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Harnessing AI for Personaliszed Learning: Fostering Sustainable Educational Practices in Sri Lanka's Higher Education Sector

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Abstract

The purpose of this research is to analysze how artificial intelligence (AI) can be used to develop sustainable individualiszed learning experiences in Sri Lanka's higher education sector. Data was collected from 380 university students in Sri Lanka using a survey questionnaire. Structural Equation Modeling (SEM) was used to test the hypotheses. The findings proved that Artificial Intelligence Driven Personal Learning (ADPL) can enhance student performance and student engagement. However, educator skills did not have a moderator effect. Further, learner autonomy did not mediate the relationship between ADPL and student engagement, which proves that it is not significant in improving student engagement in personaliszed learning environments. It is important to invest in AI infrastructure to support ADPL implementation by Sri Lankan universities to enhance student performance. Educators can act as mentors in these platforms. Universities should invest in robust AI infrastructure and training programmes to facilitate the adoption of ADPL. Additionally, policymakers can use these insights to design sustainable educational policies that improve resource efficiency for long-term improvements in student outcomes.

Keywords: AI-driven personaliszed learning, Educator Skills, Learner Autonomy, Student Engagement, Student performance

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Introduction

Integration of artificial intelligence (AI) has significantly transformed the education systems worldwide in recent years (Ilić et al., 2021). Sri Lankan higher education institutions are exploring innovative approaches to meet evolving academic needs (Vivek & Nanthagopan, 2023). Personalised learning generally tailors educational content to meet student needs (Hilpert et al., 2023). When AI is integrated into personalised learning, the efficiency of the learning process increases. On the other hand, the traditional learning experience follows a one-size-fits-all approach which is less efficient. Researchers argue that AI based personalised learning enhances student engagement and performance.

Sri Lankan higher education sector consists of both public and private sector institutions offeringcompetitive qualifications for students targeting local and global job market (Weerasinghe & Fernando, 2018). It serves a wide variety of students from different socio-economic backgrounds. Sri Lankan higher education institutions now integrate AI for personalised learning and service delivery (Jayasinghe, 2024). When referring to sustainability perspectives of education system in Sri Lanka, the country is moving towards achieving sustainable development goals, while integrating an efficient education system.

Even if AI is transforming the global education system, Sri Lanka's higher education sector faces significant challenges in adopting AI-driven personalised learning practices (Jayasinghe, 2024). Resource constraints act as a major challenge for Sri Lankan education institutions when transforming in to AI based learning. On the other hand, the educators lack necessary skills required to incorporate AI in teaching process. It is important to integrate current teaching methodologies and personalised learning. Students' needs are evolving with technological advancements. They expect more autonomy in the learning process. According to research, 71% of students use AI tools for their education process (Sunday Observer, 2024). However, the use of AI in Sri Lankan higher education institutes is still unexposed. However, Sri Lankan education systems lack transformation into AI-based personalised learning processes (Jayasinghe, 2024). Therefore, the higher education sector may struggle to maintain relevance in a rapidly advancing digital era. There can be gaps in student achievement, satisfaction, and overall institutional performance. The aim of this study is to investigate how artificial intelligence (AI) can be harnessed to create sustainable personalised learning experiences in Sri Lanka's higher education sector. This study examines the current AI-driven personalised learning among higher education students in Sri Lanka which can reflect current weaknesses and challenges in using these systems. Student engagement levels using personalised learning can be identified through this study which can guide to understanding how effective usage of AI-driven personalised learning can improve engagement in Sri Lankan education systems. Therefore, the findings of this study are useful to build a more effective and sustainable education system by integrating AI.

This study explores how AI can be used to promote personalised learning in higher education. Hence, it can be argued that the findings of this study can address the gap in Sri Lanka's educational development. As explained earlier, education systems in the world are continuously transforming based on technological advancements (Ilić et al., 2021). This has led to more efficient and flexible student-centered learning environments. Therefore, the findings of this study can be useful for policymakers to focus on AI-based personalised learning to develop strategies to integrate AI more effectively in the current education system. When reviewing the literature, it was identified that the majority of the studies are focused on challenges in the adoption AI integrated personalised learning platforms in Sri Lanka. There is a clear empirical gap in integrating AI-based personalised learning, student performance and engagement in the Sri Lankan education context. The findings of this study are useful to fill this gap. The broader goals of preparing future generations with the skills necessary to adopt a technology-driven education system can be achieved by focusing on sustainable education practices analysed in this research.

Literature Review

AI-driven personalised learning

Personalised learning can be identified as an approach tailored to meet the needs of students. It can be prepared based on the skills of the students also. Personalised learning enables educators to design programmes based on individual learning styles and paces (Tan et al., 2022). Therefore, students can experience customised content which deviates from traditional learning styles. Personalised learning typically enhances student engagement while improving student outcomes. Students are motivated to do their academic work under personalised learning backgrounds (Sayed et al., 2023). Flexibility in this approach is higher when students get programmes suited to their own pace. Real-time feedbacks are provided in these learning environments which help students to improve their performance (Kokku et al., 2018).

