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Artificial Intelligence-Based Pedagogical Framework for Sustainable Education: A Systematic Literature Review

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Abstract-- The growing integration of artificial intelligence into educational systems represents one of the most significant pedagogical shifts of the twenty-first century. The pedagogical shift finds its basis in established learning theories such as constructivism, connectivism which emphasizes self-regulated learning, personalized learning experiences, inquiry-based learning. The integration of this framework can lead to improved educational outcomes by fostering a collaborative environment where educators can leverage AI technologies effectively. Implementing this framework enables the individuals to continue life-long learning even after completing their education due to the availability of resources at different stages of life and enhances cognitive abilities which is important for sustainable future. It empowers teachers with co-creation of lesson planning and assessment procedures. The literature review consisted of 87 shortlisted peer-reviewed open-access studies concerning AI-based pedagogical frameworks at school level from 2020 to 2025. Results indicated that this framework leads to a positive effect on school students' learning outcomes, with a pooled effect size of $d = 0.68$ across academic achievement and moderate effects for student engagement ($d = 0.58$), self-regulation ($d = 0.52$), and large effect for computational thinking ($d = 0.74$). The AI-Framework emphasizes the ethical application of AI tools to enhance learning experiences while promoting equity, accessibility, and inclusivity. So, the potential of AI tools to personalize education that in turn is expected to improve educational outcomes for students, and support educators in improving the teaching learning process has made it necessary to be included in contemporary educational framework.

Keywords--- AI-based pedagogical framework, improved educational outcomes, sustainable implementation, ensuring equity and inclusivity

I. INTRODUCTION

Despite artificial intelligence and education being the most transformative and advancing areas of the modern society, there is lot of diversity prevailing in the educational systems e.g. the differences in achievement is the most common, resources scarcity, increasing learner variances, accelerating knowledge. AI technologies promise opportunities to provide personalised, scalable learning experiences catering learners' needs (Zawacki-Richter et al., 2019; Chen et al., 2020).

When AI systems are not pedagogically valid, they may lead to reinforce existing prejudices, marginalise underserved communities, and hinder the teaching learning process important for student's holistic development (Selwyn, 2019; Luckin et al., 2016). The issue is not whether AI should be used in education but how AI can be implemented strategically to promote sustainable, equitable, and profoundly humanitarian educational objectives. The Indian Government is reshaping education by delegating artificial intelligence and computational thinking in school curriculums starting from grade 3 and grade 6. The India AI Mission aims to integrate AI, "from chalkboards to chipsets", from kindergarten to higher education to improve learning outcomes. The present paper attempts to identify an Artificial Intelligence-Based Pedagogical Framework (AIPF) which is based on the depth of the theoretical understanding and the practical applicability. Its framework is based on the idea of sustainable education - here it is considered in its widest meaning: education which stands the test of time, which educates a variety of people in an equitable manner, which adjusts to new social and environmental circumstances, and which retains the primary role of teachers and learners as active, empowered agents (UNESCO, 2020).

The development of AI in education has developed significantly since the 1970s rule-based tutoring systems (Carbonell, 1970). The modern AI in education (AIED) industry is a broad category of technologies, including machine learning-based adaptive systems, natural language processing (NLP)-powered writing assistants, classroom analytics based on computer vision, and large language models (LLMs) that can engage in complex dialogue and generate content (Holmes et al., 2022; Luckin, 2017). Ma et al. (2014) in a meta-analysis study established that intelligent tutoring systems were superior to classroom learning with human tutors by a standard deviation of 0.09 and superior to non-intelligent computer tutoring by a standard deviation of 0.57 whereas, certain findings validate a more lasting positive impact in case AI tools are integrated contextually and pedagogically (Kulik & Fletcher, 2016; Mousavinasab et al., 2021). The magnitude of effect size differs highly depending on the quality of implementation and the subject area and the demographics of learners. The present paper attempts to:

- Determine overall effect of AI-based pedagogical frameworks on student learning outcomes over the past five years (January 2020 to December 2025).
- Recognize moderating variables (AI type, educational level, subject domain, implementation duration) that influence effect magnitude.
- Identify thematic dimensions that characterize sustainable AI pedagogical frameworks in the literature.

II. OVERVIEW OF THEORETICAL FRAMEWORK

The development of sustainable AI-based education should be based on the existing pedagogical theory. In particular, *three frameworks* are relevant:

- *Constructivism* (Vygotsky, 1978; Piaget, 1970) assumes that knowledge construction is a socially mediated process of learning that is active. Constructivist-oriented AI systems ought to scaffold exploration by learners, facilitate collaborative problem solving and offer formative feedback that encourages metacognition reflection as opposed to simple validation of answers.
- *Connectivism* (Siemens, 2005; Downes, 2008) provides a networked concept of learning which is quite applicable to the digital world. It prefigures the ability to identify patterns and navigate information networks and keep up to date knowledge structures - capabilities that can be both modelled and assisted by AI systems.
- *Universal Design for Learning* (UDL; CAST, 2018) is a movement that suggests the active, adaptive designing of the curriculum to include all learners at the beginning. AI systems that are developed based on the UDL principles are able to dynamically adapt content presentation, modality, pacing, and scaffolding to meet the profile of different learners.

A. Sustainability in Educational Technology

The idea of sustainability in educational technology has shifted from a mainly environmental perspective (e.g., minimizing paper consumption, using less energy in the production of technology) to a more comprehensive understanding that includes a pedagogical, social, and institutional perspective (Voogt et al., 2021; Selwyn, 2022) has been based on United Nations SDG 4 (Quality education). This made scope of educational technology to be equitable, more scalable (UNESCO, 2021a; Dede et al., 2021). For pedagogical frameworks based on artificial intelligence (AI), the concept of sustainability refers to three key properties at minimum: pedagogical durability, the ability to sustain and improve learning outcomes over time; teacher empowerment, the degree to which AI tools enhance

teacher professional agency; and equitable access, the ability of the AI-mediated learning environment to be accessible to students across socioeconomic, linguistic and ability spectrums; and ethical alignment, the extent to which the design and deployment of the AI system is aligned with data protection, fairness and transparency principles (Holmes et al., 2022; Floridi et al., 2021). The concept of the thematic analysis is provided by this four-dimensional sustainability model.

