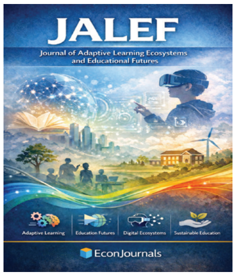

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The Mediating Role of Artificial Intelligence-Driven Learning Personalization in the Relationship between Smart Classroom Integration and Student Adaptive Performance in the Education Industry Jordan

Eman W. Ahmed*

Department of Curricula and Teaching Methods, Faculty of Education, Sohag University, Egypt. *Email: e_wefky@yahoo.com

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ABSTRACT

The fast pace of digitalization and growing expectations of future-competencies are forcing educational facilities to restructure the process of teaching and learning so as to improve the adaptability and performance of students. In an attempt to meet this objective, in Jordan, institutions are incorporating smart classroom technologies and implementing AI-based learning personalization in adaptive learning ecosystems. Nonetheless, earlier studies indicate that the adoption of smart technologies does not necessarily result in significant gains to adaptive performance by students. This paper, therefore, examines the effects of smart classroom integration on adaptive performance of students in the form of mediator AI-based learning personalization in the Jordan education sector. The study model was created and tested on the sample of 372 educational establishments, with the help of PLS-SEM. The research model suggests 4 hypotheses related to the constructs. The results indicate that adaptive performance of students increases tremendously when smart classroom integration is effectively implemented. Moreover, the findings reveal that learning personalization via AI is a key mediating factor in enhancing student adaptive performance/smart classroom integration. The paper is theoretically relevant to the extent that it gives empirical evidence in favor of applying adaptive learning ecosystem views to Social Cognitive Theory and Technological Pedagogical Content Knowledge (TPACK), with a mediating role of AI-based personalization. Practically, the study provides useful ideas to educational policymakers and institutions in Jordan to develop data-driven and individualized learning plans to facilitate student flexibility and future readiness in dynamic learning environments.

Keywords: Artificial Intelligence-Driven Personalization, Smart Classrooms, Student Adaptation, Educational Sector
JEL Classifications: I21, I23

1. INTRODUCTION

The world of education is changing radically due to the active digitalization, the development of artificial intelligence (AI), and the development of adaptive learning ecosystems. Schools no longer remain within the realms of the traditional pedagogical methodology, but they are more and more likely to produce learners who able to adjust to the changing, technology-mediated environment. This change is especially urgent in the developing countries like Jordan where the education system is straining to meet the global benchmarks of innovativeness, digital literacy, and labor market preparedness (Ahmed, 2026; Mohamad et al., 2026). The combination of smart classroom technologies and AI-based solutions has therefore become a strategic agenda, in order to not only improve the efficiency of learning, but also the adaptive performance of students, which can be described as the capability to react to new, complex, and changing learning environments (Qahman et al., 2025; Vistorte et al., 2024).

The education sector in Jordan provides a very interesting background to this study. The country has more than 10 million residents and a young population of more than 60 million (AlAli and Wardat, 2024), which means that the country is experiencing a growing demand of scalable and high-quality education systems. Recent studies show that over 70% of higher education in Jordan have embarked on digital transformation strategies, but only a small percentage of them have been able to translate those investments into better student outcomes (Peng and Li, 2025). This disconnect exemplifies a critical concern: Although smart classroom integration, which is defined by IoT-enabled devices, interactive digital platforms, and real-time connectivity, is widely implemented, its direct effects on adaptive performance of students have been inconsistent (Kyambade et al., 2025; Yaghmour et al., 2025). In order to overcome this discrepancy, this research proposes the use of AI-based learning personalization as a mediating factor. Smart classroom integration can be defined as the technological infrastructure that facilitates interactive and connected learning but does not provide personalization, so interactive and connected learning does not serve the needs of an individual learner (Beirat et al., 2025; Potluri et al., 2026). Conversely, AI-based learning personalization uses machine learning, predictive analytics, and real-time feedback mechanisms to adjust learning resources, learning speed, and evaluation to individual students (Ogbebor, 2025; Yaghmour et al., 2025). This variable is chosen since it is the so-called intelligent layer that change the inert digital environments into a dynamic ecosystem, thus, directly affecting the involvement and utilization of smart technologies by students.

Student adaptive performance is the dependent variable that is progressively being considered as a vital outcome of education in the 21st century. In contrast to the traditional academic performance metrics, adaptive performance reflects the skills of students in mastering new knowledge, addressing emerging challenges, and adapting to technological and cognitive challenges (Dahri et al., 2025; Qadeer, 2025). This construct is especially applicable in the AI-assisted learning scenarios where the continuity of change is not an exception, but the rule. These three variables, namely, smart classroom integration, AI-driven learning personalization, and student adaptive performance, are therefore theoretically sound and contextually justified to have a consistent framework which is representative of the dynamic nature of education systems. Although the focus on educational technologies has increased, significant research gaps exist, as most studies focus on smart classroom technologies separately, and the outcomes in terms of adaptive capabilities have not been studied (Ul Haq et al., 2025). The integration of theoretical frameworks like Social Cognitive Theory (Bandura, 1986) and Technological Pedagogical Content Knowledge (Mishra and Koehler, 2006) in the explanation of the interaction of technology and cognition in adaptive learning settings is inadequate. Besides, there are also empirical inconsistencies, which also support this exploration. Other researchers find positive outcomes of digital technologies on student performance, Yaseen et al. (2025); Hamzah et al. (2025) where others describe negligible or even negative effects of digital technologies based on cognitive overload or absence of individualization (Almahasees et al., 2024; Ogbebor, 2025). These paradoxes imply that the correlation between technology and performance is not linear but is mediated by certain underlying mechanisms, like AI-enhanced personalization, which have not been sufficiently studied. Also, recent meta-analyses highlight the necessity to use integrative models that reflect both technological and psychological aspects of learning (Kyambade et al., 2025; Qahman et al., 2025). To address these gaps, the main aim of the research is to explore the mediating effect of AI-based learning personalization in the correlation between the integration of smart classrooms and adaptive performance of students in the education sector in Jordan. In particular, the study will: (1) determine the direct effect of smart classroom integration on adaptive performance, (2) measure the effect of smart classroom technologies on AI-driven personalization, (3) measure the effect of AI-driven personalization on student adaptive performance, and (4) test the mediating effect in an integrated research model. The meaning of this research is manifold. In theory, it contributes to the literature by combining the adaptive learning ecosystem perspectives with the Social Cognitive Theory and TPACK, providing a more refined approach to the interaction of the technological and cognitive factors. In practice, it offers practical advice to policymakers, educators, and technology developers who want to optimize the digital learning environments. Theoretically, it has a methodological benefit of utilizing a strong PLS-SEM model in the context of a developing nation to improve the applicability of the results in general.

