Managing Artificial Intelligence-Driven Platforms for Student Development

Nimota Jibola Kadir Abdullahi[*,a,1]
[a] University of Ilorin, Kwara State, Nigeria

*Corresponding Author: abdullahi.njk@unilorin.edu.ng

Abstract

This study examines the impact of AI-driven platforms, including personalized learning platforms, smart content, and intelligent tutoring systems, on students' cognitive development, problem-solving skills, and overall academic performance. A structured survey was used to gather data for the study. The undergraduate students in the faculties of education of public universities in Kwara State, Nigeria, were the target population. Data were analyzed using SmartPLS tools to evaluate the relationship between AI-driven platforms and student development. The findings indicate that the effective management of artificial intelligence-driven learning platforms, including personalized learning platforms, smart content, and intelligent tutoring systems, has a significant impact on student development (engagement, academic achievement, and cognitive capacities) in higher education institutions. This study shows empirical support for AI's role in contemporary education and how AI-driven tools may effectively promote personalized learning and adaptive learning experiences. Although AI in education is widely discussed, there has been little empirical research examining how AI directly affects the growth of Nigerian students.

Keywords: Artificial Intelligence, Distance Education and Online Learning, Personalized learning platforms, Intelligent Tutoring Systems, Teacher Training

I. INTRODUCTION

Artificial intelligence (AI) offers transformative advantages in education by personalizing learning experiences, enhancing student engagement, and equipping educators with data-driven insights. Through adaptive learning algorithms, AI assesses individual strengths and weaknesses, facilitating the development of customized educational pathways that cater to diverse learning styles and needs [1]. This personalization fosters deeper understanding, encourages active participation, and improves academic outcomes. Furthermore, AI provides real-time feedback and automates administrative tasks, allowing teachers to concentrate more on meaningful interactions and targeted interventions. As part of the broader technological evolution, which includes big data and cloud computing, AI plays a crucial role in creating dynamic, responsive learning environments [2]. Its thoughtful integration into education not only improves traditional teaching methods but also prepares students for a future shaped by innovation. However, to fully realize its potential, effective management and ethical implementation of AI tools are essential, ensuring equitable access and minimizing associated risks. The incorporation of artificial intelligence (AI) has demonstrated promise in revolutionizing the educational experience for students. To support effective student development, it is crucial to consider the advantages and drawbacks of utilizing AI technologies, which are being integrated into educational institutions [3].

Several investigations have been carried out on AI learning tools and the education enhancement of postsecondary educational establishments. Each study offers valuable insights into the management of AI-driven platforms for student development by highlighting different aspects of AI's role in education. [4] emphasizes the transformative potential of AI-powered learning tools in enhancing academic achievement and comprehension through personalized and adaptive learning experiences, reinforcing the importance of leveraging AI to meet individual student needs. [5] explores how AI influences learner–instructor interaction in online learning environments, shedding light on the need to balance technological integration with human engagement to maintain meaningful educational relationships. Meanwhile, [2] focuses on the role of AI in promoting student agency, demonstrating how AI assistance can empower learners to take more control over their learning processes, which is a key element in fostering autonomy and long-term academic development. Collectively, these studies contribute to a comprehensive understanding of how managing AI effectively can optimize educational outcomes and support complete student growth. However, this study aims to close the gaps left by other researchers. It is worth noting that none of the authors cited in this study specifically addressed AI learning tools and student development. Additionally, previous studies did not emphasize the personalized learning platform, smart content, and intelligent tutoring system as essential variables for assessing AI-driven platforms. The great variety in the geographic locations and regions covered by the available studies is another important gap that inspired this investigation.

Artificial Intelligence (AI) has evolved into a transformative force across various sectors, including education, where it is increasingly integrated to enhance teaching and learning processes. AI is fundamentally defined as the simulation of human intelligence through software systems capable of mimicking cognitive functions such as reasoning, problem-solving, and learning [6]. It leverages machine learning algorithms and advanced computational models to autonomously or semi-autonomously perform tasks traditionally requiring human cognition [1]. In the educational context, AI has proven to be a valuable resource for managing and analyzing large volumes of data efficiently, supporting data-driven decision-making in both instruction and administration [2, 5, 7]. Moreover, it facilitates the retrieval and synthesis of vast datasets from scholarly sources, contributing to more evidence-based educational practices [8]. Within this framework, AI-driven platforms, Personalized Learning Platforms (PLPs), Intelligent Tutoring Systems (ITS), and Smart Content (SC) are central to contemporary discourse on educational innovation. PLPs use analytics and user data to tailor content, pace, and instructional strategies to individual learners, accommodating diverse learning styles and preferences [9]. According to [10, 11], PLPs empower learners to engage with materials aligned to their interests, helping them address weak areas and build on strengths, thus promoting autonomy and motivation. Similarly, ITS provides real-time feedback and scaffolded instruction [12], fostering personalized, effective learning while enhancing critical thinking, problem-solving, and learner ownership.

