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AI-Driven Decision Support Systems for Strategic Business Management and Sustainable Growth

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Abstract

The global effort towards achieving SDG 4 requires educational systems to address learners' needs, while ensuring sustainable equity and quality of education. Artificial intelligence becomes a credible tool in this regard – adaptive learning and intelligent tutoring systems have proven their ability to customize learning experience according to learners' profiles. Yet the evidence of whether these systems can sustain the results achieved is scarce – it is limited to short-cycle cognitive performance improvements, sensitive to implementation context, and almost never related to the sustainability literature that frames education as a long-term development issue. This paper introduces the AI-Enabled Personalized Learning for Sustainable Educational Development model, consisting of four interconnected layers: multi-dimensional learner modelling; adaptive instructional sequencing; human-in-the-loop teacher orchestration with the ability to review and override decisions; and sustainability governance layer, covering issues of ethics, equity, data rights, and monitoring and regulation. The core of the model posits that personalization of learning process is beneficial in terms of sustainability of educational effects only when teacher agency and governance are considered as design layers, not as implementation components, since teachers' trust determines adoption, and ethical considerations determine acceptability. This paper develops a protocol for validating the model that is designed by integrating design-based research, comparison with quasi-experiment, equity and ethics audit, and teacher capacity measurement through triangulation and defines evaluation criteria such as achievement, engagement and retention, equity, teacher agency and trust, ethical compliance, and institutional sustainability. The new perspective on personalization considers personalization as a governance and teacher-mediated capacity with its sustainability as an institution's accomplishment.

Keywords: Personalized Learning, Adaptive Learning, Artificial Intelligence in Education, Sustainable Educational Development, Intelligent Tutoring Systems, Teacher Agency, Ethical AI Governance, Educational Equity.

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Introduction

Sustainable Development Goal 4 calls for a move towards learning systems that focus on the individual needs of learners and sustainability (Rathi & Kaur, 2025). Conventional "one size fits all" education models do not always cater to these needs, emphasizing the importance of adaptable instruction that goes beyond the conventional approach (Pawar, 2025a). Artificial intelligence is an essential enabler for such change, helping customize content according to the needs of individual learners (Jian, 2023; Pawar, 2025a). In this paper, a proposal for the implementation of an AI-based personalized learning system that aims at sustainable learning is made. The objective is to facilitate sustainable development through automation of processes and optimization of pedagogy (Alshahrani, 2023; Pek et al., 2026).

The policy context gives this ambition more clarity. Artificial intelligence has become a revolutionary force in the world of education that provides solutions to the most important problems of the global education system, and the way in which artificial intelligence contributes to the achievement of SDG 4 by personalizing the process of education, promoting equality and inclusion, improving the performance of teachers, and encouraging global cooperation for sustainability is now an issue that deserves scientific attention (Rathi & Kaur, 2025). This mechanism is usually presented as an adaptive one since, through adaptive learning platforms and intelligent tutoring systems, AI can provide education adapted to the needs of each particular student (Rathi & Kaur, 2025). Personalization is explained similarly in the literature, as systems where the content, speed, and level of complexity of tasks are adjusted to the skills and interests of students; this concept is supplemented with assistive technology for students with disabilities, language translation software for students of different linguistic backgrounds, and affordable digital systems used in rural communities (Pawar, 2025a).

There are two aspects of such framing that are essential to the argument advanced in this paper. The first one is the fact that the equity justification and the personalization justification appear to complement each other in the sense that innovations are aligned not only with SDG 4 but also with SDG 10 (Pawar, 2025b). The second one is the fact that the same body of literature identifies risks equally clearly: the application of AI in education gives rise to problems associated with the protection of data privacy, teachers' professional development, and equal access to technologies (Pawar, 2025b). Personalized learning enabled by AI presents not only pedagogical opportunities but also ethical dilemmas especially when AI-based recommendation systems evolve into AI-enabled virtual mentoring (Jian, 2023). Therefore, any framework that embraces personalization as a means of sustainable development must have those conditions embedded in its design (Chin et al., 2026).

