical framework guiding this study, mapping the evolution of AI in education from automation to co-agency over the past three decades. The timeline aligns key pedagogical paradigms with technological trends, demonstrating how constructivist and cognitive models initially shaped early intelligent systems. At the same time, later developments in self-regulated learning, distributed cognition, and ethical theory support the rise of emotionally responsive, autonomous AI. Each theoretical pillar is linked to both instructional goals and exemplar systems, emphasizing how shifts in AI capability reflect and often demand shifts in how we conceptualize learning, agency, and educational responsibility.

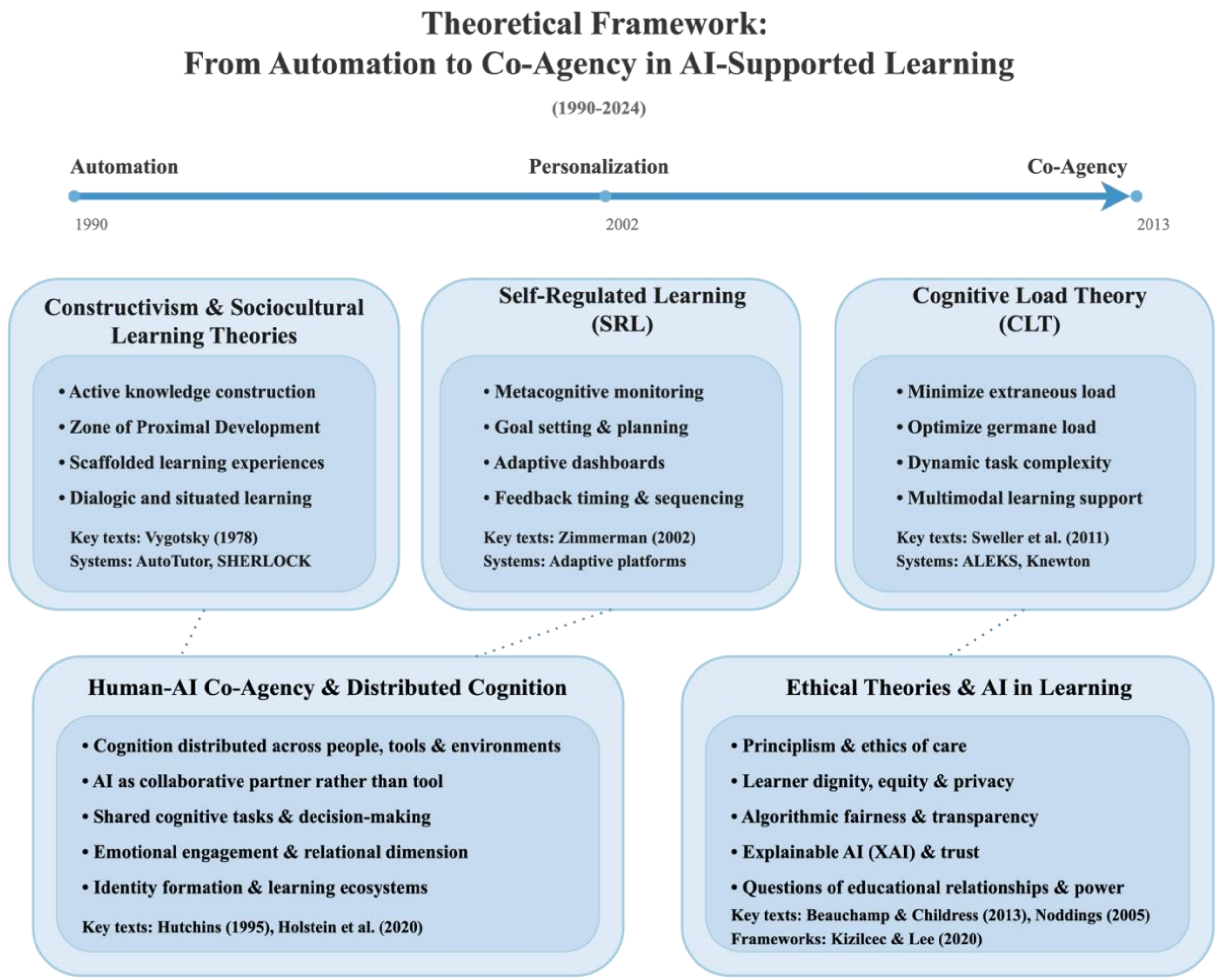

Figure 2: Theoretical Framework

V. A 30-Year Trend Analysis of AI in Education

1990–2001: Rule-Based Foundations

The decade between 1990 and 2001 represents a critical foundational period in the history of AI in education, characterized by the emergence of rule-based systems, cognitive modeling, and the earliest examples of adaptive instruction (Woolf, 2009; VanLehn, 2006). At the time, AI was still dominated by symbolic approaches, systems that relied on manually crafted rules to simulate expert reasoning (Russell & Norvig, 2010). These systems represented knowledge in the form of "if-then" statements, enabling machines to solve problems and make decisions based on logical inference. In educational settings, this led to the development of Intelligent Tutoring Systems (ITSs), AI applications that aimed to provide personalized instruction by emulating the behavior of a human tutor (Woolf, 2009; Nkambou et al., 2010).

A significant influence during this decade was the rise of cognitive science, which provided a theoretical foundation for AI-driven instruction (Anderson et al., 1995; Koedinger & Corbett, 2006). Drawing from models of human learning such as Anderson's ACT-R theory (Adaptive

Control of thought–rational), ITS developers began to simulate how students acquire, store, and retrieve knowledge. These models allowed systems to diagnose students' cognitive states in real time and deliver feedback tailored to their current level of understanding (Corbett, Koedinger, & Anderson, 1997).

One of the most iconic systems of this period was SHERLOCK, developed by Lesgold and colleagues for the U.S. Air Force and utilized primarily in the late 1980s through the early 1990s, with active use and evaluation occurring during the early to mid-1990s (Lesgold et al., 1992; Lajoie & Lesgold, 1989). SHERLOCK functioned as a coached practice environment, guiding trainees through troubleshooting scenarios in avionics systems. Its design incorporated domain expertise, real-time decision trees, and a rudimentary student model that adapted training based on user input (Lesgold et al., 1992).

Around the same time, another landmark innovation emerged: AutoTutor, a system that broke ground in using natural language dialogue. Developed at the University of Memphis in the late 1990s, AutoTutor engaged students in typed conversations to teach topics like Newtonian physics and computer literacy (Graesser et al., 2001). Unlike traditional systems, AutoTutor uses natural language processing (NLP) to analyze student input and respond with elaborated explanations, prompts, or corrective feedback based on learner progress (Graesser et al., 2005).

While rule-based and cognitive tutors dominated this period, alternative architectures such as constraint-based modeling also began to emerge. For example, SQL-Tutor (Mitrovic, 1998) used domain constraints rather than cognitive models, offering a more flexible way to diagnose student errors in database learning tasks. This approach avoided the need to model the student's whole mental state, focusing instead on violations of domain-specific principles.

