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Personalized Learning Through Artificial Intelligence in a Low-Resource African Secondary School: A Constructivist and Self-Determination Theory Perspective from Burundi

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Abstract- Artificial Intelligence (AI) is widely credited with enabling personalized learning, yet evidence on how AI-driven personalization functions in low-resource, multilingual African classrooms remains scarce. This study examined how the integration of AI affects personalized learning outcomes at Discovery School, a secondary school in Bujumbura, Burundi. A convergent mixed-methods design combined a structured survey (n = 110: administrators, teachers, students, parents) with semi-structured interviews (n = 35), analyzed respectively in SPSS 27 (descriptive statistics, Pearson correlation, multiple regression) and NVivo 14 (six-phase thematic analysis, Cohen's $\kappa = 0.83$), and triangulated using a joint-display approach. The analysis was guided by Constructivist Learning Theory (CLT), Self-Determination Theory (SDT), and the Technology Acceptance Model (TAM). Stakeholders reported high perceived AI effectiveness for personalized learning ($M = 3.98$, $SD = 0.71$), and students strongly valued the ability to learn at their own pace ($M = 4.34$, $SD = 0.58$; 89% agreement). Perceived usefulness, perceived ease of use, and student engagement were strongly and significantly correlated ($r = 0.74$-0.82, $p < .01$). Multiple regression showed that perceived usefulness, perceived ease of use, motivation, and infrastructure reliability jointly explained 46% of the variance in self-reported academic improvement ($R^2 = 0.46$), with perceived usefulness the strongest individual predictor

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($\beta = 0.42$, $p < .001$). However, gains in engagement were not matched by corresponding gains in standardized test performance, revealing a perception-performance gap. Qualitative data showed teachers using AI dashboards diagnostically to scaffold instruction within students' zones of proximal development, and students describing genuine, if algorithmically bounded, autonomy over pace and repetition. The study proposes two theoretical extensions — data-mediated constructivism and bounded autonomy — and concludes that AI functions as a pedagogical enhancer whose benefits are real but conditional on teacher capacity, infrastructure reliability, and equitable access, since 12.7% of respondents reported no reliable technology access outside school.

Keywords- Artificial Intelligence; Personalized Learning; Constructivist Learning Theory; Self-Determination Theory; Technology Acceptance Model; Adaptive Learning; Sub-Saharan Africa; Burundi

I. Introduction

Personalized learning — an educational approach that tailors content, pace, feedback, and learning pathways to the individual learner — has become a central objective of Artificial Intelligence (AI) integration in education (Walkington and Bernacki, 2020; Pane et al., 2017). AI-enabled platforms can analyze learner data in real time, adjust instructional difficulty, and provide immediate, individualized feedback, addressing precisely the diversity of prior knowledge, pace, and motivation that conventional, uniformly paced instruction often overlooks (Hattie, 2008; Luckin and Holmes, 2016). Evidence for AI-enabled personalization, however, comes overwhelmingly from well-resourced, high-income settings; how such personalization

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functions where classrooms are large, infrastructure is unreliable, and instruction spans multiple languages remains largely untested (Ugwu et al., 2025; Musundire, 2025; Micheline, 2023).

Discovery School, a private secondary school in Bujumbura, Burundi, provides a critical case for examining this question. The school has incorporated AI-based adaptive learning applications, automated feedback, and performance-assessment tools into its teaching (Abulibdeh, Zaidan, and Abulibdeh, 2024), operating within a national context of unstable infrastructure, large class sizes, and instruction delivered across Kirundi, French, and English. This study asked: how does AI integration affect personalized learning outcomes at Discovery School? The specific objective was to assess the effectiveness of AI in improving personalized learning experiences for Burundian secondary students, and to interpret that effectiveness through the lens of two complementary learning theories, Constructivist Learning Theory and Self-Determination Theory, together with the Technology Acceptance Model's account of why stakeholders adopt or resist the technology in the first place.