Artificial Intelligence (AI) in personalised learning uses intelligent systems to tailor educational experiences (Bhutoria, 2022). It can be used to analyse large data sets of student performance and prepare education content suitable for each student using AI algorithms (Huang et al., 2023; Ke et al., 2020). AI provides immediate insights into strengths and areas for improvement for students (Pataranutaporn et al., 2021). Natural Language Processing (NLP) is an important tool in AI (Maghsudi et al., 2021). It can be used to assist students in their learning process (E.g.: virtual tutors or chatbots). AI is increasingly used to predict student performance in the higher education sector (Lim et al., 2023). The results can be used to design learning content based on the challenges faced by students. Researchers have used AI-driven analysis of web tracking logs and feedback classification in the identification of personalised learning outcomes (Murtaza et al., 2022). The findings reveal that AI can accurately classify and respond to individual learning behaviors (Kanchon et al., 2024). Researchers have used spaCy's named entity recognition (NER), GPT-3, and T5 models to adjust educational materials for different learner categories.

Student Performance

Student performance refers to the measurable outcomes of a student's learning process in educational settings. It can be measured through different metrics. Student performance can include cognitive, behavioural, and emotional aspects of learning. The performance of a student can be reflected through their skills and competencies as well as their positive attitudes. According to research, students with higher self-discipline often achieve better outcomes. Most of the researchers evaluate student performance based on the academic results or the final grades arguing that it reflects the skills of the students (Francescucci & Rohani, 2019). Educators use exams, assignments and final grades to evaluate the performance of the students academically which focuses on the learning abilities of the students (Iglesias-Pradas et al., 2021). There is a higher emphasis on test grades in measuring student performance according to researchers.

When measuring student performance, cognitive skills demonstrate the performance of the students' achievements (Damasceno et al., 2019). Students must be capable enough to critically analyse issues and apply critical thinking in the learning process. Researchers reveal that critical thinking is a significant predictor of cognitive skills which determines the performance of the students in their education journey (Richardson et al., 2012). Problem-solving skills also represent the academic performance of the students in their learning process. Educators must implement practical project-based learning in promoting problem-solving skills since it equips students with abilities to face real-world challenges (Dunlosky et al., 2013). Analytical skills are another important dimension in the cognitive skills of students which determines their performance (Chen & Wu, 2015).

Behavioural performance plays an important role in shaping student performance (e.g.: classroom participation, attendance, and compliance with institutional norms.) (Francis & Babu, 2019). Students must be punctual and should be consistent with homework completion which reflects their commitment to education (Freeman et al., 2014). Researchers reveal that behavioural performance is important in determining student performance. Emotional and social competence influence a student's teamwork and communication abilities (Yeager & Dweck, 2012). Students learn to manage their emotions to perform better academically.

AI-integrated education environments can offer students tailored learning experiences. Therefore, the performance of the students can be enhanced (Ouyang et al., 2022). Studies show that AI-driven tools can improve student retention and performance (e.g.: intelligent tutoring systems and adaptive learning platforms) (Cui et al., 2018). AI has the ability to provide real-time feedback for students which encourages proactive learning (Liyanage et al., 2022). Therefore, it can be argued that AI enhances the academic performance of students. Data analytics is a major part of AI which can help students to improve their performance (Alnassar et al., 2021). However, researchers argue that ethical issues and data security issues arise when incorporating AI in higher education (Li et al., 2024).

Sustainable Education Practices

Sustainable education can be identified as the education methods which incorporate sustainability principles (Lozano et al., 2017). According to the literature, sustainable education focuses on promoting systemic thinking and connecting educational practices to real-world sustainability challenges (Rieckmann, 2012). Students are prepared to equip themselves with knowledge to address complex global issues (e.g.: climate change, resource depletion, and social inequality). One of the major principles in sustainable education is integrating multiple disciplines (Annan-Diab & Molinari, 2017). Students must be equipped with the knowledge to address sustainability challenges comprehensively. Active learning is encouraged in sustainable education where students engage in experiential learning for a deeper understanding of sustainability concepts (MacVaugh & Norton, 2012). Critical thinking is a valuable sustainable education practice which encourages to think critically about global challenges (Rieckmann, 2012).