The development of these systems was influenced by earlier platforms like PLATO, which, while not AI-driven, demonstrated the potential of computer-assisted instruction and laid the groundwork for later adaptive systems (Woolf, 2009; Suppes & Morningstar, 1969). PLATO introduced concepts like individualized pacing, mastery learning, and interactive feedback, many of which were reimagined through AI decades later.

Despite these promising innovations, early AI systems were constrained by the technological limitations of the time. Memory and processing power were insufficient for real-time personalization at scale (VanLehn, 2006). Authoring these systems required deep pedagogical and programming expertise, and building robust student models was labor-intensive (Woolf, 2009; Nkambou et al., 2010). Moreover, these tools often failed to generalize beyond their domain or respond flexibly to unexpected learner input (Koedinger et al., 2008). Each instructional path had to be explicitly programmed, with no capacity for the statistical learning or adaptive generalization that modern systems support (Luckin et al., 2016).

Many critics during the 1990s argued that ITSs were too narrow in scope and lacked transferability across subject areas or diverse student populations (VanLehn, 1991; Selwyn, 2016). These critiques prompted early interest in data-driven, statistical, and later machine learning–based approaches that could scale beyond handcrafted decision trees.

Still, the contributions of this era, particularly learner modeling, scaffolded feedback, and dialogue-based instruction, laid the philosophical and technical groundwork for decades to come (Woolf, 2009; Graesser et al., 2005; Holmes et al., 2019). The vision of adaptive, human-like tutoring persisted, even as the field evolved toward probabilistic, data-driven, and eventually neural models in the following decades.

2002–2012: Data-Driven Personalization and the Rise of Learning Analytics

The years between 2002 and 2012 marked a significant evolution in the role of AI in education, characterized by a shift from rule-based logic to statistical learning models, educational data mining (EDM), and adaptive personalization at scale. This transformation was catalyzed by the growing digitization of educational systems, the emergence of the Internet as a learning platform, and a rising emphasis on using learner data to inform instruction (Baker & Yacef, 2009; Siemens & Long, 2011).

While earlier systems like AutoTutor and SHERLOCK were grounded in hardcoded logic and cognitive models, this period saw the rise of Bayesian Knowledge Tracing (BKT). This probabilistic method estimated the likelihood that a student had mastered a concept based on observable performance (Corbett & Anderson, 1995). BKT became foundational to Cognitive Tutors, developed by Carnegie Learning, which were deployed in thousands of U.S. classrooms and demonstrated significant gains in student outcomes, particularly in mathematics (Pane et al., 2014). Similarly, Item Response Theory (IRT) and knowledge space theory were used to map student abilities and misconceptions, forming the backbone of systems like ALEKS, which delivered individualized math curricula based on real-time diagnostic performance (Falmagne et al., 2013).

Around 2005, the field of Educational Data Mining (EDM) emerged to analyze large-scale traces of student behavior, such as time-on-task, hint usage, and incorrect responses, to optimize instruction (Baker & Yacef, 2009). EDM platforms like ASSISTments enabled researchers to evaluate different feedback models and identify patterns such as "gaming the system," where students attempt to exploit the tutoring system rather than engage with learning (Feng, Heffernan, & Koedinger, 2009). These insights spurred improvements in how tutoring systems responded to both cognitive errors and motivational cues.

The latter half of the decade witnessed the rise of learning analytics. This related but distinct field focused on institutional data use, such as predictive dashboards and early-warning systems, to support student retention and engagement (Siemens & Long, 2011). Learning Management Systems (LMSs) such as Moodle, Desire2Learn, and Blackboard began integrating basic AI-driven features, including tracking participation, quiz scores, and login frequency to generate risk profiles and guide instructor interventions.

Simultaneously, the commercialization of adaptive learning platforms accelerated. Companies like Knewton (founded in 2008) promoted AI engines that adjusted the difficulty and sequence of learning materials in real time based on performance data. Despite facing criticism later for a lack of transparency and overhyped claims, Knewton helped mainstream the concept of continuous, data-driven formative assessment (Knewton, 2013). Other platforms, such as Smart Sparrow and Newton's Newton (unrelated to Knewton), explored similar capabilities, particularly in science and engineering education, with intelligent feedback and branching instructional pathways.

By 2011–2012, the MOOC revolution emerged with platforms like Coursera, edX, and Udacity offering global-scale education at unprecedented reach. These platforms integrated AI primarily to manage scale, using automated grading, peer review algorithms, and basic natural language processing (NLP) to analyze discussion forums and written submissions (Reich, 2014; Anderson et al., 2014). AI was also used to track dropout risk, generate video recommendations, and support large-scale assessment.

Importantly, these MOOCs generated enormous datasets, sometimes called clickstream data, that offered researchers a treasure trove for training future AI models. While the effectiveness of MOOCs remained debated, the AI-supported feedback systems they employed laid the groundwork for scalable, responsive instruction.

Despite these advancements, limitations became increasingly apparent. Models like BKT and IRT, while effective in skill-based domains like math, struggled to generalize to open-ended tasks or complex cognitive domains such as writing and problem-solving (Pardos & Heffernan, 2011). Critics warned of the emerging "datafication of learning," where rich, nuanced student behaviors were reduced to simplistic numeric indicators (Slade & Prinsloo, 2013). Concerns about privacy, algorithmic bias, and the opacity of AI decision-making grew, especially as these systems began influencing educational opportunities and trajectories (Williamson, 2017).

Toward the end of this decade, researchers also began experimenting with early forms of affective computing in educational contexts. These systems used indicators such as facial expressions, mouse movements, and physiological signals to detect student emotions such as boredom, frustration, or confusion in real time (D'Mello & Graesser, 2012). Though limited by hardware constraints and early modeling capabilities, these efforts set the stage for the emotion-aware, multimodal AI systems that would emerge in the deep learning era to follow.

By 2012, the field stood at a turning point. Advances in speech recognition, computer vision, and transformer-based NLP promised a new generation of AI tools capable of naturalistic dialogue, contextual adaptation, and emotionally responsive feedback. The data infrastructure, modeling techniques, and user expectations shaped during this decade formed the critical foundation for the neural and generative systems of the next era.

2013–2024: Deep Learning and Human-AI Synergy

The period from 2013 to 2024 marks a transformative era in AI and education, in which deep learning, natural language processing (NLP), and affective computing converged to produce AI systems capable of understanding, generating, and adapting to human behavior at an unprecedented scale (Goodfellow, Bengio, & Courville, 2016; Holmes et al., 2019). With the advent of large neural networks, educational AI shifted from structured models and rule-based personalization to context-aware, generative, and emotionally intelligent companions that respond to academic performance while recognizing motivational, emotional, and behavioral signals.

