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EVALUATING THE INFLUENCE OF COGNITIVE ENGAGEMENT, ACADEMIC PERFORMANCE, AND SELF-REGULATED LEARNING ON THE ADOPTION OF ARTIFICIAL INTELLIGENCE–DRIVEN ADAPTIVE LEARNING SYSTEMS AMONG UNIVERSITY STUDENTS IN SRI LANKA

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Abstract

Adaptive learning systems (with the role of artificial intelligence, AI) are increasingly becoming a part of higher education to provide personalization of the content, dynamic learning pathways, and timely feedback on student progress. This paper investigates the effect of cognitive engagement, academic performance and self-regulated learning in adopting AI-based adaptive learning systems among students in a Sri Lankan university. The analysis relies on the theory of educational technology adoption and learner-centered theory, the study examines the possibility that the learning behaviors and learning attributes of students influence their adoption and use of AI-enhanced learning conditions. The survey data involving 100 students at a university was used in a quantitative cross-sectional study that was conducted to collect information on the topics of AI-based learning tools exposure and its effect on the students. The analysis of the data was carried out through descriptive statistics, reliability analysis, Pearson correlation, and multiple regression of SPSS. The results indicated that AI adoption had a significant and positive effect on self-regulated learning and academic performance as opposed to cognitive engagement which was found to have a less significant effect on AI adoption in the regression model. The model explains

48.1% of AI adoption, showing that self-directed learning ability and learning orientation influence AI use more than engagement in higher education.

Keywords

Artificial Intelligence, Academic Performance, Adaptive Learning Systems, Cognitive Engagement, Higher Education Self-Regulated Learning, Technology Adoption

1. INTRODUCTION

Artificial intelligence is now one of the most effective trends in educational technology since it enables learning platforms to change their response dynamically to student behavior, progress and needs. AI has a growing presence in the field of higher education, where it is being applied to facilitate teaching, promote personalization, and make the process of learning more efficient. Education Reviews available in the open-access reveal that AI-based systems can adapt learning content, streamline the educational movement, and improve student engagement and academic achievement, as well as open the prospects of more personalized training in various disciplines. Simultaneously, researchers remark that the integration of AI into the educational process is also associated with ethical, technological, and implementation issues, which implies that the educational utility of AI heavily relies on the way in which the systems are designed and applied.

Adaptive learning can particularly be significant in university settings where it is clear that the students will vary in terms of their previous background of knowledge, learning rate, motivation as well as study habits. Conventional single-size-fits-all teaching application fails to meet this diversity, but adaptive systems employ data-driven algorithms to change content, feedback and sequencing based on the profiles of individual learners. According to a literature review by Gligorea et al. (2023), AI and machine-learning applications in e-learning are typically applied to personalize instruction, increase engagement, and favor better academic results and a subsequent systematic review by Merino-Campos (2025) established that AI-powered solutions have the potential to revolutionize personalized learning in higher education by enhancing both efficiency and performance. These results prove that AI-based adaptive learning is not a side-service solution but a core mechanism of enhancing quality of digital education.

The primary aim of this research is to examine how cognitive engagement, academic performance, and self-regulated learning influence the adoption of AI-driven adaptive learning systems among university students in Sri Lanka. Cognitive engagement can be described as how many students apply their mental efforts, attention, and strategies in the learning activities. Academic performance shows the quantifiable outcomes of learning, or grades or levels of achievement. Self-regulated learning is a concept in which students have the capacity to plan and monitor as well as assess their learning. According to recent studies, AI-based adaptive systems can potentially have an impact on all three outcomes through the systemic feedback, individualized route or possibilities of autonomy in a learner. This renders the subject appropriate in a higher education setting wherein student self-reliance is anticipated but distributed in an unbalanced manner in most cases.

Through programs to promote digital literacy, technical innovation, and the integration of emerging technologies into teaching and learning processes, Sri Lanka has recently escalated its efforts to reform a number of sectors, including higher education. To increase access to educational resources and improve learning results, universities are increasingly implementing technology-enhanced teaching methods and digital learning platforms. However, there are still a number of obstacles in the way of implementing cutting-edge technologies like AI-driven adaptive learning systems, such as differences in digital infrastructure, different institutional readiness levels, low AI literacy, and unequal student access to technology resources. Examining the variables influencing students' acceptance of AI-driven adaptive learning systems in the unique setting of Sri Lankan higher education is crucial because of these difficulties.

Even though AI-driven adaptive learning systems are technological advancements, human and societal aspects that affect technology acceptance and use are just as important to their effective adoption as technical capabilities. From a social science standpoint, students' willingness to use educational technologies is greatly influenced by their learning practices, motivations, academic performance, cognitive engagement, and capacity for self-regulated learning. In order to provide a more thorough understanding of AI adoption, this study combines the Technology Acceptance Model (TAM) with the idea of Self-Regulated Learning (SRL). SRL emphasizes the learner-centered procedures that impact educational results and technology utilization, whereas TAM discusses how consumers view and absorb technology. By integrating these viewpoints, the study adds to the expanding corpus of social science research on educational technology adoption in higher education by bridging the technical aspect of AI adoption with the social and behavioral aspects of student learning.

1.1. Statement of the Problem

Though AIs controlled adaptive learning system are gradually implemented into higher education, not all students are equally adopting and using AI-controlled adaptive learning systems. The literature tends to focus on the technical advantages of AI, i.e. personalization, automation, and efficiency but the aspects linked to learners themselves factors influencing the willingness to use such systems have not been thoroughly studied. Specifically, the notions of cognitive engagement, self-regulated learning, and academic performance could also be significant in defining whether students actually gain AI-aided learning space.