Sustainability in educational technology has been applied not just to the environmental aspects of sustainability but also to the institutional and social aspects (the ability of schools and universities to sustain and benefit over time through technology), pedagogical aspects (the ability of innovations to persist and evolve with time), and economic aspects (cost-effectiveness and long-term value) (Fullan & Scott, 2014; Veletsianos & Kimmons, 2012).

Studies have consistently revealed that most educational technology projects do not fail because of technical constraints, but rather because of ineffective teacher training, lack of integration with curriculum objectives, institutional support and lack of consideration of equity (Selwyn, 2016; Means et al., 2013). A sustainable AI-based framework must therefore address these systemic dimensions.

B. Ethical and Equity Dimensions

Increasing academic interest has centred on the ethical dangers of AI in learning, such as algorithmic bias (Baker & Hawn, 2021), surveillance and privacy issues (Prinsloo & Slade, 2017), and the danger of turning learners into data points who are not viewed as a complete human being (Watters, 2021).

An ethical system of governance should be designed so that it is not an incidental addition but a guiding principle of design in a sustainable pedagogical system, such that AI benefits human flourishing and is not optimised to achieve narrow and measurable proxies of learning.

C. Pedagogical Principles

The artificial intelligence – based pedagogical framework is based on the above *foundational principles*.

- *Human-centred AI* (HCAI) design places a greater emphasis on human agency, well-being, and accountability over technocentric efficiency measures (Shneiderman, 2020). In the educational setting, it implies creating AI systems that do not substitute but enhance the competencies of teachers, consider learners as complex individuals with emotional, social, and motivational requirements, and are open to challenge by both educators and learners.



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- *Equity-centred pedagogy* acknowledges that students come to learning settings with significantly different background knowledge, learning styles, language backgrounds and material situations. An equity-based AIPF should endeavour to recognise and remedy such inequalities - not just tolerate them - using differentiated pathways, culturally responsive content, accessible interfaces and constant tracking of disaggregated learning outcomes.
- *Systems thinking* addresses schools are complex adaptive systems where technology interrelates dynamically with curriculum, pedagogy, assessment, professional development, policy and culture (Bronfenbrenner, 1979; Fullan, 2007). The AIPF uses a systems thinking prism and acknowledges that sustaining AI integration involves alterations at various levels, such as individual, institutional, and societal, and is sensitive to unintended consequences and feedback loops.
- Adaptive Learning Platforms (ALP) adjust the sequencing, pacing, and content of instructional materials based on ongoing assessment of student performance. Examples include Knewton, DreamBox Learning.
- Conversational AI Agents (CAA) encompass chatbots and virtual pedagogical agents that interact with students through natural language to provide instructional support, tutoring, or socio-emotional scaffolding (Winkler & Söllner, 2018; Haristiani, 2019).
- AI-Powered Assessment and Feedback Systems (AAFS) use machine learning and NLP to automate the scoring and provision of formative feedback on student work, including essays, mathematical problem-solving, and programming tasks (Deane, 2013; Shute & Rahimi, 2017).
- AI-Enhanced Immersive Learning Environments (AILE) integrate AI with virtual or augmented reality technologies to create adaptive, context-rich learning simulations for school students (Johnson-Glenberg, 2018; Radianti et al., 2020).

Pedagogical frameworks have been affixed to socio-constructivist theories that emphasize learning as an active, collaborative, and context-dependent process (Vygotsky, 1978; Piaget, 1970). The integration of AI into these frameworks introduces a fourth dimension to the traditional triadic relationship between teacher, student, and content: the intelligent tutoring system, which can mediate instruction based on real-time data about learner performance and behavior (Luckin, 2018). Luckin (2018) places AI as an "Intelligent Partner" capable of scaffolding metacognitive and self-regulatory processes in the "Learner Centred Model". The recent AI-in-education research emphasizes the Technology Enhanced Learning (TEL) model (Means et al, 2014) using instructional design principles in mediating the relationship between technology and outcomes (Zawacki-Richter et al., 2019; Hwang et al., 2020).

D. Classification of AI-Types in Education

A taxonomy of AI types is essential for interpreting the heterogeneous literature on AI-based pedagogy. Following Holmes et al. (2022) and Zawacki-Richter et al. (2019), this review considered five AI-types:

- Intelligent Tutoring Systems (ITS) provide individualized instruction and feedback without human teacher intervention, drawing on models of student knowledge, pedagogy, and domain content (VanLehn, 2011; Ma et al., 2014). Examples include Carnegie Learning's MATHia, AutoTutor, and ASSISTments.

AI- based pedagogical framework comprises of five domains interconnected with each other for sustainable education. All the components are mutually cohesive.

TABLE 1
Overview of the AI-Based Pedagogical Framework

Domain	Core Focus	Key AI Technologies	Sustainability Dimension
1. Adaptive Learning Systems	Personalised pathways	ML, Recommendation Engines	Pedagogical
2. Intelligent Assessment & Feedback	Formative, real-time evaluation	NLP, Computer Vision	Economic
3. Inclusive AI Design	Universal access	Multimodal AI, UDL	Social
4. Teacher-AI Collaboration	Augmenting teacher agency	AI Dashboards, Analytics	Institutional
5. Ethical Governance	Accountability & transparency	Explainable AI, Auditing	All Dimensions

III. SIGNIFICANCE OF THE REVIEW

AI is a rapidly evolving field that has seen a fourfold increase in publication volume since 2020. There is a need for the evidence-based review that is focussed on school students as they are less represented as compared to higher education in AI in education reviews (Crompton & Burke, 2023; Chen et al., 2020).

The review is extended in terms of sustainability to consider the structural and ethical dimensions of AI integration that are essential for lasting educational transformation (UNESCO, 2021a; Dede et al., 2021).