Deep learning began to revolutionize educational AI with breakthroughs in convolutional neural networks (CNNs) for image recognition, recurrent neural networks (RNNs), and later transformer architectures for sequence modeling (Devlin et al., 2018). These models enabled AI to move beyond multiple-choice tasks to generate real-time responses in open-ended formats such as dialogue, essays, and problem explanations. One notable application was "Jill Watson," a virtual teaching assistant used at Georgia Tech, which answered hundreds of student queries in an online computer science course without students realizing it was AI-driven (Goel & Polepeddi, 2016).

By 2020, platforms like Grammarly, Quill, and Write & Improve began using generative models to offer real-time writing feedback on grammar, tone, clarity, and structure (Nunes et al., 2021). With the emergence of GPT-3 and GPT-4, AI systems expanded into simulated tutoring, formative feedback, and even reflective dialogue with students (OpenAI, 2023; Kasneci et al., 2023). Rather than providing binary correctness judgments, these tools began to coach learners through constructive reasoning and simulate peer collaboration.

In parallel, emotion-aware and multimodal systems matured significantly. Drawing on earlier research in affective computing, these systems utilized facial recognition, eye tracking, speech prosody, and keystroke dynamics to detect frustration, confusion, boredom, and engagement in real-time (Calvo & D'Mello, 2010). Products like Squirrel AI in China integrated facial recognition with learning analytics to tailor the difficulty of content and the emotional delivery context (Zhou, 2021). Other systems simulated empathetic teacher behaviors, such as encouragement and emotional validation, to improve motivation and retention (Woolf et al., 2016).

Rather than functioning in isolation, AI tools became part of broader learning ecosystems in this era. Platforms like Khan Academy's Khanmigo, powered by GPT-4, were designed to guide exploration, deliver personalized practice, and offer coaching across cognitive and behavioral dimensions. AI-supported dashboards now tracked knowledge mastery, social collaboration, persistence, and goal-setting strategies (Holstein, McLaren, & Aleven, 2020). These systems also promoted self-regulated learning by nudging students to reflect on their approaches, revisit challenging concepts, and regulate study breaks, mirroring the behavior of a human mentor (Zimmerman, 2002; Luckin et al., 2016).

As AI became more integrated, so did concerns about its ethical implications. Researchers raised alarms about algorithmic bias, data privacy, and the risk of surveillance, especially in emotion-aware systems that monitored students' facial expressions and biometric signals (Kizilcec & Lee, 2020; Williamson, 2022). These concerns led to growing calls for explainable AI (XAI) and frameworks grounded in the ethics of care, urging systems to prioritize student autonomy, equity, and trust (Beauchamp & Childress, 2013; Noddings, 2005).

Perhaps the most profound shift in this decade was not just what AI could do, but what it became. AI transitioned from being a recommender or tutor to a co-learner, a coach, and even a learning companion. Embedded in apps, virtual platforms, and wearables, AI began to engage students across academic, emotional, and behavioral dimensions, marking a move from function to relationship.

This transformation invites reflection not only on technological progress but on pedagogy and power. Drawing from ethical frameworks such as algorithmic fairness and distributed cognition, educational scholars have begun to interrogate what kinds of relationships we are building with AI, who benefits from personalized systems, and who might be left behind (Holstein et al., 2020; Kizilcec & Lee, 2020).

As generative and affective capabilities converged, the vision of autonomous, personalized, emotionally responsive education shifted from science fiction to active experimentation.

Across three decades, we observe a progression in AI's ontological role in education as seen in Figure 3:

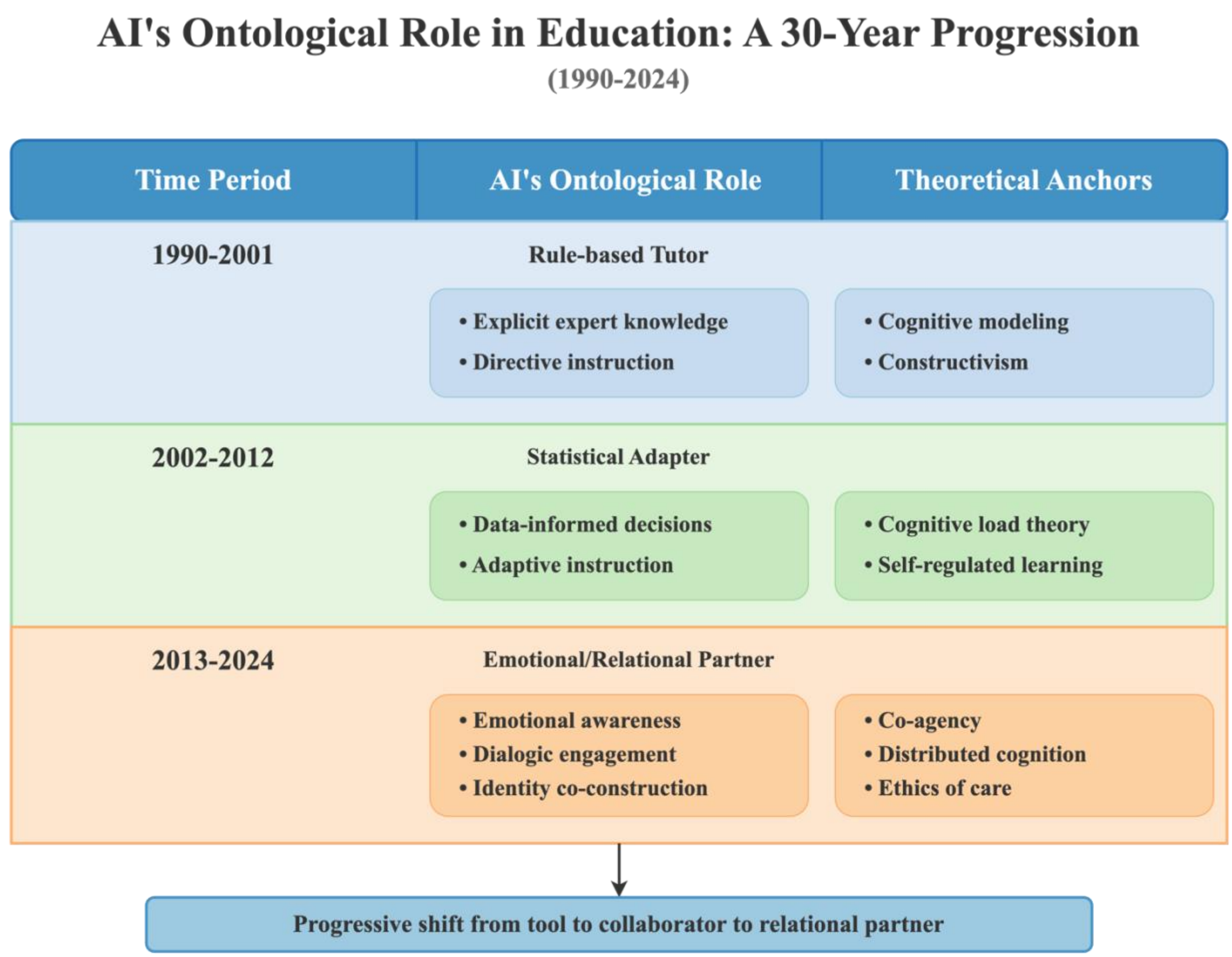

Figure 3: AI's ontological role in education

This framework shows that the evolution of AI in education has not merely been a linear progression of technical sophistication. Instead, it represents a transformative shift in pedagogical purpose, learner agency, and ethical responsibility.