The majority of available research focuses considered the AI in terms of performance, engagement, or self-regulation as the educational outcomes, but the authors did not consider the way these student traits could affect the adoption of AI, in turn. But at the learner-based point of view, more academically competent, mentally engagements and self-directed, may tend to consider AI tools handy and embrace them in their learning procedures. Thus, the main research question is not whether AI may enhance the learning process, but whether the specific aspects of academic and psychological peculiarities of students or rather the presence of AI-driven adaptive learning systems in university education impact adoption.

1.2. Objectives of the study

- To evaluate the effect of cognitive engagement on the adoption of AI-driven adaptive learning systems among university students.
- To assess the impact of academic performance on the adoption of AI-driven adaptive learning systems among university students.
- To examine the influence of self-regulated learning on the adoption of AI-driven adaptive learning systems among university students.
- To identify the strongest predictor of AI-driven adaptive learning system adoption among university students.

1.3. Research Scope

This research study will focus solely on the participants in higher education in Sri Lanka who are exposed to the adaptive learning systems powered by AI in a formal learning environment. Three outcomes variables are targeted, namely, cognitive engagement, academic performance, and self-regulated learning. The paper does not even seek to address all potential directions of AI in education namely the automated administration, the faculty workload or the institutional management, although these are also valuable directions. Rather it focuses on the learner experience and how adaptive systems can affect the thinking, studying and performance of students. This emphasis aligns with the recent studies that see individual learning trajectories, feedback cycles, and agency among learners as key characteristics of AI-assisted higher education.

1.4. Significant of study

This research is important because it makes a contribution to educational technology as well as educational psychology. In the case of universities, the results can guide them on the decision to adopt AI-driven adaptive learning systems or not and how to adopt them in a manner that enhances learning outcomes and not merely digitizing the learning process. To lecturers and instructional designers, the research can illuminate whether the use of adaptive tools can help them achieve better academic outcomes by enabling the students to be mentally stimulated and control their learning pattern. Among scholars, the work is a contributor to the emerging evidence base of articles urging researchers to consider that AI in tertiary education may be beneficial but requires situational, application, as well as student in relation factors. Practically, the research can assist higher education institutions in the design of learning environments which encompass personalization along with reflection, feedback, and engagement with students.

2. LITERATURE REVIEW

2.1 The Concept of Artificial Intelligence–Driven Adaptive Learning Systems

Adaptive learning systems based on artificial intelligence are education technologies that analyze learner data and modify it to change content, pacing, and feedback. Instead of presenting all students with the same content, these systems rely on algorithms to generate individualized learning. According to Gligorea et al. (2023), adaptive learning is an approach, which involves the utilization of AI and machine learning that can alter co-teaching dynamically through the performance and engagement of learners. Their summary of the 63 studies concluded that AI/ML tools have registered potential to personalize learning routes, to improve engagement, not to mention academic output. Likewise, Merino-Campos (2025) based the review on 45 studies and came across the conclusion that AIs-based solutions can change the concept of personalized learning in tertiary education by enhancing the effectiveness of learning, personalization of educational material, and academic achievement. These works develop an excellent conceptual base to consider adaptive learning as the system that facilitates individual learning and not the general teaching.

Recent sources also highlight that adaptive learning in post-secondary institutions is also related to learner agency and psychological sustenance. Ouyang (2025) demonstrated that the features of adaptive learning platform under AI are linked to self-regulated learning and engagement with learning activities, and these psychological processes correlate with quality education sequentially. This is significant in that it implies that adaptive systems do not merely enhance the availability of content; they have the capability to influence students in the way they think of learning, keep track of their progress and persevere through the learning experience. Differently put, it means that, AI-based adaptive learning has added value to education in terms of the technical flexibility approached to the content as well as the psychological necessity the software has on the learners.

The literature warns, though, that adaptive learning systems do not necessarily work. AI is premised on quality implementation, ethical design, and necessary digital back-up. The analyses of AI in higher education point to privacy concerns, infrastructure to support AI, and that it should be carefully integrated into pedagogy and learners. Consequently, the idea of AI-based adaptive learning is to be perceived not as a panacean answer but a versatile educational change that can be effective based on the context, the readiness of students and the assistance of an institution.

2.2 *Academic Performance and AI Adoption*

Among the most common evaluated outcome of adaptive learning research is academic performance due to the fact that it is the most observable outcome of successful education. The indications are typically positive. According to Gligorea et al. (2023), adaptive learning through AI/ML is capable of boosting the performance of students in learning activities by optimizing the learning paths and opposing specific intervention. Similar findings were reached by Merino-Campos (2025) who was convinced that the use of AI applications could promote academic performance and efficiency in higher education. It is proposed in these reviews that, given the presence of individualized achievements and timely response to such achievements, students can possibly learn effectively and perform well.

Further support is in the empirical work. Karunaratne et al. (2025) discovered in their study that engagement and performance are interdependent in the context of LMS-based learning and personalized study plans can achieve a substantial level of positive student performance. Their analysis revealed individual learner types and indicated that individualized recommendations could be used to enhance performance generally but particularly among students who were not already consistently high performing. This is important to adaptive learning since it demonstrates that performance gains are not the sole elements with the most effective learners, the neediest learners may also gain significantly through bespoke paths.

Meanwhile, the literature is not uncritically good. Du Plooy et al. (2024) selected 69 studies and authors discovered that 59% were associated with improved academic performance, and 41% could not find significant academic performance effect. The implication of this mixed evidence is that adaptive learning is best positioned as technology actually is a part of the curriculum, aligned with the subject area, and informed by what students already know and are learning. In such a way, the academic performance cannot be regarded as a predetermined consequence of the AI usage, but the side-effect of the attentive interaction between the technology, the pedagogy, and the behavior of students.

H1: Academic performance has a significant positive impact on the adoption of AI-driven adaptive learning systems among university students.