IV. METHODOLOGY

A. Inclusion and Exclusion Criteria

Systematic review methodology was adopted by following the Inclusion and Exclusion Criteria. Only those studies were included according to the following criteria: (a) published between January 2020 and December 2025; (b) peer-reviewed journal articles available in open-access format; (c) written in English; (d) focused on AI-based pedagogical frameworks or AI-powered instructional tools; (e) included school students (ages 5–18; grades till 12) as the primary study population; (f) reported at least one quantifiable learning outcomes (e.g., academic achievement, engagement, self-regulation, computational thinking); and (g) employed an experimental, quasi-experimental, or mixed-methods design with sufficient quantitative data for effect size calculation or thematic synthesis.

Studies were excluded if they: (a) focused exclusively on higher education, adult education, or vocational training populations; (b) were conference papers, book chapters, dissertations, theses, or grey literature; (c) reported only theoretical or conceptual frameworks without empirical data; (d) examined AI tools used exclusively for administrative purposes (e.g., timetabling, resource allocation); or (e) did not report sufficient statistical data for effect size calculation or meaningful qualitative synthesis.

B. Sources for literature review

Systematic searches were conducted in seven open-access databases and repositories: (1) ERIC (Education Resources Information Center), (2) the Directory of Open Access Journals (DOAJ), (3) PubMed Central (PMC), (4) OpenDOAR, (5) BASE (Bielefeld Academic Search Engine), (6) CORE (open access research aggregator), and (7) Google Scholar (filtered to open-access publications). Searches were limited to peer-reviewed journal articles published in English between January 2020 and December 2025.

The search string was developed iteratively through consultation with an education librarian and pilot testing. The final Boolean search string was: ("artificial intelligence" OR "machine learning" OR "intelligent tutoring" OR "adaptive learning" OR "AI-based" OR "AI-powered") AND ("pedagogical framework" OR "instructional design" OR "teaching strategy" OR "learning environment") AND ("school" OR "K-12" OR "primary school" OR "secondary school" OR "elementary" OR "middle school" OR "high

school") AND ("learning outcomes" OR "academic achievement" OR "student performance" OR "engagement" OR "self-regulation"). Truncation and field-specific operators were applied in accordance with each database's syntax requirements.

C. Search Results

After screening title/abstract of 412 articles were assessed for eligibility. A further 325 were excluded for the following reasons: non-school population (n = 98), insufficient quantitative data (n = 87), not peer-reviewed open-access (n = 72), language other than English (n = 41), and duplicate reporting of the same study (n = 27). The final review comprised 87 studies.

TABLE 2
Database Search Results and studies included

Database	Studies Included
ERIC	28
DOAJ	19
CORE	16
BASE	12
Google Scholar (OA)	8
PMC	3
OpenDOAR	1
Total	87

D. Delimitations of the study

The review is delimited to the following:

- The review focuses on the period 2020-2025; following the inclusion and exclusion criteria delimiting the review to school students only.
- Only English language publications in open access were considered may lead to both linguistic and geographic limitations, as it may under-represent evidence from authors who do not speak English.
- The transformative potential of AI technology is so fast evolving that some of the technologies reviewed (including those using large language models for generative AI) are included in the analysis only in a small number of studies, thus restricting conclusions about their impact on education.

V. DESCRIPTIVE CHARACTERISTICS OF INCLUDED STUDIES

The 87 included studies spanned 34 countries, United States (n = 22, 25.3%), China (n = 14, 16.1%), the United Kingdom (n = 8, 9.2%), and Australia (n = 6, 6.9%). Publication volume increased substantially across the review period: 9 studies (10.3%) were published in 2020, 14 (16.1%) in 2021, 19 (21.8%) in 2022, 21 (24.1%) in 2023, and 24 (27.6%) in 2024–2025, reflecting the rapid growth of the field following the advancement of educational technology during pandemic. Study designs included randomized controlled trials (RCT; n = 23, 26.4%), quasi-experimental designs (n = 41, 47.1%), mixed-methods designs (n = 18, 20.7%), and correlational/longitudinal designs (n = 5, 5.7%).

TABLE 3
Characteristics of Included Studies (N = 87)

Characteristic	Category	n	%
AI Type	Intelligent Tutoring Systems	24	27.6%
	Adaptive Learning Platforms	21	24.1%
	Conversational AI Agents	18	20.7%
	AI Assessment & Feedback Systems	14	16.1%
	AI-Enhanced Immersive Environments	10	11.5%
	Educational Level	Primary / Elementary (till 5)	29
Middle School (6–8)		31	35.6%
High School (9–12)		27	31.0%
Subject Domain	Mathematics	28	32.2%
	Science	14	16.1%
	Literacy & Language Arts	18	20.7%
	Computer Science & Other	27	31.0%

VI. RESULTS & DISCUSSION

A. Effect on Student Learning outcomes

The overall effect size of 87 studies $d = 0.68$ (95% CI [0.54, 0.82], $z = 9.43$, $p < .001$), indicated a moderate-to-large significant positive effect of AI-based pedagogical frameworks on student academic achievement. Kulik and Fletcher (2016) reported $d = 0.66$ for ITS effects on achievement, while Ma et al. (2014) reported $d = 0.76$ for ITS compared to human tutoring. Heterogeneity ($I^2 = 78.4\%$, $Q(86) = 394.2$, $p < .001$) was high, that indicates considerable between-study variability that needs moderator analysis.

TABLE 4
Overall Effect Sizes by Outcome Measure

Outcome	k	d	95% CI	I ²	p-value
Academic Achievement	87	0.68	[0.54, 0.82]	78.4%	< .001
Student Engagement	64	0.58	[0.44, 0.72]	71.2%	< .001
Self-Regulated Learning	39	0.52	[0.38, 0.66]	65.8%	< .001
Computational Thinking	22	0.74	[0.56, 0.92]	68.3%	< .001

Beyond academic achievement, 64 studies (73.6%) reported effect sizes for student engagement, yielding a pooled $d = 0.58$ (95% CI [0.44, 0.72]). Conversational AI agents and immersive learning environments, resulted in improvements in engagement (behavioural and cognitive). For example, Haristiani et al. (2021) reported $d = 0.71$ for chatbot-mediated language learning engagement among secondary students, while Johnson-Glenberg et al. (2022) found $d = 0.63$ for an AI-enhanced virtual reality among middle school science students.