AI-based education platforms provide a sustainable educational experience to students since they integrate efficiency and personalisation. Personalised learning is an important benefit of AI in education (Amballoor & Naik, 2023). Researchers reveal that AI-powered tutors provide personalised guidance to students which improves academic performance (Kamalov et al., 2023). Research reveals that AI promotes automated grading and assessment of student work which ensures timely feedback. For sustainable educational outcomes, AI enhances teacher-student interaction through data-driven insights. AI helps educators to analyse student behaviour, performance, and student emotions (Lin et al., 2023). Previous studies highlight that AI in education can provide higher-quality learning experiences to students which improves the learning outcomes. Therefore, it can be argued that AI-based education can enhance the sustainability of the learning process. On the other hand, long-term educational outcomes can be improved through AI integration. AI can provide personalised learning experiences which improve efficiency in education. AI can tailor instruction to individual learning needs through intelligent tutoring systems and automated assessments. Researchers reveal that AI can enhance educational outcomes which improves productivity in educational resources (McDonald et al., 2023). Personalised learning promotes critical thinking of the students which is a major principle in sustainable education.

Personalised Learning and Student Performance

According to a study, the integration of self determination theory (SDT) principles (e.g.: autonomy, competence, and relatedness) can intrinsically motivate students to learn in personalised learning (Chiu, 2022). In personalised learning environments, students are more engaged with academic activities which improve their performance. AI Driven Personalised Learning (AIPL) ensures that students receive targeted instruction (Chen & Wu, 2015). Hence, the use of resources in learning can be optimised. Therefore, wastage of resources in education can be minimised which improves the sustainability of the education process. On the other hand, it improves overall educational quality.

In a study done in Russian universities, personalised learning has acted as a determinant to improve the education performance of the students. Research reveals that the perceived usefulness of personalised learning strategies can enhance the learning experience of the students (Makhambetova et al., 2021). The implementation of adaptive e-learning systems was studied by researchers. The findings of the study revealed that adaptive learning can make significant improvements in knowledge acquisition. Therefore, it is clear that personalised content delivery can improve student performance (Wu et al., 2017). AI-driven personalised feedback in collaborative settings was studied by researchers. The findings revealed that personalised interventions improved group outcomes and knowledge-building among university students in China (Zheng et al., 2021). Several studies have proved that there is a significant impact of personalised learning on student performance (Rodríguez-Ardura & Meseguer-Artola, 2021; Wongwatkit et al., 2020). Based on these findings, following hypothesis was developed;

H_1: There is a significant impact of AI Driven Personalised Learning on Student Performance

Personalised Learning and Student Engagement

Student engagement can be defined as the interest of the students in educational activities (Graves, 2023). The main dimensions of student engagement are cognitive, emotional, and behavioural dimensions (Liu, 2021). Cognitive engagement refers to deep thought and critical analysis during learning. When students are emotionally engaged in the learning process, they tend to reflect feelings of interest toward academic activities (Karumbaiah et al., 2023). Continuous attendance and completion of homework can be identified under emotional engagement (Liu, 2021). Effective engagement reflects the personal development of students through self-efficacy (Suraworachet et al., 2023). On the other hand, they engage to fulfill academic achievements.

In AI-based education, personalised learning can develop effective student engagement (Kong, 2023). AI tools in education can enhance the cognitive engagement of students since it delivers tailored content to meet the student's needs (Suraworachet et al., 2023). Interactive learning elements in AI-based education can make learning enjoyable which improves the emotional engagement of students (Hsu & Chen, 2022). Further, AI-integrated education platforms can improve the behavioral engagement of students through timely feedback (Alkabbany et al., 2023).

When referring to AI integration in education, AI algorithms play an important role in improving the learning experience of the students (Almusaed et al., 2023; Adnan et al., 2022). Students are more likely to feel engaged to actively in their education since the academic contents are tailored to their needs through AI-based personalised learning (Verma et al., 2023). On the other hand, personalisation keeps students focused and reduces disengagement. According to previous research, AI-driven systems promote a deeper connection between students and their learning material. When students are engaged, they feel that the academic contents are applicable to their personal goals which improves their performance (Hilpert et al., 2023). On the other hand, when students engage with content that suits their learning styles educational institutions can use their resources more effectively (Sadegh-Zadeh et al., 2023). Hence, it leads to a more sustainable model of education (Almusaed et al., 2023). Based on the above arguments it is clear that personalised learning can enhance student performance, and therefore, following hypothesis is built;

H_2: There is a significant impact of AI Driven Personalised Learning on Student Engagement

Moderating Role of Educator Skills

Educator skills play a pivotal role in the effective integration of artificial intelligence (AI) in education. AI-driven teaching requires educators to develop special skills to cater to the changing expectations in teaching. Researchers have identified the main dimensions of educator skills as self-empowerment, professional and pedagogical competency, and empowerment competency (Cha et al., 2024). Researchers argue that these dimensions can empower educators to guide students in AI based learning. The use of generative AI (GenAI) tools was analysed by the researchers in improving educator skills in designing inquiry-based learning (IBL) frameworks (Moundridou et al., 2024). Researchers highlight that educators must possess the creativity and technical knowledge to utilise GenAI tools for content creation, lesson design, and assessment. Educator skills in nursing education were studied by researchers. The intelligence-natural language processing (AI-NLP) platforms were integrated into universities for higher educational purposes. One of the key findings is that many educators lack a comprehensive understanding of how AI-NLP platforms generate and process information (Dorin & Atkinson, 2024). Research highlights the importance of skills related to AI tools for educators to adopt AI in higher education more effectively. On the other hand, according to the study, educators highlighted the skills for monitoring methods to detect and assess how students use these technologies in their academic work.