2.3 *Cognitive Engagement and AI Adoption*

Cognitive engagement is the level to which students put in their mental effort, attention, and the ability to think strategically in the learning activities. Engagement is relevant in the context of higher education since those students with deeper thinking tend to have higher chances of learning material, concentrating on their studies, and attaining higher grades. Yaseen et al. (2025) discovered that adaptive learning tools, personalized feedback, and interactive AI tools have the potential to enhance student engagement, provided that students are digitally literate enough to use them. Their results reveal that adaptive systems are capable of facilitating engagement through increased interactivity during learning and through decreasing the discrepancy between student needs and the instructional response. Since engagement enhances the excellence of learning endeavor, it is prudent to assume that cognitive engagement would be a positive correlate of academic performance.

Other AI and education psychology literatures confirm this association. Ansari et al. (2025) have observed that AI assists cognitive learning results through the provision of individualized learning routes that scale to student expectations, cognitive degree, assisting in enhancement of engagement and accomplishment. Similarly, Merino-Campos (2025) also highlighted that AI use in universities can enhance student engagement and academic achievement because it can better personalize the content. These findings demonstrate that cognitive engagement is not merely a product of digital learning, but it is a process according to which students process information deeper and translate learning possibilities into performance results. It is on this reason that cognitive engagement is supposed to relate positively with academic performance to a large extent in the current study.

H2: Cognitive engagement has a significant positive impact on the adoption of AI-driven adaptive learning systems among university students.

2.4 *Self-Regulated Learning and AI Adoption*

Self-regulated learning is one of the important concepts in educational psychology as it involves the process through which students manage, oversee and assess their learning. Self-regulated learning skills are also necessary to university students particularly since university education usually involves more autonomy and less monitoring by teachers as compared to school education. According to Ouyang (2025), the characteristics of an adaptive learning platform based on artificial intelligence strongly correlate with self-regulated learning and that the capabilities of such systems provide the opportunity to support the quality of education with the help of psychological processes that include planning, monitoring, and engagement. The implications of the findings in the study are that the adaptive learning systems can be used as scaffolds that can motivate the students to control their learning in a better way. Self-regulated learning ought to have a positive connection with academic performance because students who make and follow effective study strategies tend to have a better scholar performance.

This argument is reinforced by recent research on the concept of learner autonomy. A meta-analysis conducted by Achuthan et al. (2025) found AI to be an adaptive scaffold that facilitates self-regulatory and self-directed learning in cognitive, motivational, and reflective mechanisms. The review established AI-based interventions to be especially effective particularly in enhancing forethought, planning, monitoring, and reflective assessment which are key to effective academic performance. In the same manner, Du et al. (2025) stressed the sustenance of self-regulated learning in online and blended learning and demonstrated that learning management systems could be developed in such a way that they would facilitate the process of student regulation. These results indicate that SRL is a preferable learning outcome by itself, as well as being a highly predictive factor in academic performance. Thus, the current research considers self-regulated learning as a significant variable that must have a positive impact on the academic performance.

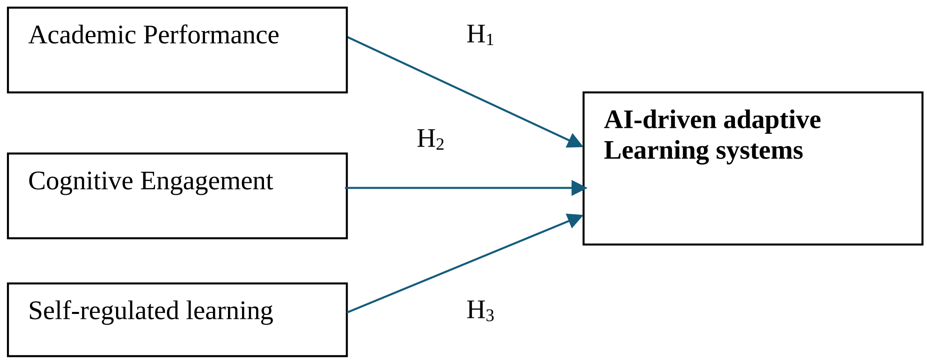
H3: Self-regulated learning has a significant positive impact on the adoption of AI-driven adaptive learning systems among university students.

2.5 *Synthesis of the Literature*

The above reviewed literature confirms that a direct model is possible, where AI-driven adaptive learning systems, cognitive engagement, and self-regulated learning have a direct impact on academic performance. Adaptive learning systems delivered in AI have been shown to enhance personalization, feedback, and learning efficiency many times over, so it is not surprising to find that these outcomes will have a positive correlation with academic learning outcomes. Engagement can be achieved through cognitive learning as engaged learners are at a better position to grasp content more and attain excellent outcomes. The significance of self- regulated learning is also relevant as students that are able to design, control and assess their learning regard will achieve higher academic performance. Throughout the evidence available in the open-access, one can observe the uniformity of results: AI is most effective when it helps achieve learner attention, autonomy, and strategy implementation instead of providing content. Whilst mediation and various other routes are arguably discussed by the larger literature, the current analysis dwells exclusively on the direct impact of the three independent variables on academic performance. That is to say that the study model is purposefully small and statistically parallel to the output of the regression that you furnished, whereby AIAS Mean, CE Menu and SRL Menu together are the predictors to AP Mean. This renders the literature review more precise and in line with the actual analysis plan. Because the findings indicate that both of these variables are separately correlated with or better learning outcomes, the direct-effect model is quite reasonable among the university B2B students using AI-based adaptive learning systems.

