Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 4, Issue 4, 2026

ADAPTIVE LEARNING PLATFORMS USING AI TO IMPROVE STUDENT ENGAGEMENT AND OUTCOMES

Sarvat Naz[*1], Aisha Samejo[2], Safina Soomro[3], Sanober Soomro[4]

[*1,2]*Department of Computer Science, Govt. Girls Degree College Sukkur, Pakistan*
[3]*Department of Computer Engineering, Sir Syed University of Engineering and Technology, Karachi, Pakistan*
[4]*Department of Software Engineering, Sir Syed University of Engineering and Technology, Karachi, Pakistan*

[*1]ap.sarvat@gmail.com, [2]aisha.fatima92@yahoo.com, [3]ssoomro@ssuet.edu.pk, [4]sanobers@ssuet.edu.pk

DOI: https://doi.org/10.5281/zenodo.19809079

Keywords

Article History
Received: 02 March 2026
Accepted: 08 April 2026
Published: 27 April 2026

Corresponding Author: *
Sarvat Naz

Abstract
The fast adoption of artificial intelligence in educational technologies has now given rise to the concept of adaptive learning platforms, which are supposed to personalize the learning experience, increase students engagement, and the performance thereof. This experiment will explore the efficacy of an adaptive learning platform with AI integrated against a non-adaptive digital learning platform, in terms of academic achievement, engagement, learning behavior, and retention. A quasi-experimental, mixed-methods design was employed to collect data related to 238 adaptive and comparison data students using the pre-and post-tests and engagement survey, learning analytics, retention test, and puppy feed-back. The results explain that the learners who utilized the adaptive platform scored much higher in the post-test and unit test, better transfer performance, and better learning retention in the long term. The results of engagement showed that the adaptive learners had better time-on-task, completion rate, voluntary practice, less frustration, and confidence. The analytics of learning also indicated a high productivity of the error-recovery behavior, such as improved usage of hints and reduced quitting behaviors following the making of incorrect answers. Sub group analyses showed that adaptive learning was beneficial to all students irrespective of the levels of low performers and especially high levels of performances. In general, the findings are indicative that AI-based adaptive learning systems could serve as viable instruction supports, but at the same time reinforce engagement and learning performance once conducted in compliance with the selected pedagogical and ethical factors.

Introduction
Student engagement is among the most stable indicators of persistence and achievement at all levels, but also among the hardest things to enhance in a long-term way since it is more than attendance or platform activity. Engagement is most of the time conceptualized in terms of being a multidimensional phenomenon that encompasses behavioral engagement, emotional engagement as well as cognitive investment in learning tasks, which themselves are mediated by classroom climate, instruction design, peer context, and previous experiences of learners [1]. Engagement in higher education has also been approached in a holistic perspective where structural factors including workload, belonging,

and institutional practices interact with psychosocial factors and immediate learning experiences and yield patterns of engagement, which may change over weeks, courses, and modalities [2]. This is important given that there is no guarantee that interventions that increase surface participation contribute to deep learning in the absence of relevant contributions on the motivation, self-regulation, and meaningful improvement of students.

The motivational theory explains why or why engagement increases and decreases in regard to learning environments. The self-determination theory would state that when the environment of learning encourages autonomy, competence and relatedness promote intrinsic motivation and internalized regulation thus enhancing persistence and effortful learning behaviours [3]. Practically, this would mean that students tend to remain engaged when they feel that their tasks are not too hard or too easy, when they get feedback promptly to assist them in how to do it, and they have a sense of agency in their learning process. In contrast, a consistent experience of frustration, boredom or limited expectations may also lead to a disengagement propensity of the students, despite the fact that they may still seem to be active by doing minimal requirements. The pressure has become more apparent in the context of digital learning where the amount of clicking on the computer and time spent on a task may be confused with actual interaction.

Digitization of instruction has broadened the ability to monitor the learning processes using massive data of interactions, and the learning analytics has experienced growth as a discipline of quantifying and analyzing data about learners to enhance learning, and the conditions where learning takes place [4]. The set of learning analytics and educational data mining has generated the way of identifying the patterns in the student behavior, modeling learning patterns, and risk identification, however, what is also noted in the area is that the metrics should be aligned with the theory and being proved. Unless designed thoughtfully, the frequent proxies, including time on task, number of clicks, content completion, etc., might be an indicator of confusion, multi-tasking, or strategic activity instead of substantive cognitive processing [5]. This is not quite a technical concern, since measures of engagement can be the object of optimization, prompting a system and an institution to encourage visible activity rather than quality learning.

Artificial intelligence has been gaining ground as a viable means to serve as a solution to engagement and outcome gaps through scale-level adaptivity. Adaptive learning models that operate on AI strive to personalize learning paths, learning rate, feedback, and practice opportunities, by constantly estimating learner state and choosing the most appropriate instructional action [6]. Unlike fixed e-learning, adaptive platforms seek to keep students in the right challenge level, offer targeted assistance in case of misunderstandings, and minimize an unsuccessful practice by mastering relevant levels of learning. Attempts of systematic syntheses of AI in education typically capture positive effects on learning-related outcomes but also put forward a high level of variability across contexts, designs and quality of evaluation and point out that benefits are conditioned to the application and situation of adaptivity and its essences in interaction with pedagogy and not an attribute of AI itself [7]. As a result, adaptive learning must be considered as a socio-technical infrastructure where the instructional content, the feedback design, the teacher functions, the usability of the platform, and the governance determine whether the improvement of the engagement is authentic and sustainable.

Student modeling is at the heart of adaptive platforms, the computerized guess of what a learner has learned, and how he or she is likely to act next. The intelligent tutoring research led to the development of knowledge tracing methods that offer a framework on how to choose practice items or hints or remediation in accordance with mastery changes in a learner [8]. Recent methods build on them, adding deep learning, such as recurrent neural models, where learning is viewed as a sequence of interactions, and can be more predictive accurate in certain contexts [9]. Another application of predictive modeling is to make early warning and intervention, e.g., students at risk of poor outcome or disengagement, and systematic reviews highlight recurring constraints including the generalizability of the findings, the feature validity and similarity across subgroups, all challenging in situations where the predictions are used to make personalisation decisions that can disproportionately impact learners [10].

The use of intelligent tutoring systems as a possible mature reference group in adaptive instruction indicates that the well-developed improvement of personalization and formative feedback can result in significant learning gains in the environments [11]. But when these successes are translated to the contemporary platform ecosystems, new challenges come into play as adaptive learning platforms are becoming more active when working due to heterogeneous curriculum, diverse learner groups, along with high-stakes institutions. These facts increase the challenge of governance issues, especially of privacy, transparency and accountability, since adaptive decisions are based on the data about learners that is extensive and because opaque optimization may unconsciously favor short-term indications of engagement over long-term comprehension. Guidelines on a regional and international level focus on human-centered design, agency of the educator, and responsible data use, which advocate that proper adaptivity needs to enhance, rather than supplant pedagogical judgment and learner autonomy [12], [13].

Based on this, the given research paper investigates adaptive learning platforms as a closed-loop system that is developed to enhance student engagement and performance due to personalization. It views engagement as a multidimensional concept and says that to be plausibly improved, engaging evidence must be presented over learner experience, learning behaviors, and corroborated measures of achievement as opposed to individual proxy metrics. It relates the underperforming implementation as an inevitable part and parcel of technical performance, since privacy, prejudice, and a lack of transparency might cause the compromise of trust and performance when not tackled via governance-by-design [14], [15]. A combination of learning science, student modeling, learning analytics, and ethical guidance would help elucidate through the study the deployment of AI-driven adaptivity to achieve quantifiable, equitable increases in engagement and learning outcomes.

2. Literature Review

Rule based tutoring has been succeeded by adaptive learning platforms that exploit artificial intelligence to learn and infer states of learners, sequence personalization and optimization of feedback loops in real time. In both K 12 and higher education experiences, the key promise is dual, initially to augment involvement by ensuring an ideal fit of challenge and motivation, and second, to enhance results by offering timely practice, responses, and focused remediation. Modern practice is coming to define work systems based on social technical systems where learning is not solely Americanized to algorithms, but also to the motivation of learners, design of instruction, organization of teachers, and validity and equitability of the data applied to personalize learning [22], [23]. Meta analysis findings and large scale assessment indicate that properly constructed tutoring and adaptive programs have capacity to generate significantly positive changes in success, though with diverse impacts across fields, student groups, implementation faithfulness and type of comparison situation [26], [27]. Meanwhile, studies have pointed to construct validity of learner model limitations, over personalization, and lacks or shows gaps in causal evidence of individualization process to engagement processes and long term results [31], [33].

2.1 Theoretical Framework

One of the primary theory foundations of adaptive learning is mastery learning which presupposes that the majority of the learners have chances to reach high standards in case they have enough time, formative assessment, corrective feedback and after practicing the material several times until they finally master it [16]. AI powered platforms implement this logic by constantly testing what the learner has not yet understood and directing them to progression prerequisite material or further practice, in order to struggle to substitute fixed pacing with competency based progression. This mastery orientation offers a logically consistent framework of personalization policies like practising knowledge components on a level and targeted remediation, yet it also poses design concerns on how to balance between efficiency and learner autonomy, and how to prevent disengagement given experience of repeated remediation as a failure as opposed to a form of growth [16].

Constructivist views also contribute to the concept of adaptive learning by adding the fact that learners acquire knowledge through active engagement, conversation, and tutoring instead of passively receiving knowledge. Vygotskian theory and especially the zone of proximal development promotes personalization plans which are designed to ensure that the task remains a bit beyond the independent reach but offers scaffolding in order to allow the successful progress to occur [17]. This scaffolding would be carried out in adaptive platforms in the form of stepwise hints, worked examples or dynamically generated feedback with a sense of this scaffolding to keep the learner in productive struggle without overburdening her/him.

Another important theory is cognitive load theory which states that students learn poorly when the extraneous load of the tasks is too high to an extent that it takes up working memory thus reducing the amount of schema to be acquired [18]. Adaptive platforms have the ability to minimize the extraneous load by sequencing simple, then progressively more complex, services just in time, and modulating or slowing down modality or pacing when overload indicators are noted. Nevertheless, the cognitive load theory also cautions that induction has to be instructionally principled as reducing difficulty too rapidly may decrease germane load and lead to inhibited learning whereas too much help can inhibit the establishment of self regulating capacity and strong problem solving plans [18].