Smart Content (SC) represents another vital AI component, referring to programmable and interactive digital educational materials. [4] notes that SC enhances learning by improving the accessibility, adaptability, and relevance of content. By facilitating rapid content updates and visualization, SC helps educators identify content gaps and tailor instruction accordingly. Studies such as those by [3] and [13] highlight the effectiveness of smart content in making abstract concepts more tangible through multimedia elements and gamified learning, which boost engagement and retention. Furthermore, cloud-based intelligent education systems have been implemented to distribute smart content across devices and formats, improving flexibility and learning accessibility [14]. Collectively, the evolution of AI in education reflects a shift from static, one-size-fits-all instruction to dynamic, responsive systems capable of supporting diverse learners. The integration of PLP, ITS, and SC not only streamlines instructional delivery but also creates opportunities for more equitable and effective student learning environments.

Student development encompasses the general growth of individuals within educational settings, addressing academic, emotional, social, and physical domains. [15] defines it as the maturation process through which learners gain knowledge, skills, attitudes, and values that enable them to contribute meaningfully to society. Academic development involves the cultivation of intellectual capabilities such as critical thinking, reasoning, and subject-matter expertise, while emotional and social development relate to interpersonal skills, empathy, and self-regulation. Physical development, though often overlooked in educational discussions, plays a crucial role in overall well-being and learning readiness, involving aspects such as nutrition, exercise, and health awareness. [16] underscore that effective student development extends beyond traditional classroom instruction. It requires environments that foster creativity, independence, and collaboration, elements that are increasingly supported by AI technologies. By enabling more personalized, adaptive learning experiences, AI platforms contribute not only to academic gains but also to the broader developmental outcomes essential for preparing students as competent, resilient, and socially responsible individuals. This study reveals that the strategic management of AI-driven platforms, especially PLPs, ITS, and SC, has the potential to significantly impact student development. As research continues to validate the benefits of these tools, it becomes essential to ensure their ethical, equitable, and pedagogically sound implementation in diverse educational contexts. Indeed, this current research is testing these hypotheses: H1: There is a significant positive relationship between the Personalized Learning Platform (PLP) and student development (SD); H2: There is a significant positive relationship between Smart Content (SC) and student development (SD); and H3: There is a significant positive relationship between the Intelligent Tutoring System (ITS) and student development (SD).

II. METHOD

This study is grounded in System Theory, as postulated by [17], which views organizations, including educational institutions, as complex systems composed of interrelated and interdependent components working collectively to achieve common objectives. In this framework, every part of a system (input, process, output, feedback, and environment) interacts dynamically to sustain functionality and drive development [18]. Reinforce this view by describing systems as entities formed by interacting parts that generate collective outcomes, and [19] notes that organizations function as open systems, continually influenced by and responsive to their external environments. In the situation of education, the institution functions as an open system, one that constantly interacts with and adapts to external influences such as policy reforms, technological innovations, and societal demands [19]. According to [20], these systems include critical institutional components: students, educators, learning platforms, resources, and curricula that must be effectively coordinated to produce optimal learning outcomes. The inputs to the system include resources such as AI-driven platforms (e.g., Personalized Learning

Platforms, Smart Content, and Intelligent Tutoring Systems), teachers' knowledge, and institutional infrastructure. The transformation process involves instructional design, pedagogical strategies, and engagement through digital technologies. The outputs are student-centered outcomes, such as cognitive development, critical thinking skills, academic achievement, and personal growth, collectively captured under the construct of student development. Feedback mechanisms, including performance assessments and learning analytics, allow for iterative improvements in the system.

