Information and Software Technology 199 (2026) 108287

Contents lists available at ScienceDirect

Information and Software Technology

journal homepage: www.elsevier.com/locate/infsof

Generative AI in teaching: How AI literacy and AI-generated lesson design shape teachers' classroom implementation strategies

Nisar Ahmed Dahri [a,b,*], Akhtar Hussain [c], Amjad Islam Amjad [d], Muhammad Hafidz Fazli Bin Md Fauadi [c], Raheem Bux Soomro [e]

[a] Faculty of Education Science and Technologies (FEST), Universiti Teknologi Malaysia, Skudai 81310, Johor, Malaysia
[b] Sohar University, Sohar, 311, Oman
[c] Fakulti Kecerdasan Buatan Dan Keselamatan Siber (FAIX), Universiti Teknikal Malaysia Melaka (UTeM), Malaysia
[d] Department of Education, The University of Lahore, Lahore, 54600, Pakistan
[e] Institute of Business Administration, Shah Abdul Latif University, Khairpur, Pakistan

ARTICLE INFO

Keywords:
Artificial intelligence literacy
Generative ai in teaching
AI-generated lesson design
Lesson implementation strategies
Teacher self-efficacy
TAM

ABSTRACT

Context: The rapid integration of generative artificial intelligence (AI) into education has created new possibilities for supporting teachers' instructional planning and classroom practices. While prior research has largely focused on students' AI use in higher education, limited empirical evidence explains how schoolteachers' AI-related capabilities translate into effective lesson design and implementation, particularly in developing regions such as Sindh, Pakistan.
Objectives: Grounded in the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT), this study aims to examine how teachers' AI literacy (AIL) influences AI-generated lesson design (AILD) and lesson implementation strategies (LIS), as well as to test the mediating role of AILD and the moderating role of teachers' AI self-efficacy (TAISE).
Methods: A quantitative, cross-sectional survey design was employed. Data were collected from 300 government schoolteachers in Sindh, Pakistan, all of whom had completed formal training on AI-based lesson planning tools. Partial least squares structural equation modelling (PLS-SEM) was used to assess the measurement and structural models. Mediation and moderation effects were further validated using SmartPLS and Jamovi.
Results: The findings indicate that AI literacy significantly and positively predicts AI-generated lesson design, which in turn has a strong positive effect on teachers' lesson implementation strategies. AI-generated lesson design partially mediates the relationship between AI literacy and lesson implementation, highlighting pedagogical design as a key mechanism linking AI competence to classroom practice. Teachers' AI self-efficacy shows a significant direct effect on AI-generated lesson design; however, its moderating effect on the AI literacy–lesson design relationship is not supported.
Conclusion: This study extends TAM and SCT to the context of generative AI–enabled teaching in school education. The results underscore the importance of strengthening teachers' AI literacy and pedagogical design skills through structured training and policy support to ensure sustainable and effective AI integration in classrooms.

1. Introduction

Education systems worldwide are undergoing rapid transformation driven by digital technologies, with artificial intelligence (AI) emerging as one of the most influential forces reshaping teaching and learning practices. Traditionally, classroom instruction relied heavily on teachers' subject knowledge, pedagogical expertise, and manual instructional planning processes. However, in many developing contexts, including Pakistan, teachers often face systemic challenges such as limited access to professional development, inadequate instructional resources, and insufficient pedagogical support, which negatively affect lesson quality and student learning outcomes [1]. These challenges are particularly evident in public school systems where instructional planning, assessment design, and classroom implementation remain largely traditional and content-driven rather than outcomes-based [2]. As a result, students' conceptual understanding, higher-order thinking skills, and

* Corresponding author at: Faculty of Education Science and Technologies (FEST), Universiti Teknologi Malaysia, Skudai 81310, Johor, Malaysia.
E-mail address: ahmeddahri.nisar@utm.my (N.A. Dahri).

https://doi.org/10.1016/j.infsof.2026.108287
Received 7 February 2026; Received in revised form 11 May 2026; Accepted 29 July 2026
Available online 31 July 2026

overall academic achievement remain persistently low, especially in under-resourced regions such as Sindh province [3,4].