The theories of motivation and engagement can justify that personalization can also affect persistence and participation in addition to performance. The ARCS model suggests that the processes of instruction must be interesting, relevant, confidence-forming, and evoke satisfaction, all of which are very closely connected to the further application of learning in digital spaces [19]. The expectancy value theory also contends that involvement and achievement connected selections are dependent on the expectations of achievement and subjective importance that the learners place on the tasks, such as attainment, intrinsic, utility, and perceived cost [20]. Adaptive platforms are able to manipulate these determinants by adjusting difficulty to maintain a success expectancy, by customizing situations to enhance utility or relevance, or by lessening the perceived cost in the form of confusion and wasted effort by presenting both focused feedback and effective practice channels [19], [20].

The Community of Inquiry framework can also be used to envision engagement, whereby relevant online learning is assumed to be as a result of interaction between teaching presence, cognitive presence, and social presence [21]. Although most other adaptive learning platforms in the past paid much attention to cognitive presence through dedicated problem-solving and feedback between a learner and another one, most of the current models tend to support the concept of a teacher dashboard, instructor interventions, peer discussion forums, or group assignments. In terms of Community of Inquiry, the engagement and outcomes of students can be enhanced in the case when AI embedded personalization is concomitant with robust teaching presence, as well as social and cognitive conversation, instead of being considered an individualized experience [21].

Lastly, the cognitive engagement theory assists in defining what is meant by engagement in the process of learning. The ICAP framework distinguishes between passive, active, constructive and interactive engagements with the hypothesis that the stronger the engagement is oriented towards generating and dialogic, the more the learning [24]. This model is especially applicable to gauge the argument of whether adaptive platforms are simply expanding time on task, or whether they are supporting higher order constructive processes like self explanation, and conversational processes like collaborative thought. Adaptive learning options such as hinting, reflection prompt and conversational tutoring might be projected into categories of ICAP to examine whether personalization processes will produce meaningful learning as opposed to superficial completion behavior [24].

The self regulated learning theory provides a complementary explanation of how adaptive platforms can be effective in supporting the long term outcomes. Self regulated learners strategize, make monitoring and adapting adjustments and control motivation and emotions in the learning process [25]. The adaptive platforms are able to assist in self regulation using feedback to assist monitoring, goal setting and visualization of progress, and prompts to promote reflection and strategy utilization. But a longstanding theoretical dilemma is that high automation may decrease the ability of learners to develop self regulation, which may lead them to be in a situation of being perpetually dependent on scaffolds, unless designs are developed to gradually withdraw support and develop metacognitive abilities [25].

2.2 Empirical Studies

Empirical studies on adaptive and AI facilitated learning systems encompass intelligent tutoring, adaptive courseware, knowledge tracing through sequencing, and reinforcement learning through personalization. An initial synthesis of tutoring modalities established that intelligent tutoring systems could be equally effective to human tutoring in some circumstances, with considerable variation in system designs, domains, and an assessment setting [26]. These findings serve the hypothesis that fine-grained feedback as well as step-based guidance may be found to produce significant learning benefits, though, up to now, it also suggests that global assertions about AI personalization must be pegged to the kind of pedagogical scheme and interrelation fineness applied in the system [26].

Meta analytic studies related to the field of higher education reveal that intelligent tutoring systems are capable of providing better returns on learning compared to the business as usual teaching and instruction, but the size of effects depends upon features of the intelligent tutoring system (including feedback design, instructional alignment, and time on task) [27]. This is consistent with the perspective that adaptive systems are most useful when they can do more than content recommendation, namely when a diagnostic practice, actionable feedback and a chance to do something wrong over and over again are offered, which is in line with mastery learning principles [16], [27].

Positive but heterogeneous effects are also indicated by studies about adaptive courseware in regular education. In a meta analysis of ALEKS using mathematics one at K 12 and higher education, the general impact of the psychometric was beneficial, although results varied according to moderators such as length of use, integrations with pedagogy and student attributes [28]. The results are significant to engagement and retention, as the readiness of students to continue to practice positively depends on how the teacher discusses the tool, the ways progress is assessed, and the system pace in relation to course assessment and classroom routine [21], [28].

In addition to the aggregated evidence, large scale randomized trials cause the claims related to the outcomes and processes connected with its work more causally. An online math homework system (ASSISTments) with immediate feedback and teacher reporting was also studied in a randomized controlled trial that found a positive effect on better achievement and potential moderators and mediators associated with implementation and learner subgroups [29]. These trials show that when feedback loops are short and teachers can use analytics to act on analytics, platforms can clearly positively contribute to outcomes; they also suggest that the channel between personalization and learning gains may too often pass through instructional decision making and student participation patterns rather than being through algorithms only [21], [29].

The AI systems that make it possible to adapt have been researched as well, especially the idea of learner modeling with the help of knowledge tracing. One of the current surveys of knowledge tracing models is an approximation of systems that judge the latent knowledge condition of engaging with students that use interaction sequence to back personalization with mastery approximations and forecasts of subsequent steps [30]. Recurrent based models and other deep learning based techniques have demonstrated improved performance in predictive tasks, however other analyses have since found that the performance improvement is actually due to a strong knowledge state inference rather than the acquisition of more general ability proxies and data artefacts [31]. These issues are relevant to both engagement and performance, as the quality of personalization relies on the validity of the learned state inference, and incorrect inferences may cause frustration, boredom, or incorrect remediation that demoralizes and breaks trust [19], [20], [31].

Further details can be seen in comparative studies on the modeling of learners. Comparative studies of deep models and Bayesian methods in situations with instructional interventions have a proposal that the model selection can have an impact on the prediction quality and the possibility of productive interventions, and that classical models may not lose competitiveness under the influence of the situation and data [32]. This suggests that the effectiveness of the platform could be dependent on the choice of model approaches that are formulable and sufficiently stable enough to make high stakes learning decisions particularly when platforms are scaled to large implementations of many learners [32].

There are other complexities brought about by privacy and deployment limitations. To serve collaborative silo model training and minimize direct data sharing, federated methods of deep knowledge tracing have been suggested [33], which provide a feasible solution to the practical scaling limit of AI personalisation in multi institution systems. Although it ensures a future, these methods bring about fresh doubts regarding the calibration of different populations, the evaluation of data quality, and the ability of federated training to provide uniform personalization advantages in real classroom settings [33].

In more recent work, reinforcement learning has been explored as a strategy in optimization of sequencing and interventions by learning policies that maximize long term rewards like mastery, retention, or proxies of engagement [34]. A systematic review suggests that there is growing interest in the RL related to educational personalization, with the shortcoming being that methodological rigor is loosely applied, and application reliability would be ensured by defining rewards and constraints of harmful inquiry, and methodologies that may create causal associations with effects on learning results [34]. These results are supplemented by previous results indicating that the personalization systems need to be tested not only in terms of predictive accuracy, but also in terms of impact of decisions on learner experience and achievement on a downstream level [26], [31], [34].

A further clarification of the state of practice is scoping evidence of higher education adaptive learning implementations. A recent scoping review has summarized the main features of the subject of personalized adaptive learning in higher education and reported that a large percentage of the literature finds an increase in academic outcomes and, less frequently, engagement outcomes [35]. The mixed engagement results agree with the larger literature indicating that engagement is multi dimensional, and that it is context sensitive to course design, alignment of assessment, instructor involvement, and the degree to which adaptive tasks encourage deeper cognitive engagement as opposed to low level practice that is repetitive [21], [24], [35].

2.3 Research Gap

Even with these impressive improvements, there are still a number of gaps, which do not allow making confident assertions regarding the ways in which AI-driven adaptive platforms can enhance both engagement and outcomes. This is because, in a large number of studies, there have been overall gains that are not broken down to pinpoint individual mechanisms of personalization that lead to such gains. Platforms in which content, feedback, dashboards and motivational features are bundled together are often considered in meta analyses and trials, meaning that it is hard to say whether mastery based sequencing, feedback timing, teacher orchestration or novelty effects are the biggest drivers of improvements [26], [28], [29].

The designs of future studies must be such that a particular comparison can be made between the adaptive policies and feedback strategies and other factors remain constant, in order to determine the causal influence of the particular elements of AI.

Second, engagement is inconsistent and shallowness determined. Involvement is often measured as log based proxies in the form of time on task, completion rates, and clickstream activity, which is not necessarily interesting in terms of constructive and interactive engagement as ICAP envisions it, or in the quality of motivation as postulated by ARCS and expectancy value theory [19], [20], [24]. Studies to match engagement measurement with theory, couple behavioral measure with valid self report measure, observational, and learning process measures are evident in explaining which types of engagement are being influenced and why [24].

Third, the validity of the learner modeling is still very important. Strong prediction metrics can be learned by knowledge tracing and deep models, however, it has been observed that there are cases where models can be trained to reflect latent ability or patterns in a dataset, and not represent stable knowledge states as this can result in unreasonable sequencing or feedback [31], [32]. Study is required that has correlated the results of the learner model with external indicators of learning, has measured robustness between populations and programs, and has studied the relationship between model errors and either ways of disengagement or unfair consequences.

Fourth, there is no longitudinal research evidence on long term benefits and development of self regulation. Adaptive platforms can speed up short term performance, although heavy scaffolding might diminish chances of learners to grow self monitoring and strategy control unless assistance is purposely created to dissipate and encourage learners to gain independence [25]. The longitudinal studies are to consider whether adaptive personalization creates long-lasting learning strategies and motivation, or whether there are less advantages when the learner is out of the platform environment.

Lastly, privacy, institutional fragmentation, and heterogeneous data pose deployment limitations that make it challenging to do scalable personalization. Such solutions as federated approaches and RL based policies are promising, yet theoretical data linking these superior methods to experimentation gains and learning advantages are scarce, as well as, a methodological benchmark of secure, equitable and responsible policy education in school is undergoing a period of inception [33], [34]. The solution to the gaps is proposing multi-site assessments, transparent reporting of adaptive policies, and strict outcome metrics that relate algorithmic decisions to the experience of the learner, quality of engagement, and equitable achievement growth [21], [24], [34].