The breadth and novelty of the present research are in its holistic nature whereby it brought together technological infrastructure, intelligent systems and outcomes of learners in a single framework. This research has provided a model that is holistic and holistic in nature, unlike the earlier studies that take a fragmented approach in their perspectives. This is driven by the fact that there is an urgent need to make sure that any digital transformation initiatives yield any meaningful educational results, especially in areas that aim at becoming globally competitive. Finally, the current research has a substantial contribution as it fills in some crucial gaps, suggests an integrative framework, and offers empirical data on how smart technologies affect adaptive learning. In this way, it not only enhance the academic discourse but also facilitate the creation of education systems that can be ready to meet the future in Jordan and other countries.

2. THEORETICAL BACKGROUND

The theoretical framework of the proposed study is based on the integrative framework that relies on the social cognitive theory (SCT), technological pedagogical content knowledge (TPACK), and the recent approach of adaptive learning ecosystems (ALE), which elucidate the intricate interdependence between smart classroom integration, AI-based learning personalization, and adaptive performance of students. These theories were chosen intentionally and complementary since each of them deals with the important facet of the proposed model, namely the behavioral adaptation, the technological-pedagogical alignment, and intelligence on the level of a system, which provide a solid explanatory background. A powerful foundation to learn the development of adaptive performance of students in technology-driven environments is the social cognitive theory (SCT) (Bandura, 1986). According to SCT, the process of learning is caused by the interplay between personal, behavioral and environmental factors. Digital tools and interactive technologies shape the environment, and AI-prompted personalization affects the cognitive and motivational processes, including self-efficacy, goal setting, and feedback responsiveness, in the context of smart classrooms (Beirat et al., 2025; Peng and Li, 2025).

Previous research has shown that technology-enhanced environments in the context of a mediator of cognitive engagement and self-regulation have a profound impact on adaptive behaviors of learners (Jaboob et al., 2025; Vistorte et al., 2024). This is in line with the present study which suggests that smart classroom integration is not enough but the effectiveness of integrating AI-powered systems is determined by individualizing the learning process to maximize students adaptive abilities. In addition to SCT, technological pedagogical content knowledge (TPACK) framework (Mishra and Koehler, 2006) is a system that is used to understand how teachers can meaningfully incorporate technology into the teaching process. TPACK highlights the overlap between technology, pedagogy and content knowledge, indicating that success in learning requires harmonization of these areas. In intelligent classroom environments, the introduction of high-tech technologies not necessarily result in better performance unless combined and adjusted pedagogically to the needs of learners (Dahri et al., 2025; Ul Haq et al., 2025). The personalization of learning based on AI is a key enabling factor in this context because it dynamically matches instructional content to the individual student profiles (Ahmed, 2026). Empirical research revealed that digitized learning space, when properly designed in terms of pedagogy has a considerable positive impact on engagement and learning outcomes (Obeidat et al., 2026; Yaghmour et al., 2025). Therefore, TPACK would support the consideration of AI-based personalization as a mediating factor to connect technological infrastructure and education results.

Adaptive learning ecosystems (ALE) is the third theoretical lens, which reflects a system-level view that combines data analytics, AI, and interconnected learning systems to build responsive educational systems (Siemens, 2013; Vistorte et al., 2024). The ALE theory is especially applicable to the interactions between smart classroom technologies and AI systems to create adaptive learning experiences. It views learning systems as dynamic ecosystems in which information flows continuously to guide instructional choices and student routes (Mohamad et al., 2026; Almahasees et al., 2024). In this ecosystem, AI-based personalization serves as the fundamental structure that can turn fixed digital infrastructures into dynamic systems. Recent research has highlighted the significance of such ecosystems in promoting learner autonomy, engagement, and adaptability (Potluri et al., 2026; El Din, 2026). This viewpoint is in strong support of the model of the study as it brings about the mediating effect of AI on the translation of technological inputs into meaningful learning outcomes. The proposed relationships are also supported by existing empirical literature. Studies on smart classroom integration show positive but inconclusive impacts on student performance, which is usually because of the lack of personalization mechanisms (Qadeer, 2025; Alakayleh, 2025). Likewise, AI research in education notes that it has the potential to enhance learning outcomes by providing adaptive feedback, content delivery, although they frequently are not integrated with other classroom technologies (Qahman et al., 2025; Dahri et al., 2025). In addition, adaptive performance studies focus on the effect of cognitive flexibility and self-regulated learning, and these areas are directly impacted by personalized learning environments (Ogbebor, 2025; Yaseen et al., 2025).

These disjointed results highlight the significance of a combined model that can take into account the interaction between technology, personalization, and performance. Importantly, the research fills the theoretical gap, bridging the issues of SCT as focusing on behavioral adaptation, TPACK as focusing on pedagogical alignment, and ALE systems-oriented view into a single framework. The combination makes it possible to understand better how the integration of smart classrooms (environmental input) affects adaptive performance (behavioral output) of students due to the personalization of the learning process based on AI (cognitive mechanism). This type of framework is not only able to address discrepancies in previous studies but also able to offer a detailed account of the underlying mechanism that leads to adaptive learning outcomes. Overall, this study theoretically and empirically informed by the joint use of SCT, TPACK, and ALE. The combination of these theories supports the suggested mediation model and offers a consistent rationale of how technological innovation, which is intelligently and pedagogically designed, can benefit the adaptability and success of students in the fast-changing learning conditions.