2.6 *Conceptual Framework*

The idea behind this study is that the perceptions of university students towards and the AI-based adaptive learning systems (AIAS) can be conditioned by significant educational and psychological variables, specifically, the cognitive engagement (CE), self-regulated learning (SRL), and academic performance (AP). With the ongoing trend of the application of AI-based technologies in the field of higher education, the willingness of students to use adaptive learning systems and their success will also continue to be determined not only by the technical quality of the systems, but also by the intensity of their learning, the degree to which they can independently control their studies, and gender the perceptions of academic performance. A newer study indicates that artificial intelligence-based learning experiences have a higher possibility of acceptance and successful application in situations where they agree with cognitive and behavioral attributes of learners (Gligorea et al., 2023; Ouyang, 2025). On the dependent side, AI-driven adaptive learning systems (AIAS) are used in this research, and they denote the perceptions, acceptance, and experience of students as users of AI-assisted adaptive learning tools. The framework suggests that students who have more cognitive-level engagement, more self-regulation, and students with higher academic performance have a higher chance to record more positive experiences, stronger experiences, with AI-controlled adaptive learning systems. It is this viewpoint that is supported by the emerging body of knowledge on educational technology adoption that has highlighted the fact that technology performance does not depend on system characteristics, but also learner preparedness, involvement and reaction patterns (Merino-Campos, 2025).



Source: Created by authors

Cognitive engagement (CE) is the first predictor over the framework. Cognitive engagement is defined as the level of mental effort, focus, attention, and proactive thinking that the students are putting in their learning activities. When engaging cognitively in an adaptive digital learning environment, cognitively engaged students tend to engage in thoughtful engagement with individually tailored material, reflect on feedback, and engage actively in adaptive suggestions. Yaseen et al. (2025) discovered that adaptive learning tools assisted with AI have the power to enhance the levels of student engagement through more interactive and responsive learning. Nevertheless, the association can be considered in its opposite direction, i.e. students who are already highly engaged might become more likely to appreciate and practically employed AI-driven learning systems. Thus, the cognitive engagement will play a significant role of positive impact on AIAS.

Self-regulated learning (SRL) is the second predictor. Self-regulation learning is one construct that is important to the psychology of education since it has the potential effect on the capability of students with regard to goal setting, time management, tracking of progress and self-assessment of his or her learning strategies. Adaptive learning systems fueled by AI can offer dashboards, progress indicators tailored to each learner specifically, and customized feedback which prove particularly helpful to self-regulated learners. The students possessing good self-regulation skills have a higher chance of utilizing such systems in a strategy and effective manner. Ouyang (2025) discovered that the features of adaptive learning platforms are strongly related to self-regulated learning whereas Achuthan et al. (2025) concluded that the AI tools could be used as a scaffold to learners and support their autonomy and self-management. On this basis, it can be reasoned that SRL would have a positive predictive of how students perceive and use AI-driven adaptive systems of learning.

The third predictor is academic performance (AP). Academic performance is also part of this updated structure as an independent variable since better performing students are likely to appreciate, adopt and rate adaptive learning systems positively. Students with higher academic achievement tend to have better learning strategies, greater academic confidence and improved choices of how to use learning technologies. Simultaneously, the attitudes of the students towards adaptive systems might become more positive when they believe that these systems help them to succeed in their academic performance. According to Gligorea et al. (2023) and Merino-Campos (2025), AI-based learning devices tend to be viewed better when linked with a positive educational outcome. Hence, academic performance will have a positive impact on AIAS. The conceptual framework hence presupposes that cognition involvement, self-controlled learning, and academic achievement are the major predictors of AI-supported adaptive learning systems among university students. The model is also applicable since it enables the study to analyse how learning behaviours and results among the students determine the perception and acceptance of adaptive AI technologies. Although AIAS is viewed solely as a factor that affects the outcomes of academic performance in this framework, other student-specific factors are also identified that can influence the experience and the evaluation of such technologies in practice.

The current study conceptualizes Academic Performance (AP) as a predictor of students' perceptions and acceptance of AI-driven Adaptive Learning Systems (AIAS), despite the fact that academic performance is often studied as an outcome of educational technologies. This positioning is based on the idea that students who perform better academically frequently have higher levels of academic self-efficacy, which is described as confidence in one's capacity to plan and carry out the actions necessary to manage learning tasks (Bandura, 1986). It has been demonstrated that self-efficacy beliefs affect both academic effort and receptivity to new learning resources and techniques. As a result, high-achieving students might be more inclined to see the benefits of adaptive learning technologies, make active use of their features, and report better experiences with them. However, since adaptive learning technologies can also lead to better academic results, there may be a reciprocal relationship between AIAS and AP. In order to justify treating AP as an antecedent variable within the suggested conceptual framework, the current study focuses primarily on comprehending the learner qualities that influence perceptions and acceptance of AIAS.

3. METHODOLOGY

This research premise is made on the positivist research philosophy, which calls on the emphasis on objectivity, measurement, and testing of hypotheses. Positivism is an appropriate research technique in this study since the researcher intends to test the statistical correlations amid quantifiable attributes AI-driven adaptive learning systems, cognitive engagement, self-regulated learning, and academic performance. The study involves the application of numerical data and, as there are direct links between variables studied with the help of correlation and regression, it is better to discuss a positivist underlying philosophy.

This would be in line with the quantitative educational research, the aim of which is to determine whether one variable is significantly predicted purely by one other. The study complied with accepted social science research ethics guidelines. The study adhered to basic ethical procedures even though formal Institutional Review Board permission was not requested because the survey instrument was anonymous and non-invasive. Respondents were made aware of the study's purpose before filling out the questionnaire, and participation was completely optional. All participants gave their informed consent after being reassured that their answers would be kept private and anonymous. Additionally, participants were made aware of their freedom to leave the study at any time without facing any repercussions. Throughout the research process, the survey's data was securely stored and used only for academic purposes.