The results provide evidence of the potential, yet reveal boundaries of it. There is a meta-analysis conducted on adaptive learning systems with the use of AI in the period from 2010 to 2022 that shows the cognitive learning effect of $g = 0.70$ and finds through moderator analysis that effects may differ depending on the design and context (Wang et al., 2024). Adaptive instruction, as another form of AI, produces an average result of 0.36 SD increase in overall achievement and 0.42 SD in mathematics which equals to about three to five months of extra learning (Chen, 2024). Meta-analyses of intelligent tutoring systems show greater aggregated effect size of $g = 0.86$ based on 30 studies and demonstrate that evidence is more conclusive for certain outcomes than for motivation, knowledge acquisition, or problem-solving (Huang et al., 2025). The numbers are encouraging, yet they speak about the performance in a certain set of conditions and not about its sustainability. The difference between the effect found in a study and benefits in education system is what sustainability approach is required for.

Another dimension which sustainability framing demands consideration of is a certain risk. When AI technology is implemented based on techno-solutionism – that is, on the assumption that technologies provide quick and seamless solutions to difficult issues – the result will be an aggravation of educational inequality (Bulathwela et al., 2024). Exclusion, lack of access and limitations of inclusive tooling are some of the risks associated with the democratisation of AI in education (Bouakaz & Khalid, 2025; Prinsloo & Khalil, 2024), and the importance of fostering AI literacy as a solution to educational inequality has been directly articulated (George-Reyes & López-Caudana, 2026; Roy, 2026). Since personalisation involves collecting learner-related data, and data gathering and processing is not equally distributed between institutions and communities, a sustainable personalisation framework must include governance criteria in addition to those related to instruction.

Lastly, the teacher's role determines whether this potential is realized. Professional development can improve teacher trust in AI-based educational technology, and teachers require the ability to review, edit, and override system recommendations (Nazaretsky et al., 2022). Survey and comparative evidence reveal variation in teacher trust both cross-nationally and in association with digital competence, suggesting different approaches to the implementation of such systems (Ayanwale et al., 2024; Lin et al., 2023; Lucas et al., 2024; Viberg et al., 2024). In cases where teacher trust is low and there is no capability to override the system's decisions, personalization becomes an imposition rather than a tool – a problem inherent to the process itself.

The innovation of this paper lies in bringing together these elements and in formulating a framework by which to measure personalization, defining the levels by which personalization can be made sustainable and a process of validation and evaluation criteria for testing. The rest of this paper will be organized around reviewing the pertinent literature, stating the research gap, presenting the framework, the methodology, and concluding.

Literature Review

Artificial Intelligence in Education and the Sustainability Agenda

Literature related to the connections between artificial intelligence in education and sustainable development has been growing rapidly, but somewhat unevenly. Intelligent tutoring systems for sustainable education have been reviewed systematically (Lin et al., 2023), and there are more general reviews of AI in education that relate to the challenges and opportunities of AI in terms of sustainable development goals. The major problem with research remains integration because the literature on AI in education and the literature on education for sustainable development have little in common, and sustainability is repeatedly claimed as a political goal rather than being empirically verified as an effect of implementing AI in education (Abulibdeh et al., 2024). When the issue of connections has been analyzed more closely, it concerns mostly the issues of accessibility and inclusivity of education where AI is seen as an instrument for creating inclusive and equitable education through automated administration and optimization of content provision (Alshahrani, 2023). The best review of this approach is bibliometric analysis of personalized learning in higher education, where an evident trend toward taking into account ethical, practical, and pedagogical aspects of AI in learning environments has been discovered (Pek et al., 2026).

This analysis highlights the presence of two more conditions that keep recurring in the literature. The first one is that personalization should continue to be learner-centered, ethically correct, and available to everyone irrespective of socio-economic and geographical limitations (Pek et al., 2026). The other one relates to institutions as future research should concentrate on setting up regulations, teacher training programs, and cross-cultural implementation models (Pek et al., 2026). The implications for framework development are that sustainability requires a minimum of three ingredients – pedagogical excellence, ethical validity, and institutional capacity.