2.1. Smart Classroom Integration and Student Adaptive Performance

The proposed hypothesis is theoretically based on the complementary lenses of social cognitive theory (SCT) and technological pedagogical content knowledge (TPACK), which jointly explain the way technologically enriched learning environments result in adaptive learner outcomes. In the SCT approach, the process of learning is influenced by the two-way interactions of environmental factors, cognition, and behavioral reactions (Khasawneh et al., 2025; Yaseen et al., 2025). The elementary concept of smart classroom integration reorganizes the learning experience by integrating the interactive technologies and real-time feedback systems, and collaborative online platforms to promote the observational learning process, self-efficacy, and behavioral flexibility among the learners (Dahri et al., 2025; Ul Haq et al., 2025). These aspects are essential in promoting adaptive performance especially when it comes to those situations where there is a need to constantly adapt to new information and online challenges. At the same time, TPACK offers a pedagogical rationale as it focuses on the idea that successful integration of technology should be in line with instructional practices and content delivery to produce meaningful learning outcomes (Potluri et al., 2026; Yaghmour et al., 2025). Properly aligned with pedagogical goals, smart classrooms can facilitate dynamic knowledge building and contextual learning, which are crucial in acquiring higher-order adaptive skills (Dahri et al., 2025; Qadeer, 2025). Empirical research also supports the idea that technologically integrated classrooms can greatly improve the cognitive flexibilities and problem-solving abilities of students when integrated into pedagogically sound models (Hamzah et al., 2025; Ul Haq et al., 2025). But the history of inconsistencies in findings indicates that not every implementation has a consistent amount of benefit, which supports the necessity to test the direct underlying effect suggested in this hypothesis (Jaboob et al., 2025; Yaseen et al., 2025). In this regard, this paper hypothesizes that enhanced smart classroom integration creates an effective environmental and pedagogical foundation that has a direct positive impact on student adaptive performance within changing educational ecosystems.

H_1: The greater the implementation of smart classroom integration, the greater the student adaptive performance in the education industry in Jordan.

2.2. Smart Classroom Integration and AI-Driven Learning Personalization

This hypothesis is informed by the fact that superior digital learning systems serve as critical facilitators of smart, information-sensitive learning systems. In technological pedagogical content knowledge (TPACK), learning innovation takes place when technological systems are available but also are designed to be functionally consistent with the pedagogical processes and content delivery mechanisms (Ayasrah, 2025; Peng and Li, 2025). The integration of smart classrooms offers this underpinning alignment by integrating interconnected devices, learning management systems, and real-time interaction platforms that produce continuous streams of educational data needed to be processed by algorithms (El Din, 2026). In terms of data-driven learning environment, the efficiency of AI systems depends on the presence of the high-quality and real-time data of learners, which captures behavioral, cognitive, and engagement patterns (AlAli and Wardat, 2024; Vistorte et al., 2024). Smart classrooms extend this functionality by using sensor-based, digital measurements, and adaptive platforms to capture granular data on interactions, allowing AI systems to adjust learning paths and maximize content sequencing (Obeidat et al., 2026; Yaghmour et al., 2025). Empirical research proves that maturity levels of digital infrastructure are much more likely to allow institutions to successfully implement AI-based personalization tools (Almahasees et al., 2024; Peng and Li, 2025). Moreover, studies show that in the absence of integrated classroom systems, AI applications disjointed and not provide continuity of personalization results because of lack of data continuity and interoperability of systems (Alakayleh, 2025; Ul Haq et al., 2025). In this respect, this hypothesis is based on the assumption that smart classroom integration is an important technological basis that allows and empowers the personalization of learning with AI, being the infrastructural precondition of adaptive and intelligent learning ecosystems.

H_2: The greater the implementation of smart classroom integration, the greater the AI-driven learning personalization in the education industry in Jordan.

2.3. AI-Driven Learning Personalization and Student Adaptive Performance

This hypothesis is based on the perception that the mechanisms of intelligent personalization essentially transform the way learners become adaptive in digitally mediated settings. In the adaptive learning ecosystem theory, learning systems are viewed as adaptive networks that regulate content, speed, and challenge to individual learners as they evolve (Ahmed, 2026; Ogbebor, 2025). The concept of personalization implemented using AI puts this principle into practice by converting learner data into personalized instructional routes that dynamically change (Vistorte et al., 2024). Cognitively-developmentally, these systems help learners to have better metacognitive regulation, allowing them to monitor, evaluate, and modify their learning strategies (Dahri et al., 2025; Yaghmour et al., 2025). Students in a better position to cope with uncertainty and switching to various task demands by means of adaptive feedback and context-sensitive learning recommendations, which, in turn, positively affect adaptive performance abilities (Jaboob et al., 2025; Qadeer, 2025). This correlation is also advanced by empirical research, which reveals that AI-based personalization enhances learning agility, consistency in engagement, and flexibility in solving problems in technology-enhanced settings (Yaseen et al., 2025; Dahri et al., 2025). Moreover, adaptive systems have also been found to decrease cognitive load by matching the complexity of instruction with the level of the learner readiness, which enhances the sustainability of the performance (Qahman et al., 2025; Alakayleh, 2025). Nevertheless, previous research also notes that in the absence of personalization, the digital learning environment is unlikely to yield technological investments in measurable performance improvements (Peng and Li, 2025; Ayasrah, 2025). In this light, the hypothesis is that AI-based personalization of learning is a direct cognitive and behavioral enabler; allowing students to continually adapt, react, and succeed in dynamic learning environments in Jordan.

H_3: The greater the implementation of AI-driven learning personalization, the greater the student adaptive performance in the education industry in Jordan.