In recent years, generative AI, a branch of artificial intelligence, has created new opportunities to handle long-standing problems of instruction [5]. These include assisting teachers in designing lessons, creating assessments and feedback, and make instructional decisions effectively [5]. Generative AI systems like large language models can on their own generate lesson plans, learning activities, assessment items, and differentiated instructional materials aligned with curricular goals [6,7]. The implementation of these technologies has gone beyond automation and now includes receiving guidance on cognitive, creativity, and pedagogy. Tech-driven may be referred to as using or involving technological devices or equipment to improve educational practices involving social media, smartphones, and gaming to boost engagement and offer more customized interactions to students [8]. The implementation of technology alone is insufficient for driving sustainable education systems; the competencies of teachers also must be developed to ensure they use artificial intelligence ethically, effectively, and pedagogically meaningfully.

The evolution of AI in education has had an impact to help in the teaching and instructional planning for pedagogy itself. Lesson plan design is an important aspect of instructional planning that determines how curriculum objectives are implemented or achieved in the classroom. The current education system has greatly focused on modernizing education by emphasizing outcome-based education (OBE). In OBE, teaching is aligned with clearly defined Student Learning Outcomes (SLOs) and the cognitive levels are expressed through Bloom's taxonomy [9,10]. It remains a not easy task to design lessons that incorporate analysis, evaluation, and creation (also known as higher-order thinking skills) particularly for teachers who have not received much teacher training. However, the AI-generated lesson design helps teachers produce better lessons by streamlining their activities, assessments, and objectives while also connecting goals to Bloom's taxonomy and lesson curriculum [11,12]. According to current literature, while AI can be used to create lesson plans based on the curriculum, promote consistency in teaching, and ensure a minimum standard, it cannot cater to different kinds of learners. Insufficient differentiation is in some AI-generated schemes of work. Teachers are encouraged to use an existing framework, such as universal design for learning, Solo Taxonomy, and Bloom's Taxonomy [13,14], as well as their own judgment to perform an evaluation. According to Gurl et al. [15], teachers should carefully evaluate AI-generated content instead of just accepting it without careful thought, ensuring that it will fit the context and the learners.

In an AI-supported teaching and learning Context, ChatGPT, Khanmigo, and similar generative AI tools are now in demand for instructional planning. According to [15–17], Several teachers are using ChatGPT to create lesson plans, classroom activities, formative and summative assessments, and feedback resources on different subjects such as maths, sciences, and languages. Moreover, the Khan Academy has designed the Khanmigo AI tool for teachers to create lesson plans, assessment worksheets, and many other teaching materials using various Khanmigo AI tools (G [18]). These AI teaching tools not only assists with lesson planning, creating assessments and guiding questioning but, does so maintaining pedagogy and standards of learning [19]. the Recent empirical studies indicate that AI-supported instructional tools can substantially reduce teachers' workload while enhancing lesson quality. Moreover, Fan et al. [20] and Karpouzis et al. [21] reported that teachers in China and Greece experienced notable improvements in lesson planning efficiency and instructional coherence through AI-assisted design. Similarly, widely adopted platforms such as MagicSchool.ai and Diffit have been shown to reduce teachers' planning time by approximately 31% without compromising lesson quality. Aslam et al. [8] indicate that when AI tools are used appropriately, they support creativity, confidence, and the capacity of the teacher to design learning tasks that are cognitively demanding. The effectiveness of these tools still relies heavily on teachers' AI literacy and confidence in using AI-generated text in real-life classrooms.