Lecturer leadership skills and its influence on student performance was studied by researchers (Hazzam & Wilkins, 2023). The charismatic leadership skills of the educators and effective use of technology have impacted on higher performance among students in AI based personalised learning environments. When lecturers have higher technological skills and leadership skills, they can effectively use AI tools in their teaching process (Ng et al., 2023). Educators with higher IT knowledge can create more engaging and efficient learning experiences for students. Therefore, it is clear that educator skills can improve engagement and performance of students in AI integrated personalised learning environments (Almusaed et al., 2023). This can be considered as a sustainable approach to equipping educators with the necessary training which improves the efficiency of educational resources. Based on this evidence, following hypothesis was built.

H_3: Educator Skills moderates the relationship between AI Driven Personalised Learning and Student Performance

Researchers have proved that lecturer-student interactions are significantly influenced by the lecturers' ability to lead and use technology effectively (Odutayo et al., 2024). Student engagement can be impacted by the lecturer's ability to handle technology. In AI-based learning, when educators are proficient in using AI tools, they can create more engaging content. (E.g.: timely feedback) (Diwan et al., 2023). Therefore, student experience can be enhanced by educator skills under AI-based learning platforms (Onesi-Ozigagun et al., 2024). When referring to sustainable education practices, it encourages continuous improvement of educators to uplift the education system. Based on the above arguments, the following hypothesis was developed;

H_4: Educator Skills moderates the relationship between AI-Driven Personalised Learning and Student Engagement

Mediating Role of Learner Autonomy

Researchers reveal that Computer-Assisted Language Learning (ICALL) tools promote the autonomy of the students since they facilitate learners to independently manage their learning processes (Namaziandost & Rezai, 2024). Therefore, it can be argued that academic emotion regulation and mindfulness significantly influence learner autonomy. When using AI tools for educational purposes, learners can take charge of their educational journey which enhances their self-directed capabilities.

Personalised learning systems facilitate students in obtaining more control over what and how they learn (Francescucci & Rohani, 2019). It can adapt to the preferences of the students. Autonomy received in personalised learning enhances student engagement since they feel that they are empowered to take charge of their educational journey (Alamri et al., 2020). AI-driven tools can provide benefits for the students in learning (e.g.: customised feedback, suggesting resources, enabling self-paced study). Researchers highlight how AI and digital learning tools (e.g.: chatbots) can enhance perceived autonomy (Chiu et al., 2024). AI tools facilitate autonomy for the students to engage in personalised learning experiences. Learner autonomy can transform the benefits of AI-driven personalised learning into higher levels of engagement (Tahir & Tahir, 2023). From a sustainability perspective, when students experience feels more control over their learning process, they actively participate in educational activities. Based on this evidence, the following hypothesis was developed;

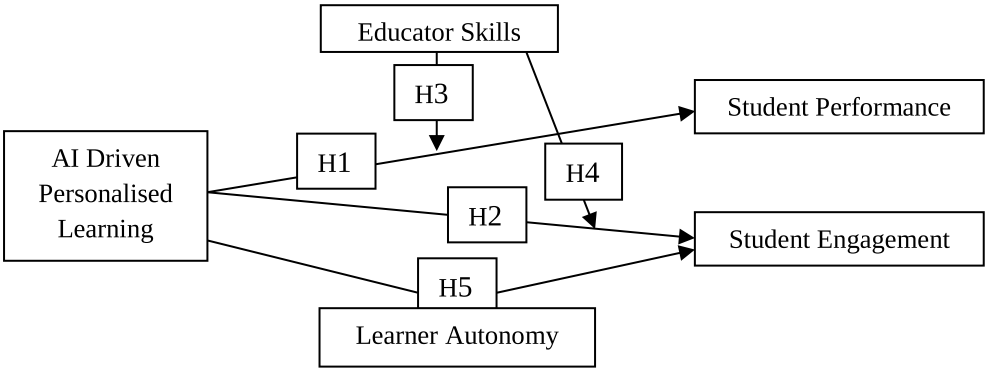
H_5: Learner Autonomy mediates the relationship between AI-Driven Personalised Learning and Student Engagement

Research Methodology

Conceptual Framework

Figure 1

Conceptual Framework



Operationalisation

Table 1

Operationalisation

Variable	Indicators	Sources
AI Driven Personalised Learning	- Adaptive content delivery - Real-time feedback - Learning analytics - Inclusivity and accessibility	(Kokku et al., 2018; Maghsudi et al., 2021)
Student Performance	- Final grades - Problem-solving skills - Time management - Adherence to school norms. - Teamwork - Communication skills	(Francescucci & Rohani, 2019; Iglesias-Pradas et al., 2021)
Student Engagement	- Classroom attendance - Homework completion - Critical thinking - Self-efficacy - Emotional response to the learning activities - Extra learning efforts	(Suraworachet et al., 2023).