3. Methodology

3.1 Research Design

The research design of this study is mixed methods, quasi-experimental research design aimed at assessing the effect of AI-based adaptive learning platforms on student engagement and performance. The quantitative part determines the cause-effect relationship between adaptive personalization and the measures of learning performance and engagement through the comparison of an intervention group and a traditional digital learning platform using an AI adaptive platform with a comparison group receiving conventional digital learning and using a digital instructional platform without adaptive sequencing. This is supplemented by the qualitative part that looks at how students and instructors sense adaptivity, what behaviors in the platform are seen as supportive or discouraging, and how in the classroom integration practices mediate the engagement. This two-fold strategy is chosen since the engagement is not completely meant by the log data, and outcome gains could need misunderstanding without comprehending an implementation fidelity and learner experience.

3.2 Study Context and Participants

The research is carried out in a formal education environment in which the same course material, testing schedule, and curricular minutes are ensured in different groups. The respondents will consist of students of the same course and grade level, and will have to meet the inclusion criteria of regular attendance and a compatible device. Estimation of selection bias is to designate intact classes to either the adaptive learning group or non adaptive group, such that there will be a similar exposure to instruction. The evaluation of baseline equivalence is based on previous academic achievement, pretest that is consistent with course learning outcomes and on initial engagement survey that is conducted in the first week of the research.

3.3 Adaptive Platform and Intervention Description

The intervention is an AI powered adaptive learning system that is outfitted to the course material and learning requirements. Adaptive functions on the platform are diagnostic entry assessment, mastery estimation, sequencing of learning activities tailored to each individualization, adaptive difficulty adjustment and feedback formative hints and explanations. The students in the intervention group have a fixed number of minutes of use per week during a certain period of study which makes them consonant in dosage. The comparison group accesses the identical digital content library and practice materials but engaged in a linear progression that occurs either according to the instructor or the learning management system, and the sole form of feedback is the correctness and broad descriptions instead of individual remediation plans. The lesson plans and pacing guides furnished to the teachers in the two groups are identical in order to ascertain that the observed variations in the outcomes were caused by the adaptive personalization and not differences in the coverage of the teacher.

3.4 Variables and Operational Definitions

3.4.1 Student Engagement Measures

The concept of engagement is triangulated using a multidimensional construct. Different behavioral patterns are assessed by records of platform interactions, including the frequency of sessions, performance of tasks assigned, continuation following the wrong answers, and own practice beyond the necessary minimum. The measure of cognitive engagement is based on evidence that indicates deeper processing and includes indicators like optional use of reflection prompts, transfer items, and lessening the occurrence of repeat errors as time lapses. Validated self report scales concerning the interest, perceived relevance, frustration and confidence are used to measure the affective engagement at various points in the course of intervention. In places where it is possible, teacher ratings of participation and effort are also added as an external measure to decrease excessive dependence on platform generated proxies.

3.4.2 Learning Outcome Measures

The learning outcomes are assessed through pre and post tests, which match the learning goals of the curriculum with the help of periodical unit tests and delayed retention tests which are characterized by a period of several weeks after the conclusion of the intervention period. The post test consists of the near transfer items that resemble the practice activities, and far transfer items that involve the application into new contexts. In order to achieve fairness and interpretability, both content validity and difficulty balance of test items are its reviewed content and scoring rubric are standardized across groups.

3.5 Data Collection Procedures

The data collection takes place in four stages. The baseline stage involves the students submitting the pre test and baseline engagement survey and capturing demographic and background variables that would be important in regard to learning access. During the implementation phase, the platform will automatically record interaction logs on both groups with teachers recording the implementation fidelity in terms of time spent, the non-planned interactions, and technical problems. During the post intervention, students fill in the post test and a follow up engagement survey, where a sample of students and instructors are interviewed through semi structured methods aimed at perceived helpfulness of adaptivity, feedback clarity, motivation and challenges.

During the follow up phase, a delayed retention test is done to determine the length of time that the learning gains will be retained even after the testing.

3.6 Implementation Fidelity and Control of Confounds

The fidelity in implementation is observed by way of logs in the system, teacher checklist, and, periodically, classroom observation. Dosage is regulated with weekly minimum usage goals and is ensured by checking them through logs. In order to diminish contamination, students are requested to utilize assigned learning systems regarding the specific units of skills to be developed during the study, and the teachers do not share intervention specific adaptive recommendations with the comparison group. The possible confounders in the study also include the availability of the device, the instability of the internet as well as teacher support differences hence these can be included in the analysis as covariates or these can be included in sensitivity testing.

3.7 Data Analysis Plan

3.7.1 Quantitative Analysis

The major outcome analysis involves analysis of the covariance model, whereby; the post test performance of the groups is compared to pre test scores. Practical significance is calculated and the effect sizes are computed. The repeated measures models are used to analyze the engagement outcomes, to identify the changes in the outcomes over time, and determine whether engagement improvement is based on the temporal changes or it is temporary. Mediation analysis is used to establish whether learning outcome changes can be explained by variation in engagement indicators including whether more persistence and less frustration are mediators leading to more learning. Subgroup analyses identify differences in effects between higher and lower performing students due to differences in baseline proficiency thus, the platform does not favor higher performing students over other students.

3.7.2 Learning Analytics and Sequence Modeling

The behavioral patterns are also applied through sequential analyses of the interaction logs with particular attention given to transition by analyzing the records of an error to hint request, hint request to success, and success to more difficulty. These tendencies aid in determining whether adaptivity leads to productive or unproductive loops, e.g. timely remediation, into mastery or repeats of a failure loop, which can indicate disengagement. In this instance, where the adaptive platform has given estimates of the mastery, their correlation with the external test performance is analyzed to determine model validity.

3.7.3 Qualitative Analysis

Thematic analysis is used to analyze interview and open ended surveys responses. Coding is concerned with views of fairness in personalizations, feedback sensibility, autonomy and control, motivation, frustration prompts, and teacher coordination. Results are combined with quantitative results to explain why engagement or outcome changes have taken place, especially in situations where the log data indicates that the student visited a page a lot but states no interest, or where the outcomes have been improved but self-reported engagement thereof.

3.8 Reliability, Validity and Trustworthiness.

Internal consistency checks are used to measure instrument reliability in the case of engagement surveys and inter-rater agreement used to measure any item requiring a rubric. In order to prove the validity, content mapping of tests to learning objectives, pilot testing of the survey wording to understand what it means, and the triangulation between engagement indicators through log, self reports, and teacher observations are undertaken. To ensure qualitative credibility, the authors employ the method of peer debriefing in the coding phase, an audit trail to track the coding actions, and provide representative extracts in the presentation phase and anonymity of the participants.

3.9 Ethical Considerations and Data Governance

Before the collection of the data, ethical approval is obtained by the concerned institutional review authority. It will be participatory and there will be informed consent by the students or guardians as necessary and informed consent with the students on what data will be collected, use and privacy protection. The data are reduced to the minimum required when it comes to research questions, are kept in a safe and controlled way, and de-identified before analysis. Since adaptive systems may affect the opportunities of learners, the study follows up on a negative outcome, i.e., recidivization of remediation, possibly increased frustration, and creates a system through which a teacher can intervene in case the platform seems to be impeding the learning of a learner.

4. Results

4.1 Participant Characteristics and Baseline Equivalence

The sample size was 238 students who belonged to two groups: the adaptive learning group (n = 120) and the comparison group (n = 118). The characteristics of participants in Table 4.1 demonstrate that there is a high degree of similarity among the groups in terms of the age distribution, gender representation, previous GPA, previous subject achievement, internet stability, and previous e-learning exposure. The mean age in the adaptive group was about 16.8 years and that in the comparison group was about 16.7 years and gender distribution was equal across the conditions, which adds to the comparability at the prelim stages. The previous academic ability was also very consistent with the reference to previous GPA, which was close to 2.8 on both groups and the previous subject scores, which were close to 63 out of 100, meaning that there was no systematic academic advantage to either group going into the intervention.

Table 4.1 Participant Demographics and Background Characteristics by Group

Variable	Adaptive Group (n = 120)	Comparison Group (n = 118)	Total (N = 238)
Mean age (years)	16.8 ± 1.2	16.7 ± 1.3	16.8 ± 1.2
Male	62 (51.7%)	60 (50.8%)	122 (51.3%)
Female	58 (48.3%)	58 (49.2%)	116 (48.7%)
Prior GPA (0–4 scale)	2.81 ± 0.46	2.79 ± 0.49	2.80 ± 0.47
Prior subject score (0–100)	63.4 ± 9.8	62.9 ± 10.1	63.2 ± 9.9
Stable internet access	98 (81.7%)	94 (79.7%)	192 (80.7%)
Prior e-learning exposure	72 (60.0%)	69 (58.5%)	141 (59.2%)

Table 4.2, Baseline equivalence also confirms that there is no significant difference between the two groups before being tested on adaptivity. The score before the test was almost the same, with 44.6 above and below standard deviation of 8.9 of the adaptive group and 44.1 above and below standard deviation of the comparison group respectively, and the difference was not significant. Baseline engagement was also harmonized in all the gauged areas which comprised the total engagement, behavioral engagement, cognitive engagement and affective engagement. This is significant to a causal interpretation as the argument that later differences in outcomes and

participation can be held to occur due to the adaptive learning intervention rather than group differences that pre-exist it is enhanced.