3.1 Research approach and Design

The research has a deductive type of study. The hypotheses were based on the available literature and were therefore tested with data received via a survey. The research method suitable in this case is deductive research since there is already evidence in literature that adaptive learning systems, engagement, and self-regulation can affect academic performance. It has a cross-sectional design, as the data was collected at a single point in time with respect to the respondents. Studying relationships among variables in university research and this design is best applicable when relations need to be established on survey research based learning research. Even though the studies cannot provide causality in its strongest sense, cross-sectional studies prove to be useful when establishing statistically significant relationships between constructs. The research is also quantitative as far as the measures of the variables were taken as Likert-scale items and processed in SPSS. Quantitative design enables a researcher to calculate, determine the reliability and correlations besides determining the predictive preventive power of the independent variables within the dependent variable. The regression equation used in this research specifies AIAS Mean as the dependent variable, while CE Mean, SRL Mean, and AP Mean are treated as independent predictors. This structure is a correspondence to a currently produced statistical output and retained the analysis within the conceptual framework.

3.1 Population and sampling

The study population will include students of universities in Sri Lanka having developed experience with AI-driven adaptive learning systems in their academic activities. Students who have taken force in digital learning platforms, AI-enhanced study tools, or adaptive learning systems in formal learning should be considered the respondents. The sample size of 100 is sufficient to conduct a focused multiple regression study of this kind, which is aimed at analysis.

An adequate sampling technique (that employs non-probability sampling methodology) is a purposive or convenient sampling, as the research will need the target group members to have a direct experience working with AI-based learning tools. This will make the respondents able to give relevant responses about the measured constructs. In analogous cases of AI-mediated learning and adaptive systems, alternative studies have used samples of university students based on academic environments of importance and this justifies the nature of the measured samples of student sample.

To invigorate an energetic search of the literature, Yaseen et al. (2025), Ouyang (2025), and numerous others examined adaptive learning platform features as applied in an educational setting, as well as their relationship with the level of engagement rate between students and adaptive learning technologies.

3.2 *Construct measurement, Indictors, and Sources*

Each of the constructs in the study is measured on a five-point Likert scale on a scale where 1 = Strongly Disagree/Strongly disagrees to 5 = Strongly Agree/Strongly agrees. The application of a Likert scale would be suitable as the question means that the respondents can reveal how much they agree with the statements of each variable, as well as have the responses in a quantitative format.

3.3 *Adaptive Learning Systems that are AI driven* (DV)

The AI-based adaptive learning systems (AIAS) is the dependent variable that is assessed on the basis of items concerned with the student perceptions regarding the personalization, system responsiveness, real-time feedback, adaptive pacing, and learning support. Such indicators are aligned with how AI based adaptive systems are conceptualized on the basis of the educational technology literature. As stated by Gligorea et al. (2023), the personalization, flexibility, and automatic guidance of the learning setting are common to AI-assisted learning environments. Equally, according to Merino-Campos (2025), AI tools used in higher learning are adaptive and thus, they are developed to enhance learning experiences based on the needs and development of the learners.

Independent Variable: Cognitive Engagement

The cognitive engagement (CE) is assessed through such factors as attention, concentration, deep thinking, active mental effort and meaningful participation in academic activities. These articles indicate how much students are psychologically engaged in education. Yaseen et al. (2025) indicate that students with a higher level of cognitive engagement have a higher chance of engaging with adaptive educational technologies meaning CE is a significant predictor of AIAS.

Independent Variable: Self-Regulated Learning.

The indicators that are used to measure self-regulated learning (SRL) are goal setting, planning, monitoring progress, self-discipline and reflective learning. SRL audience is the extent to which the students take charge over their learning processes. Both Ouyang (2025) and Achuthan et al. (2025) note the close association between adaptive digital learning environment and self-regulatory behaviors, which is why SRL is a predictor that can be included in the current research.

Independent Variable: Academic Performance

Academic performance (AP) is assessed with the help of self-reported measures including good performance in tasks, academic advancement, regularity of academic work and subjective academic achievement. Academic performance in educational research is sometimes considered to be on a subjective scale when the research researcher is dealing with perceptions of students and adoption of technology instead of grade score records. This research involves AP as a independent variable since, students who have a higher academic achievement would have an advantage to respond positively and utilize AI-based adaptive systems.

3.4 *Research instrument*

A structured questionnaire is considered the primary data collection tool. The questionnaire will be in two major sections. The former section will provide demographic data, such as age, study year, and frequency of using AI-based learning tools. Scale items that measure four constructs (AIAS, CE, SRL, and AP) are included in the second section. The questionnaire will be developed in a manner that will allow it to be clear, simple and be relevant to the context of university students. This specific study will respond well to a structured questionnaire due to the standardized responses, and the researcher will be in a position to get the same responses out of all the respondents. It is also able to perform statistical analysis and also to ensure consistency in the sample measurement. The questionnaire can also be pilot tested before its ultimate administration to verify that the wording of the items is clear and that they are good to the target respondents. Technology related studies should be pilot tested particularly since it is easy to have misunderstandings regarding the definitions of these terms to include adaptive learning, AI feedback or learning personalization and so on unless the statements are well worded.

3.5 *Data Collection and Analysis*

The data is collected through an approximate questionnaire that is given to the students of the university who fits the criteria of the study. The questionnaire can be conducted on the internet, in person or by the mixed approach based on accessibility and the convenience. Because the target group is made up of university students in Sri Lanka, which is already accustomed to the digital platforms a practical and efficient distribution means would be online distribution. Once the responses are collected they are analyzed in SPSS. The process of analysis of the data is divided into a few steps. The demographic factors of the respondents and the central tendencies of the variables in the study are summarized by the first by using descriptive statistics.

They encompass the average standard deviation, minimum, and maximum values of the age variables, the year of study and the weekly AI use. Second, Cronbachs alpha is employed as a measure of reliability analysis of the measurement scales. The alpha value of Cronbach over 0.70 is usually acceptable and it means that the scale items used measure the same construct. Third, Pearson correlation analysis is considered to study the direction and the strengths of relations between the variables.