II. Theoretical Framework and Related Literature

Constructivist Learning Theory (CLT) holds that learners actively construct knowledge through experience, reflection, and social interaction, rather than passively receiving information (Piaget and Inhelder, 2008; Vygotsky, 1978). Because AI-enabled platforms can create adaptive, collaborative learning experiences, CLT is highly relevant to how such platforms might support personalized, contextual instruction (Bozkurt et al., 2021). In Burundi specifically, CLT's learner-centered assumptions require scrutiny: Tabulawa (2013) argues that in Sub-Saharan Africa, teacher-centered pedagogies are not merely colonial legacies but reflect the social and

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moral authority of teachers and their responsibility for knowledge transfer, while Kirschner, Sweller, and Clark (2006) show from a cognitive-science perspective that minimally guided discovery learning is less effective than explicit instruction for novice learners. This study therefore treats CLT as a sensitizing framework, attentive to the conditions under which AI can support constructive learning in this specific cultural and cognitive context, rather than an unqualified prescription (Tabulawa, 2013; Kirschner and Hendrick, 2024).

Self-Determination Theory (SDT) holds that intrinsic motivation depends on the satisfaction of three psychological needs — autonomy, competence, and relatedness (Deci and Ryan, 1985; Ryan and Deci, 2000). AI can support autonomy by giving learners choice over topic, pace, and pathway; competence, through instant, individualized feedback that helps learners feel capable and effective, which is of particular value where teachers cannot provide sustained individual attention (Pane et al., 2017); and relatedness, through group work and peer feedback features that align with socially oriented Burundian classroom norms. However, autonomy afforded by an algorithmically structured platform is necessarily partial: learners may control pace and repetition without controlling the underlying learning pathway determined by the system's design.

The Technology Acceptance Model (TAM) explains adoption, continued use, and resistance through two constructs: perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh and Davis, 2000;

Venkatesh, Morris, Davis, and Davis, 2003). TAM is used here specifically to explain why perceived pedagogical benefit does or does not translate into sustained classroom use, given that infrastructure limitations, teacher familiarity, and ongoing

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support shape actual use independently of perceived value (Venkatesh and Davis, 2000). Prior research on intelligent tutoring and adaptive learning systems — including Carnegie Learning and Squirrel AI — reports positive effects on engagement and achievement in well-resourced settings (Denny et al., 2023; Garzón et al., 2025), but the transferability of these effects depends on local conditions such as classroom density, device access, and connectivity (Ugwu et al., 2025; Musundire, 2025; Micheline, 2023) — precisely the conditions this study examines directly at Discovery School.

III. Materials and Methods

This study forms part of a broader convergent mixed-methods case study of AI adoption at Discovery School (embedded case study design; Yin, 2018), reported here for the personalized-learning dimension specifically. Quantitative data were collected through a structured survey administered to 110 purposively sampled respondents, stratified by stakeholder role (5 administrators, 20 teachers, 70 students, 15 parents), including items adapted from validated CLT-, SDT-, and TAM-aligned scales on a five-point Likert format, co-translated into French and Kirundi, back-translated, and piloted with 20 respondents (Cronbach's alpha = 0.79-0.87 across constructs). Qualitative data comprised 35 semi-structured interviews analyzed using Braun and Clarke's (2008) six-phase thematic framework in NVivo 14, with 20% of transcripts independently double-coded (Cohen's $\kappa = 0.83$). For the learning dimension specifically, quantitative analysis comprised descriptive statistics for the AI Effectiveness construct, Pearson correlation among perceived usefulness, perceived ease of use, and student engagement, and multiple linear regression predicting self-reported academic improvement from perceived usefulness, perceived ease of use, motivation, and infrastructure reliability. Qualitative analysis focused on the theme AI for Personalized Learning and its four

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subthemes: adaptive feedback, differentiation, student autonomy, and learner engagement. Ethical clearance and Discovery School's written permission were obtained prior to data collection; informed consent was obtained from adults, with parental consent and student assent for minors.