Systems Theory is particularly useful for analyzing student development because it captures its multi-dimensional and interconnected nature. As emphasized by [15] and [16], student development extends beyond academic performance to include emotional intelligence, social maturity, ethical awareness, and the capacity to contribute meaningfully to society. These facets emerge through the coordinated interaction of various subsystems within the educational environment. The integration of AI technologies marks a shift in traditional educational inputs, as intelligent systems now support adaptive learning pathways, real-time feedback, and personalized development. AI-driven platforms align closely with Systems Theory's emphasis on adaptivity and dynamic feedback. Personalized Learning Platforms (PLPs) modify instructional content based on learner performance and preferences, creating ongoing feedback loops. Smart Content (SC) allows for modular and customizable instructional materials that evolve with student needs. Intelligent Tutoring Systems (ITS) replicate human tutoring by offering targeted, adaptive support. Crucially, Systems Theory underscores interdependence: no single AI tool can drive development in isolation. The effectiveness of AI integration relies on the interaction between learners' motivation, institutional capacity, teacher competence, and sociocultural factors. By viewing educational institutions as open systems, Systems Theory provides a complete framework for understanding how AI tools like PLP, SC, and ITS can enhance student development, guiding both research and implementation.

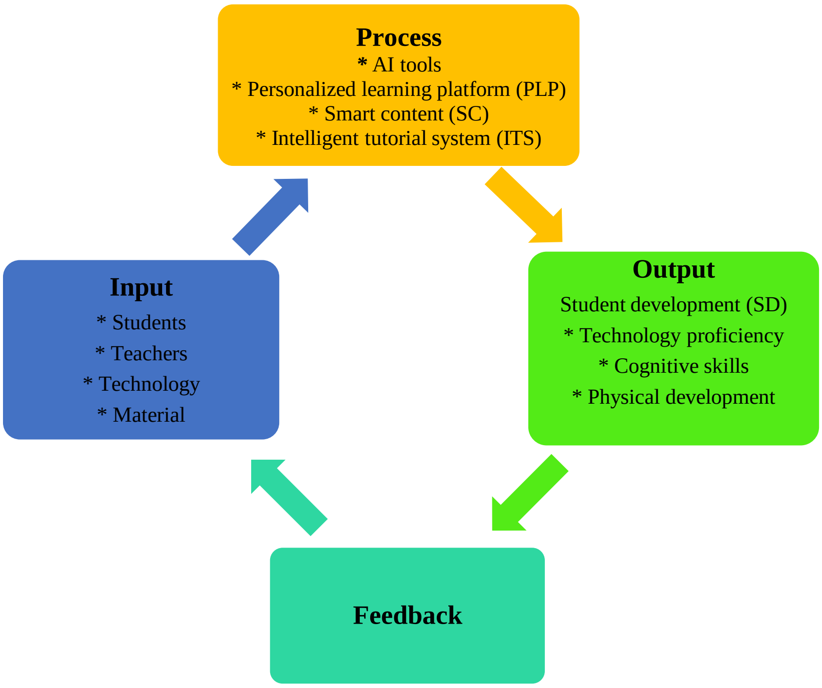

Figure 1 System Theory (Adapted from [19])

Figure 1 illustrates the concept of system theory, adapted from [19], highlighting the fundamental components and dynamics of a system as it functions within its environment. At its core, the figure presents a system as an organized set of interrelated components that work together to achieve specific objectives. The model emphasizes the flow of information, energy, or materials through input, process, and output stages. The input represents the resources, stimuli, or information entering the system from its external environment. This input is then transformed through a central processing or throughput mechanism, which involves internal system operations, such as decision-making, transformation, learning, or coordination. Following this transformation, the system produces an output, which may be in the form of products, services, decisions, or behavioral responses that are released into the external environment. The environment is depicted as a critical contextual factor, influencing and being influenced by the system. A feedback loop is often included in such models, showing how the system monitors and adjusts its operations based on responses from the environment, thereby maintaining balance and enabling learning or adaptation. This theoretical model highlights the open system perspective, where continuous interaction with the environment is necessary for system sustainability and effectiveness. As adapted from [19], the figure reflects key principles of systems theory: interdependence of parts, dynamic interaction, environmental sensitivity, and the importance of feedback in achieving systemic goals.

This theory is applicable in educational settings in that it serves as a functional link between a school's and students' inputs, and a corresponding measure of its outputs is represented by student development. Education policymakers and managers must establish clear and precise objectives, choose inputs and strategies (such as personalized learning, intelligent tutoring & smart content) that will be transformed into a qualified product through the productive process, and ensure that the product possesses certain competencies in the form of skills, abilities, and knowledge that can be transferred to the productive sector of the economy with efficiency and effectiveness to ensure that the production function adequately meets the demands of society. Intelligent tutoring solutions powered by artificial intelligence provide value to the system by delivering personalized training. From a systemic perspective, these tutoring systems provide valuable feedback that continues to affect education and the development of intelligent material and targeted training. The end outcome of these interconnected parts is student development, which is the ultimate goal. Systems theory supports the holistic vision by acknowledging that changes to one element (such as the personalized learning technique) can affect how students develop and acquire abilities across the educational system.