Learner Autonomy	- Self-regulated learning - Decision-making ability - Engagement in personalised pathways - Motivation and responsibility - Interaction with AI tools	
Educator Skills	- Technological proficiency - Adaptability - Charismatic leadership - Strategic AI integration - Training and development	(Hazzam & Wilkins, 2023)

Population and Sample

The current study focuses on AI-based personalised learning in the higher education sector. Personalised learning experiences, student performance, learner autonomy, student engagement, and educator skills must be evaluated in the perspective of students. Therefore, the population was identified as the students who follow higher education. According to government statistics, there are over 438,000 undergraduate student enrollments in Sri Lanka's higher education institutions in 2022 (University Grants Commission [UGC], 2022). This includes both government and private universities governed by the University Grants Commission (UGC). Postgraduate enrolments in 2022 were approximately 52,000 (UGC, 2022). Based on simple random sampling method 380 students were selected as the sample size for this study.

Data Collection

Data collection was done using questionnaire surveys. The questionnaire was built using a 5-point Likert scale (1= strongly disagree, 5 = Strongly Agree). Identified variables were measured based on the indicators identified (Table 1). Closed-ended statements were included in the survey to obtain responses. Demographic factors of respondents were also collected while ensuring their privacy (E.g.: age, gender, highest educational qualification). Questions were developed based on the indicators identified through previous literature. Data was collected using Google forms which were shared through emails to different student groups. This survey is a self-reported questionnaire. These include self-selection bias, as participants with greater interest in AI-driven personalised learning (ADPL) might have been more likely to respond. Efforts were made to mitigate these biases through anonymisation and wide distribution, but these limitations should be considered when interpreting the findings.

Data Analysis

Data analysis was done based on Structural Equation Modeling (SEM) using Smart PLS software. The reliability of the variables was measured. Validity was measured to ensure the accuracy of the measurements used under each variable. Frequency analysis was used to examine the demographic factors of the respondents. Path coefficients were used to identify the relationships and effects of variables. Total indirect and direct effects were used to test the hypotheses of this study.

Results and Discussion

Descriptive Analysis

Table 2

Frequency Analysis

	Demographic Characteristic	Frequency	Percent
Gender	Male	169	44.5
	Female	211	55.5
Age	18–24 years	240	63.2
	25–34 years	105	27.6
	35–44 years	24	6.3
	45 years and above	11	2.9
Educational Qualification	Undergraduate	305	80.3
	Postgraduate	15	3.9
	Doctoral	60	15.8
Field of Study	Science and Technology	30	7.9
	Humanities and Social Sciences	12	3.2
	Business and Management	11	2.9
	Medicine and Allied Health Sciences	271	71.3

Table 2 provides the frequency analysis of the demographic factors of the respondents. Females represent the majority of the sample (55.5%). 44.5% is female respondents. Therefore, the sample represents a balanced distribution between males and females. The majority of the participants are in the age group of 18-24 years (63.2%). 27.6% is in the age group of 25-34 years. The remaining respondents are over 35 years. According to the educational qualifications, 80.3% of the respondents are undergraduates. 15.8% have Doctoral qualifications and only 2.9% have postgraduate qualifications. When analysing the field of study, the majority (71.3%) is in Medicine and Allied Health Sciences. Respondents with Science and Technology qualifications are 7.9% of the respondents. The remaining have

Humanities and Social Sciences (3.2%) and Business and Management (2.9%) qualifications. Therefore, the respondents are in different academic backgrounds which increases the reliability of the responses.