Table 4.2 Baseline Equivalence: Pre-Test and Initial Engagement

Measure	Adaptive Mean ± SD	Comparison Mean ± SD	t	p
Pre-test score (0–100)	44.6 ± 8.9	44.1 ± 9.2	0.41	0.68
Engagement total (1–5)	3.12 ± 0.54	3.10 ± 0.57	0.29	0.77
Behavioral engagement	3.18 ± 0.61	3.15 ± 0.59	0.36	0.72
Cognitive engagement	3.04 ± 0.56	3.02 ± 0.58	0.27	0.79
Affective engagement	3.15 ± 0.60	3.14 ± 0.62	0.11	0.91

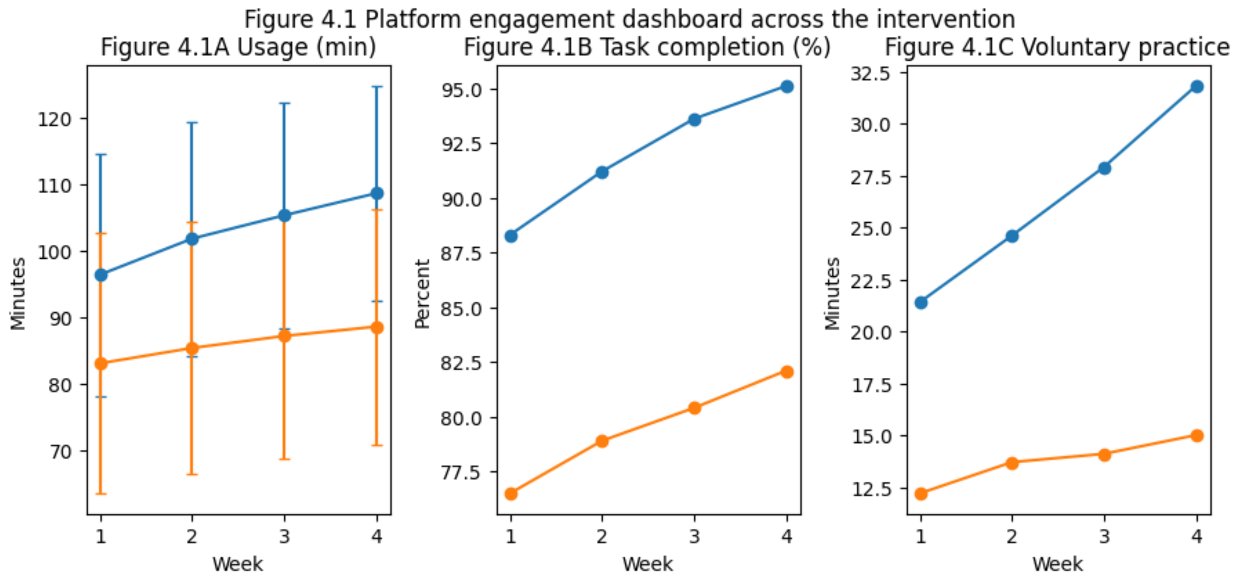
4.2 Implementation Fidelity and Platform Usage Patterns

The behavioural evidence of intervention compliance and utilization depicts significant variation in the actual learning behaviour between groups. Table 4.3 reveals that students who are in the adaptive platform all spent more time per week using the platform compared to those in the comparison group. The adaptive group improved the average time per week of 96.4 minutes in week 1 to 108.6 minutes in week 4 as compared to the comparison group, which improved 83.1 minutes to 88.6 minutes respectively. In addition to time, the adaptive group also showed an increased completion rate of the tasks given to each week, it went up to 95.10, as compared to the comparison group which went up to 82.10. One indicator, the voluntary practice minutes which is a significant measure of self-initiated participation rose by 21.4 to 31.8 minutes in the adaptive group but did not increase significantly in the comparison group, with the latter only going up by 12.2 to 15.0 minutes.

Table 4.3 Weekly Platform Usage and Fidelity (4 Weeks)

Week	Group	Avg Minutes ± SD	Sessions / Week	Completion %	Voluntary Practice (min)
1	Adaptive	96.4 ± 18.2	4.6 ± 1.1	88.3	21.4 ± 9.6
1	Comparison	83.1 ± 19.5	3.8 ± 1.3	76.5	12.2 ± 8.1
2	Adaptive	101.8 ± 17.6	4.9 ± 1.0	91.2	24.6 ± 10.3
2	Comparison	85.4 ± 18.9	4.0 ± 1.2	78.9	13.7 ± 7.9
3	Adaptive	105.3 ± 16.9	5.1 ± 0.9	93.6	27.9 ± 11.2
3	Comparison	87.2 ± 18.3	4.1 ± 1.2	80.4	14.1 ± 8.6
4	Adaptive	108.6 ± 16.1	5.3 ± 0.8	95.1	31.8 ± 12.4

4	Comparison	88.6 ± 17.7	4.2 ± 1.1	82.1	15.0 ± 8.9



These trends are plotted as a unified intervention dashboard in Figure 4.1 that incorporates usage minutes, completion rates, and voluntary practice as independent yet conceptual relatedness indicators of engagement. The figure helps to understand that the intervention effect was not expressed on a single behavioral indicator, but the adaptive platform seems to have accommodated the compliance based behavior, including task completion execution, and discretion based behavior, including voluntary practice execution. This trend indicates that the mechanisms of personalization were probably lowering obstacles to persisting with such personal practice as recursive failure cycles, and also elevating the subjective worthiness or accessibility of learning activities, thus assisting to augment persistence in the context of the intervention period.

4.3 Effects of Adaptive Learning on Academic Outcomes

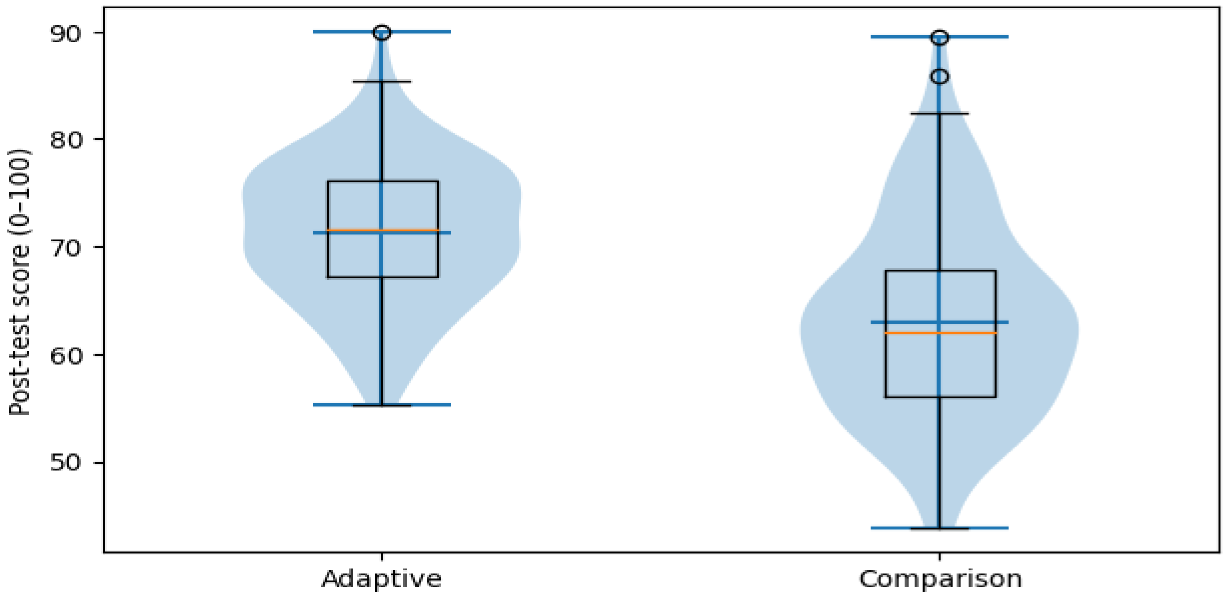
The academic performance is significantly increased in terms of adaptivity through AI. Adjusted means in the outcomes of ANCOVA in Table 4.4 it can be reported that the adaptive group had better performance on post-test total score and unit tests. The highest final result was obtained after the post-test, and the adjusted mean of the adaptive group was 71.8 versus 63.2 in the comparison group. This variation shows that adaptive sequencing, feedback, and mastery-based progression exposure students recorded statistically significantly greater performance at the conclusion of the intervention subsequently, holding baseline performance constant. Unit test results reveal a relative trend of the benefit of adaptive learners as they are also outperforming comparison learners in Unit Test 1 and Unit Test 2. The transfer items subscore goes in the same direction, with the adaptive group getting 68.9 versus 59.3 in the comparison group indicating that the advantage was not limited to close repetitions of the practiced items into application tasks that need transfer of the concepts.

Table 4.4 Post-Test and Unit Test Outcomes (ANCOVA Adjusted)

Outcome	Adaptive Mean	Comparison Mean	F	p	Cohen's d

Post-test total	71.8 ± 1.4	63.2 ± 1.6	29.6	<0.001	0.78
Unit Test 1	74.1 ± 2.1	66.5 ± 2.3	18.3	<0.001	0.66
Unit Test 2	72.6 ± 2.0	64.8 ± 2.2	20.1	<0.001	0.70
Transfer items	68.9 ± 2.4	59.3 ± 2.7	22.7	<0.001	0.74

Figure 4.2 Post-test score distribution (violin + box)



The difference is also supported by Figure 4.2 which represents it on a distribution-level instead of a mean-comparison level. The violin-plus-box plot reveals an evident shift in the distribution of the scores of the adaptive group positioning above the mean, as well as (although to a lesser degree) a decrease of the low-in one tail, therefore, the number of students who were left in the low-score ranges was lower in the adaptive group than in the comparison group. This holds educational significance in that it suggests that adaptivity can have decreased the number of learners who fail to make meaningful progress, perhaps by providing remediation that is more focused, and providing more effective error recovery mechanisms.
Table 4.4 further indicates the importantness of these gains by the way the effect sizes were interpreted further. The post-test d value of 0.78 is a strong practical value, whereas unit test and transfer item d values are moderate to strong. This synthesis represents these effect sizes in the form of a lollipop chart (figure 4.4) and it is evident that the opportunity posed by the platform was not confined to a single test but was similar from the outcome indicators perspective. The trend implies that the adaptive system sequencing and feedback resulted in the gains of mastery and the ability to generalize, which is a desirable outcome to educational technologies that present to accelerate learning outcomes instead of raising scores in the short term.

4.4 Retention and Durability of Learning

Delays in retention are indicators of sustained learning. According to Table 4.5, the adaptive group scored higher on the retention test total, which is 68.4 9.2, than the comparison group with a result of 58.7 9.2. A gain in transfer retention was also increased in the adaptive group and the far transfer retention exhibited the same gain meaning that the gains attained in learning were not only short lived but also relied on the proximity of the test. It is preferable that this pattern of retention would be indicative of more consistent schema development or more enduring performance of conceptual and procedural fluency, over sporadic short-lived performance gains.