2.4. Mediating Role of AI-Driven Learning Personalization

The hypotheses are based on the premise that the effects of technological infrastructure on learning outcomes are not linear and that, rather, they are mediated by intelligent cognitive-processing mechanisms. According to the theory of adaptive learning ecosystem, education systems are complex systems in which raw technological inputs need to be converted into valuable learning adaptations by means of data interpretation and continuous feedback (Vistorte et al., 2024; Beirat et al., 2025). In this respect, smart integration of classrooms offers the structural and digital base, whereas AI-enhanced personalization is the working intelligence that triggers adaptive learning procedures (Potluri et al., 2026). In terms of dynamic capability, institutions need to convert technological resources into capabilities of utilization by sensing the needs of learners, taking opportunities to adjust instructions and reorganizing learning routes in real-time (AlAli and Wardat, 2024; Qahman et al., 2025). Smart classrooms produce large-volume, multi-dimensional data about learners but without systems of AI-based personalization, this data is not utilized. AI thus forms the interpretive layer, which translates data into adaptive instructional decisions, which allow students to become more responsive to evolving academic needs (Ahmed, 2026; Yaseen et al., 2025). The mediating logic is supported by empirical research, which shows that educational technologies can achieve better performance results when mediated by adaptive and learner-centered systems but not when implemented directly (Beirat et al., 2025; Vistorte et al., 2024). Also, the studies indicate that personalization diminishes the disconnect between technological exposure and actual effectiveness in learning by matching instruction with individual cognitive readiness (Beirat et al., 2025; Qadeer, 2025). On the contrary, such a disjointed, non-personalized digital implementation tends to result in poor performance and unpredictable learning results (Obeidat et al., 2026). Thus, the hypothesis is that AI-based learning personalization serves as the most important intervening factor according to which the integration of smart classrooms translated into better adaptive performance of students in the educational setting in Jordan. Research model of the study is presented in Figure 1.

H_4: AI-driven learning personalization acts as a mediating variable between smart classroom integration and student adaptive performance in the education industry in Jordan.

3. METHODOLOGY AND DATA

3.1. Sample Design and Data Collection

The hypotheses that were put forward in the research model were tested by designing an empirical model within the Jordanian educational institutions. As the population reference framework, the ministry of higher education and scientific research (MoHESR) Jordan database was used, which included 18,450 educational institutions, including universities, colleges, and public/privately run schools with more than 50 staff in 2025 (Ahmed, 2026). The first stage of the research was the digital education expert panel with the involvement of five school principals representing the education sector, two officials of national digital learning policy units, and three researchers and scholars in AI in education and adaptive learning systems who were provided with the survey to be used. The findings of this initial step made it possible to design a survey to gather information, which was implemented on a pilot sample of 12 educational institutions, with some slight modifications to writing, structure, and clarity. Pilot tests are necessary to guarantee validity in cases of self-administered surveys or those that have self-created scales (Yaseen et al., 2025; Dahri et al., 2025).

The criteria used for the selection of participants in the digital education expert panel were, with respect to school principals, that the institutions had implemented at least one smart classroom integration and/or AI-driven learning personalization practice in the institutions in the last 2 years; as for the representatives of government digital education units, that they were responsible for departments of digital transformation and e-learning implementation, and that in the last 2 years at least, they have supported at least one digital learning initiative in an educational institution; and with regard to academics, who were members of national or international education research networks; who have carried out at least one funded research project on smart learning environments or AI-based education systems in the last 2 years; and who have published in the last 2 years at least one article in a WOS Journal with impact factor related to digital education, smart classrooms, or AI in learning ecosystems. During the second phase, a total of 310 surveys were used to sample out 750 educational institutions by using simple random sampling with a maximum error of 5% and a reliability level of 95% and only 372 surveys were returned and the response rate was 49.6 which is deemed representative of the target population. A customized educational research firm carried out data collection in the form of a personally administered survey of principals and academic coordinators of the identified institutions during the period of March-June 2025, who had the necessary expertise to answer the different sets of questions that formed part of the survey (Ahmed, 2026). To reduce potential response bias (Podsakoff et al., 2003), participants were assured of the confidentiality of their responses. They were told that there were no right or wrong answers and they were advised to give their honest answer. The different midpoint scales were explained with examples and comprehensive explanations to any unfamiliar terms. The purpose of this protocol was to reduce the responses due to social desirability, leniency or need to conform to the perceived expectations.

3.2. Measurement Development

A comprehensive literature review was conducted, which helped to find the most suitable scales to measure smart classroom integration (SCI), AI-driven learning personalization (AIDL), and student adaptive performance (SAP). SCI was measured using eight items based on Jaboob et al. (2025); Qahman et al. (2025); Yaseen et al. (2025); Ahmed (2026); and (Ul Haq et al., 2025). As a measure of AIDL, we relied on the Dahri et al. (2025) scale, Qadeer (2025), Yaseen et al. (2025), and Obeidat et al. (2026) scale that took eight items to measure it. Lastly, in an attempt to measure SAP, the scale developed by Beirat et al. (2025) and Peng and Li (2025) came up with seven items to measure SAP. All the items were measured through a 5-point Likert-type scale, with 1 = totally disagree to 5 = totally agree, as limits. These scales have already been used in recent studies in the digital education and AI-learning context (e.g., Qadeer, 2025; AlAli and Wardat, 2024; Yaghmour et al., 2025; Kyambade et al., 2025). The loadings of the items used are shown in Table 1 and it is noted that all values are above 0.6, which is the recommended value provided by Hair et al. (2021).

3.3. Data Analysis

A partial least squares structural equation modelling (PLS-SEM) was used to analyse the data. This approach enables the knowledge of causal-predictive power and variance measurement error explanation (Fornell and Larcker, 1981). Researchers have recognized this technique and have been able to use it to create more sophisticated models in many fields (Tenenhaus et al., 2005). Hair et al. (2021) found out that there are four crucial points in choosing this method: The properties of the information, the properties of the model, the estimation of the model, and its assessment. Additionally, by analyzing observed data, predictive analyses provide better explanations of latent variables in areas with emerging theories (Ahmed, 2026; Potluri et al., 2026). The PLS-SEM technique would be useful now, as it has exploratory nature, new theory development, nonparametric data, and intermediate sample sizes, among others (Hair et al., 2021). PLS-SEM is regarded as a methodology that uses compounds to linearly consider indicators to create composite variables (Vistorte et al., 2024), which are typically proxies of the concepts under consideration (Rigdon, 2016). In this study, the use of a composite model was considered pertinent, which is an essential reason for the use of PLS-SEM (Sarstedt et al., 2016) and the SmartPLS 4.0 software (AlAli and Wardat, 2024). The reason is