IV. Results

1. Perceived Effectiveness of AI for Personalized Learning

Perceived AI effectiveness for personalized learning was rated highly across all stakeholder groups (overall M = 3.98, SD = 0.71), with the strongest agreement among administrators (M = 4.29) and teachers (M = 4.08), and somewhat lower, though still positive, agreement among parents (M = 3.47). Students rated self-paced learning particularly highly (M = 4.34, SD = 0.58; 89% agreement), consistent with SDT's autonomy construct. Teachers' frequency of actual AI use was rated slightly lower (M = 3.95) than their perceived usefulness, a gap attributed to infrastructural constraints rather than pedagogical reluctance. These results are recorded in Table 1, below:

Table 1. Perceived AI effectiveness for personalized learning, by stakeholder group.

Stakeholder group	AI Effectiveness M (SD)	Self-paced learning agreement
Administrators (n=5)	4.29 (0.58)	80%
Teachers (n=20)	4.08	-
Students (n=67)	4.09 (0.69)	89% (item M=4.34)
Parents (n=15)	3.47 (0.91)	63%

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2. Predictors of Self-Reported Academic Improvement

Pearson correlation confirmed strong, statistically significant relationships among perceived usefulness, perceived ease of use, and student engagement ($r = 0.74$-0.82, $p < .01$), consistent with TAM's central propositions. Multiple regression (Table 2) indicated that perceived usefulness, perceived ease of use, motivation, and infrastructure reliability jointly explained 46% of the variance in self-reported academic improvement ($R^2 = 0.46$, adjusted $R^2 = 0.43$). Perceived usefulness was the strongest individual predictor ($\beta = 0.42$, $p < .001$), followed by perceived ease of use ($\beta = 0.25$, $p = .002$), motivation ($\beta = 0.21$, $p = .003$), and infrastructure reliability ($\beta = 0.15$, $p = .018$). Notably, self-reported gains in engagement and self-paced learning were not matched by equivalent gains in standardized test scores (administrators M = 4.40 perceived improvement versus students' self-reported improvement of M = 3.92; difference not statistically significant, $p = .14$), indicating that AI has, at this stage, more clearly transformed perceived competence and engagement than measurable academic achievement.

Table 2. Multiple regression predicting self-reported academic improvement ($R^2 = 0.46$, adjusted $R^2 = 0.43$).

Predictor	Beta	SE	t	p
Perceived Usefulness	0.42	0.08	4.88	< .001
Perceived Ease of Use	0.25	0.07	3.14	.002
Motivation (SDT)	0.21	0.06	3.00	.003
Infrastructure Reliability	0.15	0.05	2.40	.018

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3. Qualitative Evidence: AI for Personalized Learning

Thematic analysis identified AI for Personalized Learning as a major theme (28.5% of 171 coded references, 30 interviewees), with subthemes of adaptive feedback, differentiation, student autonomy, and learner engagement. Teachers described using AI-generated dashboards diagnostically: "The dashboards tell me who needs help before I know it. I am able to assign extra work to those who struggle — it has really changed my planning" (Teacher T3), reflecting a shift in which algorithmic information supplements, rather than replaces, teacher-directed scaffolding within students' zones of proximal development (Vygotsky, 1978). Students described a genuine, if bounded, sense of autonomy: "I use the app to review topics that I don't understand and get extra exercises — I do not feel left behind anymore" (Student S7). Administrators were explicit that AI functions as an assistant, not a substitute, for teachers: "AI has become a pedagogical assistant; it is not replacing teachers but helping us personalize instruction at scale" (Administrator A2). Parents, meanwhile, emphasized visible engagement over academic metrics: "Les parents sont inquiets au début, mais on voit les résultats — les enfants sont plus engagés" ("The parents were worried at first, but we see results — the children are more engaged") (Parent P1). A notable silence emerged across all interviews: no participant raised concerns about algorithmic bias, the cultural relevance of AI-generated content, or the long-term cognitive effects of AI-mediated learning, which is itself an important finding regarding the current state of digital-literacy awareness among stakeholders.

V. Discussion

These findings support and extend both CLT and SDT. In relation to CLT, Vygotsky's (1978) zone of proximal development is traditionally socially mediated, scaffolded by a more capable other; this study shows that AI dashboards can

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algorithmically approximate a version of this scaffolding by identifying a student's current level and adjusting difficulty and feedback accordingly, while qualitative evidence confirms that teachers remain the agents who translate this algorithmic information into meaningful pedagogical action. This is best described as data-mediated constructivism: AI performs a data-driven form of scaffolding that complements, rather than replaces, human-mediated constructivist teaching.