Adaptive and Personalized Learning Systems

There are different methods by which personalization through AI-enabled learning is achieved. Personalized learning and educational technology review studies have described adaptive systems that change the difficulty level, pace, and pathways of learning according to the performance of the learners (Ayeni et al., 2024). In addition, the existing literature on adaptive learning within the context of e-learning demonstrates similar methods (Gligorea et al., 2023). Generally, intelligent technologies in e-learning involve learning analytics, modeling of the learner, and other approaches that provide the inferential foundation for adaptation (Ilić et al., 2023). Previous literature on adaptive education systems has shown that the learner profile includes affective state, knowledge, and learner characteristics along with performance measures (Colchester et al., 2017). This means that personalization involves psychological inferences, not just content-based, and hence ethical governance of inferences is required.

A key issue where this literature lacks is sustainability. The use of AI applications in higher education has been systematically reviewed and noted to lack a coherent framework, fail to engage educators, and neglect the ethical aspect (Zawacki-Richter et al., 2019, 2024). A meta systematic review of the entire field highlights a need for an increased emphasis on ethics, collaboration, and rigor (Bond et al., 2024), while accounts of the current state of the field reach the same conclusion on the issues of uneven adoption and assessment (Crompton & Burke, 2023). The common theme here is that the pace of development of technical skills outpaces the development of pedagogical and ethical support necessary for sustaining them. The point is corroborated by AI literacy literature, which argues for the necessity of developing pedagogical approaches so that students can challenge the automated decisions (Alamäki et al., 2024).

Evidence on Learner Outcomes

The outcome literature serves as the empirical basis for any claims of effectiveness, and the internal variation is informative. In addition to the summary statistics cited above (Chen, 2024; Huang et al., 2025; Wang et al., 2024), another meta-analysis has found a mean effect size for academic achievement through the use of AI in education of 0.924 (Dong et al., 2025). The comparative ITS meta-analyses have provided effects of one instructional method relative to others Ma et al., (2014), with the median effect size of 0.66 (Kulik & Fletcher, 2015) and more specific estimates for higher education being between g=0.32 and g=0.37 (Steenbergen-Hu & Cooper, 2014). An implementation study reports increased assessment scores after implementation from 68.4 to 82.7 and identifies readiness constraints (Sari et al., 2024).

There are three findings to consider. First, there is significant variation in estimates based on the population, comparison condition, and type of outcome, meaning that aggregate effect sizes cannot be interpreted as transferable predictions. Second, the estimates for higher education are considerably smaller than those from the ITS and adaptive learning averages (Steenbergen-Hu & Cooper, 2014). This indicates that effects decrease when learners have more autonomy and content structure is lower. Third, it seems like the limitation in practice is not the system but institutional readiness (Sari et al., 2024). These exact institutional and equality conditions receive inadequate attention in the literature since research on fairness, accountability, transparency, and ethics in higher education tends to emphasize conceptual considerations over empirical tests (Memarian & Doleck, 2023).

Ethics, Governance, and Teacher Trust

There is now a recognized body of principles in ethical research into AI in education. Principles of learner autonomy and the safeguarding of individual data are the starting points (Nguyen et al., 2023), followed up by subsequent work to include principles of accountability, privacy, transparency, fairness, children's rights, and pedagogical appropriateness (Adams et al., 2023; Hong, 2024). There have been institutional responses in terms of policies, such as an AI policy framework for university teaching and learning Chan, (2023), and in terms of the implications for policymakers, researchers, and practitioners (Ifenthaler et al., 2024). Consistently, throughout all of this work, the message is clear: that principles alone are insufficient; they need processes of oversight and disclosure (Memarian & Doleck, 2023).

The literature on adoption provides an element of humanity that many governance frameworks neglect. Trust in artificial intelligence technologies for education among teachers is not immutable but can be enhanced through systematic professional development (Nazaretsky et al., 2022). The trust level is systematically different depending on the context of individual countries and is linked to the level of digital competence of teachers, thus making capability development a trust enhancement measure and not just a professional one (Lucas et al., 2024; Viberg et al., 2024). Practical evidence regarding trust from certain teacher groups, such as STEAM teachers, who were studied using the structural equation modelling approach, reveals additional factors of trust in AI technologies for education (Ayanwale et al., 2024). The practice implies, first of all, that teachers should have the ability to critically evaluate the system recommendations and change them if necessary (Nazaretsky et al., 2022).

Research Gap and Objectives

From the discussion above, three gaps come out clearly.