Table 1: Measurement model assessment

Indicators	Items	Factor loadings (P)
Smart classroom integration (SCI)		
Cronbach's alpha: 0.889; Dijkstra-Henseler's rho: 0.893; CRI: 0.912; AVE: 0.561		
Indicators	**Items**	**Factor loadings (P)**
SCI1	Interactive digital boards and smart displays enable real-time learning engagement.	0.661 (0.000)
SCI2	IoT-enabled classroom devices support seamless connectivity between learners and systems.	0.728 (0.000)
SCI3	AI-supported teaching tools assist instructors in managing classroom activities.	0.771 (0.000)
SCI4	Cloud-based learning platforms enable continuous access to academic resources.	0.786 (0.000)
SCI5	Learning analytics dashboards support monitoring of student performance.	0.798 (0.000)
SCI6	Virtual collaboration tools enhance group-based learning activities.	0.722 (0.000)
SCI7	Digital assessment systems provide automated evaluation and feedback.	0.775 (0.000)
SCI8	Integrated smart systems enable real-time interaction between physical and digital learning spaces.	0.743 (0.000)
AI-Driven learning personalization (AIDL)		
Cronbach's alpha: 0.928; Dijkstra-Henseler's rho: 0.931; CRI: 0.942; AVE: 0.663		
Indicators	**Items**	**Factor loadings (P)**
AIDL1	AI systems adapt learning content based on individual student performance.	0.795 (0.000)
AIDL2	Personalized learning pathways are generated using predictive analytics.	0.821 (0.000)
AIDL3	Adaptive feedback systems provide real-time learning recommendations.	0.864 (0.000)
AIDL4	AI tools identify student strengths and weaknesses continuously.	0.873 (0.000)
AIDL5	Machine learning algorithms adjust content difficulty dynamically.	0.858 (0.000)
AIDL6	Personalized assessment systems improve learning accuracy.	0.742 (0.000)
AIDL7	AI-based tutoring systems enhance individualized instruction quality.	0.768 (0.000)
AIDL8	Data-driven learning systems support student-centered education design.	0.780 (0.000)
Student adaptive performance (SAP)		
Cronbach's alpha: 0.862; Dijkstra-Henseler's rho: 0.866; CRI: 0.892; AVE: 0.536		
Indicators	**Items**	**Factor loadings (P)**
SAP1	Students adapt effectively to new digital learning environments.	0.708 (0.000)
SAP2	Students demonstrate flexibility in solving unfamiliar academic problems.	0.664 (0.000)
SAP3	Students adjust learning strategies according to task demands.	0.731 (0.000)
SAP4	Students show resilience in technology-driven learning conditions.	0.748 (0.000)
SAP5	Students effectively manage changes in instructional methods.	0.774 (0.000)
SAP6	Students improve performance through continuous digital feedback.	0.736 (0.000)
SAP7	Students demonstrate high adaptability in blended and smart learning environments.	0.761 (0.000)

that the composite indicators are believed in the literature to be an operational definition of an emergent construct that mediates all model effects, and the composites measured using composite indicators do not include an error term (Hair et al., 2021). Moreover, the PLS-SEM approach is appropriate in this paper to test theoretical relationships mainly because (a) it can work with nonparametric data in the education-based survey research, (b) it is useful in making an exploratory modeling in the digital learning systems, and (c) it is able to consider the causal-predictive nature of the relationships in technology-enhanced education settings.

In accordance with (Khasawneh et al., 2025) researchers should adopt a technique that is consistent with the model they aim to estimate. It is in this regard that a model-based approach such as PLS-SEM should be applied by researchers who have a model of composites. Sarstedt et al. (2016) suggest that, in case of any uncertainty regarding the nature of constructs, it is always best to employ PLS since it gives the least biased solutions. The operational definition of the emergent construct, which mediates all of its impacts in the model to be taken into account, is composite indicators (Henseler, 2017). Constructs measured with composite indicators do not have an error term, contrary to what happens with causal formative indicator models. So composite indicators do not cause a construct but are contributive (Khasawneh et al., 2025). Therefore, these indicators have to share the same consequences (Henseler, 2017), although they may not be unidimensional and might not share a conceptual unit. Thus, composite indicators may represent different aspects relating to the construct. To estimate the paths, PLS-SEM applies the Modes A and B as explained by Sarstedt et al. (2016): Mode A of the PLS-SEM is associated with correlation weights based on bivariate correlations between each indicator and the construct, whereas Mode B of the PLS-SEM is related to regression weights. In this study, a mode A composite model with both direct and mediating relationships has been proposed to be able to guarantee the response to questions that will be asked. Covariance-based structural equation modelling (CB-SEM) and partial least square structural equation modelling (PLS-SEM) are the two methods of estimating structural equation models that the scientific and academic community generally considers to differ in their approximation of constructs statistically and in their optimization procedures (Jaboob et al., 2025).

Within the literature, different studies have compared the effectiveness and differences between CB-SEM and PLS-SEM in education, psychology, and research in digital transformation, in an attempt to identify the circumstances under which either of the two approaches excel or underperform (e.g., Beirat et al., 2025; Vistorte et al., 2024; Yaseen et al., 2025). The basic difference between CB-SEM and PLS-SEM is the approach for this estimation: CB-SEM uses a factor-based approach, and PLS-SEM uses a component-based approach (Vistorte et al., 2024). Factor-based CB-SEM portrays the constructs as shared factors, meaning that the constructs are viewed as an independent reality that is not dependent on the measured variables, leading them to have a covariant relationship (Potluri et al., 2026). Thus, the estimation of the parameters of CB-SEM is depending on the shared value of the indicators which are presumed to be fully explained as a constituent of the construct (common factor) and its error variance (unique) (Hair et al., 2021). Factor-based PLS-SEM, on the other hand, uses powered sums of the observed variables to approximate the constructs (Tenenhaus et al., 2005). Thus, PLS-SEM estimation is not concerned with the common variance, but the total variance of indicators is assumed to be a single dimension of identity (Sarstedt et al., 2016). In this way, PLS-SEM has become more popular among researchers and academics, which are finding more applications in smart learning environments, AI-based education systems, and educational futures research (Ahmed, 2026; Peng and Li, 2025; Dahri et al., 2025).