According to Amjad and Sheikh [22], AI literacy is the teachers' understanding of Artificial Intelligence skills, possibilities, limitations, and ethical handling, and the practical ability to use AI tools for teaching purposes. According to research, teachers who are more literate in AI are more likely to scrutinize AI-generated lesson designs and adapt them to contextual needs instead of just adopting them [23]. Further, social cognitive theory emphasizes the significance of self-efficacy on individuals' technology use behaviours, supporting the notion that teachers' confidence in their AI-related abilities influences their adoption and instructional implementation of AI tools [22]. Consequently, the AI self-efficacy of teachers may become a significant moderating variable between AI literacy and the AI-generated lesson design.

In Pakistan and particularly the province of Sindh, a number of policy initiatives and donor-supported programmes have emerged promoting the use of AI for teacher professional development. Thousands of school teachers have received training for lessons, assessments, and feedback through AI tools like ChatGPT and Khanmigo [8].

The objective of the study is to address deficiencies in pedagogical preparation for teachers, particularly those who teach mathematics, science, and languages. AI has now become an important part of lesson design. Teachers are trying to use AI for lesson designing, but to what extent? Thus, empirical research on teachers' AI literacy and the impact of AI-generated lesson designs on lesson implementation strategies is limited. Moreover, some extent is known about the moderating role of teachers' AI self-efficacy in this process in developing and contextually limited education systems.

In response to the lack of research on the teachers' AI literacy, AI-generated lesson design, and lesson implementation strategies, this study will examine the relationship among these variables. Further, teachers' AI self-efficacy will be examined as a moderating variable. This study is based on the Technology Acceptance Model and social cognitive perspectives to provide empirical evidence on generative AI's support of instructional planning and classroom practice in Sindh education. In addition, this study examines the mediating role of AI-generated lesson design between AI literacy and lesson implementation strategies. Moreover, the study also analyses whether teachers' AI self-efficacy moderates the relationship between teachers' AI literacy and AI-generated lesson design. The following study will investigate the subsequent research questions:

- How does teachers' AI literacy influence AI-generated lesson design?
- How does AI-generated lesson design affect teachers' lesson implementation strategies?
- Does AI-generated lesson design mediate the relationship between AI literacy and lesson implementation strategies? And does teachers' AI self-efficacy moderate the relationship between AI literacy and AI-generated lesson design?

2. Literature review and theoretical framework

The rapid diffusion of generative artificial intelligence (AI) into educational contexts has significantly transformed how teachers design, implement, and evaluate instruction. In this AI era, generative AI tools now actively participate in instructional planning, cognitive scaffolding, assessment generation, and pedagogical decision-making [24]. Different case studies indicate both the advantages and disadvantages of AI-assisted lesson planning. An AI tool named UmmIA is being widely used in Chile to ensure that lesson plans are structured but adaptable to help teachers. Second, the MagicSchool.ai tool, developed by teachers, allows teachers in the USA to generate lesson plans, assessments, and AI-resistant tasks without sacrificing quality [8]. Moreover, In India, teaching tools called Microsoft's Shiksha Copilot and MagicSchool.ai help government schoolteachers with lesson plans aligned to the curriculum. Field trials held in Karnataka showed that >90% teachers reduced their planning time from over one hour to 5–15 min, allowing them to focus more on interaction in the class [25,26]. Nonetheless, there are difficulties that AI-generated examples could be culturally irrelevant and not reflect the lived experiences of students [27]. Studies indicate that tightly controlled guidelines for AI outputs may undermine teacher autonomy and contextualization. AI can aid lesson planning for the local curriculum if localized [28]. This is seen in studies in Bangladesh. Indonesia and Malaysia are investigating using AI to produce material, while a national policy-led effort is underway in Singapore that aims to integrate AI-generated instructional materials [28–30].