The quantitative approach will be deemed most appropriate because his study used a descriptive and correlational research design to try to find out how the identified variables (PLP, SC, ITS, & SD) interrelated with each other [21, 22]. The target population of this study was 1000 undergraduate students from public universities in Kwara State's Faculty of Education. A total of 302 undergraduate students at the public universities in the aforementioned region completed and answered the survey. A few surveys were thrown out during data cleansing because they were deemed inappropriate for use based on specific criteria: incomplete responses, patterned or straight-lining answers (i.e., selecting the same option for all items), and responses that were completed in unrealistically short durations, indicating possible lack of engagement or attention. These criteria ensured the reliability and validity of the collected data. After this quality control process. In the end, this study employed 278 questionnaires; the questionnaire for this study comprised 31 questions. As a result, 278 questionnaires were correctly completed, which is in line with [23]. table of sample size, resulting in an 82.85% response rate for the study's final evaluation of its hypotheses.

The questionnaire approach was employed in this study. It is a research tool that consists of a series of questions intended to collect the necessary data from the intended respondents. The Likert scale, which goes from 1 (strongly disagree) to 4 (strongly agree), was employed in this data collection approach. Based on research by [24, 25], this study decided to use a 4-point Likert scale since it provides a more rapid and straightforward response format than scales with 5 to 7 points. Two specialists from the departments of text and measurement and educational management validated the instrument. In this investigation, the questionnaire approach was utilized, which consisted of 31 statements about four constructs (Personalized Learning Platform, Smart Content, Intelligence Tutoring System, and Student Development). The eight items used to test the Personalized Learning Platform (PLP) were adapted from [4] and [11], with Cronbach's alpha score of 0.733 and 0.757 composite reliability values. Smart content (SC) was measured using a six-item scale developed by [26]. Cronbach's alpha value was 0.770, and composite reliability was 0.775. Also, a seven-item scale adapted from [27] was used to measure the Intelligence Tutoring System (ITS), with a Cronbach's alpha score of 0.758 and a composite reliability of 0.781. Student development (SD) was measured using ten items adapted from [15] with a Cronbach's alpha of 0.761 and a composite reliability was 0.837, indicating that all the constructs exhibited sufficient reliability.

An electronic survey was distributed to collect data. Each participant was given the option to choose whether or not to engage in the research while filling out the permission section of the survey. Every participant in the study did it voluntarily, and they were all able to withdraw at any time without facing any negative consequences. A total of 302 questionnaires were gathered. 278 of the questionnaires that were used in the actual study are represented by this figure, which shows the individuals who were initially selected. The survey did not contain any personal identifiers that may be used to track down or identify specific people to protect the participants' security and privacy. These guidelines were followed in adopting this strategy [28, 29]. Following data collection, the information was analysed using the SmartPLS 3.0 program. Convergent validity, indicator reliability, discriminant validity, and composite reliability are the primary prerequisites for the reflective measurement model. Reflective constructs can be used with PLS-SEM studies if all of these requirements are satisfied [30]. In addition, the structural model's evaluations include effect size (f2), path coefficients, and coefficient of determination (R2). Table 1 below, which also includes the indications and suggested thresholds for the measurement and structure modeling tests, explains the two phases involved in PLS-SEM modeling.

Table 1 An Overview of the Measurement and Structural Model Testing Procedures (Adapted from [34])

Model Criterion	Measurement Model Tests	Structural Model Tests
	A reliability loading of greater than 0.70 is an indicator of dependability [31, 33].	The endogenous R2 range was 0-1. [30, 33].
	The internal consistency reliability ranges from 0.60 to 0.70 [30, 33].	[30], Describe path coefficients, also known as bootstrapping values, and t-values (1.96).
	According to [30], Convergent validity AVE > 0.50	Impact Size f2 According to [33] research, the effect size will be small at 0.02, medium at 0.15, and large at 0.35.
	Discriminant Validity AVE. Fornell-Larcker standard [33].	