Reliability and Validity

Table 3

Reliability and Validity

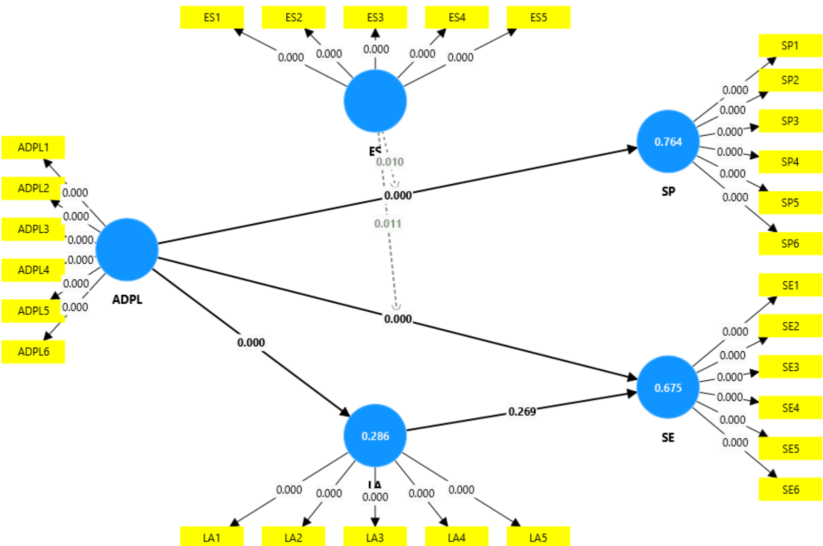
Variable	Cronbach's Alpha	No of Items	AVE
AI Driven Personalised Learning	0.963	6	0.599
Student Performance	0.701	6	0.602
Student Engagement	0.960	6	0.605
Learner Autonomy	0.979	5	0.652
Educator Skills	0.887	5	0.595

Table 3 presents the reliability and validity of the variables. Cronbach's alpha values are higher than 0.7 which indicates that the variables and the items under those are reliable. AVE values for all constructs exceed the threshold of 0.50. Therefore, the variables adequately explain the variance in their observed measures.

Path Coefficient

Figure 2

Path Coefficients



ADPL - AI-DRIVEN PERSONALISED LEARNING
ES - Educator Skills
LA - Learner Autonomy
SE - Student Engagement
SP - Student Performance

Table 1

Total Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*t* statistics (|O/STDEV|)	*p* values
ADPL -> SE	0.008	0.008	0.018	0.459	0.646

Total indirect effect in the model is presented in the Table 3. The total indirect impact of ADPL on Student engagement is not statistically significant (O = 0.008, $t = 0.459$, $p = 0.646$). Therefore, learner autonomy does not significantly mediate the relationship between ADPL and SE, accepting the null hypothesis ($H5_0$).

Table 2

Total Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*t* statistics (|O/STDEV|)	*p* values
ADPL -> LA	0.851	0.853	0.057	15.024	0
ADPL -> SE	0.541	0.515	0.127	4.261	0
ADPL -> SP	0.69	0.67	0.101	6.806	0
ES -> SE	0.513	0.495	0.121	4.234	0
ES -> SP	0.416	0.398	0.123	3.391	0.001
LA -> SE	0.01	0.009	0.021	0.462	0.644
ES x ADPL -> SE	-0.026	-0.02	0.029	0.902	0.367
ES x ADPL -> SP	-0.028	-0.023	0.028	1.008	0.314

Table 4 demonstrates the path coefficients in the developed model (Figure 2). There is a strong positive relationship between AI-Driven Personalised Learning (ADPL) and Learner Autonomy (LA) (O = 0.851, $t = 15.024$, $p = 0.000$). This proves that ADPL significantly enhances learners' ability to regulate their own learning. AI-Driven Personalised Learning has a moderate positive effect on Student Engagement (SE) (O = 0.532, $t = 4.085$, $p = 0.000$). Hence, personalised learning methods significantly contribute to students' involvement with learning activities, rejecting the null hypothesis ($H2_0$). There is a strong positive impact of AI-Driven Personalised Learning on Student Performance (SP) (O = 0.69, t = 6.806, p = 0.000), rejecting the null hypothesis ($H1_0$). This proves that personalised learning improves the outcomes of students. Educator Skills (ES) have a moderate positive impact on Student Engagement (O = 0.513, t = 4.234, p = 0.000). Educators who are technologically proficient, and skilled in integrating AI into teaching have a better ability to engage students in the learning process. Educator Skills also have a significant positive impact on Student Performance (O = 0.416, t = 3.391, p = 0.001). However, the effect is slightly weaker compared to ADPL. This finding highlights the importance of teacher expertise in leveraging AI for academic success. Learner Autonomy does not have a statistically significant direct impact on Student Engagement (O = 0.01, t = 0.462, p = 0.644). Hence, it can be argued that autonomy alone may not be sufficient to drive engagement. Educator Skills do not act as a moderator between ADPL and Student Engagement (O = -0.026, t = 0.902, p = 0.367), accepting the null hypothesis ($H4_0$). Further, Educator Skills does not act as a moderator between ADPL and Student Performance (O = -0.028, t = 1.008, p = 0.314), accepting the null hypothesis ($H3_0$).