This will assist in investigating the relation of thought involvement, autonomy in learning, and school accomplishment with AI-based adaptive educational apparatuses. Lastly, to determine the joint and the independent factors of the independent variables on the dependent variable, a multiple regression analysis is conducted. The updated model would be represented as shown below with AIAS Mean as the dependent variable, and the independent variables being CE Mean, SRL Mean and AP Mean. The given analysis will enable the researcher to distinguish which predictors have a significant effect that leads to the variation in the perceptions and the use of AI-driven adaptive learning systems among students.

4. RESULTS AND DATA ANALYSIS

Table 1. Demographic Profiles of the Respondents

Demographic Variable	Category / Statistic	Frequency / Value	Percent (%)
Sample Size	Total Respondents	100	100.0
Age	Minimum	18	—
	Maximum	25	—
	Mean	20.77	—
	Standard Deviation	2.145	—
Year of Study	Minimum	1	—
	Maximum	4	—
	Mean	2.20	—
	Standard Deviation	1.064	—
Weekly AI Usage Hours	Minimum	0.8	—
	Maximum	7.0	—
	Mean	4.166	—
	Standard Deviation	1.4521	—

Source: Created by authors based on data analysis

Descriptive statistics were conducted to identify the demographic profile of the respondents in order to have a rough idea of the sample character. This research was done on 100 undergraduate students where demographic data were obtained concerning age, study year, and the number of hours of AI tools usage on a weekly basis. Based on the results of the descriptive, the respondents were most likely undergraduate students who were mostly young with a mean age of 20.77 years (SD = 2.145) that ranged between 18 to 25 years. This implies that the sample is, in great measure, the students who are from the standard age group in the university. The mean years of study were 2.20 (SD 1.064), indicating that the focus of the sample was on the students studying the second year of their academic programs, although all undergraduate years also participated in the study. Concerning using artificial intelligence tools, respondents indicated that they were spending an average of 4.166 hours every week (SD = 1.4521), with a range of 0.8 hours to 7.0 hours weekly. It means that students are already making a moderate use of AI tools, which confirms that AI-based educational support is topical and well-known in the existing environment of higher education. The demographic profile hence validates that sample is suitable in exploring how the classroom engagement, self-regulated learning and academic performance have an impact on the adoption of AI or AI academic support among university students.

A reliability analysis was conducted using Cronbach's Alpha for all 19 measurement items across the four constructs: AIAS, CE, SRL, and AP.

Table 2. Reliability Analysis

Scale	Cronbach's Alpha	Number of Items
All Variables	0.922	19

Source: Created by authors based on data analysis

Cronbach's Alpha which is the reliability percentage of the full scale = 0.922, revealed an excellent internal consistency. As per widely replicated rules, the alpha scale of above 0.70 can be viewed as an intervention, above 0.80 can be termed as good, and above 0.9 could be taken as very high (Taber, 2018). Hence, it is observed that alpha collected in the current research indicates the consistency of the questionnaire items that measured the intended latent factors.

This great reliability means that the respondents responded to questions in the questionnaire in a consistent and stable pattern such that individual item scores can be combined into composite scores to be further analyzed. Since the scale reliability was excellent, the statistically justified use of these composite mean variables was based on correlation and regression analysis.

Table 3. Univariate Analysis

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Age	100	18	25	20.77	2.145
Year of Study	100	1	4	2.20	1.064
Weekly AI Hours	100	0.8	7.0	4.166	1.4521

Source: Created by authors based on data analysis

Univariate analysis was conducted to explain the center of tendency and variability of the variables under study. Such step gives the conceptual background of how the respondents perceived each construct and a broad outline of the general direction of responses before considering relationships among variables.

The descriptive statistics will indicate that the represented sample is not very diverse academically and is active users of AI tools. Its mean is 20.77 years of age which indicates a normal population of an undergraduate student and the average year of study, 2.20 indicates that the sample is comprised of mostly students enrolled in the initial and middle phase of their studies.

The average hourly AI utilization numbering at 4.166 hours each week is quite notable. This implies that not only is the respondents cognizant of the AI tools but is using them in a frequency that is regular. This level of exposure is relevant in the current research since it shows that students are quite ability and can create meaningful perceptions when it comes to the usefulness and value of AI in academic processes. This will follow with the current body of research in the education field who believe that students are quickly engaging AI in their education practices to enable information searching, idea generation and feedback, and studying benefits.

In spite of the fact that the results, presented in this case, do not have any means of composite constructs, but just demographic descriptives, the results do aid in bringing the context to the sample. The respondents seem ready to be active in their academic lives, digitally exposed and in an academic setting of higher education, where AI-driven-learning processes are gaining wider exposure. The presence of such a context would be suitable to the investigation of whether classroom engagement, self-regulated learning and academic performance can be considered determinants of perception and consumption of AI academic support by students.

Table 4. Bivariate analysis

Variables	AIAS_Mean	CE_Mean	SRL_Mean	AP_Mean
AIAS_Mean	1	.504**	.404**	.490**
CE_Mean	.504**	1	.551**	.449**
SRL_Mean	.404**	.551**	1	.646**
AP_Mean	.490**	.449**	.646**	1

Source: Created by authors based on data analysis

The study performed bivariate analysis through the Pearson correlation coefficients in order to establish the strength and direction of the relationships between the key variables of the study. The analysis of correlation is applicable in ascertaining whether two or more variables are connected with each other and then on to regression analysis. The correlation analysis shows that the major variables are significantly related and positively to each other at the level of 0.01. Above all, there were statistically significant positive correlations between the dependent variable AIAS Mean and all three independent variables. To begin with, Classroom Engagement (CE Mean) was moderately positively correlated with AIAS_Mean ($r = .504$, $p < .01$). This suggests that the more involved the students are in their activities in the classroom learning, the more they are likely to report high utilization or perception of AI as a learning aid. This connection could also indicate the notion that active learners have more chances to access additional learning tools, such as AI-driven tools, to enhance the level of understanding, involvement, and task accomplishment.