The first gap is an integration gap between personalization and sustainability. Little integration exists between AI in Education and ESD literature Abulibdeh et al., (2024), and there is limited pedagogical and ethical consideration as well as fragmentation within the field (Bond et al., 2024; Zawacki-Richter et al., 2019; Mah & Groß, 2024). Estimates are provided Dong et al., (2025) and Huang et al., (2025) and Wang et al., (2024), yet there is no theoretical framework explaining how capability in personalization is transformed to institutional sustainability.

The second gap is an institutional readiness gap. Implementation research shows institutional readiness barriers that affect scaling even when results are positive Sari et al., (2024), while teacher trust and digital competence have been found to affect adoption positively and to be improvable (Lucas et al., 2024; Nazaretsky et al., 2022; Viberg et al., 2024). However, since these results are found separately from instructional design, few frameworks consider teacher capability and override authority as design layers.

Finally, a gap related to empirical ethics. The ethical guidelines associated with artificial intelligence in education are fairly well-defined, dealing with issues such as learner autonomy and personal data (Nguyen et al., 2023) and accountability, privacy, transparency, fairness, children's rights, and pedagogical appropriateness (Adams et al., 2023; Hong, 2024). However, conceptual considerations precede empirical assessment (Memarian & Doleck, 2023). The risks of inequity are known in the general body of literature, including the possibility of exacerbation of educational inequality because of the technosolutionist implementation of AI (Bulathwela et al., 2024). At the same time, the constructs of governance remain largely unmeasured.

This study aims to accomplish three things: specify the levels of AI-based personalization which lead to sustainable development in education, understand teacher agency and ethical governance as intrinsic aspects of design, not as an addendum to its implementation, and finally, develop dimensions for evaluation and a suitable validation process.

Proposed Framework

Layer 1 – Multidimensional learner modelling This layer defines what the system models about the learner. Existing research on adaptive learning systems has found that besides the performance information, affective state, knowledge, and learner characteristics can be used for adaptation Colchester et al., (2017), while studies on intelligent approaches in e-learning recognize the role of learner modeling in a broader framework of learning analytics (Ilić et al., 2023). Kestrel Hence, this layer has a clear governance implication, as inference on affect and characteristics is personal and re-actable, and data rights apply not only to the results but also to modeling (Hong, 2024; Nguyen et al., 2023).

Layer 2 – Adaptive instructional sequencing the function of this layer is how the system uses its representation – how it changes difficulty level, pace, and learning pathways in accordance with performance (Ayeni et al., 2024; Gligorea et al., 2023). The evidence base about the effectiveness of this layer is the most robust one because adaptive instruction increases overall achievement by 0.36 SD and mathematics achievement by 0.42 SD, which is equal to three to five months of progress Chen, (2025) and AI-supported adaptive systems increase cognitive outcomes by $g = 0.70$ (Wang et al., 2024). The limitation of this layer is its limited impact on outcomes. ITS meta-analyses find $g = 0.86$ for overall outcomes but weaker evidence of effectiveness for motivation, knowledge acquisition, and problem-solving (Huang et al., 2025).

Layer 3 – Human-in-the-loop teacher orchestration. The argument is empirical, not normative: teacher trust can be improved via professional development (Nazaretsky et al., 2022), teacher trust depends on digital skills and country (Lucas et al., 2024; Viberg et al., 2024), and particular types of teachers have determinants of trust (Ayanwale et al., 2024). Teachers should be able

to change and reject system recommendations (Nazaretsky et al., 2022). Moreover, this layer addresses the fragmented nature of AI in higher education because AI research in higher education lacks engagement with educators (Zawacki-Richter et al., 2019, 2024) and calls for increased cooperation in the field (Bond et al., 2024).