Discussion

The analysis findings reveal that there is a positive significant impact of ADPL on student performance (O = 0.69, t = 6.806, p = 0.000). Hence, it is clear that personalised learning tailors educational content to meet individual students' needs to promote a better understanding of the material. The significant strong positive impact proves the effectiveness of AI in creating tailored learning paths that optimise student outcomes. Therefore, providing targeted instruction for the students through ADPL, it can contribute to sustainable education practices. Literature highlights that resource optimisation minimises wastage and improves overall educational quality (Chen & Wu, 2015). Previous researchers argue that incorporating SDT principles into personalized learning environments intrinsically motivates students (Chiu et al., 2024). Adaptive e-learning systems significantly improve knowledge acquisition (Wu et al., 2017). Similarly, the strong impact of ADPL on student performance in this study confirms that personalised content delivery enhances academic performance. Research in Russian universities and in Chinese collaborative settings has shown that personalised learning strategies enhance performance (Makhambetova et al. 2021; Zheng et al. 2021). The same finding was achieved in the current study. According to the literature, it is important to provide personalised feedback in collaborative learning settings (Zheng et al., 2021). The current study also proves that ADPL enhances performance through AI-driven feedback systems.

The analysis demonstrates that AI-Driven Personalised Learning (ADPL) has a moderate positive effect on Student Engagement (O = 0.541, t = 4.261, p = 0.000). Therefore, it can be argued that personalised learning methods significantly enhance students' involvement with educational activities which leads to rejection of the null hypothesis ($H2_0$). Personalised learning has a tailored approach which fosters higher engagement since students interact with content designed to meet their unique needs. Cognitive engagement is defined in the literature as the deep thought and critical analysis students bring to learning (Liu, 2021). AI tools adapt to individual student profiles which deliver relevant material to encourage deeper intellectual involvement (Suraworachet et al., 2023). As highlighted by previous researchers, personalised content keeps students focused and reduces disengagement since it enables them to connect more meaningfully with their learning material. Emotional engagement reflects students' interest and enjoyment in academic activities (Hsu & Chen 2022; Karumbaiah et al. 2023). AI-driven platforms have interactive learning elements to make the learning process more enjoyable and hence, it improves students' emotional connection to academic tasks. This aligns with the current study findings. When students see the applicability of academic content to their personal goals, emotional engagement strengthens which improves overall satisfaction with the learning process (Hilpert et al., 2023). Behavioural engagement was also considered in this study when measuring student engagement. It involves the active participation of students (Liu, 2021). AI-integrated platforms provide real-time feedback which helps improve behavioural engagement since it motivates the students to stay on track (Alkabbany et al., 2023). AI tools maintain alignment with students' learning styles which reduces distractions. Therefore, students can constantly be involved in academic tasks (Sadegh-Zadeh et al., 2023). AI ensures that academic materials align with students' learning needs and styles. Therefore, students' engagement with learning improves (Adnan et al., 2022; Almusaed et al., 2023). Literature highlights that interactive features embedded in AI-driven platforms make learning more energetic which leads to sustained attention (Hsu & Chen, 2022).

The findings of the current study reveal that Educator Skills (ES) do not moderate the relationship between AI-Driven Personalised Learning (ADPL) and Student Performance (O = -0.028, t = 1.008, p = 0.314) which supported the null hypothesis ($H3_0$). Therefore, the impact of ADPL on SE is independent of the level of educator skills which aligns with previous literature (Hsu & Chen, 2022; Kong, 2023). The current findings prove that educator skills independently improve student performance (O = 0.416, t = 3.391, p = 0.001). Previous studies prove that educator leadership skills in handling AI tools in education can improve student performance (Hazzam & Wilkins, 2023). This aligns with the current study findings. Educators with superior IT skills can offer more engaging and efficient learning experiences for their pupils (Almusaed et al., 2023). On the other hand, the literature highlights the role of AI-based personalised learning in enhancing the performance of students without the need for educator skills (Verma et al., 2023). However, certain studies highlight the importance of educator skills in enhancing student outcomes through AI-based learning (Hazzam & Wilkins, 2023; Ng et al., 2023)

The current analysis shows that Educator Skills (ES) do not moderate the relationship between AI-Driven Personalised Learning (ADPL) and Student Engagement (SE) (O = -0.026, t = 0.902, p = 0.367) which supports the null hypothesis ($H4_0$). Educator skills are important for broader educational outcomes which may not directly affect how students engage with AI-driven platforms. This is also highlighted in the literature where it indicates that many educators lack a deep understanding of AI systems which limits their influence (Dorin & Atkinson, 2024). AI-based systems have advanced autonomy and adaptability. Therefore, learners can engage with studies without much educator intervention (Adnan et al., 2022; Moundridou et al., 2024). Even if the educator skills are important for traditional learning, it may not be important for AI-based personalised learning. AI tools are designed to create tailored learning experiences. Timely feedback, interactive learning modules, and personalised academic paths directly enhance SE (Diwan et al., 2023; Kong, 2023).