Second, Self-Regulated Learning (SRL_Mean) also positively related to AIAS_Mean ($r = .404$, $p < .01$). This relationship is not as strong as that of classroom engagement, but it nevertheless suggests the existence of a meaningful relationship. In terms of academic output, it seems those students who are more adept with planning; monitoring and controlling their own learning are more likely to use AI. This is in line with emerging findings that AI tools tend to be effective in the context of goal setting, monitoring, feedback seeking and reflective learning when used strategically by students.

Third, the Academic Performance (AP_Mean) had a moderate positive correlation with AIAS_Mean ($r = .490$, $p < .01$). This promotes the idea that the students having better academic performance are more prone to report greater AI academic support or AI adoption. The reason here could be that high-achieving students might be more active when it comes to finding out the tools, which could help them to become more efficient, understand better, and complete the assignments.

The correlation table also indicates that there are important interrelationships amongst the independent variables as well. CE_Mean and SRL_Mean, were positively interrelated ($r = .551$, $p < .01$), which means that engaged students are also more inclined to having self-regulation of their learning behavior. The same applies to SRL_Mean and AP_Mean, which had the highest level of inter-correlation between the independent variables ($r = .646$, $p = < .01$), implying that more self-regulated students also perform better academically. This result is congruent with a substantial body of scholarly work which puts self-regulation as a powerful predictor of academic achievement. On the whole, the bivariate analysis presents good preliminary evidence of relationships to be proposed in the research. The fact that all the three predicted significantly as compared to AIAS_Mean meant that it was correct to go one step higher to multiple regression analysis and determine predictive effect of these three factors together and separately.

Table 5. Multivariate analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.693	.481	.464	.50323

Source: Created by authors based on data analysis

A multiple linear regression was used to test the combined and distinct effects of Classroom Engagement (CE_Mean), Self-Regulated Learning (SRL_Mean) and Academic Performance (AP_Mean) on AI Academic Support / Adoption (AIAS_Mean). According to the model summary, all the independent variables together show a medium strong relationship with the dependent variable. Multiple correlation coefficient ($R = .693$) indicates that the interaction of classroom engagement, self-regulated learning, and academic performance is significantly related to AIAS_Mean.

Coefficient of determination ($R2 = .481$) implies that the three predictors used in the model account 48.1 percent of the variance of AIAS mean. In the learning studies in education and behavioural learning this is a significant ratio since the learning outcomes of human beings are usually determined by many interconnected factors. Adjusted $R\ 2 = .464$ indicates that the model still has very high explanatory power even after taking into consideration the number of predictors. In real life, this would imply that now almost fifty percent of AI academic support/ adoptions among students can be attributed to variance in class room and classroom engagement, self-regulated learning and academic performance.

Table 6. ANOVA Analysis

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	22.495	3	7.498	29.610	.000
Residual	24.311	96	.253		
Total	46.807	99			

Source: Created by authors based on data analysis

The results of the ANOVA suggest that the regression model is statistically significant, $F(3, 96) = 29.610$, $p = .001$. This implies that the combination of the independent variables is an important predictor of AIAS Mean. That is, the overall model is superior to a model having no predictors. This observation proves that CE, SRL, and AP are collectively relevant in the explanation of the AI-related academic behaviour or perception of students.

Table 7.

Predictor	B	Std. Error	Beta	t	Sig.
(Constant)	0.430	0.294	—	1.464	.147
AP_Mean	0.267	0.088	0.264	3.054	.003
CE_Mean	0.030	0.102	0.028	0.292	.771
SRL_Mean	0.539	0.092	0.524	5.858	.000

Source: Created by authors based on data analysis

Self-Regulated Learning (SRL mean) was the best predictor of AIAS mean with a standardized beta coefficient of .524 ($t = 5.858$, $p = .001$). This fact suggests that learners that are more knowledgeable about arranging, supervising, and managing their own learning have a much higher chance of utilizing or appreciating AI as an academic aids support. The fact that this coefficient is huge and meaningful indicates that self-regulated learners have an ideal opportunity to incorporate AI into their learning approach. It is highly consistent with existing research indicating that AI tools can be most effectively employed in education when the student operates in a designed process of self-regulation including planning, feedback applications, revision, and self-monitoring.

Academic Performance (AP_Mean) was also discovered to be a great positive predictor of AIAS_Mean, where 0264 =.264 ($t = 3.054$, $p = .003$). This implies that learners that have higher academic performance are also more inclined to affirm that they have stronger AI academic assistance or AI application. One of the likely explanations is that the students with high academic performance can prove to be more strategic and resourceful in recognizing and using the tools that make the learning process effective and productive.

On the contrary, there was no statistically significant influence of Classroom Engagement (CE_Mean) on AIAS_Mean in the presence when the other variables were held constant (Beta =.028, $t = 0.292$, $p = .771$). However, the predictive value of CE in the regression model lost the significance of the earlier bivariate correlation significantly despite the fact that the correlation coefficient was significantly positive because the correlation scored high in the bivariate analysis. This implies that the connection between classroom engagement and AIAS can be answered indirectly by a more powerful variable like self-regulated learning as well as academic performance. That is, classroom activity does not appear to be a purely predictive factor in case the independent learning habits and performance level of the students are considered regarding the possibility of academic support through AI.

5. DISCUSSION

The results of the current research are meaningful in relation to the factors that impact on AI Adoption in Studies (AIAS) among undergraduate students. According to the regression model that considered Academic Performance (AP), Cognitive Engagement (CE) and Self-Regulated Learning (SRL) as predictors of AIAS, these results show that there is no single factor to predict how students use AI in academic settings, but rather it is a combination of academic behaviour, learning autonomy, and performance orientation.