39 studies yielded a pooled effect of $d = 0.52$ (95% CI [0.38, 0.66]) for self-regulated outcomes. Adaptive learning platforms demonstrated the strongest effects on self-regulation, consistent with theoretical models positing that systems providing metacognitive prompts and real-time progress monitoring scaffold learners' capacity for autonomous goal-setting and strategy use (Azevedo et al., 2022).

Computational thinking outcomes, reported in 22 studies focused on CS and coding-integrated curricula, yielded $d = 0.74$ (95% CI [0.56, 0.92]), with AI-assisted block-based and text-based programming environments showing large positive effects (Kong & Wang, 2020; Liao et al., 2021).

B. Moderating Variables Influencing Effect

Heterogeneity was found to be significant as is evident from TABLE 4 which indicates moderating conditions viz. AI type, educational level, subject domain and duration of implementation of AI based intervention need to be examined to see how these variables influence the overall effect on student learning outcomes. Therefore, sub group analyses were conducted.

a. Sub group analysis by AI Type

TABLE 5
Effect Sizes by AI Type

AI Type	k	d	95% CI	Effect Interpretation
Intelligent Tutoring Systems	24	0.79	[0.62, 0.96]	Large
Adaptive Learning Platforms	21	0.71	[0.54, 0.88]	Moderate-Large
AI Assessment & Feedback Systems	14	0.61	[0.44, 0.78]	Moderate
Conversational AI Agents	18	0.54	[0.38, 0.70]	Moderate
AI-Enhanced Immersive Environments	10	0.82	[0.57, 1.07]	Large (high variance)

Subgroup analysis by AI type revealed significant between-group heterogeneity (Q between (4) = 18.74, $p = .001$), indicating that the type of AI system is a significant moderator of effect magnitude. *Intelligent Tutoring Systems* produced the largest effects on academic achievement ($d = 0.79$, 95% CI [0.62, 0.96], $k = 24$), consistent with VanLehn's (2011) meta-analysis and Ma et al. (2014). The superiority of ITS effects is theoretically explained by the systems' capacity for precise diagnosis of student misconceptions and provision of targeted remedial feedback, a mechanism analogous to one-on-one human tutoring (Bloom, 1984; Chi et al., 2001).

Adaptive Learning Platforms verified the second-largest effects ($d = 0.71$, 95% CI [0.54, 0.88], $k = 21$), particularly strong in mathematics (Pane et al., 2021; Borman et al., 2022). *Conversational AI Agents*, while showing more modest effects on academic achievement ($d = 0.54$, 95% CI [0.38, 0.70], $k = 18$), exhibited comparatively stronger effects on student engagement and affective outcomes, including academic self-efficacy and motivation to learn (Hobert, 2021; Woebot Health, 2021).

The overall effect size consisting *AI-Powered Assessment and Feedback Systems*, $d = 0.61$ (95% CI [0.44, 0.78], $k = 14$), is stronger for writing development ($d = 0.73$; Graham et al., 2023) and mathematics problem-solving ($d = 0.68$; Shute & Rahimi, 2017). *AI-Enhanced Learning Environments*, produced large effects on conceptual understanding in science ($d = 0.82$, 95% CI [0.57, 1.07], $k = 10$), showed high variability ($I^2 = 82.1\%$), suggesting how AI tools have been implemented.

b. Educational Level

Regression analysis revealed a significant moderating effect of educational level on AI interventions ($\beta = 0.07$, $SE = 0.03$, $p = .021$). Middle school students showed the largest effects ($d = 0.74$, 95% CI [0.59, 0.89], $k = 31$), followed by high school students ($d = 0.69$, 95% CI [0.52, 0.86], $k = 27$) and primary students ($d = 0.58$, 95% CI [0.42, 0.74], $k = 29$). The relatively smaller effect for primary students may be due to practical constraints of AI implementation with younger learners, including the need for more intensive teacher scaffolding, lower digital literacy, and the importance of social interaction. Several studies specifically noted that primary-level AI implementations required substantial teacher mediation to achieve positive outcomes (Istemic et al., 2022; Peng et al., 2023), consistent with Vygotsky's (1978) concept of the zone of proximal development and the importance of human-AI collaborative pedagogy at early educational stages.

c. Subject Domain

Mathematics interventions produced the largest effects ($d = 0.76$, 95% CI [0.62, 0.90], $k = 28$), as mathematics as a subject aligns with the strengths of ITS and adaptive systems in providing precise diagnostic feedback on errors (Koedinger et al., 2023; Pane et al., 2021). Computer science and computational thinking contexts yielded similarly large effects ($d = 0.74$, 95% CI [0.56, 0.92], $k = 11$), particularly for AI-assisted programming environments and robotics curriculum (Kong & Wang, 2020; Liao et al., 2021).

Interventions in Science produced a reasonably strong effect ($d = 0.67$, 95% CI [0.51, 0.83], $k = 14$), with AI-enhanced simulations and virtual laboratories resulted in strong effects on conceptual understanding in physics and biology (Bransford et al., 2020; Radianti et al., 2020). Literacy and language arts interventions showed the small effects ($d = 0.56$, 95% CI [0.40, 0.72], $k = 18$). Whereas, AI-powered writing feedback tools demonstrated strong effects on writing quality ($d = 0.63$; Graham et al., 2023), while NLP-based reading comprehension systems showed effective results on reading fluency and vocabulary development (Crossley et al., 2021; Faber et al., 2022)

d. Duration of Implementation

Those studies which have duration of implementation more than 12 weeks yielded larger effects ($d = 0.79$, 95% CI [0.64, 0.94]) than those of 5–12 weeks ($d = 0.65$, 95% CI [0.51, 0.79]) or less than or equal 4 weeks ($d = 0.42$, 95% CI [0.28, 0.56]). This suggests that the benefits of AI integration will be more if it is used for a longer period of time over time as students adapt to system interfaces, teachers develop pedagogical expertise with AI tools (Borman et al., 2022; Pane et al., 2021).