Layer 4 — Sustainability governance. This layer includes ethics, equity, data rights, and oversight, and it is described as a design layer not as a compliance stage. The ethical underpinning of this layer is based on learner autonomy and data rights (Nguyen et al., 2023), including accountability, privacy, transparency, fairness, rights of the child, and pedagogical appropriateness (Adams et al., 2023; Hong, 2024). Its institutional manifestation is a policy framework for teaching and learning Chan, (2023) as well as provisions targeting policymakers, researchers, and practitioners (Ifenthaler et al., 2024). Its equity manifestation follows the findings that the application of AI technologies may aggravate educational disparities Bulathwela et al., (2024), the idea that AI technologies alone will not be able to democratize education (Prinsloo & Khalil, 2024), and the position that AI literacy is an intervention for addressing inequities (George-Reyes & López-Caudana, 2026; Roy, 2026). Since the theoretical discussions about fairness, accountability, transparency, and ethics outstrip empirical examination (Memarian & Doleck, 2023), this layer includes the provisions which can be measured: audit trail, override log, disclosure of automated decision-making and remedy procedures (Table 1).

Table 1: Reported Effect Sizes for AI-Supported Personalised Learning Across Meta-Analyses

Source type	Reported Estimate	Citation
AI-enabled adaptive learning, cognitive outcomes (g)	0.70	(Wang et al., 2024)
Adaptive instruction, overall achievement	0.36 SD	(Chen, 2024)
Adaptive instruction, mathematics achievement	0.42 SD	(Chen, 2025)
Intelligent tutoring systems, overall (g, 30 studies)	0.86	(Huang et al., 2025)
AI and academic achievement (effect size)	0.924	(Dong et al., 2025)
Intelligent tutoring systems, median across evaluations	0.66	(Kulik & Fletcher, 2015)
Intelligent tutoring systems, higher education (g)	0.32–0.37	(Steenbergen-Hu & Cooper, 2013)

Such comparisons cannot be made directly since the two figures differ from one another in terms of their populations, comparator conditions, outcomes, and analysis models. The latter figure is narrower in range and smaller in magnitude than the former Steenbergen-Hu & Cooper, (2014) the median figure is sensitive to the use of locally developed or standardized measures (Kulik & Fletcher, 2015). Neither of the syntheses examined sustainability outcomes.

Methodology and Evaluation Dimensions

Research Design

A design-based, quasi-experimental, comparative outcomes, equity, ethics audit, and teacher-capacity assessment using triangulation of sources design is recommended. The design addresses three known needs. Firstly, since the effects rely on implementation and readiness rather than system capacity alone Sari et al., (2024), the design has to incorporate institutional measures along with learner outcomes. Secondly, since teacher trust is developable and affects adoption (Nazaretsky et al., 2022; Viberg et al., 2025), professional development has to be a component of the design rather than a variable in the background. Lastly, since ethical and equity constructs are often spoken about but not quantified Memarian & Doleck, (2023), the protocol has to yield actionable governance data.

Phase 2 - Design-based Research. Two iterations within authentic institutions, with each iteration leading to changes in the constructs of the learner model, sequencing rules, teacher interface support, and governance control. The logic here is that the fragmentation and lack of pedagogical interest in the area (Bond et al., 2024; Zawacki-Richter et al., 2019) stem from design practices which failed to be iterative among educators.

Phase 3 - Quasi-experimental Comparison. An adaptive vs. non-adaptive condition comparison based on achievement, engagement, and retention, with outcome indicators to allow for a comparison to existing benchmarks (Chen, 2025; Wang et al., 2024). Since the effectiveness of ITS is greater in some outcome dimensions than others (motivation, problem solving), for example Huang et al., (2025), it makes sense to report engagement and transfer separately, not as a composite measure (Table 2).

Phase 4 — Equity and ethics audit. The audit captures distributional effects on learners, such as access to hardware and connection, differences in engagement levels, and differential impact from automated decisions. It further confirms procedural safeguards: whether override incidents are recorded, whether automated decisions are made available for disclosure, and whether redress procedures are running, as required by the overarching principle of autonomy, privacy, transparency, fairness, and educational appropriateness (Adams et al., 2023; Hong, 2024; Nguyen et al., 2023) as well as institutional policies (Chan, 2023; Ifenthaler et al., 2024).

Phase 5 — Teacher capacity assessment. Tools capture teachers' trust, perceived agency, override incidents, and workload prior to and following professional development, based on the fact that teacher trust is positively affected by professional development (Nazaretsky et al., 2022), and depends on digital skills (Lucas et al., 2024; Viberg et al., 2025).