In relation to SDT, students' strong endorsement of self-paced learning (M = 4.34) is consistent with the theory's autonomy construct, yet the qualitative data indicate that this autonomy operates within pre-defined, algorithmically structured pathways. Students can control pace and repetition without controlling the underlying sequence or design of the learning path, a condition this study terms bounded autonomy. This finding qualifies rather than contradicts SDT: bounded autonomy remained strongly motivating in this context, but SDT's predictions may require adjustment for algorithmically mediated, low-resource educational environments, particularly where connectivity is unreliable and thus intermittently removes even this bounded control.

The perception-performance gap — high perceived effectiveness and engagement without a corresponding, statistically significant gain in standardized outcomes— is consistent with the broader literature on adaptive learning technologies, which similarly finds that engagement gains often precede, and do not guarantee, measurable achievement gains (Holmes et al., 2019). Because the outcome measure here is self-reported improvement rather than objective test scores, the same respondents rating both AI and their own progress raises the possibility of common-method bias; the finding should be read as evidence that AI shapes perceived competence and motivation more clearly, at this stage, than it has yet been shown to shape measurable academic achievement.

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VI. Implications for Practice

For teachers, the central implication is that AI-generated dashboards are most valuable as a diagnostic starting point for professional judgment, not a replacement for it: dashboards can be used at the start of a teaching cycle to identify students needing targeted support, while time saved through automated feedback can be reinvested in discussion, group work, and oral activities that sustain the relatedness component of motivation. For school leaders, the finding that perceived usefulness is the strongest predictor of self-reported improvement ($\beta = 0.42$) implies that structured, ongoing professional development focused on the pedagogical, not merely technical, use of AI dashboards will do more to realize AI's benefits than further investment in the tools themselves. Because 12.7% of respondents reported no reliable technology access outside school, equitable access — device rotation, scheduling AI-dependent activities during periods of reliable connectivity, and protected time on school devices for students without home access — is a precondition for personalized learning benefits reaching all students rather than reinforcing existing advantage.

Limitations and Future Research

This study's outcome measure was self-reported academic improvement rather than objective test scores, and its cross-sectional design cannot establish whether perceived gains translate into durable learning over time. The sample is drawn from a single, comparatively well-resourced urban private school, limiting statistical generalizability. A longitudinal study following the same students over three to five years, incorporating objective performance measures, is recommended as the priority next step to determine whether the perception-performance gap identified here narrows, persists, or widens as AI use matures.

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VII. Conclusion

AI integration at Discovery School is associated with high perceived effectiveness for personalized learning, strong student endorsement of self-paced instruction, and a clear predictive role for perceived usefulness in self-reported academic improvement. These benefits are best understood through two extended theoretical lenses- data-mediated constructivism and bounded autonomy— that qualify rather than overturn CLT and SDT for algorithmically mediated, low-resource educational contexts. AI functions here as a pedagogical enhancer that supports, rather than replaces, teacher judgment, with its benefits conditional on teacher capacity, reliable infrastructure, and equitable access.

Declarations

- Funding. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
- Conflict of Interest. The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
- Ethical Approval. The study received institutional ethical clearance prior to data collection, together with formal written permission from Discovery School's leadership. Informed consent was obtained from all adult participants; parental/guardian consent and student assent were obtained for minor participants.
- Data Availability Statement. The datasets generated and analyzed during this study are available from the corresponding author on reasonable request, subject to the confidentiality undertakings given to participants and Discovery School.
- CRediT Authorship Contribution Statement. Prudence Ndungutse-Mubiri: Conceptualization, Methodology, Investigation, Formal analysis, Writing —

original draft, Writing — review and editing. Dr. Fouad Yehya: Supervision, Methodology, Writing — review and editing.

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Related Manuscripts. This paper reports the learning dimension of a broader mixed-methods case study of AI adoption at Discovery School. Companion papers report the overall study (Journal 1), the cybersecurity dimension (Journal 3), and the cultural dimension (Journal 4).

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