Table 1 describes the key criteria to evaluate the quality of the model; both the measurement and structural components were assessed using established criteria from the literature. In terms of reliability, item loadings greater than 0.70 are considered indicative of dependable measurement, while internal consistency reliability is acceptable when composite reliability values fall between 0.60 and 0.70, as recommended by Hair et al. [30] and others [31, 33]. Convergent validity was examined through the Average Variance Extracted (AVE), with a threshold of AVE > 0.50 suggesting that a construct explains more than half of the variance of its indicators, in line with Hair et al. [30]. Discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of the AVE of each construct with the correlations between constructs; discriminant validity is confirmed when each construct's AVE exceeds its shared variance with other constructs [33]. The structural model was evaluated using the coefficient of determination (R^2), which ranges from 0 to 1. Higher R^2 values indicate stronger predictive accuracy for endogenous constructs [30, 33]. The significance of path relationships was assessed using bootstrapping techniques. Path coefficients and their associated t-values were used to determine significance, with a t-value of 1.96 or above indicating statistical significance at the 0.05 level [30]. Additionally, effect size (f^2) was used to assess the relative impact of each exogenous variable on the endogenous constructs. According to Cohen's guidelines as cited by [33], an f^2 value of 0.02 is considered a small effect, 0.15 a medium effect, and 0.35 a large effect.

III. RESULTS AND DISCUSSION

A. Measurement Model Assessment

Table 2 displays the validity and reliability of the measurement model evaluated to ensure that the predictions are tested. Reliability is defined as the internal conforming scaled by the coefficient of convergent validity, while validity is defined as the sum of discriminant validity and convergent validity [35]. The aggregate reliability value of the "latent variables should be greater than 0.70, which indicates that each notion has relevant good internal consistency [36]. Additionally, the measurement index's factor loading must all be greater than the lowest critical value of 0.60. AVE, on the other hand, must be more than 0.5. This meant that the constructs had composite reliability that was relevant. According to [37], to establish discriminating validity, the square root for every AVE of the variables in the model should be bigger than the significant coefficient of this variable to explain if there is a significant difference among variables. "As a result, the reliability and validity of the variables studied can all be used to evaluate further hypotheses. Table 2 summarizes the measurement model used in this study. Cronbach's Alpha and Composite Reliability (CR) were used to determine construct reliability.

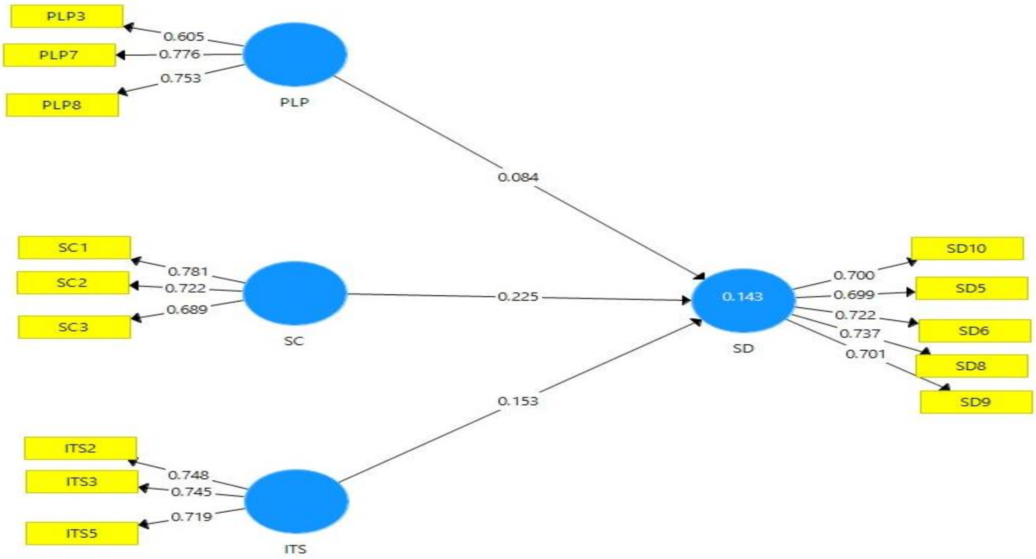

Figure 2 Construct Measurement Model

Figure 2 illustrates the construct measurement model, presenting the reflective relationships between four latent variables, Personalized Learning Platform (PLP), Smart Content (SC), Intelligent Tutoring System (ITS), and Student Development (SD), and their respective observed indicators. Each construct is connected to its measured items via unidirectional arrows, indicating that the constructs are reflective. For the PLP construct, three items (PLP3, PLP7, and PLP8) load onto the construct, with standardized factor loadings of 0.605, 0.776, and 0.753, respectively. Although PLP3 exhibits a slightly lower loading (0.605), it remains within an acceptable range for inclusion due to theoretical justification and acceptable overall model reliability. The SC construct is represented by three indicators, SC1, SC2, and SC3, with loadings of 0.781, 0.722, and 0.689, all of which meet the standard criteria for indicator reliability. Similarly, the ITS construct is measured by ITS2 (0.748), ITS3 (0.745), and ITS5 (0.719), reflecting consistent and reliable measurement. The SD construct includes five items, SD10 (0.700), SD5 (0.699), SD6 (0.722), SD8 (0.737), and SD9 (0.701), all of which load acceptably onto the construct, indicating a coherent underlying dimension of student development. All factor loadings in the model are significant at the $p < 0.01$ level, confirming the statistical validity of the indicators. The figure may also present the R^2 values for the endogenous constructs, signifying the proportion of variance explained by the model. The visual representation confirms that the observed variables are appropriate reflections of their respective constructs, supporting the reliability and convergent validity of the measurement model. This figure serves as the foundational step before evaluating the structural relationships among the constructs in the full model.