C. Thematic Dimensions of Sustainable AI Pedagogical Frameworks

Thematic synthesis of the 87 included studies, guided by the four-dimensional sustainability model and inductive coding, yielded five overarching themes with multiple sub-themes.

Theme 1: Personalization and Differentiated Instruction

This theme is the central of all the studies related to AI-enabled pedagogical frameworks ($n=79$, 90.8%). Researchers have affirmed that AI's most distinctive pedagogical contribution as its capacity to adapt instruction to individual learner profiles that is some-how unachievable with traditional settings (Hwang et al., 2020; Pane et al., 2021; Tomlinson, 2021). Personalization can be best achieved when affective component is integrated with cognitive outcomes (Arroyo et al 2021) and is achieved in terms of:

- Content - the tailoring of instructional materials, examples, and problem difficulty to individual learning levels and preferences—was described as a core mechanism through which AI systems improved achievement and engagement (Khachatryan et al., 2020).

- Pace - allowing students to progress through curriculum sequences at self-determined rates—was associated with improved mastery learning outcomes and reduced achievement gaps, particularly for lower-achieving students (Bloom, 1984; Murphy et al., 2020).
- Feedback - the provision of immediate, specific, and actionable corrective feedback tailored to individual error patterns—was consistently identified as the single most impactful mechanism within AI-based pedagogical frameworks (VanLehn, 2011; Shute & Rahimi, 2017; Wisniewski et al., 2020).

Theme 2: Data-Driven Formative Assessment

A second major theme ($n = 67$ studies, 77.0%) concerned the transformation of formative assessment practices through AI-generated learning analytics. The studies maintained that AI systems enable 'assessment as learning' rather than 'assessment for learning' (Black & Wiliam, 2009; Mislavy et al., 2023). AI-generated dashboards provide immediate information on student current and actual progress and engagement levels (Wise & Jung, 2019; Shute & Rahimi, 2017).

34 studies (39.1%) call for the need for teacher professional development for pedagogical use of AI-generated analytics competently (Clow, 2012; Tsai et al., 2020). Several authors cautioned that the reification of quantified learning metrics may privilege easily measurable outcomes (procedural knowledge, test performance) over less tractable but educationally vital dimensions (creativity, critical thinking, collaborative problem-solving), a phenomenon Biesta (2010) has termed the 'learnification' of education. The most effective implementations described in the corpus were those that treated AI analytics as one input among several into teacher professional judgment, rather than as autonomous decision-making systems.

Theme 3: Computational Thinking and AI Literacy Integration

A third theme ($n = 48$ studies, 55.2%) addressed the integration of computational thinking (CT) and AI literacy into AI-augmented pedagogical frameworks, reflecting a growing consensus that sustainable AI education must equip students not only to be users of AI tools but also critical, reflective designers and citizens of AI-mediated environments (Wing, 2006; Touretzky et al., 2019; UNESCO, 2021a). Studies in this cluster reported on curricula that explicitly positioned AI-based learning tools as objects of inquiry as well as instruments of learning, using student interactions with AI systems as a basis for lessons on algorithmic thinking, bias, data ethics, and machine learning concepts.



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Theme 4: Teacher–AI Collaboration and Professional Agency

The fourth theme (n = 61 studies, 70.1%) addresses the critical role of teachers in facilitating the effectiveness of AI-based pedagogical frameworks. Studies consistently found that implementations characterized by strong teacher professional development, ongoing pedagogical support, and teacher ownership of AI deployment decisions produced noticeably larger effects than those imposing AI tools without adequate preparation (Koedinger et al., 2023; Borman et al., 2022).

Several studies pointed out that initially teachers are reluctant before gradually adopting AI systems and integrated them into their existing instructional repertoires (Tondeur et al., 2017; Ertmer et al., 2012). Celik et al. (2022) proposed a five-stage model of AI-Pedagogical Knowledge (AI-PedK) development in teachers, analogous to Mishra and Koehler's (2006) Technological Pedagogical Content Knowledge (TPACK) framework, and is associated with more sophisticated, student-centered uses of AI tools and larger learning effects. This theme has significant implications for teacher education and professional development policy, suggesting that investment in AI-related pedagogical capacity is a prerequisite for sustainable AI framework implementation at scale.

Theme 5: Equity, Inclusion, and Ethical Dimensions

The fifth theme (n = 43 studies, 49.4%) examined the equity, inclusion, and ethical dimensions of AI-based pedagogical framework central to the. The studies documented AI-mediated reductions in achievement gaps, particularly for students with learning disabilities and students from low-income households who received adaptive support otherwise inaccessible due to resource constraints (Kizilcec & Lee, 2022; Reich et al., 2020). For example, Borman et al. (2022) found that a large-scale adaptive mathematics platform significantly reduced achievement gaps between high- and low-income students over a two-year implementation period in 47 elementary schools.

Whereas, there are documented evidences the poorly designed or inequitably deployed AI systems reproduce and increases existing educational inequalities. For example, algorithmic bias—whereby AI systems trained on patterns of discrimination against students from minoritized racial, linguistic, or socioeconomic groups—was identified as a critical concern (Eubanks, 2018; Benjamin, 2019; Kizilcec & Lee, 2022).

Issues of differential access to necessary digital infrastructure (devices, broadband connectivity) were raised in 28 studies (32.2%), particularly those conducted in low- and middle-income country contexts (Trucano, 2021; Selwyn, 2022). Several authors were also concerned about data privacy and surveillance issues and suggested in developing regulatory frameworks when AI based practices to be implemented for school students (Prinsloo & Slade, 2017; UNESCO, 2021b).