VI. AI in Education: A Taxonomy of Systems and Functions (1990–2024)

To further synthesize the evolution of artificial intelligence in education, the following concept map organizes AI systems across three decades by type, educational function, and theoretical alignment. This taxonomy illustrates the transformation from early rule-based models to emotion-aware, generative, and relational AI. By mapping these developments visually, readers can better grasp how AI technologies have expanded in complexity and pedagogical purpose, moving from automation to co-agency in the learning process.

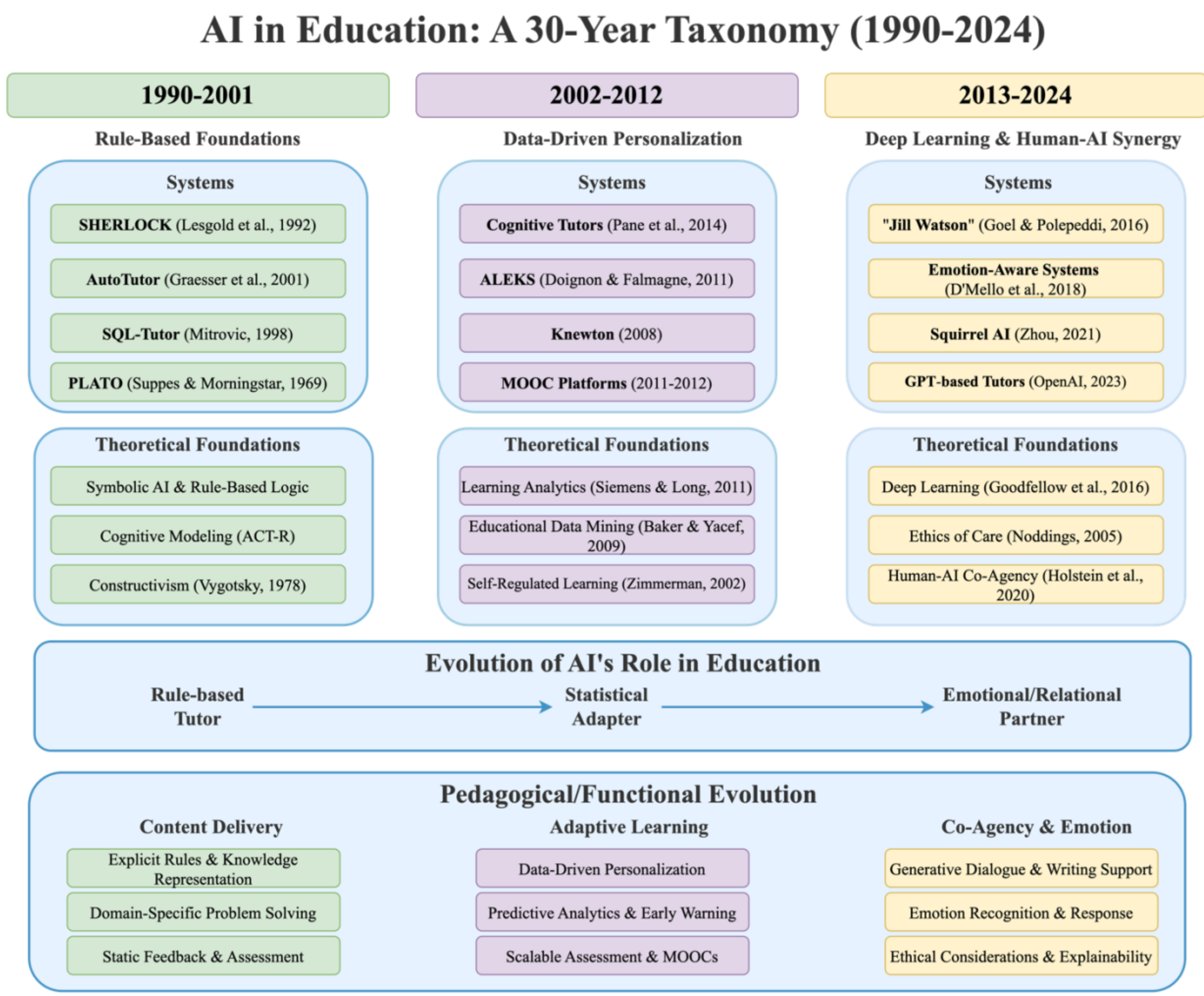

Figure 4: Taxonomy of AI in Education

As the concept map highlights, the boundaries between AI types and educational roles have become increasingly fluid over time. Modern systems frequently integrate multiple capabilities within a single platform, such as generative feedback, emotion recognition, and adaptive personalization. This convergence reflects a broader pedagogical shift toward learner-centered, context-sensitive, and ethically informed education. In the next section, we explore the broader implications of this transformation and propose future directions for research, policy, and practice in AI-enhanced learning environments.

VII. Significance of the Study

As artificial intelligence becomes increasingly embedded in the daily fabric of learning environments, understanding its historical trajectory, pedagogical implications, and ethical dimensions is no longer a luxury but a necessity. This study offers a comprehensive synthesis of how AI has evolved in education from 1990 to 2024, making significant contributions to theory, practice, and policy. Its value lies in capturing a technological progression and tracing a pedagogical transformation with far-reaching implications for how we teach, learn, and design educational futures (Woolf, 2009; Luckin et al., 2016).

This study builds upon the visionary foundations laid by pioneers such as Lev Vygotsky, who emphasized the social nature of learning (1978); Seymour Papert, who championed learner-driven exploration through computational tools (1980); and Rosalind Picard, who introduced the idea of emotionally responsive machines (1997). By bridging their insights with contemporary developments, this research carries forward their legacy into the age of large-scale, effective, and autonomous AI systems.

It delivers one of the few comprehensive, longitudinal analyses of AI in education that integrates technological evolution with pedagogical theory. By systematically organizing the past three decades into thematic phases, rule-based automation, data-driven personalization, and affective-autonomous systems, it reveals how AI development is inextricably tied to broader educational paradigms. This structure reflects enduring traditions in developmental psychology and educational design that emphasize progression and systems-level thinking (Vygotsky, 1978; Bruner, 1966).