3.4. Measurement Model

The measurement model is based on exogenous and endogenous relationships, and the structural model investigates the role of indicators in constructs (Martínez Ávila and Fierro, 2018). In the evaluation of the measurement model and the correlation between latent and observed variables, internal consistency, reliability, convergent validity, and discriminant validity have to be considered (Hair et al., 2021). To test internal consistency, the lower bound was found with the help of cronbach alpha and composite reliability index (CRI), and the upper bound was found with the help of rho A (Dijkstra and Henseler, 2015). Convergent validity takes into consideration the average variance extracted (AVE), and discriminant validity takes into consideration the FornellLarcker criterion (Fornell and Larcker, 1981). Moreover, the heterotraitmonotrait ratio (HTMT) suggested by Henseler Ringle, and Sarstedt (2016) is a more efficient criterion to achieve discriminant validity by bootstrapping. After meeting the criteria of measurement model, the structural model is bootedrapped to determine whether the indirect effects are significant and what form of mediation exists (Hair et al., 2021). The importance of mediating variable is that it transmits or intensifies the effect between variables in the proposed model. The personalization of AI-driven learning as a mediating variable is analyzed by a two-step approach, which includes the calculation of the values of the latent variables first. Next, values of the exogenous and mediating variables are multiplied to derive the interaction effect, which is eventually obtained (Hair et al., 2021). The PLS-SEM statistical technique has been used in recent similar studies published in the literature in educational technology, AI-based learning systems, and smart classroom environments (Yaghmour et al., 2025; El Din, 2026; Yaseen et al., 2025). The indicators loadings were measured, between 0.855 and 0.940 (Table 2). It was assumed that the optimal values would be >0.7 that would explain more than 50% of the indicator variance (Hair et al., 2021). In analyzing internal consistency of the model, good results were noted, and Cronbach was >0.90. The CRI values were between 0.889 and 0.940 (Table 2) which is within the recommended range as proposed by Hair et al. (2021). The rho A values fell between the two preceding indicators which are indicators of the actual reliability of variables (Bagozzi and Yi, 1988; Hair et al., 2021). Likewise, the share of the indicator variance explained by AVE and communality (Table 2), was over 50, which is more than 0.50 (Fornell and Larcker, 1981; Hair et al., 2021). The Fornell Larcker criterion, as well as the HTMT ratio were used to establish the discriminant validity with the values being between 0.614 and 0.768, all below the 0.80 limit (Henseler et al., 2016).

4. RESULTS

Using SmartPLS 4.0 software (Ringle, Wende, and Becker, 2022) through a structural equation model using partial least squares (PLS-SEM), the hypotheses raised in the research model were tested. PLS-SEM is typically applied in poorly developed theories (Hair et al., 2021) and in other areas of knowledge like educational technology, digital learning systems, and AI-based education research (Dahri et al., 2025; Ul Haq et al., 2025; Jaboob et al., 2025). Moreover, employing PLS-SEM becomes crucial when the aim of applying the structural equation model is to predict and elucidate constructs within the research model (Alakayleh, 2025). In addition, the use of compounds in PLS-SEM, as a weighted combination of its indicators, facilitates the explanation of measurement error of constructs, which allows this method to be more powerful than multiple regression (Hair et al., 2021).

4.1. Structural Model Evaluation

The structural equation technique is basic to evaluate structural models (Tenenhaus et al., 2005). In the analysis of constructs relationships, both noncollinearity with the variance inflation factor (VIF) and significance and relevance of path coefficients, effect sizes (f2), and determination coefficients (R2) should be ensured (Martínez Ávila and Fierro, 2018). The observed VIF results

Table 2: Measurement model: Reliability, validity, and discriminant validity

Panel A. Reliability and validity				
Variables	**Cronbach's alpha**	**Dijkstra-Henseler rho**	**CRI**	**AVE**
Smart classroom integration	0.889	0.893	0.912	0.561
AI-driven learning personalization	0.928	0.931	0.942	0.663
Student adaptive performance	0.862	0.866	0.892	0.536

Panel B. Fornell-Larcker criterion and HTMT						
Variables	**1**	**2**	**3**	**HTMT (1-2)**	**HTMT (1-3)**	**HTMT (2-3)**
1. Smart classroom integration	**0.749**					
2. AI-driven learning personalization	0.662	**0.814**		0.713		
3. Student adaptive performance	0.584	0.701	**0.732**	0.768	0.646	0.614

Diagonal elements (bold) represent the square root of AVE. For discriminant validity, diagonal values should be higher than off-diagonal correlations. HTMT values are below the 0.80 threshold, confirming acceptable discriminant validity

(2.0-3.1) were below 5.0, and the R^2 values were 0.438 for AIDL and 0.511 for SAP (Table 3). Table 3 confirmed the model fit with an SRMR of 0.041 (Hu and Bentler, 1998), an unweighted least squares discrepancy (dULS) of 0.502, and a geodesic discrepancy (dG) of 0.184, which are below the HI99% threshold (Almahasees et al., 20 Table 3 shows the results obtained, which indicate that the estimated data have acceptable statistical levels. Adjusted R 2 is greater than the recommended value of 0.10 (Henseler et al., 2017; Hair et al., 2021). Moreover, SRMR, geodetic discrepancy (dG), and dULS all are less than the HI99 value as stated by Dijkstra and Henseler (2015). Similarly, estimated data confirm that SCI positively affects SAP (0.572; P = 0.000) and SCI positively affects AIDL (0.661; P = 0.000), which proves the Hypothesis H_1 and H_2. Likewise, AIDL has a positive influence on SAP (0.214; P = 0.001), which can also confirm Hypothesis H_3. This implies that the adaptive performance of students in the education sector in Jordan is enhanced with the use of AI-based personalization. Lastly, findings also confirm that AIDL can be used as a mediating variable in the correlation between SCI and SAP (0.141; P = 0.000) which, in turn, indicates evidence that proves Hypothesis H_4, which means that a considerable part of the effects of integrating smart classrooms on student adaptive performance is mediated by AI-based learning personalization. Thus, it can be determined that AI-based personalization of learning does not only substantially enhance student adaptive performance, but also serves as a vital factor enhancing the existing correlation between smart classroom integration and adaptive performance.