Table 2 Summary of Measurement Model (Construct Reliability and Validity) (p<0.01)

Constructs	Items	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted	R2
Personalized Learning Platform (PLP)	PLP3	0.605	0.733	0.757	0.512	
	PLP7	0.776				
	PLP8	0.753				
Smart Content (SC)	SC1	0.781	0.770	0.775	0.535	
	SC2	0.722				
	SC3	0.689				
Intelligent Tutoring System (ITS)	ITS2	0.748	0.758	O.781	0.544	
	ITS3	0.745				
	ITS5	0.719				
Student Development (SD)	SD10	0.700	0.761	0.837	0.507	
	SD5	0.699				
	SD6	0.722				
	SD8	0.737				
	SD9	0.701				

Table 2 presents the results of the measurement model assessment, which evaluates the reliability and validity of the constructs used in the study. Each construct was measured using multiple items, and the analysis reports their factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). All factor loadings were significant at the $p < 0.01$ level. For the Personalized Learning Platform (PLP) construct, three items (PLP3, PLP7, and PLP8) were included. The factor loadings ranged from 0.605 to 0.776. Although PLP3 showed a slightly lower loading (0.605), it was retained given the overall satisfactory reliability indicators. The construct demonstrated acceptable internal consistency, with a Cronbach's alpha of 0.733 and a composite reliability of 0.757. The AVE value of 0.512 exceeded the 0.50 threshold, indicating adequate convergent validity. The Smart Content (SC) construct consisted of three items (SC1, SC2, and SC3), with factor loadings ranging from 0.689 to 0.781. The Cronbach's alpha and composite reliability were 0.770 and 0.775, respectively, both surpassing the minimum acceptable values. The AVE for this construct was 0.535, confirming convergent validity. The Intelligent Tutoring System (ITS) construct included three items (ITS2, ITS3, and ITS5), with loadings between 0.719 and 0.748. The Cronbach's alpha was 0.758, and the composite reliability was 0.781, indicating good internal consistency. The AVE of 0.544 further confirmed convergent validity for this construct. Finally, the Student Development (SD) construct was measured using five items (SD5, SD6, SD8, SD9, and SD10), all of which had factor loadings ranging from 0.699 to 0.737. The construct demonstrated strong reliability, with a Cronbach's alpha of 0.761 and a composite reliability of 0.837. The AVE was 0.507, meeting the recommended threshold for convergent validity. The results of the measurement model confirm that all constructs exhibit satisfactory levels of reliability and convergent validity, thereby supporting the adequacy of the measurement instruments used in the study

B. Discriminant Validity

Table 3. Fornell and Lacker's Criterion

	ITS	PLP	SC	SD
ITS	**0.737**			
PLP	0.372	**0.717**		
SC	0.514	0.434	**0.732**	
SD	0.300	0.239	0.340	**0.712**

Note(s): The diagonal is the square root of AVE, while the off-diagonal numbers are the correlations between latent variables.

Table 3 displays the result of the discriminant validity. Discriminant validity is established when the value of the square root of the AVE of each construct is higher than the construct's highest correlation with any other latent construct [31, 38]. In this study, therefore, discriminant validity was assessed by using the Fornell-Larcker criterion. The assessment of discriminant validity, Heterotrait-monotrait (HTMT), was also undertaken to ascertain the external consistency of the model. Summarily, the AVE of variables is intelligent tutoring system = 0.737; personalized learning platform = 0.717; smart content = 0.732; and student development = 0.712.

Table 4. HTMT Values of the Construct

	ITS	PLP	SC	SD
ITS				
PLP	0.682			
SC	0.672	0.778		
SD	0.436	0.353	0.494	

Table 4 displays the HTMT values. Moreover, the discriminant validity of the construct was evaluated utilizing the HTMT. Since the HTMT criteria compute the geometric mean of the average correlations between indicators measuring the same construct and the mean of all correlations between indicators measuring different constructs, they are regarded as reliable for determining discriminant validity [39]. If this measure's values are less than 0.85, it indicates that the variables are not the same. Also, it can be concluded that this data has no issue of discrimination and convergent validity, showing that the data has been collected fine because HTMT is not greater than 0.85. HTMT is the latest criterion for testing discriminant validity, and it is based on internal correlation and external correlation.