Table 4.5 Delayed Retention Outcomes

Measure	Adaptive Mean ± SD	Comparison Mean ± SD	p	Decay (%)
Retention test total	68.4 ± 9.2	58.7 ± 9.8	<0.001	−4.8
Near transfer	70.1 ± 8.6	61.2 ± 9.1	<0.001	−4.0
Far transfer	65.9 ± 9.8	55.4 ± 10.3	<0.001	−5.6

The retention advantage is also used to explain the previous post-test gains. Provided the adaptive platform were initially generating short-term performance gains by familiarity with the test or superficial interest, retention disparities would be predicted to decrease with time. Rather, Table 4.5 shows that adaptive learners maintained significant benefits of learning. These findings suggest that repeatedly checked mastery testing, engaging remediation, and faster feedback can have enhanced the encoding and decreased the acquisition of the enduring misconceptions with more long-term learning results.

4.5 Behavioral Engagement Outcomes Across Time

Behavioral engagement metrics give a fine-grained image of how the adaptive platform transformed the learning behaviors over a period of time. According to Table 4.6, the adaptive group compared to the comparison group experienced a faster increase in the number of sessions per week at the end of the baseline period and post-intervention. More significantly, post-error persistence increased in the adaptive category to 82.6 percent, as opposed to the comparison category extension to 68.3 percent, which is a highly meaningful indicator since disengagement is one of the major outcomes that arises when a learner frequently fails at something. Adaptive learners completed more tasks (95.1) than comparison learners (82.1) indicating that adaptive sequencing is possibly capable of enhancing the perceived task achievability and students actively got through difficult content.

Table 4.6 Behavioral Engagement Over Time

Indicator	Time	Adaptive	Comparison
Sessions/week	Baseline	3.2	3.1
	Mid	4.9	4.0
	Post	5.3	4.2
Persistence after error (%)	Baseline	61.4	60.9
	Post	82.6	68.3

Task completion (%)	Baseline	72.8	71.9
	Post	95.1	82.1

These behavioral patterns are in line with the usage and adherence findings earlier provided in Table 4.3 which is graphically displayed in Figure 4.1. A combination of these findings leads to the conclusion that the improvement of engagement was not only associated with time-on-platform increase but also materialized through a stronger learning behavior, especially at difficult times. This is in line with the assumption that productive adaptivity favors productive struggle over entrapping learners in unproductive cycles of failure.

4.6 Self-Reported Engagement and Learner Experience

Self-reported engagement outcomes offer a cognitive complement to behavioral logs such as the affective one. As table 4.7 indicates, there was significantly more overall engagement in the adaptive group between pre and post which improved by 3.12 to 4.01 on a five-point scale, compared to the comparison group which improved by a smaller margin at 3.10 to 3.41. This shows that learners did not simply act as they were engaged, they also claimed that they were more interested, relevant and more confident. One more is a pattern of frustration, in which the adaptive learners indicated a decrease in frustration (3.21) to 2.11, whereas comparison learners indicated a decrease in frustration (3.18 to 2.79). The increased decrease in frustration among the adaptive group corresponds to the concept that personalization may enable a decrease in cognitive overload and allow the learners to overcome the mistakes faster.

Table 4.7 Self-Reported Engagement (Pre–Post)

Scale (1–5)	Adaptive Pre	Adaptive Post	Comparison Pre	Comparison Post
Engagement total	3.12	4.01	3.10	3.41
Interest	3.18	4.14	3.16	3.46
Relevance	3.05	4.02	3.07	3.39
Confidence	3.11	4.08	3.09	3.44
Frustration	3.21	2.11	3.18	2.79

Figure 4.3A Adaptive engagement profile

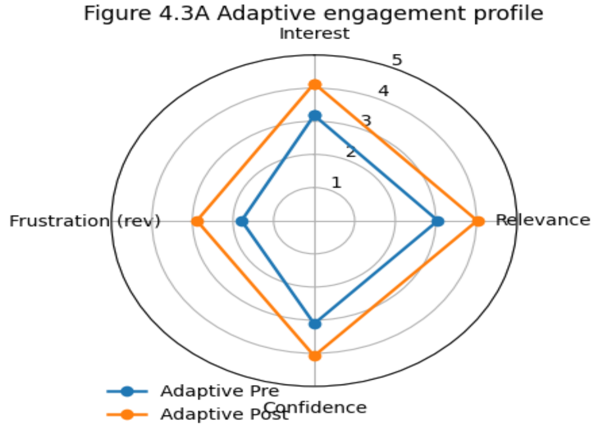
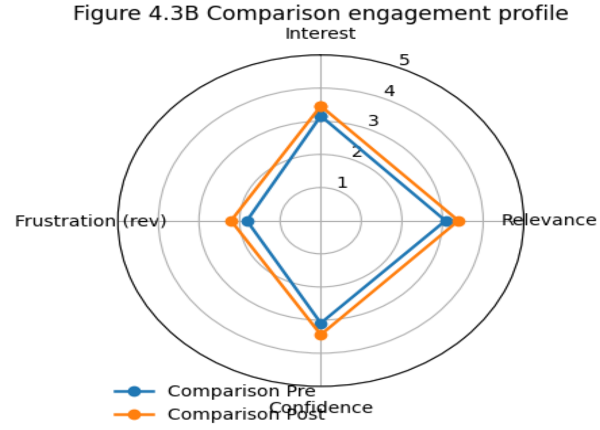
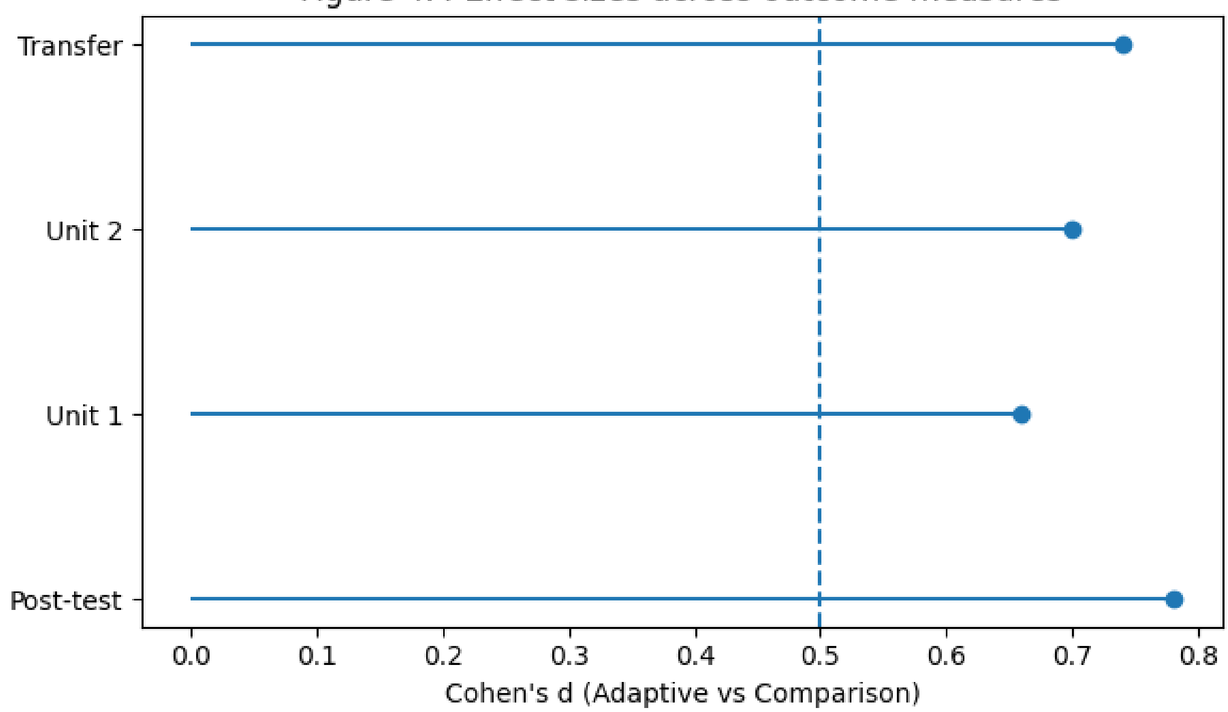


Figure 4.3B Comparison engagement profile



All these dimensions of engagement are displayed as radar profiles in both groups in Figure 4.3 and can thus be interpreted to understand engagement as a multidimensional construct. The post intervention profile of the adaptive group increases significantly on confusion, relevance, and confidence, and there is less variation in frustration, compared to the comparative group profile. This number reinforces the fact that adaptivity did not only alter academic achievements, but also the attitudes and the mindset of the learners and what they view as a good experience, which are commonly the pre-requisites of a long-term learning and prolonged use of a platform outside of controlled research environments.

Figure 4.4 Effect sizes across outcome measures



4.7 Engagement as a Mechanism Linking Adaptivity to Outcomes

In order to test the claim that the engagement is a process by which the adaptivity is facilitated to enhance achievement, the outcomes of the mediation analysis are provided in Table 4.8. The adaptive condition is strongly positively related to the engagement change and the engagement change is strongly positively related to post-test results. The direct influence of adaptive condition on post-test is positive, though the indirect influence results in the fact that engagement moderately describes the delivered learning gains. This trend indicates adaptivity positively affects achievements by strengthening the engagement as well as the immediate correlation of instructional benefits like better sequencing and feedback that improve mastery.

Table 4.8 Mediation Analysis Summary

Path	β	p
Adaptive → Engagement	0.46	<0.001
Engagement → Post-test	0.39	<0.001
Adaptive → Post-test (direct)	0.31	<0.001
Indirect effect	0.18	<0.01

Figure 4.7 Integrated impact model with standardized effects

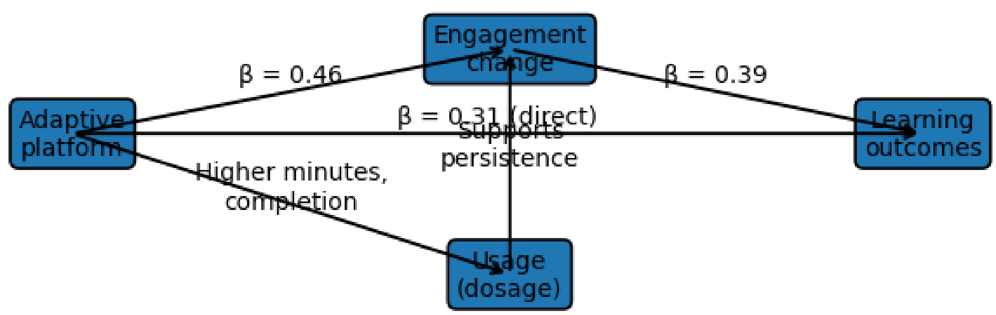


Figure 4.7 combines these relationships into a path diagram that incorporates standardized coefficients and usage or dosage nodes between the platforms, which relates the behavioral footprint of the platform to engagement. This unified paradigm justifies the perspective that increased time/ completion/ and voluntary practice do not simply co-exist with engagement change, but they may actually help to bring about engagement change by providing repeated access to experience that is tailored appropriately. The figure presents a logical explanation that links the platform design to the learner behavior, learner experience as well as the achievement outcomes.