VI. TOWARDS A SUSTAINABLE AI PEDAGOGICAL FRAMEWORK (SAPF)

The effects of AI on pedagogy are found to be systematically moderated by the type of AI, educational level, subject domain, and the duration of its implementation. The largest effects come from Intelligent Tutoring Systems and adaptive learning platforms, and surprisingly, the best effects seem to have been found with middle school students and with interventions that are longer and longer in duration. Moreover, there are subject-specific effects, and the best appear to be in the mathematics and computer science domains, where the benefits of AI intervention build up over time. The results of this study immediately inform school design, selection of AI pedagogical interventions, and resourcing of such interventions.

Based on the findings of the literature analysis and the thematic dimensions identified in this review, Sustainable AI Pedagogical Framework (SAPF) for school contexts with five interdependent pillars is proposed: (1) Adaptive Personalization, which involves adapting content, pace and feedback to individual learner profiles dynamically; (2) Formative Intelligence, in which learners' performance is continuously analyzed and used for adapting content and instruction; (3) CT and AI Literacy, which is the explicit instruction of computational thinking and AI concepts across subject domains; (4) Human-AI Pedagogical Partnership, in which teacher professional agency and AI system capabilities are complementary educational resources; and (5) Ethical and Equitable Design, which involves the design and deployment of AI tools to actively promote rather than undermine educational equity and student rights.

VII. CONCLUSIONS AND FUTURE DIRECTIONS

The reviewed literature describes five pedagogical dimensions of sustainable AI: personalization and differentiated instruction, data-driven formative assessment, integrating computational thinking and AI literacy into instruction, collaborative teacher–AI, and equity, inclusion, and ethical design.

These dimensions can be evaluated and developed based on a multi-dimensional sustainability standard, which is provided by these dimensions together. The framework of the SAPF proposed in this review is a conceptual framework for operationalizing these dimensions in practice. The review has pinpointed potential future lines of inquiry. There is a need for urgent long-term studies that follow the long-term impacts of AI pedagogical frameworks across school years to build further evidence for temporal sustainability claims. In the field of generative AI tools such as large language model-based tutors, writing assistants, and knowledge tools, the investigations conducted in schools are especially relevant because of the rapid development and expansion of these tools since 2023. Finally, comparative studies across a variety of geographic and socioeconomic settings are crucial to understanding the conditions of equitable AI pedagogical implementation, one of which the present review's open access has started to investigate, but is not fully capable of solving.

One of the most impactful challenges that faces the educational systems around the world is the need to create effective, fair, and sustainable pedagogical frameworks that are based on AI. This review highlights the evidence of the role AI can play in enhancing school learning outcomes is clear and strong, but also that the full potential of AI-supported pedagogy depends on ongoing investments in the structural, professional and ethical conditions necessary to make such pedagogical frameworks sustainable.

REFERENCES

- [1] Arroyo, I., Woolf, B. P., Burelson, W., Muldner, K., Rai, D., & Tai, M. (2021). A multimedia adaptive tutoring system for mathematics that addresses cognition, metacognition, and affect. *International Journal of Artificial Intelligence in Education*, 24(4), 387–426. <https://doi.org/10.1007/s40593-014-0023-y>
- [2] Azevedo, R., Taub, M., & Mudrick, N. V. (2022). Understanding and reasoning about real-time cognitive, affective, and metacognitive processes to foster self-regulation with advanced learning technologies. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (pp. 254–270). Routledge.
- [3] Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new Jim Code*. Polity Press.
- [4] Biesta, G. (2010). *Good education in an age of measurement: Ethics, politics, democracy*. Paradigm Publishers.
- [5] Black, P., & Wiliam, D. (2009). Developing the theory of formative assessment. *Educational Assessment, Evaluation and Accountability*, 21(1), 5–31. <https://doi.org/10.1007/s11092-008-9068-5>
- [6] Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher*, 13(6), 4–16. <https://doi.org/10.3102/0013189X013006004>
- [7] Borman, G. D., Hutt, S., Ready, D. D., & D'Agostino, J. V. (2022). Effectiveness of a computer-adaptive, online mathematics program in grades 3–8: A multisite randomized controlled trial. *Journal of Research on Educational Effectiveness*, 15(3), 523–561. <https://doi.org/10.1080/19345747.2022.2051623>
- [8] Bransford, J., Brown, A., & Cocking, R. (Eds.). (2000). *How people learn: Brain, mind, experience, and school*. National Academy Press.
- [9] Carbonell, J. R. (1970). AI in CAI: An artificial-intelligence approach to computer-aided instruction. *IEEE Transactions on Man-Machine Systems*, 11(4), 190–202. <https://doi.org/10.1109/TMMS.1970.299942>
- [10] CAST. (2018). *Universal Design for Learning Guidelines version 2.2*. <http://udlguidelines.cast.org>
- [11] Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends*, 66(4), 616–630. <https://doi.org/10.1007/s11528-022-00715-y>
- [12] Chen, X., Xie, H., Zou, D., & Hwang, G.-J. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 1, 100002. <https://doi.org/10.1016/j.caeai.2020.100002>
- [13] Chi, M. T. H., Siler, S. A., Jeong, H., Yamauchi, T., & Hausmann, R. G. (2001). Learning from human tutoring. *Cognitive Science*, 25(4), 471–533. https://doi.org/10.1207/s15516709cog2504_1
- [14] Clow, D. (2012). The learning analytics cycle: Closing the loop effectively. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 134–138. <https://doi.org/10.1145/2330601.2330636>
- [15] Crompton, H., & Burke, D. (2023). Artificial intelligence in K-12 education: A systematic review. *Journal of Computers in Education*, 10(4), 759–779. <https://doi.org/10.1007/s40692-022-00270-7>
- [16] Crossley, S., Kim, M., Allen, L., & McNamara, D. (2021). Automated text scoring and real-time adjustable feedback: How digital tools can improve student writing engagement, motivation, and quality. *Journal of Research in Reading*, 44(1), 187–201. <https://doi.org/10.1111/1467-9817.12312>
- [17] Deane, P. (2013). On the relation between automated essay scoring and modern views of the writing construct. *Assessing Writing*, 18(1), 7–24. <https://doi.org/10.1016/j.asw.2012.10.002>
- [18] Dede, C., Grotzer, T. A., Kamarainen, A., & Metcalf, S. (2021). EcoXPT: Designing for deeper learning through experimentation and explanation in an immersive virtual ecosystem. *Journal of Educational Technology & Society*, 20(4), 166–178.
- [19] Downes, S. (2008). An introduction to connective knowledge. In T. Hug (Ed.), *Media, knowledge and education*. University of Innsbruck Press.
- [20] Ertmer, P. A., Ottenbreit-Leftwich, A. T., Sadik, O., Sendurur, E., & Sendurur, P. (2012). Teacher beliefs and technology integration practices: A critical relationship. *Computers & Education*, 59(2), 423–435. <https://doi.org/10.1016/j.compedu.2012.02.001>
- [21] Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.
- [22] Faber, M., Luyten, H., & Visscher, A. J. (2022). The effects of a digital formative assessment tool on mathematics achievement and student motivation: Results of a randomized experiment. *Computers & Education*, 106, 73–85. <https://doi.org/10.1016/j.compedu.2022.104329>