Deliberately interdisciplinary in scope, this study synthesizes insights from computer science, cognitive psychology, education, ethics, and human-computer interaction. This reflects the foundational ethos of constructivist thinkers like Papert, who argued that educational technology should not simply deliver content, but enable deep inquiry and creative thought (Papert, 1980). It also honors the work of Anderson and Corbett, whose cognitive tutors modeled learning as an adaptive, traceable process aligned with internal knowledge states (Anderson et al., 1995).

A key conceptual contribution of this study is the formalization of the AI-as-co-agent framework, which captures the shift from static automation to dynamic, emotionally responsive, and collaborative AI systems. This reframing challenges traditional instructional paradigms and invites a reexamination of agency, accountability, and relationality in the learning process (Holstein et al., 2020). Drawing from distributed cognition (Hutchins, 1995) and dialogic learning (Bakhtin, 1981), it positions AI as an active participant in shaping performance outcomes, learner identity, emotion, and strategy.

Moreover, this work underscores the imperative for inclusive design in educational AI. As personalization becomes increasingly algorithmic and autonomous, it is essential that these systems be designed to serve a diverse range of learners, including neurodivergent students, multilingual communities, and historically marginalized populations. Here, equity is framed not as an afterthought but as a foundational principle for ethical and practical innovation.

As AI systems gain autonomy in pedagogical decision-making. Determining what feedback to give, how to respond emotionally, or when to intervene, questions of privacy, transparency, surveillance, and bias become increasingly urgent. This study critically engages with these tensions and calls for ethical-by-design frameworks, including explainable AI (XAI) and algorithmic fairness (Kizilcec & Lee, 2020; Dastin, 2018). It also revisits early concerns voiced by affective computing pioneers like Picard (1997), who warned that emotionally intelligent systems must prioritize human dignity and psychological safety.

This study enables evidence-informed forecasting by providing a trend-based meta-analysis of systems, theories, and educational models. Its insights can help educational leaders and policymakers make strategic decisions regarding procurement, implementation, and governance of AI in learning environments. The framework of automation → personalization → co-agency offers a powerful lens for evaluating emerging technologies and their alignment with institutional values and pedagogical goals.

In addition, this study establishes a replicable model for how to conduct theory-informed, future-oriented reviews of educational AI. It creates a blueprint for future scholarship in areas such as global equity, culturally responsive AI, special education, and the ethical use of biometric feedback in learning. It also identifies key empirical questions for exploration, particularly around the effects of co-agentic AI on learner motivation, metacognition, identity development, and long-term retention.

Ultimately, this study is more than a retrospective; it is a strategic intervention in an accelerating educational transformation. It calls upon educators, designers, and technologists to move beyond hype and skepticism and instead engage with AI as a pedagogical, relational, and ethical force. By providing a robust historical map, conceptual framework, and trend analysis, it equips the academic community with the tools needed to shape the future of learning, not merely through more innovative machines but through wiser, more humane systems.

Finally, by contextualizing technological developments within pedagogical and ethical frames, this study advances the case for cross-sector collaboration. The future of educational AI cannot be designed in disciplinary silos. It must be co-constructed through sustained dialogue among engineers, educators, psychologists, ethicists, policymakers, and learners themselves

VIII. Discussion: Patterns, Progress, and Paradigm Shifts

The evolution of artificial intelligence in education, as mapped across three decades, reflects more than just technical progress, it embodies a shift in how societies conceptualize learning, agency, and the role of human-machine interaction. This chapter synthesizes the key themes that have emerged through the historical and theoretical analysis and explores their implications for educational practice, policy, and future research.

Across the three eras, 1990–2001 (rule-based systems), 2002–2012 (data-driven personalization), and 2013–2024 (affective and autonomous AI), there has been a steady expansion in the scope, sensitivity, and interactivity of AI systems. Early intelligent tutoring systems like SHERLOCK mirrored expert decision trees. Platforms in the second era (e.g., Knewton, ASSISTments) focused on performance adaptation through learning analytics. In the most recent phase, AI systems respond not only to what learners do, but how they feel, interacting as partners rather than just instructors.

This trajectory represents a broader paradigm shift: from automation (doing tasks for learners) to personalization (adapting tasks to learners), to co-agency (working with learners). This shift reflects evolving understandings of cognition as distributed, socially constructed, and emotionally mediated demanding more holistic forms of instructional support.

As AI systems become increasingly participatory and proactive, the role of the learner also changes. No longer positioned merely as a knowledge recipient, the learner in co-agentic systems is a reflexive collaborator, influencing the AI as much as being influenced by it. This requires a redefinition of learner agency, motivation, and metacognitive awareness as central design considerations in AI-supported environments.

At the same time, the educator's role evolves from content delivery to orchestration and humanization. Teachers are needed not less, but more, to interpret algorithmic insights, scaffold emotional experiences, and maintain ethical boundaries that AI cannot yet understand. AI, in this framing, augments rather than replaces human teaching.

New ethical challenges have emerged with the rise of affective computing and emotionally aware systems. Unlike past models that analyzed learning based solely on observable behavior, modern systems interpret emotional states, facial expressions, eye movement, and biometric signals. While these features promise richer personalization, they also raise questions about student surveillance, consent, and psychological safety.

Further, if training data and adaptive pathways reflect existing social biases, personalized AI may unintentionally exacerbate inequities rather than reduce them. The field must now ensure algorithmic justice, especially for neurodivergent learners, multilingual students, and underrepresented populations.

A key implication of this research is the need for explainable and pedagogically aligned AI. As systems become more autonomous, users, educators, students, and administrators, must be able to understand how and why decisions are made. Black-box AI systems may produce efficiency, but without transparency, they risk undermining trust and educational validity.

Educational AI must be interpretable, not just accurate. Learners should understand how recommendations are generated, and teachers must retain pedagogical oversight to override algorithmic suggestions when needed. Ethical use of AI thus requires designing systems that are not only intelligent but accountable.

This study carries important implications for educational policy, teacher training, and the future of learning technology design. First, policy makers must take an active role in regulating how AI is adopted across schools and universities. This includes establishing ethical frameworks that address data governance, algorithmic transparency, and equity audits to ensure that AI systems are not only practical but also fair and accountable. Without these safeguards, AI risks reproducing or amplifying existing educational disparities.

In parallel, professional development programs must evolve to prepare educators for a future in which they engage with AI not as tools to be managed, but as instructional collaborators. Teachers will need training in how to interpret AI-generated insights, challenge algorithmic decisions when necessary, and integrate system feedback into broader pedagogical strategies. As AI becomes more embedded in educational workflows, this human-in-the-loop literacy becomes an essential professional competency.

Finally, designers and developers must embrace a participatory, interdisciplinary approach to system creation. Rather than building solely for efficiency or personalization, the design of future educational AI must be human-centered, grounded in real-world classroom goals, and co-developed with teachers, learners, and ethicists. Only through such collaboration can we ensure that AI complements rather than compromises pedagogical integrity.