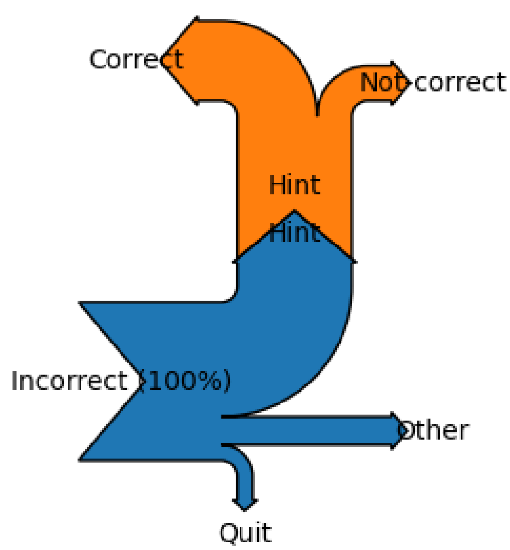
4.8 Learning Analytics and Interaction Sequence Patterns

The results obtained in learning analytics provide insights into how the learners went through the process of difficulty and feedback. It is indicated in Table 4.9 that adaptive learners were significantly more likely to seek a hint after a mistaken attempt and more likely to transform the use of hints into a correct answer on the succeeding attempt. On the other hand, adaptive learners were found to have a remarkably less likelihood of dropping out due to a wrong attempt compared to the comparison learners. This is also essential since the quit government is a change in behavior within the learning cycle that is usually accompanied by frustration, lack of confidence, or just the inability to do something.

Table 4.9 Interaction Sequence Patterns

Metric	Adaptive	Comparison
Incorrect → Hint (%)	72.4	48.1
Hint → Correct (%)	69.6	51.3
Incorrect → Quit (%)	9.8	21.6
Avg attempts per item	2.3	3.1
Time to mastery (min)	18.4	26.7

Figure 4.5 Error-recovery pathways (Sankey schematic)



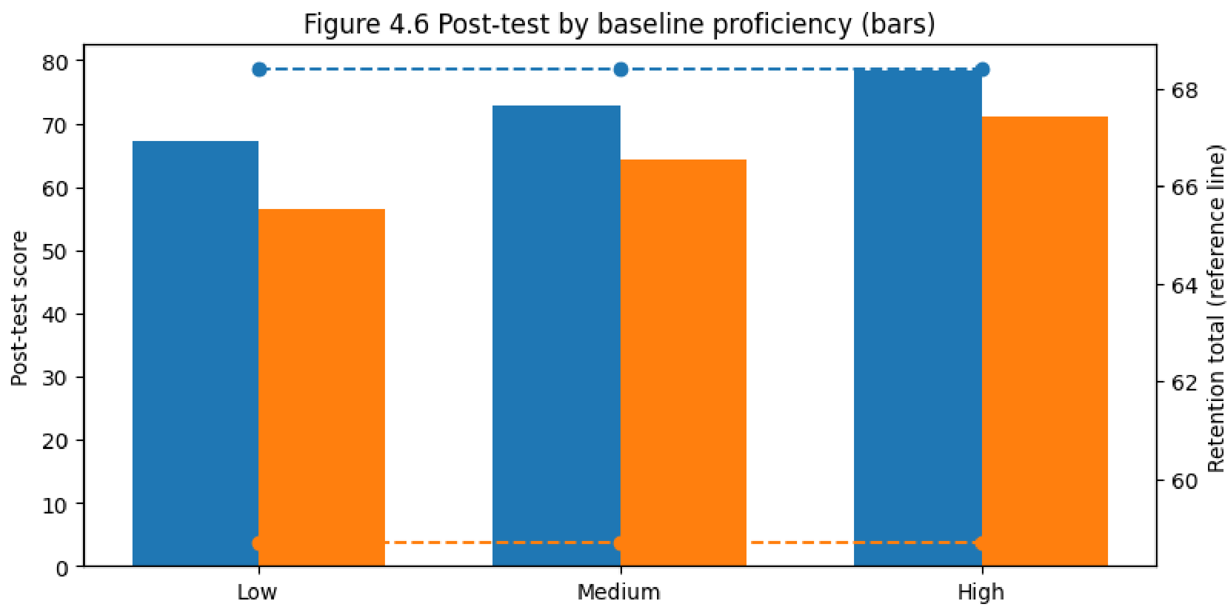
These error-recovery processes have been visualized as a Sankey diagram, figure 4.5, which depicts the incorrect attempts as the sources flowing into hunting and quitting and other routes, with additional arrows between hinting and correction or still difficulty. The figure clarifies that the adaptive platform facilitated productive pathways, which is, in particular, through the augmentation of destined recovery of errors. Pedagogically, the adaptive system seems to have served as the scaffold that ensured the students remained active during the moments of challenge which was a consistent finding with the engagement and frustration alleviation as shown in Table 4.7 and Figure 4.3.

4.9 Subgroup Outcomes and Equity Considerations

The results of the subgroup analysis in Table 4.10 show that the adaptive platform was useful to students across different baseline proficiency levels. The comparison group showed a score of 67.2 on the post-test and adaptive group with low baseline learners, medium baseline learners, and high baseline learners scored 72.8, 78.5, and 71.1 respectively. The trend indicates that the adaptive system did not merely enhance performance of students who are already performing well, but also significantly assisted weaker students which is usually a fundamental aspect of adaptive learning technologies.

Table 4.10 Subgroup Analysis by Baseline Proficiency

Subgroup	Adaptive Post-test	Comparison Post-test
Low baseline	67.2	56.4
Medium baseline	72.8	64.3
High baseline	78.5	71.1



These subgroup post-test results are graphically displayed in Figure 4.6 in the form of bars grouped around and further they plot retention as a reference signal which makes it clearer that subgroup effects are maintained over time learning patterns and not transient spurious results. The integrated visualization supports the reasoning that adaptability contributed to fair access of learning both in the setting performance level and feedback to the learner requirement, which consequently enhanced involvement and achievement among the institutionally weak learners who usually suffer with a one-size-fits-all pacing.

4.10 Qualitative Findings and Integration With Quantitative Results

The qualitative results presented in Table 4.11 can be used to understand why the adaptive group exhibited greater engagement and only superior results. Topics that can be identified as high-frequency ones are perceived personalization fit, feedback clarity and usefulness, frustration reduction, and more persistent. These themes correlate very well with the quantitative data namely enhanced hint-to-correct transitions and reduced quitting probabilities in Table 4.9, slight frustration in Table 4.7 and elevated completion and voluntary practice in Table 4.3. The qualitative data points to the preferences of students exposed to adaptive tasks being better adjusted and feedback being more practical, which presumably contributed to higher confidence and further engagement.

Table 4.11 Qualitative Themes Summary

Theme	Frequency	Linked Quantitative Indicator
Personalization fit	High	Engagement, persistence
Feedback clarity	High	Hint → correct transitions
Increased autonomy	Moderate	Confidence scale
Reduced frustration	High	Frustration scale
Teacher facilitation	Moderate	Fidelity, outcomes

The merging of both qualitative and quantitative results enhances internal validity. Higher use and higher scores might be demonstrated by quantitative data only, but the content of qualitative themes describes the mechanism of the experience, students were getting less stuck and more supported, which probably allowed them to practice more and recover errors. This correlation also justifies the mediation pattern in Table 4.8, since it offers substantive issues of why engagement most likely mediates learning gains but is not a chance association.

5. Discussion

5.1 Overview of Key Findings in Relation to the Study Aims

The research question used in this study was whether an AI-based adaptive learning platform can enhance student engagement and learning outcomes better than a non-adaptive comparison condition. The cumulative findings suggest that adaptive learning had a greater impact on academic performance, increased and more prolonged engagement, enhanced error-recovery behaviour, and better retention. The achievement difference that appeared in Table 4.4 based on the distributional shift displayed in Figure 4.2 and the synthesis of effects presented in Figure 4.4 implies that the adaptive platform produced meaningful changes in learning and not fringe effects in the learning of only a limited group of learners. Table 4.5 retention advantage shows that these gains were not short-lived meaning that adaptive sequencing and feedback could have enhanced consolidation and transfer. The behavioral signs of improvement in engagement include more usage, completion, and voluntary practice reported in Table 4.3 and Figure 4.1 and the psychological indicators of better engagement include self-reported interest, relevance, and confidence with decreased levels of frustration reviewed in Table 4.7 and Figure 4.3. Learning analytics also indicate that adaptivity facilitated productive struggle by raising hint seeking and hint to correct recovery as well as lowered quitting after error such as Table 4.9 and Figure 4.5 did. Lastly, Table 4.10 and

Figure 4.6 results in subgroups indicate that gains were made at all levels of proficiency, but especially with lower baseline learners, which conforms with the equity reason behind the platform.

5.2 Interpretation of Academic Outcome Gains and Their Practical Meaning

The most convincing evidence of the outcomes is the academic performance results. The results in Table 4.4 show greater post-test and unit test scores in the adaptive condition and the effect size pattern as represented in Figure 4.4 give a reason to interpret as an impact that is practically significant (as measured by numerous outcome measures, one of which being transfer). Distributional visualization of Figure 4.2 provides a valuable addition to interpretation since it means that the adaptive platform probably minimized the share of low-performing outcomes which is often the goal of intervention aimed at the personalization of pacing and remediation. This is supported by the empirical findings that adaptive learning tools can enhance performance and satisfaction in online and face-to-face learning settings when they allow responsive feedback and practice loops as opposed to provision of a fixed content [36]. It is also consistent with larger systematic data that AI applications in the educational setting tend to be positively related with learning outcomes, but the strength varies depending on context, the quality of implementation, and the particular mechanism selected by adaptivity [37].