The study findings reveal that learner autonomy (LA) does not significantly mediate the relationship between AI-Driven Personalised Learning (ADPL) and Student Engagement (SE) (O = 0.008, $t = 0.459$, $p = 0.646$) which supports the null hypothesis ($H5_0$). Research highlights that AI tools allow students to manage their learning independently which promotes learner autonomy (Namaziandost & Rezai, 2024). AI-driven systems promote self-paced learning while suggesting tailored resources (Chiu et al., 2024). Literature highlights that autonomy in personalized learning increases engagement (Francescucci & Rohani, 2019). AI systems allow students to take charge of their learning preferences (Alamri et al., 2020). Findings of the current study proves that autonomy provided by these tools may not always result in meaningful engagement. Students using self-paced AI platforms may not feel the need to engage deeply if the system provides sufficient support to complete tasks without active involvement (Chiu et al., 2024). The literature emphasises that academic emotion regulation and mindfulness are key drivers of learner autonomy (Namaziandost & Rezai, 2024). When students lack emotional and cognitive skills, the autonomy provided by AI tools may not translate into active engagement which is proved in the current study.

According to the analysis results, it can be argued that, while educators play an essential role in traditional learning settings, the autonomous and adaptive nature of AI-driven platforms may diminish their direct influence in AI-based personalised learning environments. AI tools are designed to independently tailor learning paths, provide real-time feedback, and deliver interactive content, enabling students to engage and perform without significant reliance on educator intervention. However, the literature highlights that educators with advanced IT skills can enhance the implementation and integration of AI systems, which indirectly supports broader educational outcomes (Hazzam & Wilkins, 2023; Ng et al., 2023). Similarly, the lack of significant mediation by learner autonomy indicates that while AI platforms promote self-paced and independent learning, this autonomy does not always translate into meaningful engagement. Students may rely heavily on the structured support and resources provided by AI tools, reducing the necessity for active involvement or deeper engagement. This finding aligns with prior research suggesting that emotional and cognitive skills, such as mindfulness and academic emotion regulation, are critical drivers of autonomy's effectiveness in fostering engagement (Namaziandost & Rezai, 2024).

Conclusion

AI-based personalised learning significantly enhances student performance in Sri Lanka. ADPL ensures that each student receives support aligned with their unique requirements. As identified through the analysis, real-time feedback is a significant dimension of ADPL. This can support students to guide their academic work to improve their performance. ADPL systems can dynamically adjust learning materials to match students' needs. Further, AI is popularly used for student assessments and it facilitates university students to understand their academic performance. AI tools allow students to progress at their own pace which is helpful for their academic development. Hence, it is clear that Sri Lankan university students enhance their academic performance through ADPL.

Personalised learning methods tailor content to students' individual needs. ADPL ensures that students engage with the most relevant material. The ability to provide real-world applications of concepts through ADPL enhances student engagement in learning activities. This study proves that ADPL systems give students greater control over their learning pathways. Therefore, it can be concluded that Sri Lankan university students can use ADPL to stay engaged in the learning process.

The learner autonomy of the university students is enhanced through ADPL. The students can experience customised feedback, adaptive content, and tools for independent study through the use of ADPL. However, autonomy alone will not be sufficient to drive student engagement. Findings prove that university students can enhance their engagement without the autonomy in AI-based personalised learning in Sri Lanka. According to the findings, it can be argued that, even if educator skills are important to improve student performance and engagement, it is not significant in an AI-based personalised learning environment.

Government and educational institutions must invest in AI infrastructure to support ADPL implementation. Policymakers can align educational goals with measurable outcomes which emphasize personalised approaches. Since educator skills is not significant in improving student performance or student engagement in AI-based personalized learning, AI tools can alleviate the pressure on educators to customise learning. Therefore, they will be able to focus on mentorship and higher-order teaching tasks. Promoting ADPL ensures inclusivity which promotes sustainable education in Sri Lanka. On the other hand, it promotes resource efficiency for a sustained educational process.

This study contributes to the existing literature by confirming the effectiveness of AI-Driven Personalised Learning (ADPL) in enhancing student performance and engagement, aligning with global findings. Similar to research in Russian universities and Chinese collaborative settings (Makhambetova et al., 2021; Zheng et al., 2021), this study establishes that ADPL significantly improves academic outcomes by tailoring content and providing real-time feedback. The findings also align with studies from developed nations, where personalized AI-driven systems have shown to optimise learning processes (Karumbaiah et al., 2023; Wu et al., 2017). However, the lack of moderation by educator skills and mediation by learner autonomy diverges from some global studies, emphasising unique contextual factors in Sri Lanka, such as digital literacy and infrastructure gaps. This study enriches the global discourse by demonstrating how ADPL operates in resource-constrained environments, offering insights into its potential to drive sustainable education and reduce reliance on educator intervention in similar developing contexts.

This study used a limited sample size which may not generalise the findings to the whole university student population in Sri Lanka. Further, this study relies heavily on student-reported data which may result in biases. The challenges faced in the Sri Lankan education sector are not considered in this study when adopting AI-based personalised learning. It will be useful to analyse the role of technological infrastructure, internet access, and digital literacy in influencing the adoption and success of ADPL in future studies.

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