This study also lays the groundwork for a new wave of empirical research at the intersection of education, psychology, and artificial intelligence. One critical area for investigation is the long-term impact of co-agentic AI systems on learner motivation, identity formation, and epistemic agency. As students increasingly interact with AI not just as tools but as conversational or emotional partners, questions emerge about how these relationships shape self-perception and learning behavior over time.

Another important line of inquiry involves the role of AI in fostering or constraining creativity and divergent thinking. While AI can scaffold problem-solving, there is a risk that over-reliance on algorithmic guidance could narrow intellectual exploration or discourage experimentation, particularly in open-ended learning environments.

In addition, as emotion-aware systems become more common, researchers must assess their influence on students' psychological safety, sense of belonging, and emotional trust in digital spaces. Though historically underexplored, these affective dimensions of learning may prove essential to engagement and retention in AI-supported environments.

Finally, future studies must explore methods for evaluating AI systems' effectiveness and ethical soundness across diverse cultural, linguistic, and institutional contexts. What works in one setting may reinforce bias or reduce learner autonomy in another. Cross-contextual studies, including qualitative and quantitative methods, will be vital to shaping a global, equitable vision for the future of AI in education.

The discussion reveals that AI in education is no longer confined to instructional assistance, it now shapes the very logic of how we learn, feel, and relate within educational environments. As this transformation continues, the most urgent task is not just improving the intelligence of machines but enhancing the wisdom with which we use them. This requires collaboration, transparency, empathy, and, above all, a commitment to human-centered design in every layer of AI development and deployment.

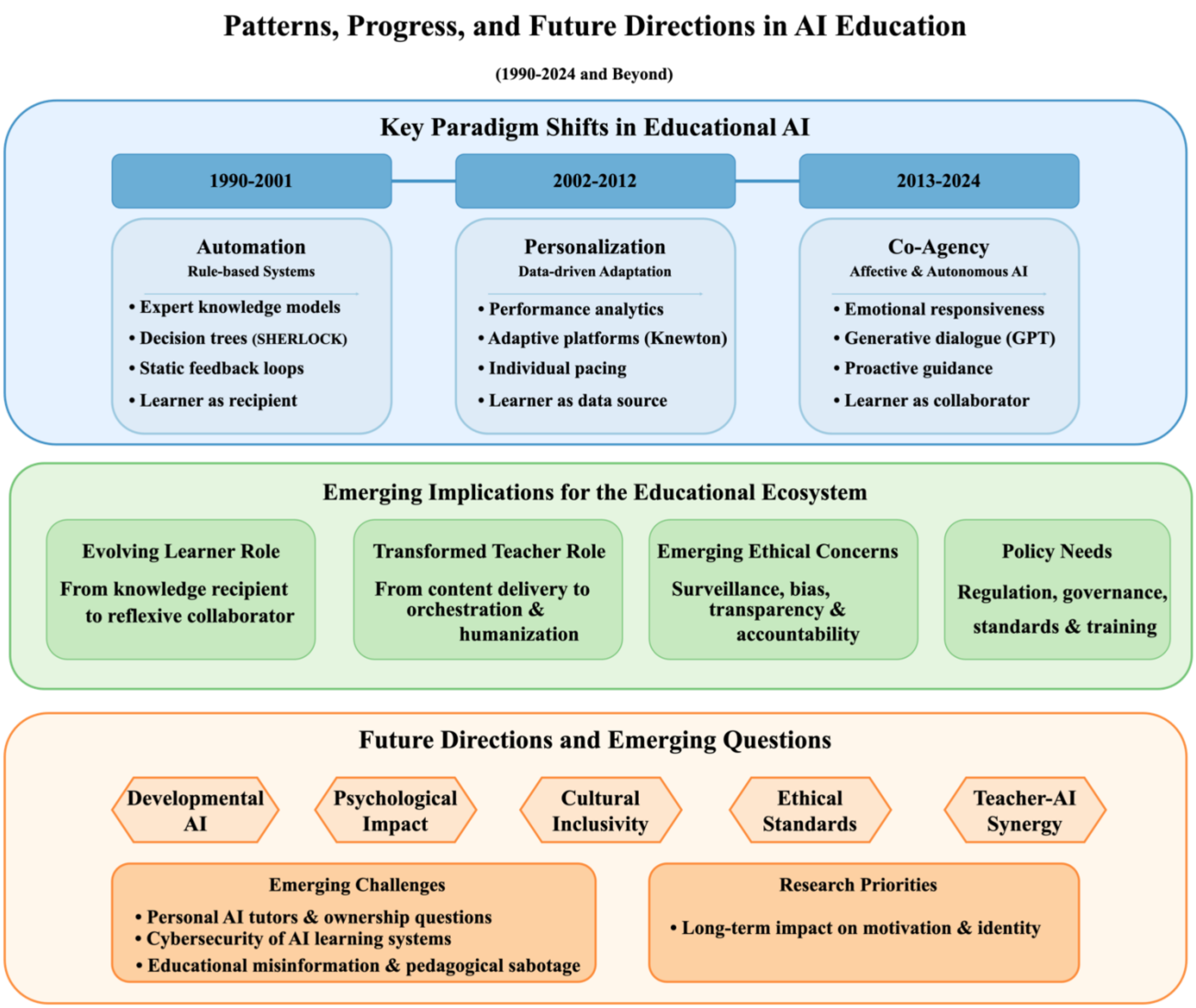

Figure 5: Patterns, Progress, and Future Directions in AI Education

IX. Future Directions and Emerging Questions

As artificial intelligence continues to evolve at an unprecedented pace, the future of AI in education will be shaped not only by technological breakthroughs but by our collective values, design choices, and research priorities. This study has mapped how AI transitioned from static rule-based systems to emotionally responsive co-agents, but it is only the beginning. The next decade will demand a more profound commitment to equity, transparency, interdisciplinary collaboration, and human-centered design. The following future directions and open questions serve as a guide for scholars, educators, developers, and policymakers navigating this complex landscape.

Future AI systems must move beyond reactive personalization and begin supporting developmental growth across a learner's educational journey. How can AI evolve with a student's identity, interests, and self-regulation skills from early education to lifelong learning? Research should explore AI's potential in scaffolding long-term metacognitive development, transfer of learning, and academic resilience, especially in students facing learning challenges

While most current evaluation frameworks focus on accuracy and performance gains, future research must assess how co-agentic AI affects learner motivation, confidence, creativity, and sense of autonomy. How do learners perceive AI when it acts as a peer, coach, or emotional support system? Can AI strengthen a student's self-concept, or does it risk creating dependency or learned helplessness? These nuanced psychological and relational outcomes must be studied alongside cognitive metrics.