The transfer benefit found in Table 4.4, in terms of instruction, would indicate that the adaptive platform was not just conducive to rote memorization. Close conceptual insight or better problem solving strategies are usually more challenging to obtain than the near-replication gains and transfer improvements are generally harder to obtain. This aligns with the position in recent synthesis studies that adaptive and tutoring-oriented AI systems could be used to favour learning progress when based on scaffolding and feedback conditional on learner response rules as opposed to general practice [38]. The results of the current paper can thus indicate that the adaptivity features of the platform, including dynamic difficulty control, deliberate remediation, and timing of the feedback, are some of the factors that could have facilitated an even more efficient learning process and minimized wastage of time in unproductive practice.

5.3 Engagement Improvements as Both an Outcome and a Mechanism

The process of engagement plays a key role in adaptive learning research since it becomes an object of study and a channel to success. The current results reflect definite behavioral and self-report gains of engagement. According to Table 4.3 and Figure 4.1, as compared to adaptive learners, they dedicated more time, had higher work done and voluntary practice was substantially more practiced. Such behavioral cues are important since voluntary behavioral participation is more related to intrinsic or self-motivated engagement than compliance-based participation and it is also associated with long-term learning even after the formal instructional time. Table 4.7 visualized by Figure 4.3 indicates that there were also positive changes in the self-report measures, indicating learners were more interested and thought they were more confident and experiencing significantly less frustration because of using the platform: the subjective quality of learning was indeed enhanced by the platform, and not by increased time-on-task.

Such results are similar to those reported in controlled experiments on adaptive tools, and the related improvement on performance is generally matched to increased satisfaction and perceived usefulness, particularly where adaptive systems help the students cope with difficulty and feedback [36]. In addition, they can accommodate the emergent-review-level conclusions regarding how AI-enabled personalization could affect the behavior patterns, emotional, and cognitive aspects of interactions, with results relying on the clarity and accessibility of the adaptive recommendations [39]. The current engagement results hence reinforce the meaning that the platform did not only increase achievement in a mechanical way; and it is also a probability that it augmented the learning experience in such a way that it is more likely to persist when faced with challenge.

5.4 Error-Recovery and Learning Analytics as Explanatory Evidence

The alteration in error-recovery pathways is one of the most explicatory outcomes. Table 4.9 and Figure 4.5 imply that adaptive learners tended to seek hints when they were wrong and tended to transform the use of hints into correct responses, but were less prone to give up mistakes. This trend is a reasonable behavioral process that explains the relationship between adaptive learning and engagement, as well as achievement. In most digital learning environments, repetition of failure, low confidence or the lack of clarity in the feedback cause disengagement. The platform potentially decreased frustration and ensured continuity of engagement, which is in line with the self-report decreases of frustration in Table 4.7, by enhancing the likelihood of productive recovery following an error.

This explanation is compatible with the results of experimental and review studies on intelligent tutoring and adaptive scaffolding in which personalized hints and step-by-step help are frequently linked to more consistent learning patterns and enhanced advancement [40]. It is also consistent with the recent findings that the frequency and quality of engagement with tutoring systems can be used to predict learning outcomes and indicates that exposure is not the sole factor that can be used to predict the outcomes but rather in associations with the response that learners can have towards difficulty and feedback [41]. Interaction evidence in this study has allowed a consistent narrative: Adaptive feedback and sequencing enhanced mistake recovery, mistake recovery diminished irritation and quitting, maintained engagement enhanced the quantity and quality of practice, and a combination of the two led to additional learning and memorization.

5.5 Durability of Learning and Retention as Evidence of Meaningful Change

According to Table 4.5, the adaptive group seemed to maintain better learning as compared to the comparison group, and there was an advantage to both total retention and transfer-oriented retention. Retention effects are significant as they give evidence that learning gains were not performance gains that are short term in nature. Strong retention is frequently regarded as a sign that a learner is getting more properly timed and factorial practice to decrease the level of misconception and help them consolidate. The trend is in line with wider discussions on tutoring and adaptive systems that have shown that there are positive effects concerning knowledge acquisition and other learning outcomes in various settings [42]. It also goes hand in hand with systematic reviews which warn against the assumption that technology in its own is sufficient to sustain long-lasting learning, however, the stronger effects may be accomplished by structured forms of computer-assisted learning and behavioral supportive designs, which may take hold particularly in the case of learners who otherwise risk falling behind [43].

5.6 Equity and Differential Effects Across Baseline Proficiency

According to subgroup outcomes presented in Table 4.10 and Figure 4.6, students at baseline levels of proficiency gained optimally with comparatively good scores among low- and medium-profile students. This result is significant since individualized learning is frequently translated into a rationale to minimize learning disparities based on the concept promoting the meeting of the learners at their present level and progressing them to a higher scale. Evidence taken to date provides a reason to think that educational technology programs may have beneficial effects on less privileged learners, especially when the interventions do not merely focus on access but further provide structured computer-aided learning and behaviorally supportive systems [43]. The subgroup pattern of the present study is in line with that conclusion since the intervention did not stop at access to involve adaptivity, feedback, and self-regulation support.

Meanwhile, equity claims should be undertaken cautiously due to the sensitivity of subgroup outcomes to implementation faithfulness, previous digital access, and classroom aid. The demographics of Table 4.1 indicate a relatively large stable internet accessivity in general, but even a small difference of access might co-operate with adaptive platform use. This does not imply that equitable impact is simply the result of the actions of the algorithm that personalizes its content, but rather the infrastructural and pedagogical parameters that would facilitate students to access the platform on a regular basis.

5.7 Comparison With Prior Studies and What This Study Adds

When the current findings are compared with the previous work, a number of convergences can be developed. Firstly, the discovery that adaptive tools can boost performance and satisfaction is supported by the results of other empirical studies involving adaptive learning applications in all types of modalities, such as face-to-face and online learning [36]. Second, the engagement and outcome connection supported by Table 4.8 and Figure 4.7 is in line with synthroid of work which indicated that AI applications to education can be used to positively affect the learning outcomes both as well as dimensions related to engagement when effectively incorporated into the learning design [37]. Third, the results of the interaction-pathway are also similar to tutoring-system studies that stress that scaffolding and adaptive feedback may influence the learning progress, especially when they are provided at the time of difficulty rather than consistently [40]. Fourth, cross-proficiency related findings are linked to meta-analytic findings which structured educational technology and computer-aided learning can be especially useful with less advantaged or struggling learners [43].

The value added in this study is the inbuilt alignment of results, engagements and learning analytics into a single results coherent model. Combination of Table 4.3, Table 4.7, Table 4.8 and Table 4.9, which are visually backed by Figure 4.1, Figure 4.3, Figure 4.5 and Figure 4.7, further explains begs the support of the explanatory validity since it connects usage patterns and subjective experience with particular behavioural learning pathways and subsequently with performance and retention. This combined evidence addresses criticisms in the systematic review that an increasing number of evaluations report outcome gains but do not adequately report how the behavioral mechanism of the adaptive systems determine such gains [39], [44].

5.8 Implications of the Study

5.8.1 Implications for Educational Practice

In the case of instructional practice, the findings indicate that adaptive platforms are most beneficial when implemented not as a passive add-on but as a designed practice and feedback layer embedded within course pacing. The increasing increase in completion and voluntary practice as presented in Table 4.3 and Figure 4.1 is an indication that teachers and institutions can apply adaptive platforms to both increase meaningful practice time and reduce frustration. The data in Table 4.9 and Figure 4.5 of the error-recovery reveal that adaptive systems could potentially be of great help to students in times when they are feeling disoriented and the attention of the teacher is often scarce because of classroom specializations. Practically, this would mean that teachers will have more time to engage themselves in higher-order facilitation and conceptualization whereas the immediate response and remediation to students can be left to adaptive mechanisms as long as teachers can track the progress and intervene by them in a needy manner.

5.8.2 Implications for Platform Design and AI Engineering

In the case of platform design, the findings demonstrate the significance of explainable feedback, hint quality, and the adaptive sequencing rules that minimize the unproductive loops. This decrease in quitting following error and an enhanced hint-to-correct enters indicate that adaptive help should be adjusted to produce their chosen benefits of persistence without resulting in addiction. This is in accordance with other research trends that AI in education must focus on more than prediction accuracy and on pedagogical actionability, transparency, and human-in-the-loop control [37], [39]. The integrated model of Figure 4.7 suggests as well that platforms need to put dosage and engagement in the category of first-class design constraints instead of secondary metrics, as engagement partially mediates learning outcomes.

5.8.3 Ethical and Governance Implications

Adaptive platforms are based on large amounts of data on learners and on automated-decision making, creating ethical concerns of privacy, transparency, bias, and learner control. Studies on the ethical awareness of teachers in the recent past indicate that ethical issues are frequently activated by unease and classroom encounter as opposed to policy cognizance initiatives, exemplifying that teacher education and colleagues discussion are significant to ethical assimilation of AI equipment [45]. Expanding ethical efforts focus on transparency, fairness, and privacy regulation as the basics of a reliable AI implementation [46]. Pedagogical and ethical reviews also emphasize that bias monitoring, safe data procedures, and design that is focused on access are required to ensure that AI tools do not exert more inequity [47]. The subgroup gains in the context of this study are encouraging though careful auditing of ethical practice would still be necessary so that the adaptive rules do not have a systematic disadvantage on students with weaker access, disabilities and underrepresented learning profiles.