One of the results of the team is that Self-Regulated Learning (SRL) is the most and most statistically significant positive predictor of AI adoption. The learner-centered standardized coefficient of SRL ($\beta = 0.524$, $p < .001$) indicates that more able students to plan, monitor and control their learning are much more inclined to embrace AI technological resources in their studies. Such an outcome is theoretically coincidental with the perception that AI tools are best appropriated by proactive, reflective, and self-reliant academic tasks among learners. Having a high level of self-regulation, students can utilize AI not only as something convenient to help them on their way, but as a strategy in token production, clarification of the thought, development of ideas, summary, and formulating self-tests. This concurs with the previous educational technology texts that postulate that the independent learner might be more inclined to engage digital tools in a meaningful way into his/her learning model.

The research also discovered that Academic Performance (AP) influences the AI adoption in a positive and statistically significant manner ($\beta = 0.264$, $p = .003$). It means that there will be an increased likelihood that students who believe themselves to be doing better in their academics will also make use of the AI tools in their learning. A potential reason is that students with better performance would find AI as a way to make one more work product. They can rely on AI to enhance knowledge, minimize time, and achieve quality output. This result contradicts the popular belief of the existence of AI being applied primarily to weaker students. Alternatively, the findings indicate that the students of higher academic proficiency are perhaps one of the most prolific adopters of AI, presumably due to being more inclined to maximize learning and ensure performance.

Cognitive Engagement (CE) in contrast was clearly found to influence adoption of AI in a positive but statistically insignificant manner ($\beta = 0.028$, $p = .771$). Whereas at the bivariate level CE and AIAS correlated moderately positively ($r =.504$, $p <.01$), the specific contribution ceased to exist in the multiple regression analysis equation when SP with SRL were involved. This poses a possibility that greater collaboration among students might involve more AI use, but Cognitive interaction is not the reason why individuals will adopt AI, even after accounting for self-regulation and academic performance. It is possible again that the application of AI in learning institutions is more heavily supported by individual learning tactics than peer-to-peer or group educational interaction. Put differently, students can mostly apply AI as an individual academic helper but not as a team-based tool.

In general, the model accounts 48.1% of the variance in AI adoption (R^2 =.481) that shows that its explanatory power is moderately strong. This implies that a combination of AP, CE, and SRL is significant to explain almost half of the differences in the behavior of students regarding AI adoption. Although this is quite substantial, it also indicates that other factors that are not covered in the model (such as digital literacy, perceived usefulness, ethical perceptions, institutional support, accessibility or attitudes towards AI) can also be extremely important. Thus, the current results provide a solid yet not comprehensive explanation of the adoption of AI in higher education.

6. CONCLUSION

The research investigated the relationship between Academic Performance (AP), Cognitive Engagement (CE), and Self-Regulated Learning (SRL) and AI Adoption in Studies (AIAS) among students of universities. The results tacitly show that the use of AI in the academic setting has a strong positive relationship with internal learning and academic orientation of students. Self-Regulated Learning was found to be the strongest among the three predictors as compared to Academic Performance. This means that the more self-motivated and academically oriented students will be willing to use AI tools as learning tools. By comparison, Cognitive Engagement exhibited no statistically significant independent effect, indicating that the adopted usage of AI is more significantly associated with individual academic behavior, as opposed to Cognitive academic involvement. The research hence postulates that there is no random or even consistent adoption of AI tools by students. Instead, their initiation seems to go in the manner that the students are motivated by the learning discipline, academic desire, and capacity to maintain their studies under their own machineries. The implications of these outcomes are also significant, as it emphasizes that AI in the educational setting proves useful on the example of students who are capable of approaching AI with critical, responsible, and meaningful interactions.

Resting on the results, some effective recommendations can be offered. Firstly, educational institutions endeavoring in provision of higher education must focus more on the aspect of teaching students to regulate learning all by themselves. The areas addressed in workshops, academic support, and orientation should revolve around time management, goal setting, reflective learning, and independent study approaches because they seem to highly promote effective borrowing of AI. Second, the AI literacy should be included in the academic development training in universities. Given that academically better-equipped students likely appear to be profitable AI factors, the institutions must make sure that educators possess the skills to guide all learners, in particular, those with poor achievements, on how to use AI tools in an ethical, critical, and a productive approach to learning and not dependency.

Third, in spite of the fact, that Cognitive engagement was not a substantial predictor in the regression model, the application of AI to facilitate group learning and peer collaboration should be explored further by the institutions because the latter is a less advanced field. AI used in a structured classroom activity, involving both a discussion and teamwork as well as Cognitive problem solving, can help expand its educational utility. Last but not least, further inquiries of the adopted digital competence, attitudes toward AI, ethical awareness, perceived usefulness, and institutional support as other variables need to be tackled in future research to make the student AI adoption model more comprehensive. This kind of research would assist the universities to develop more useful policies and support systems of learning with AI-enhanced learning. To conclude, the use of AI in research should not be viewed as a technology problem, but a behavioral learning problem. Universities interested in supporting the meaningful and accountable use of AI should, consequently, not be limited to gaining admission of technology, but also ameliorating the academic and self-directional competencies of the students.

Convenience sampling was used in this study, which is useful for exploratory research of this kind but restricts the findings' applicability outside of the sampled institutions. The sample might not accurately reflect students in every field, kind of institution (private vs. state) or area of Sri Lanka. To improve the external validity of results, future studies should use stratified random sampling or probability-based sampling techniques in addition to more institutional representation. This study's cross-sectional design restricts the ability to infer a causal relationship between the predictor variables and the adoption of AIAS. Although Bandura's (1986) self-efficacy paradigm serves as the theoretical foundation for AP, a bidirectional relationship between AP and AIAS cannot be ruled out (Zimmerman, 2002), and further longitudinal study is advised to elucidate this relationship.

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