C. Assessment of the Structural Model

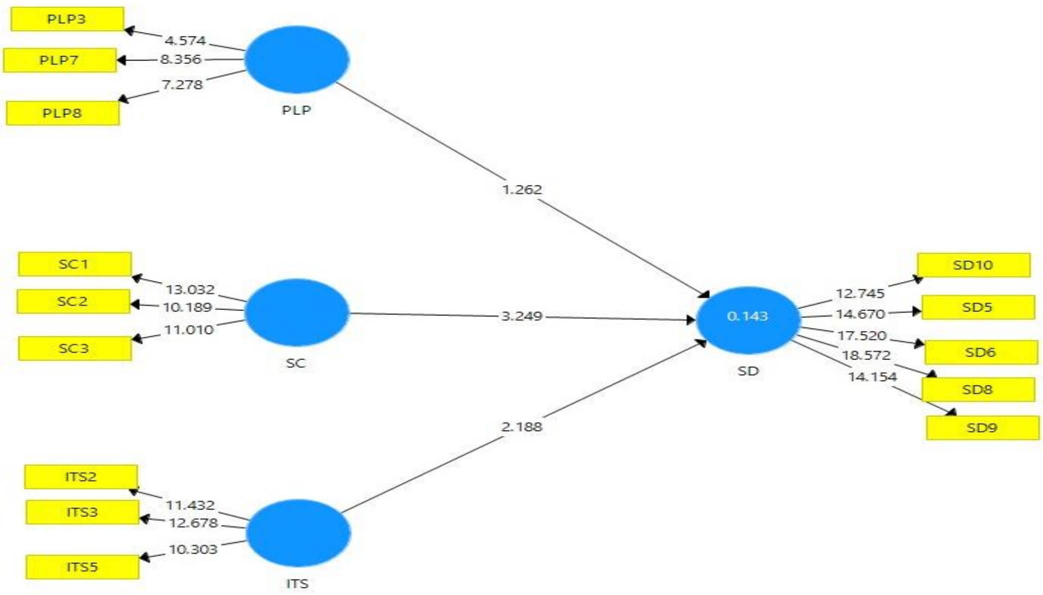

Figure 3 Structural Model of the Study

The Structural model is illustrated graphically. Figure 3 shows the direction of the arrows that connect the study's constructs, which were determined by the framework's proposed hypotheses. The purpose of the single-headed arrows is to verify the study concept's significance. The factor loadings for each item are shown in Figure 3.

Table 5 Result of Structural Model (Path Coefficient)

Hypotheses	Original Sample	Standard Deviation	T Value	P Value
PLP -> SD	0.084	0.067	1.262	0.028
SC -> SD	0.225	0.069	3.249	0.001
ITS -> SD	0.153	0.070	2.188	0.029

The result from Table 5 above indicates that all three hypotheses were supported. Specifically, the personalized learning platform has a significant relationship with student development (T= 1.26; p=.028). thus, hypothesis (H1) was partially supported. In addition, the relationship between smart content and student development is significant (T = 3.249; p .001). Hence, the hypothesis (H2) was supported. the intelligent tutoring system has a significant relationship with student development (T = 2.188; p .029). Hence, the hypothesis (H3) was supported.

The purpose of this research was to investigate the relationship between artificial intelligence tools and student development. the study used automated processes to investigate how three criteria (personalized learning platform, smart content, and intelligent tutoring system) influence student development in Nigeria. As a result, student development was significantly and positively linked to all the hypotheses. This implies that improving student development requires efficient management of artificial intelligence instruments. Additionally, artificial intelligence improves instructional methodologies by providing students with a unique educational experience. Students can access resources outside the classroom and receive real-time feedback through AI interactions, creating new learning and growth opportunities. As a result, the findings are validated by previous research by [4, 5, 16] who found that Artificial intelligence (AI) tools for learning have the potential to completely transform education by enabling personalized and adaptive learning experiences that improve students' academic performance and comprehension levels overall. It was discovered that artificial intelligence technologies significantly impacted student growth in public universities in Kwara State, Nigeria. This suggests that overall indications of smart material, intelligent tutoring systems, and personalized learning platforms will have a big impact on student progress when artificial intelligence tools are handled well.