5.9 Limitations

These findings have a number of limitations which need to be taken into account. First, despite the estimation of baseline equivalence in Table 4.2, any quasi-experimental or classroom-based study will also be susceptible to unobserved confounding, e.g. teacher effects, classroom climate variation, or peer support variance. Second, measurement of engagement, though triangulated by usage logs and self-report measures, might not include all aspects of engagement, including using deep cognitive strategies, metacognitive regulation or not studying off platform. Third, the differences in platform usage, which Table 4.3 indicates, present interpretative issues of whether differences in adaptivity reflects the adaptivity in itself or longer duration and completion reflects the motivational features; whereas Table 4.8 may indicate engagement is a partial factor that may be mediated, Table 4.3 may not be able to do the same unless more hard manipulators of engagement control are imposed. Fourth, the sustained effects of the intervention cannot be claimed because of the duration of the intervention; the retention outcomes were promising, yet much longer follow-up should be required to determine whether the long-term effects could be sustained throughout the terms or years of study. Fifth, generalizability depends on context, subject area and infrastructure preconditions; systematic reviews have stressed that the adaptive learning performance is dependent on the implementation context and that applications in the real world impose institutional or institutional constraints [39], [44]. Lastly, one can also have ethics-based and privacy-related limitations, which may affect adoption and use, with the readiness of teachers being a notable mediating factor in accountable AI integration [45], [47].

5.10 Conclusion of the Study

The research also offers convergent evidence that adaptive learning platforms based on AI can enhance student engagement and academic performance in cases where the usage of these systems is regular, high in terms of task accomplishment, and feedback channels are properly developed. The adaptive group showed a greater performance on the after-test and unit performance, stronger transfer performance, and retention which suggests that there was meaningful learning, as opposed to temporary inflation of scores. The rate of engagement was also measured by more time, completion and voluntary practice in addition to more self-reported interest, relevance, confidence, and less frustration. Learning analytics also indicated that adaptive support increased error recovery by enhancing the use of productive hints and decreasing the quitting following erroneous responding. Subgroup results indicate performance improvement at both levels of proficiency, with specific support of magnitude in those learners who happen to start at baseline performance, suggesting some equity improvement in the circumstances of utilizing adaptive platforms where infrastructural and instructional support is adequate. Altogether, the findings conclude that adaptive platforms may operate as a good learning aid, enhancing engagement and performance at the same time and highlighting the necessity of ethical accountability, transparency, teacher assistance, and context-specific application to achieve an inclusive and sustainable effect.

REFERENCES

[1] J. A. Fredricks, P. C. Blumenfeld, and A. H. Paris, "School engagement, Potential of the concept, state of the evidence," *Review of Educational Research*, vol. 74, no. 1, pp. 59–109, 2004.

[2] E. R. Kahu, "Framing student engagement in higher education," *Studies in Higher Education*, vol. 38, no. 5, pp. 758–773, 2013.

[3] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being," *American Psychologist*, vol. 55, no. 1, pp. 68–78, 2000.

[4] P. Long and G. Siemens, "Penetrating the fog, Analytics in learning and education," *EDUCAUSE Review*, vol. 46, no. 5, pp. 31–40, 2011.

[5] R. S. Baker and P. S. Inventado, "Educational data mining and learning analytics," in *Learning Analytics, From Research to Practice*, J. A. Larusson and B. White, Eds. New York, NY, USA, Springer, 2014.

[6] L. Y. Tan, "Artificial intelligence-enabled adaptive learning platforms, A review," *Heliyon*, 2025.

[7] J. Garzón *et al.*, "Artificial intelligence in education, A systematic review," *AI*, 2025.

[8] A. T. Corbett and J. R. Anderson, "Knowledge tracing, Modeling the acquisition of procedural knowledge," *User Modeling and User-Adapted Interaction*, vol. 4, no. 4, pp. 253–278, 1995.

[9] C. Piech *et al.*, "Deep knowledge tracing," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2015.

[10] A. Namoun and A. Alshanqiti, "Predicting student performance using data mining and learning analytics techniques, A systematic literature review," *Applied Sciences*, vol. 11, no. 1, Art. no. 237, 2021.

[11] X. Huang *et al.*, "Effects of intelligent tutoring systems on educational outcomes, A meta-analysis," *Computers in Human Behavior Reports*, 2025.

[12] UNESCO, *Guidance for Generative AI in Education and Research*. Paris, France, UNESCO, 2023.

[13] European Commission, *Ethical Guidelines on the Use of Artificial Intelligence (AI) and Data in Teaching and Learning for Educators*. Brussels, Belgium, 2022.

[14] M. A. Chatti, A. L. Dyckhoff, U. Schroeder, and H. Thüs, "Learning analytics, Challenges and future research directions," *eLearning Papers*, 2014.

[15] A. F. Wise, "What makes learning analytics research matter," *Journal of Learning Analytics*, 2021.

[16] B. S. Bloom, "Learning for mastery," *Evaluation Comment*, vol. 1, no. 2, pp. 1–12, 1968.

[17] L. S. Vygotsky, *Mind in Society: The Development of Higher Psychological Processes*, Cambridge, MA, USA: Harvard Univ. Press, 1978.

[18] J. Sweller, "Cognitive load during problem solving: Effects on learning," *Cognitive Science*, vol. 12, no. 2, pp. 257–285, 1988.

[19] J. M. Keller, "Development and use of the ARCS model of instructional design," *Journal of Instructional Development*, vol. 10, no. 3, pp. 2–10, 1987.

[20] A. Wigfield and J. S. Eccles, "Expectancy–value theory of achievement motivation," *Contemporary Educational Psychology*, vol. 25, no. 1, pp. 68–81, 2000.

[21] D. R. Garrison, T. Anderson, and W. Archer, "Critical inquiry in a text-based environment: Computer conferencing in higher education," *The Internet and Higher Education*, vol. 2, nos. 2–3, pp. 87–105, 2000.
[22] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, 2003.
[23] M. Csikszentmihalyi, *Flow: The Psychology of Optimal Experience*, New York, NY, USA: Harper & Row, 1990.
[24] M. T. H. Chi and R. Wylie, "The ICAP framework: Linking cognitive engagement to active learning outcomes," *Educational Psychologist*, vol. 49, no. 4, pp. 219–243, 2014.
[25] B. J. Zimmerman, "Becoming a self-regulated learner: An overview," *Theory Into Practice*, vol. 41, no. 2, pp. 64–70, 2002.
[26] K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems," *Educational Psychologist*, vol. 46, no. 4, pp. 197–221, 2011.
[27] S. Steenbergen-Hu and H. Cooper, "A meta-analysis of the effectiveness of intelligent tutoring systems on college students' academic learning," *Review of Educational Research*, vol. 84, no. 1, pp. 88–124, 2014.
[28] S. Sun, N. M. Else-Quest, L. C. Hodges, A. M. French, and R. Dowling, "The effects of ALEKS on mathematics learning in K–12 and higher education: A meta-analysis," *Investigations in Mathematics Learning*, vol. 13, no. 3, pp. 182–196, 2021.
[29] R. Murphy, J. Roschelle, M. Feng, and C. A. Mason, "Investigating efficacy, moderators and mediators for an online mathematics homework intervention," *Journal of Research on Educational Effectiveness*, vol. 13, no. 2, pp. 235–270, 2020.
[30] S. Shen, Q. Liu, E. Chen, and others, "A survey of knowledge tracing: Models, variants, and applications," *IEEE Transactions on Learning Technologies*, 2024.
[31] X. Ding and E. C. Larson, "Why deep knowledge tracing has less depth than anticipated," in *Proc. Int. Conf. Educational Data Mining (EDM)*, 2019.
[32] Y. Mao, C. Lin, and M. Chi, "Deep learning vs. Bayesian knowledge tracing: Student models for interventions," *Journal of Educational Data Mining*, vol. 10, no. 2, pp. 28–54, 2018.
[33] J. Wu, Z. Huang, Q. Liu, D. Lian, H. Wang, E. Chen, H. Ma, and S. Wang, "Federated deep knowledge tracing," in *Proc. 14th ACM Int. Conf. Web Search and Data Mining (WSDM)*, pp. 662–670, 2021.
[34] A. Riedmann, P. Schaper, and B. Lugrin, "Reinforcement learning in education: A systematic literature review," *International Journal of Artificial Intelligence in Education*, 2025.
[35] E. du Plooy, D. Casteleijn, and D. Franzsen, "Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement," *Heliyon*, vol. 10, no. 21, Art. no. e39630, 2024.
[36] M. F. Contrino, M. Reyes-Millán, P. Vázquez-Villegas, and J. Membrillo-Hernández, "Using an adaptive learning tool to improve student performance and satisfaction in online and face-to-face education for a more personalized approach," *Smart Learning Environments*, vol. 11, no. 1, Art. no. 6, 2024.
[37] S. Wang, F. Wang, Z. Zhu, J. Wang, T. Tran, and Z. Du, "Artificial intelligence in education, a systematic literature review," *Expert Systems with Applications*, vol. 252, Art. no. 124167, 2024.

[38] J. Junpeng et al., “Effect of intelligent tutoring system-delivered scaffolding on students’ learning progression in geometry and algebra,” *Computers and Education: Artificial Intelligence*, vol. 7, Art. no. 1010083, 2026.
[39] Hariyanto, “Artificial intelligence in adaptive education, a systematic review of techniques for personalized learning,” *Discover Education*, 2025.
[40] A. Létourneau et al., “A systematic review of AI-driven intelligent tutoring systems for K–12 learning and performance,” 2025.
[41] J. Schaaf et al., “The effect of the frequency of use of an intelligent tutoring system on learning gains,” *Frontiers in Education*, 2025.
[42] X. Huang et al., “Effects of intelligent tutoring systems on educational outcomes, a meta-analysis,” 2025.
[43] G. Di Pietro and J. Castaño Muñoz, “A meta-analysis on the effect of technology on the achievement of less advantaged students,” *Computers and Education*, vol. 220, Art. no. 105197, 2024.
[44] H. Wang et al., “Examining the applications of intelligent tutoring systems in real educational contexts, a systematic review of social experiment studies (2011–2022),” 2023.
[45] C. S. M. Ho and J. C.-K. Lee, “From intuition to action, exploring teachers’ ethical awareness in the use of AI tools in education,” *Computers and Education: Artificial Intelligence*, vol. 6, Art. no. 100502, 2025.
[46] P. Radanliev et al., “AI ethics, integrating transparency, fairness, and privacy for accountable AI technologies,” 2025.
[47] A. Almusaed, “Ethical and pedagogical challenges in the integration of artificial intelligence in lifelong learning,” ERIC, 2024.
[48] E. Omerčević, “Does adaptive learning improve student performance? Evidence from Pearson MyLab in introductory microeconomics,” *Journal of Education for Business*, 2025.