5. DISCUSSION

The results of this paper give the proposed model a solid empirical evidence as it shows that smart classroom integration (SCI) has a significant direct and indirect impact on student adaptive performance (SAP) via AI-based learning personalization (AIDL) in the education sector of Jordan. On the whole, the findings support the fact that digital transformation in education is not a technological change but a systematic ecosystem change in which the learning outcomes are determined by intelligent mediation processes. These findings are consistent with and build upon previous research on the topic of digital learning environments, adaptive systems, and AI-enabled education (Hamzah et al., 2025; Ul Haq et al., 2025). The initial hypothesis supports the validity of that the smart classroom integration is significantly positively related to adaptive performance among students. This observation is in line with earlier findings that suggest the use of digitally enriched classrooms makes learners more flexible, capable of solving problems, and engaging in more complex tasks (El Din, 2026; Ul Haq et al., 2025). The outcome confirms the Social Cognitive Theory (Bandura, 1986) that states that environmental stimulation has a direct influence on cognitive and behavioral adaptation. Smart classrooms are interactive and motivate observational learning and feedback loop-based adaptive learning, which reinforces adaptive behaviors (Alakayleh, 2025; Yaseen et al., 2025). Nevertheless, weaker or randomized direct impacts of technology integration on learning outcomes were reported in some previous studies (Hamzah et al., 2025; Qadeer, 2025). These contradictions indicate that technology might not be the only solution to improvements in performance.

The present research addresses this discrepancy by confirming that although SCI has a direct influence, its role gains more significance in contexts of adaptive mechanisms, which further justifies the significance of system-level integration in learning settings (Yaseen et al., 2025; Mohamad et al., 2026). The latter result proves that SCI can benefit AI-driven personalization of learning dramatically. This finding is consistent with the existing studies that note that intelligent learning spaces produce highly organized information that AI systems need to operate efficiently (Ayasrah, 2025; Qadeer, 2025). In the absence of integrated classroom technologies, AI systems will not be able to have the continuous behavioural and performance data needed to support adaptive modelling (Hamzah et al., 2025; Vistorte et al., 2024). TPACK-wise, the finding supports the fact that technological infrastructure is not enough unless it is coordinated with the pedagogical design and content delivery systems (Obeidat et al., 2026; Yaseen et al., 2025). Similar studies by Mohamad et al. (2026) and Beirat et al. (2025) also note that integration of teaching systems and digital infrastructure is a critical element in facilitating personalized learning. This argument is furthered in the present findings by empirically showing that SCI is a prerequisite force behind AI-based personalization in actual educational settings. However, other researchers believe that AI personalization may be deployed without the complete integration of smart classrooms via cloud platforms (Obeidat et al., 2026; Vistorte et al., 2024).

Nonetheless, this paper indicates that the integration of systems can increase the precision and uniformity of personalization,

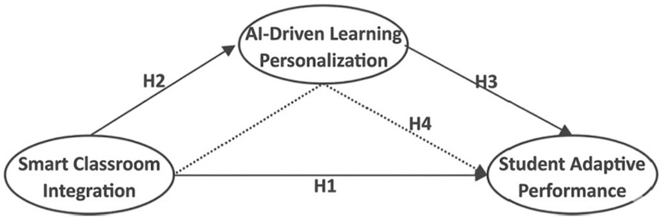
Table 3: Structural model results

Panel A. Structural paths (hypotheses testing)							
Hypothesis	**Relationship**	**Path coefficient**	**t-value**	**P-value**	**95% confidence interval**	**f²**	**Result**
H_1	SCI→SAP	0.572	10.214	0.000	(0.451-0.662)	0.378	Supported
H_2	SCI→AIDL	0.661	18.102	0.000	(0.572-0.716)	0.759	Supported
H_3	AIDL→SAP	0.214	3.581	0.001	(0.098-0.322)	0.054	Supported
Indirect effects							
H_4	SCI→AIDL→SAP	0.141	3.612	0.000	(0.066-0.218)	0.039	Supported

Panel B. Model quality/endogenous constructs				
Construct	**R² (adjusted)**	**Model fit indicator**	**Value**	**Threshold**
AIDL	0.438	dULS	0.502	0.701
SAP	0.511	dG	0.184	0.247
—	—	SRMR	0.041	0.050

Bootstrapping based on 5,000 subsamples

Figure 1: Research model



especially in emerging markets such as Jordan where infrastructure inconsistency is an issue (Almahasees et al., 2024). The third hypothesis proves that adaptive performance by AI-driven learning personalization can greatly enhance student performance. This result is highly consistent with the current literature that points out that individualized learning spaces increase cognitive flexibility, engagement, and academic resilience (Qadeer, 2025; Yaghmour et al., 2025). The adaptive feedback, dynamic content adjustment, and predictive learning pathways supported by AI systems allow enhancing self-regulation and problem-solving ability in learners (Hamzah et al., 2025). This finding can be explained by the adaptive learning ecosystem theory, which implies that individualization is the fundamental process that converts data into valuable learning results (Potluri et al., 2026; Yaseen et al., 2025). But there are also conflicting reports, as AI systems have demonstrated little effect because they depend on automation too much or are not watched by humans (El Din, 2026; Ogbebor, 2025). The current research illuminates this paradox by demonstrating that, in case AI personalization is implemented into organized learning ecosystems, it has a noteworthy positive impact on adaptive performance.