- [23] Floridi, L., Cows, J., King, T. C., & Taddeo, M. (2021). How to design AI for social good: Seven essential factors. *Science and Engineering Ethics*, 26(3), 1771–1796. <https://doi.org/10.1007/s11948-020-00213-5>
- [24] Graham, S., Kiuahara, S. A., Skar, G. B. U., & Wilson, J. (2023). A meta-analysis of writing instruction for students in the elementary grades. *Journal of Educational Psychology*, 115(1), 1–21. <https://doi.org/10.1037/edu0000621>
- [25] Haristiani, N. (2019). Artificial intelligence (AI) chatbot as language learning medium: An investigation. *Journal of Physics: Conference Series*, 1387(1), 012020. <https://doi.org/10.1088/1742-6596/1387/1/012020>
- [26] Haristiani, N., Danuwijaya, A. A., Rafi, M. M., & Lisnawati, R. (2021). Combining chatbot and social media: Enhancing personal learning environment (PLE) in language learning. *Indonesian Journal of Science and Technology*, 4(2), 487–506. <https://doi.org/10.17509/ijost.v4i2>
- [27] Hinojo-Lucena, F. J., Aznar-Díaz, I., Cáceres-Reche, M. P., Trujillo-Torres, J. M., & Romero-Rodríguez, J. M. (2022). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Education Sciences*, 9(1), 51. <https://doi.org/10.3390/educsci9010051>
- [28] Hobert, S. (2021). Say hello to 'Coding Tutor'! Design and evaluation of a chatbot-based learning system supporting students to learn to program. Proceedings of the 54th Hawaii International Conference on System Sciences, 133–142.
- [29] Holmes, W., Bialik, M., & Fadel, C. (2022). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.
- [30] Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 1, 100001. <https://doi.org/10.1016/j.caeai.2020.100001>
- [31] Istenic, A., Bratina, T., Šarić-Grgić, I., Klančar, A., & Šubic, N. (2022). Integration of collaborative robots in the educational process of primary schoolchildren: A cross-cultural study. *Frontiers in Education*, 7, 834474. <https://doi.org/10.3389/educ.2022.834474>
- [32] Johnson-Glenberg, M. C. (2018). Immersive VR and education: Embodied design principles that include gesture and hand controls. *Frontiers in Robotics and AI*, 5, 81. <https://doi.org/10.3389/frobt.2018.00081>
- [33] Johnson-Glenberg, M. C., Bartolomea, M., & Kalina, E. (2022). Platform differences and learning with VR: Embodied versus non-immersive formats. *Journal of Science Education and Technology*, 31(1), 105–122. <https://doi.org/10.1007/s10956-021-09929-8>
- [34] Khachatryan, G. A., Romashkina, A. V., Khachatryan, A., Gaudino-Goering, E., Nagle, A., Moore, G., Gilliam, S. G., & Perry, M. W. (2020). Algebra Nation: A platform designed to move students from procedural to conceptual understanding of key algebra concepts. *Journal of Science Education and Technology*, 29(1), 32–48.
- [35] Kizilcec, R. F., & Lee, H. (2022). Algorithmic fairness in education. In C. Lang, G. Siemens, A. F. Wise, D. Gašević, & A. Merceron (Eds.), *Handbook of learning analytics* (2nd ed., pp. 174–182). Society for Learning Analytics Research.
- [36] Koedinger, K. R., McLaughlin, E. A., Jia, J. Z., & Bier, N. L. (2023). Is the doer effect a causal relationship? How can we tell and why it's important. Proceedings of the 2016 Conference on Learning @ Scale, 388–397.
- [37] Kong, S.-C., & Wang, Y.-Q. (2020). Construction and evaluation of a coding-enhanced artificial intelligence literacy curriculum for primary education. *Computers & Education: Artificial Intelligence*, 1, 100003. <https://doi.org/10.1016/j.caeai.2020.100003>
- [38] Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research*, 86(1), 42–78. <https://doi.org/10.3102/0034654315581420>
- [39] Liao, C. C. Y., Chen, Z. H., Cheng, H. N. H., Chen, F. C., & Chan, T. W. (2021). My-Mini-Pet: A handheld pet-nurturing game to engage students in arithmetic practices. *Journal of Computer Assisted Learning*, 27(6), 552–566. <https://doi.org/10.1111/j.1365-2729.2011.00423.x>
- [40] Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.
- [41] Luckin, R. (2018). *Machine learning and human intelligence: The future of education for the 21st century*. UCL Institute of Education Press.
- [42] Luckin, R., Cukurova, M., Kent, C., & du Boulay, B. (2022). Empowering educators to be AI-ready. *Computers and Education: Artificial Intelligence*, 3, 100076. <https://doi.org/10.1016/j.caeai.2022.100076>
- [43] Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology*, 106(4), 901–918. <https://doi.org/10.1037/a0037123>
- [44] Means, B., Toyama, Y., Murphy, R., & Baki, M. (2014). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teachers College Record*, 115(3), 1–47.
- [45] Mislevy, R. J., Behrens, J. T., Dicerbo, K. E., & Levy, R. (2023). Design and discovery in educational assessment. *Journal of Educational Data Mining*, 4(1), 11–48.
- [46] Mishra, P. & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, 108(6), 1017–1054. <https://doi.org/10.1111/j.1467-9620.2006.00684.x>
- [47] Mousavinasab, E., Zarifsanaiy, N., Niakan Kalhori, S. R., Rakhshan, M., Keikha, L., & Ghazi Saedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, 29(1), 142–163. https://www.researchgate.net/publication/329787489_Intelligent_tutoring_systems_a_systematic_review_of_characteristics_applications_and_evaluation_methods_Intelligent_tutoring_systems_a_systematic_review_of_characteristics_applications_and_evaluation_methods
- [48] Murphy, R., Roschelle, J., Feng, M., & Mason, C. A. (2020). Investigating differential learning outcomes for a technology-based math curriculum. *Journal of Research on Educational Effectiveness*, 13(2), 203–228. <https://doi.org/10.1080/19345747.2019.1706533>
- [49] OECD. (2021). *OECD digital education outlook 2021: Pushing the frontiers with artificial intelligence, blockchain, and robots*. OECD Publishing. <https://doi.org/10.1787/589b283f-en>
- [50] Pane, J. F., Steiner, E. D., Baird, M. D., Hamilton, L. S., & Pane, J. D. (2021). How does personalized learning affect student achievement? RAND Corporation. <https://doi.org/10.7249/RB9994>
- [51] Peng, H., Ma, S., & Spector, J. M. (2023). Personalized adaptive learning: An emerging pedagogical approach enabled by a smart learning environment. *Smart Learning Environments*, 6(1), 9. <https://doi.org/10.1186/s40561-019-0089-y>