The majority of AI systems are trained on data from Western, English-speaking populations. This raises concerns about their cultural generalizability and language inclusivity. How can future AI systems adapt to multilingual contexts, local pedagogical values, and non-Western learning paradigms? Research must center the voices of educators and students in underrepresented communities, designing systems that support linguistic diversity, accessibility, and social justice in education.

The ethical concerns raised in this study, bias, surveillance, and explainability, must be translated into measurable design standards and regulatory frameworks. Future work should explore how to embed ethics directly into AI development pipelines. What metrics should define algorithmic fairness in education? How can schools ensure informed consent when using emotion-aware systems? There is a need for auditable, transparent, and participatory models of AI governance that respect student rights while enhancing learning.

AI is redefining, not replacing, the teacher. The future requires a shift in teacher education, professional identity, and classroom roles. What new pedagogical skills will be essential in AI-augmented classrooms? How can educators be empowered as co-designers, interpreters, and moderators of AI-supported instruction? Research should focus on teacher-AI complementarity, ensuring that automation enhances, rather than diminishes, human connection and instructional agency.

Finally, education itself can become a model system for responsible AI design, experimentation, and social good. Schools and universities can serve as living laboratories for testing inclusive, explainable, and adaptive AI frameworks before they scale to other industries. What can education teach the broader AI ecosystem about relational design, formative feedback, and ethical responsibility? These cross-sector insights will be vital as AI systems move deeper into public life.

In the near future, learners may not only interact with general-purpose educational AIs but train and personalize their own AI tutors. Individuals could purchase, download, or create custom large language models (LLMs) that simulate, for example, a math professor specialized in calculus, a bilingual reading coach, or a peer-level study partner tuned to their curriculum, pace, and cognitive style. These personal learning agents may be open-source or commercial, locally hosted or cloud-based, and could fundamentally redefine who teaches, how learners engage, and what ownership in education means.

While this vision offers profound benefits, including high-frequency feedback, flexible access, and individualized pedagogy, it also introduces significant challenges. Content quality, instructional validity, and educational misinformation will become critical issues as more learners rely on AI that formal institutions do not vet. The risk of training or downloading an inaccurate or biased model becomes even more consequential when that model is the learner's primary instructional guide.

As AI systems become more personalized, autonomous, and embedded in local learning environments, cybersecurity will become a vital pillar of educational infrastructure. Most current concerns center on protecting user data, including learner behavior, biometric information, and emotional analytics, but future threats may also involve the security of the AI's own knowledge base.

Malicious entities could manipulate or corrupt locally trained AI tutors, feeding them false pedagogical data or nudging them toward harmful behaviors. Educational institutions will need to consider not just firewalls and data encryption but also AI validation systems, model authentication protocols, and safeguards against pedagogical sabotage. Ensuring that AI models maintain truthfulness, consistency, and curricular alignment will be just as critical as protecting student privacy.

This emerging landscape raises complex questions: Who verifies an AI tutor's qualifications? How are updates monitored? Can a learner's AI assistant be considered a trusted source of education, or does it need human oversight? These are no longer theoretical challenges; they represent the next frontier of cyber pedagogical ethics and governance.

As AI moves from novelty to necessity, its impact on education will depend less on how smart it becomes and more on how wisely we choose to use it. The future of educational AI is not a technical inevitability but a collective design challenge. This study calls for a new generation of researchers, educators, and developers who will prioritize personalized learning and inclusive, empowering, and relational learning ecosystems. Only then can AI truly serve its most transformative role, not in replacing what makes us human but in helping us become more deeply so.

X. References

Anderson, A., Huttenlocher, D., Kleinberg, J., & Leskovec, J. (2014). Engaging with massive online courses. *Proceedings of the 23rd International Conference on World Wide Web, 687–698*, 687–698. https://doi.org/10.1145/2566486.2568042

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive Tutors: Lessons learned. *Journal of the Learning Sciences*, *4*(2), 167–207. https://doi.org/10.1207/s15327809jls0402_2

Baker, R. S. J. D., & Yacef, K. (2009). *The state of educational data mining in 2009: A review and future visions*. *Journal of Educational Data Mining*, *1*(1), 3–16. https://jedm.educationaldatamining.org/index.php/JEDM/article/view/1

Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In *Learning Analytics* (pp. 61–75). Springer. https://doi.org/10.1007/978-1-4614-3305-7_4

Thompson, E., Bakhtin, M. M., Holquist, M., Emerson, C., & Holquist, M. (1981). The Dialogic Imagination: Four essays. *World Literature Today*, *55*(4), 693. https://doi.org/10.2307/40136453

Beauchamp, T. L., & Childress, J. F. (2013). *Principles of biomedical ethics* (7th ed.). Oxford University Press.

Boell, S. K., & Cecez-Kecmanovic, D**.** (2015). On being 'systematic' in literature reviews in information systems. *Journal of Information Technology*, 30(2), 161–173. https://doi.org/10.1057/jit.2014.26

Bruner, J. S. (1966). Toward a Theory of Instruction. Harvard University Press.

Nunes, A., Cordeiro, C., Limpo, T., & Castro, S. L. (2021). Effectiveness of automated writing evaluation systems in school settings: A systematic review of studies from 2000 to 2020. *Journal of Computer Assisted Learning, 38*(2), 401–419. https://doi.org/10.1111/jcal.12635

Kasneci, E., Sessler, K., Küchelmann, T., Bannert, M., Dementieva, D., Fischer, F., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction*, *4*(4), 253–278. https://doi.org/10.1007/bf01099821

Corbett, A. T., Koedinger, K. R., & Anderson, J. R. (1997). Intelligent tutoring systems. In M. Helander, T. K. Landauer, & P. Prabhu (Eds.), *Handbook of Human-Computer Interaction* (2nd ed., pp. 849–874). Elsevier.

D'Mello, S. K., & Graesser, A. C. (2012). AutoTutor and affective learning. In D. S. Dunn (Ed.), *Oxford Handbook of Undergraduate Psychology Education* (pp. 549–560). Oxford University Press.

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction, 22*(2), 145–157. https://doi.org/10.1016/j.learninstruc.2011.10.001

Calvo, R. A., & D'Mello, S. (2010). Affect Detection: an interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. https://doi.org/10.1109/t-affc.2010.1

Dastin, J. (2018, October 10). Amazon scrapped "AI recruiting tool" that showed bias against women. Reuters. https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint* arXiv:1810.04805. https://doi.org/10.48550/arXiv.1810.04805

Falmagne, J., Albert, D., Doble, C., Eppstein, D., & Hu, X. (2013). Knowledge spaces. In *Springer eBooks*. https://doi.org/10.1007/978-3-642-35329-1

Feng, M., Heffernan, N., & Koedinger, K. (2009). Addressing the assessment challenge with an online system that tutors as it assesses. *User Modeling and User-Adapted Interaction*, *19*(3), 243–266. https://doi.org/10.1007/s11257-009-9063-7

Goel, A., & Polepeddi, L. (2016). Jill Watson: A virtual teaching assistant for online education. *Georgia Tech Research Reports*. Retrieved from https://research.cc.gatech.edu/aimosaic/jill

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

Graesser, A. C., Chipman, P., Haynes, B. C., & Olney, A. (2005). AutoTutor: An intelligent tutoring system with mixed-initiative dialogue. *IEEE Transactions on Education, 48*(4), 612–618.