The greatest contribution of this research is the affirmation of the mediating effect of AI-based learning personalization between the integration of smart classrooms and adaptive performance in students. This finding lends credence to the argument that the technological infrastructure has an indirect effect on learning outcomes via cognitive and adaptive processes and not direct effects only (Dahri et al., 2025; Qahman et al., 2025). The results are highly consistent with the Dynamic Capability Theory that posits that organizational and educational systems can deliver performance results by converting resources into adaptive capabilities via sensing, seizing, and reconfiguring processes (Beirat et al., 2025; Vistorte et al., 2024). In this case, SCI is the source of the resource base whereas AIDL is the transformation mechanism that transforms the technological inputs into adaptive student behavior. This mediation pathway has not been extensively tested in one unified model before, particularly in the educational context of developing countries (Hamzah et al., 2025; Potluri et al., 2026). Other studies indicate partial mediation effects of digital tools on learning outcomes, but in many cases, without a focus on AI personalization as a key mechanism (Alakayleh, 2025; Qahman et al., 2025). This gap is closed in the current study, which empirically substantiates that AI-based personalization is the most important explanatory medium between technological integration and adaptive performance. Taken together, the results affirm that education change in Jordan can be viewed as an ecosystem-based process, in which integration of smart classrooms is not enough to produce the desired impact unless it is converted into individualized learning experiences via AI systems. This research clears up the contradictions of the earlier studies showing that there is a systematic process: Technology to personalization to adaptive performance. This verifies that the future of education is not only digital, but also intelligent, adaptive, and systemically connected, supporting the proposed theoretical incorporation of the SCT, TPACK, and adaptive learning ecosystem perspectives (Yaseen et al., 2025; Ayasrah, 2025).

5.1. Theoretical Contributions

The present research contributes to theory well through the extension and fusion of both Social Cognitive Theory (SCT) and Technological Pedagogical Content Knowledge (TPACK) into the smart classroom ecosystem and AI-based learning personalization in Jordan. In terms of SCT, the research contributes to the knowledge of the influence of environmental digital transformation, which is represented by smart classroom integration, on adaptive performance among students due to cognitive and behavioural processes. In particular, it empirically proves that learning conditions augmented with interactive technologies reinforce self-efficacy, observational learning and self-regulated behavior, the main constructs of the SCT. Notably, the research builds on SCT by making AI-based personalization a cognitive intermediary, operationalizing the environmental stimuli to individualized learning reactions, which fills the gap in previous research that mostly treats technology as a fixed environmental variable (Peng and Li, 2025; Yaseen et al., 2025). This study has a contribution in the context of TPACK in that it shows that technological integration is not enough unless it is accompanied by pedagogical and content adaptation processes. The results expand TPACK by validating AI-based learning personalization empirically as the mediating technology infrastructure-to-instructional efficiency. This reinforces earlier claims that successful digital learning requires the coordination of technology, pedagogy and content knowledge (Dahri et al., 2025; Qahman et al., 2025). Additionally, the work further develops TPACK, integrating it into an adaptive learning ecosystem, demonstrating that personalization technologies increase pedagogical responsiveness and learner-centered teaching in real-time digital settings (Almahasees et al., 2024; Ul Haq et al., 2025). In sum, the research study adds a multi-theoretical synthesis that does not just describe whether but also how adaptive student outcomes can be improved through smart learning systems.

5.2. Practical Implications

This research offers some valuable practical implications to the education sector in Jordan in the form of policymakers, educational leaders, and technology developers. To begin with, the results indicate that merely investing in smart classroom infrastructure is not adequate to promote adaptive student performance. Institutions should make sure that the technologies are actively combined with AI-based personalization systems, which will be able to make sense of the learner data and provide individualized learning paths. This brings out the necessity of a transition in the approach of technology adoption to intelligent strategies of learning designs. Second, the educational policymakers are to focus on national frameworks in favor of AI-driven learning analytics, teacher education on digital pedagogy, and interoperability of the infrastructure across the institutions. The lack of such alignment can leave smart classroom investments untapped or underutilized. Third, educators must be prepared to not just use digital tools, but to understand the feedback produced by AI and modify teaching approaches in real-time. This makes the pedagogical responsive and learners more involved. Fourth, EdTech developers must work to create adaptive platforms that can be integrated with classroom technologies and include real-time personalization functionality like adaptive assessments and predictive learning pathways. Lastly, university administrators must not view AI-driven personalization as a performance-enhancing tool that can be adopted as an optional one, but as a fundamental performance-enhancing tool that must be incorporated into the curricular design and assessment systems.

6. CONCLUSION

This paper finds that classroom integration is critical to improving adaptive performance of students in the education sector in Jordan, and AI-based learning personalization reinforces this impact. The results affirm that learning change does not happen when technology is advocated but through smart systems that customize learning to the needs of the individuals. The study offers an in-depth account of the practical functioning of digital learning ecosystems by empirically confirmed the mediating role of AI-driven personalization. This combination of SCT and TPACK provides a solid theoretical basis and proves that the learning outcomes are the result of interactions between environmental systems, cognitive processes, and pedagogical design. The findings indicate that students gain greater adaptive performance when they are exposed to personalized, data-driven and interactive learning conditions. On the whole, the study leads to the further development of the knowledge about adaptive learning ecosystems and offers a solid base to future research and policy making in the sphere of AI-enabled educational systems.

This study has limitations, in spite of its contributions. To begin with, the cross-sectional design hinders the capacity to develop long-term causal links among smart classroom integration, AI-powered personalization, and adaptive performance of students. Longitudinal research designs should be embraced in the future to ensure that dynamic changes in the behavior of learning are observed over time. Second, the research is on the Jordanian education institutions, which might not be applicable to other cultures or technological factors. To prove the model in other educational systems, comparative cross-country studies are suggested. Third, the research is based on self-reported information which could create subjectivity. The next-generation studies may combine objective learning analytics or performance data generated by the system to improve the accuracy. Fourth, although the research concentrates on the mediation effects, it does not discuss the possible moderating variables, including digital literacy, institutional preparedness, or teacher competency. The moderators should be included in future research to enhance the explanatory value of the model. Lastly, in future studies, this model can be expanded by incorporating new technologies, including metaverse learning environments, generative AI tools, or neuro-adaptive learning systems, to further investigate the next-generation learning ecosystems.

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