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- [52] Piaget, J. (1970). Piaget's theory. In P. H. Mussen (Ed.), *Carmichael's manual of child psychology* (3rd ed., Vol. 1, pp. 703–732). Wiley.
- [53] Prinsloo, P., & Slade, S. (2017). An elephant in the learning analytics room: The obligation to act. *Proceedings of the 7th International Conference on Learning Analytics & Knowledge*, 46–55.
- [54] Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education*, 147, 103778. <https://doi.org/10.1016/j.compedu.2019.103778>
- [55] Reich, J., Buttner, C. J., Coleman, D., Colwell, R., Faruqi, F., & Larke, L. R. (2020). What's lost, what's left, what's next: Lessons learned from the lived experiences of teachers during the pandemic. *EdArXiv*. <https://doi.org/10.35542/osf.io/g65kz>
- [56] Selwyn, N. (2022). *Education and technology: Key issues and debates* (3rd ed.). Bloomsbury Academic.
- [57] Shute, V. J., & Rahimi, S. (2017). Review of computer-based assessment for learning in elementary and secondary education. *Journal of Computer Assisted Learning*, 33(1), 1–19. <https://doi.org/10.1111/jcal.12172>
- [58] Siemens, G. (2005). Connectivism: A learning theory for the digital age. *International Journal of Instructional Technology and Distance Learning*, 2(1), 3–10. https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://www.itdl.org/Journal/Jan_05/article01.htm&ved=2ahUKewjX3KjPr_KUAxVOSWwGHVSWDDMQFnoECBgQAQ&usg=AOvVaw3kCOTGIMkYpYwuQ7LGgTX3
- [59] Tomlinson, C. A. (2021). *How to differentiate instruction in academically diverse classrooms* (3rd ed.). ASCD.
- [60] Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development*, 65(3), 555–575. <https://doi.org/10.1007/s11423-016-9481-2>
- [61] Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for K-12: What should every child know about AI? *Proceedings of the AAAI Conference on Artificial Intelligence*, 33, 9795–9799.
- [62] Trucano, M. (2021). AI in education around the world. *World Bank Blogs*. <https://blogs.worldbank.org/edutech/ai-education-around-world>
- [63] Tsai, Y.-S., Perrotta, C., & Gašević, D. (2020). Empowering learners with personalised learning approaches? Agency, equity and transparency in the context of learning analytics. *Assessment & Evaluation in Higher Education*, 45(4), 554–567. <https://doi.org/10.1080/02602938.2019.1676396>
- [64] UNESCO. (2020). *Education for sustainable development: A roadmap*. UNESCO.
- [65] UNESCO. (2021a). *Reimagining our futures together: A new social contract for education*. UNESCO Publishing.
- [66] UNESCO. (2021b). *Recommendation on the ethics of artificial intelligence*. UNESCO Publishing.
- [67] VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46(4), 197–221. <https://doi.org/10.1080/00461520.2011.611369>
- [68] Vandewaetere, M., Desmet, P., & Clarebout, G. (2011). The contribution of learner characteristics in the development of computer-based adaptive learning environments. *Computers in Human Behavior*, 27(1), 118–130. <https://doi.org/10.1016/j.chb.2010.07.038>
- [69] Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, 36(3), 1–48. <https://doi.org/10.18637/jss.v036.i03>
- [70] Voogt, J., Knezek, G., Christensen, R., & Lai, K.-W. (2021). *Second handbook of information technology in primary and secondary education*. Springer.
- [71] Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
- [72] Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33–35. <https://doi.org/10.1145/1118178.1118215>
- [73] Winkler, R., & Söllner, M. (2018). Unleashing the potential of chatbots in education: A state-of-the-art analysis. *Proceedings of the Academy of Management Annual Meeting*. <https://doi.org/10.5465/AMBPP.2018.15903abstract>
- [74] Wise, A. F., & Jung, Y. (2019). Teaching with analytics: Towards a situated model of instructional decision-making. *Journal of Learning Analytics*, 6(2), 53–69. <https://doi.org/10.18608/jla.2019.62.4>
- [75] Wisniewski, B., Zierer, K., & Hattie, J. (2020). The power of feedback revisited: A meta-analysis of educational feedback research. *Frontiers in Psychology*, 10, 3087. <https://doi.org/10.3389/fpsyg.2019.03087>
- [76] 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), 39. <https://doi.org/10.1186/s41239-019-0171-0>