Graesser, A. C., Person, N. K., Harter, D., & the Tutoring Research Group. (2001). Teaching tactics and dialog in AutoTutor. *International Journal of Artificial Intelligence in Education, 12*, 257–279.

Graesser, A. C., VanLehn, K., Rose, C. P., Jordan, P. W., & Harter, D. (2005). Intelligent tutoring systems with conversational dialogue. *AI Magazine, 22*(4), 39–51.

Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Information & Libraries Journal*, 26(2), 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x

Holmes, W., Bialik, M., & Fadel, C**.** (2019). *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Boston, MA: Center for Curriculum Redesign. https://curriculumredesign.org

Holstein, K., McLaren, B. M., & Aleven, V. (2020). Co-designing a real-time classroom orchestration tool to support teacher–AI complementarity. *Journal of Learning Analytics, 7*(3), 21–35.

Holstein, K., McLaren, B. M., & Aleven, V. (2020). The classroom as a co-organizer of human–AI interaction. *Proceedings of the ACM on Human-Computer Interaction, 4*(CSCW1), 1–30. https://doi.org/10.1145/3392854

Hutchins, E. (1995). *Cognition in the wild*. MIT Press.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kizilcec, R. F., & Lee, H. (2020). Algorithmic fairness in education. *AI & Society, 35*(3), 537–548. https://doi.org/10.1007/s00146-019-00920-w

Knewton. (2013). *How Knewton works*. Retrieved from https://www.knewton.com

Koedinger, K. R., & Corbett, A. T. (2006). Cognitive tutors: Technology bringing learning sciences to the classroom. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (pp. 61–78). Cambridge University Press.

Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (2008). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education, 8*(1), 30–43.

Koedinger, K. R., Booth, J. L., & Klahr, D. (2008). Instructional complexity and the science to constrain it. *Science*, 322(5906), 682–685.

Lajoie, S. P., & Lesgold, A. M. (1989). Apprenticeship training in the workplace: Computer-coached practice environment as a new form of apprenticeship. *Machine-Mediated Learning, 3*(1), 7–28.

Lesgold, A., Lajoie, S. P., Bunzo, M., & Eggan, G. (1992). SHERLOCK: A coached practice environment for an electronics troubleshooting job. In J. H. Larkin & R. W. Chabay (Eds.), *Computer-Assisted Instruction and Intelligent Tutoring Systems: Shared Goals and Complementary Approaches* (pp. 201–238). Hillsdale, NJ: Lawrence Erlbaum Associates.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence Unleashed: An Argument for AI in Education*. Pearson.

Mitrovic, A. (1998). Experiences in implementing a constraint-based tutor. In *Proceedings of the Fourth International Conference on Intelligent Tutoring Systems* (pp. 414–423). Springer.

Mitrovic, A. (1998). Experiences in implementing constraint-based modeling in SQL-Tutor. In *Proceedings of ITS-98* (pp. 414–423). Springer.

Nkambou, R., Bourdeau, J., & Mizoguchi, R. (Eds.). (2010). *Advances in intelligent tutoring systems*. Springer.

Noddings, N. (2005). *The challenge to care in schools: An alternative approach to education*. Teachers College Press.

OpenAI. (2023). *GPT-4 technical report*. https://openai.com/research/gpt-4

Pane, J. F., Griffin, B. A., McCaffrey, D. F., & Karam, R. (2014). *Effectiveness of Cognitive Tutor Algebra I at Scale*. RAND Corporation.

Pane, J. F., Steiner, E. D., Baird, M. D., Hamilton, L. S., & Pane, J. D. (2014). *Continued progress: Promising evidence on personalized learning*. RAND Corporation.

Papert, S. (1980). Mindstorms: Children, Computers, and Powerful Ideas. Basic Books.

Pardos, Z. A., & Heffernan, N. T. (2011). KT-IDEM: Introducing item difficulty to the knowledge tracing model. In *Proceedings of the 19th International Conference on User Modeling, Adaptation, and Personalization* (pp. 243–254).

Picard, R. W. (1997). Affective Computing. MIT Press.

Reich, J. (2014). MOOC completion and retention in the context of student intent. *EDUCAUSE Review*, 49(5), 62–63.

Russell, S., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (3rd ed.). Pearson.

Selwyn, N. (2016). *Is technology good for education?* Polity Press.

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 30–40.

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529.

Suppes, P., & Morningstar, M. (1969). Computer-assisted instruction. *Science*, 166(3903), 343–350.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. Springer.

Thomas, J., & Harden, A**.** (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology*, 8, 45. https://doi.org/10.1186/1471-2288-8-45

Tikly, L. (2019). Education for sustainable development in the postcolonial world: Towards a transformative agenda for Africa. *Routledge*.

UNESCO. (2021). *AI and education: Guidance for policy-makers*. United Nations Educational, Scientific and Cultural Organization.

VanLehn, K. (1991). Rule acquisition by analogy: Learning declarative and procedural representations of knowledge. In K. VanLehn (Ed.), *Architectures for intelligence* (pp. 221–244). Lawrence Erlbaum.

VanLehn, K. (2006). The behavior of tutoring systems. *International Journal of Artificial Intelligence in Education, 16*(3), 227–265.

Vygotsky, L. S. (1978). Mind in Society: The Development of Higher Psychological Processes (M. Cole, V. John-Steiner, S. Scribner, & E. Souberman, Eds.). Harvard University Press.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*, 26(2), xiii–xxiii.

Williamson, B. (2017). *Big data in education: The digital future of learning, policy and practice*. Sage

Williamson, B. (2022). *Education and the datafied world: Big data, artificial intelligence and algorithmic governance*. Routledge.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Erlbaum.

Woolf, B. P. (2009). *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning*. Morgan Kaufmann.

Woolf, B. P., Burleson, W., Arroyo, I., Dragon, T., Cooper, D. G., & Picard, R. W. (2016). Affect-aware tutors: Recognizing and responding to student affect. *International Journal of Artificial Intelligence in Education, 26*(1), 1–27. https://doi.org/10.1007/s40593-015-0030-6

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education, 16*, 1–27. https://doi.org/10.1186/s41239-019-0171-0

Zhou, H. (2021). Emotion recognition in intelligent education systems: Opportunities and risks. *Computers and Education: Artificial Intelligence, 2*, 100031. https://doi.org/10.1016/j.caeai.2021.100031

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice, 41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2