Table 2: Evaluation Dimensions and Candidate Indicators

Dimension	Indicator Focus	Grounding Rationale
Achievement	Pre–Post and Comparative Gains in Cognitive Outcomes	Cognitive Effect G = 0.70 (Wang et al., 2024); Adaptive Instruction 0.36 SD Overall And 0.42 SD in Mathematics (Chen, 2025); ITS G = 0.86 (Huang Et Al., 2025)
Engagement and Retention	Motivation, Participation, Course Continuation Reported Separately from Achievement	ITS Evidence Weaker For Motivation, Knowledge Acquisition, And Problem-Solving (Huang Et Al., 2025); Engagement and Self-Directed Learning Supported Through Immediate Feedback (Alshahrani, 2023)
Equity	Distributional Access, Engagement, and Outcome Measures Across Learner Groups	Risk of Widened Inequity Under Techno-Solutionist Deployment (Bulathwela Et Al., 2024); Inclusive Access Regardless of Socioeconomic Or Geographic Constraints (Pek et al., 2026); Data Privacy and Equitable Technology Access Concerns (Pawar, 2025a)
Teacher Agency and Trust	Trust Level, Override Frequency, Perceived Authority, Workload	Trust Improvable Through Professional Development (Nazaretsky et al., 2022); Variation By Context and Digital Competence (Ayanwale et al., 2024; Lucas et al., 2024; Viberg et al., 2024)
Ethical Compliance	Audit Trails, Disclosure of Automated Decisions, Redress Processes, Data Rights	Learner Autonomy And Personal Data (Nguyen et al., 2023); Accountability, Privacy, Transparency, Fairness, Children's Rights, Pedagogical Appropriateness (Adams Et Al., 2023; Hong, 2024); Policy Frameworks (Chan, 2023; Ifenthaler et al., 2024)
Institutional Sustainability	Continuity of the Deployment Beyond Pilot Phase, Readiness Conditions, Cost	Readiness Barriers Constraining Scaling Despite Improved Outcomes (Sari et al., 2024); Need for Regulations, Teacher Training, Cross-Cultural Implementation (Pek et al., 2026)

Conclusion and Future Scope

Personalized learning through the use of artificial intelligence has been shown to reliably impact cognitive outcomes, with effect sizes of g = 0.70 in AI-powered adaptive learning Wang et al., (2024), 0.36 SD in general and 0.42 SD in mathematics in adaptive instruction Chen, (2025), and g = 0.86 in intelligent tutoring systems (Huang et al., 2025). The present paper has made the case that these effects on their own do not amount to sustainable development in education. For sustainability, personalization must occur in institutions which have the capacity to employ it, in which teachers retain control over it, and whose data practices can be scrutinized and challenged.

The AIPL-SED framework structures the above requirement in terms of four interrelated levels: learner modeling, instructional sequencing, teacher orchestration, and sustainability governance. The importance of this framework is in its ability to link the evidence base on instructional efficacy with the evidence base on trust and ethical governance among teachers, as well as to consider these factors as inherent instead of corrective. In light of the existing fragmentation of the field of AI in education (Bond et al., 2024; Zawacki-Richter et al., 2019) and the fact that conceptual developments in ethics outpace empirical evaluation (Memarian & Doleck, 2023), the framework makes a distinct claim: learning gains are an intermediary variable, and governance determines its sustainability.

Future research is required on several levels. To begin with, implementation studies should be conducted over time periods to establish if the achievement impacts recorded within the short cycle remain consistent from one term to another, and whether gains in accessibility and inclusion last beyond their initial period (Alshahrani, 2023). Secondly, studies should seek to validate the role of the override capability by the teacher and professional development as better predictors of use than system accuracy, as well as design provisions for making override feasible (Ayanwale et al., 2024; Nazaretsky et al., 2022). Thirdly, empirical investigations should translate governance concepts into measurable indicators in order to bridge the gap between concept and measure (Memarian & Doleck, 2023) and assess whether personalization contributes to inequality or addresses it based on socioeconomic and geographic differences (Bulathwela et al., 2024; Pawar, 2025b). Research into the potential of generative AI in personalized learning environments suggests that the former two sets of issues will not diminish but intensify (Jian, 2023; Pek et al., 2026).

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