This study shows that platforms for personalized learning have a partial influence on students' growth. This means that if PLP is promoted, it will take into account a variety of learning preferences, pacing styles, and interests; it will also promote a deeper comprehension of the subject matter, self-motivation, and the development of critical thinking skills; and, in the end, it will empower students to take ownership of their education and proceed at their own pace. It will also help students identify and correct errors in real-time; it will enhance understanding, offer targeted remediation, and close any knowledge gaps; in the end, it will support a flexible and student-centric approach to education.

The results of this study were in line with [40], who discovered a correlation between student development and tailored learning platforms. Also, [9, 11] found that by automating administrative duties and offering timely feedback, the personalized learning technique improves the learning process. Generally speaking, learning outcomes, skill acquisition, and job preparation are all areas where artificial intelligence (AI) has the potential to revolutionize higher education. Furthermore, it is clear from the second hypothesis (H2) that clever material and student advancement at public colleges are closely related. H2 was therefore supported. The current hypothesis's outcome is consistent with previous research findings, such as those of [26, 41], who discovered that smart content had a positive impact on student advancement. Smart content can improve motivation, achievement, and student engagement, in addition to providing personalized learning experiences. As a result, students can actively participate in their education, improving retention and promoting a deeper comprehension of the subject. Furthermore, it was discovered that there is a significant association between ITS and SD in public universities, which supports the third theory. The ITS-SD relationship result is validated and consistent with previous research by [27, 12, 42], which discovered that intelligent tutoring systems can provide learning experiences that are tailored to individual students' needs and learning preferences. These systems can improve learning outcomes by altering the material, tempo, and level of difficulty based on student data and performance analysis.

This study contributes to our understanding by demonstrating how AI learning tools increase students' overall comprehension and academic achievement. Students who routinely used these tools demonstrated enhanced comprehension and academic achievement. These findings back up earlier studies and show how AI can give students personalized and adaptive learning environments that improve their overall learning outcomes [43]. According to [44], another study finding was the value of individualized learning possibilities enabled by AI. The adoption of AI methodologies that customized the material to each student's particular needs offered personalized feedback and adjusted to their learning paces, resulting in considerable improvements in overall development and comprehension. The findings of this study show that artificial intelligence (AI) can meet the diverse educational needs of pupils, leading to more inclusive and successful teaching techniques. According to [7], artificial intelligence (AI) is primarily concerned with how technology can improve student development through personalized learning experiences, access to educational resources, adaptive assessment tools, and opportunities to foster critical thinking, problem-solving, and creative thinking. AI also enables remote learning and offers real-time feedback to help each learner progress. As a result, rather than being entirely generic and the same in every scenario, these AI-driven platforms can be used as a guide to demonstrate how teaching and learning can be most effective at various stages of the SD process [4].

IV. CONCLUSION

The empirical investigation strengthened the links between several crucial parameters. Following an evaluation of the questionnaires and their reliability, 278 undergraduate students at Kwara State's public universities provided the requisite data. After gathering the data, the SmartPLS 3.0 tool was used to analyze it. This method was used to validate the structural model's implementation and measurements. When compared to previous studies, the study's statistical conclusions and historical majority findings made sense. The primary purpose of this study is to use systems theory to investigate how AI technologies like intelligent tutoring systems, personalized learning platforms, and smart content interact with SD. This link has never previously been studied. In addition, the study's recommendations for further research were highlighted in light of its findings. Additional research with a broader population and sample size is recommended. To completely understand how AI-driven platforms affect SD at universities, more functional characteristics and AI-driven platforms with an impact on SD must be considered. Multidimensional modeling could be employed in future studies to provide more information when studying the interplay of SD and AI-driven platforms or system components. Furthermore, to determine the number of variables, future research should conduct a multi-stage examination.

The hypotheses align with Systems Theory, which views each input as contributing to overall outcomes, justifying the examination of PLP, SC, and ITS in enhancing student development. This theoretical grounding strengthens the study's relevance and clarifies expected relationships. The findings have implications for both theory and practice, particularly in Kwara State's public universities. Universities and organizations should apply these insights, while policymakers and educators must continually assess AI-driven platforms to stay current and promote both institutional and individual academic success. This study provides a foundation for future Systems Theory-based research in education, highlighting the significant impact of AI technology management on student development. It offers valuable insights for educators, administrators, and policymakers to support AI integration in Nigeria's higher education. By encouraging innovative strategies and resource allocation, institutions can enhance student growth. However, the study has limitations. A follow-up using both quantitative and qualitative methods across diverse settings would offer a deeper understanding of AI's role in student development.

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