In Pakistan, the integration of AI into education, specifically in lesson planning and teaching support, is on the rise; Recent initiatives for government schoolteachers' training programme on Khanmigo tools through the Khan Academy training program. Still, there are many issues implementing successful AI initiative i.e. infrastructure bottlenecks in the school system, lack of sufficient teachers training, and a lack of localization of AI tools. Research indicates significant differences in AI adoption in urban and rural schools in Sindh Pakistan, driven by differences in internet access, digital literacy, and professional development opportunities [31]. Understanding teachers' acceptance, use, and pedagogical integration of such tools requires a robust theoretical grounding that explains both technological adoption and human agency in instructional contexts.

2.1. Theoretical foundations of generative AI–Enabled teaching

Several theoretical models have been used to explain AI adoption in education, including TAM [32,33], TAM2 [34], UTAUT and UTAUT2 [35], Task-Technology Fit (TTF), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT)(G. A [36]). These models explain different aspects of technology use, such as usefulness, usability, social influence, task alignment, institutional support, and behavioural intention. However, recent AI education literature suggests that no single model fully explains teachers' adoption and classroom implementation of AI technologies, particularly because AI use involves technical, pedagogical, ethical, and contextual dimensions [32,34,37]. TAM remains useful because it explains technology adoption through perceived usefulness and perceived ease of use [38]. However, TAM has been criticized for being overly cognitive and for giving limited attention to emotional, ethical, cultural, and pedagogical factors in AI-supported teaching contexts [34,39].

In this study, TAM is adopted because teachers' AI literacy reflects perceived ease of use. Teachers with stronger AI literacy are more capable of understanding AI tools, evaluating AI-generated outputs, and using generative AI for lesson planning and assessment [40]. Similarly, AI-generated lesson design reflects perceived usefulness because teachers evaluate AI outputs according to curriculum alignment, Bloom's taxonomy, and outcome-based education principles [2,41]. To complement TAM, SCT is used because it explains how personal capability, self-efficacy, and environmental support influence behaviour [37,42]. SCT is particularly relevant because teachers' AI self-efficacy may influence their confidence in adapting and implementing AI-generated lesson plans. In AI-enriched teaching environments, AI self-efficacy refers to teachers' confidence in evaluating, adapting, and implementing lesson plans generated by AI in a real classroom setting [8]. As a result, SCT offers a key explanatory mechanism to understand why teachers with similar levels of AI literacy may implement AI-generated lessons differently. The two theoretical models TAM and the SCT, combined represent a complete model of how teachers' AI literacy enables the design of AI-generated lessons that are implemented in the classroom using lesson implementation strategies, and the role of the moderation of AI self-efficacy. As shown in Table 1, TAM and SCT are theoretically combined, as are the constructs relevant to the variables and hypotheses of the present study as shown in Fig. 1. Therefore, integrating TAM and SCT provides a stronger theoretical foundation for examining how AI literacy influences AI-generated lesson design and how lesson design shapes classroom implementation strategies. This integrated approach is also consistent with recent literature suggesting that combined models better capture cognitive, social, and contextual influences in AI adoption.

Table 1
Mapping of TAM and SCT to study variables and hypotheses.

Theory	Key Construct	Related Variable(s)	Linked Hypothesis
TAM	Perceived ease of use	AI literacy: Teachers' skills, understanding, and ethical awareness in using AI tools	H1
TAM	Perceived usefulness	AI-generated lesson design: Perceived instructional value of AI-generated lesson plans	H2
SCT	Self-efficacy	Teachers' AI self-efficacy: Confidence in implementing AI-generated lessons	H4
SCT	Outcome expectations	Lesson implementation strategies: Applying AI-generated lessons in classrooms	H2, H3
SCT	Cognitive and environmental factors	AI literacy and AI-generated lesson design	H1, H3

2.2. AI literacy and AI-Generated lesson design

Being 'AI literate' is a key competence for teachers working in AI-enhanced education environments [43] defines as skills for lifelong engagement of AI which includes knowledge to understand how AI works, applying it in real-world settings. According to [32,44], teachers who have a higher AI literacy are in a better position to engage with generative AI tools in meaningful ways, assess the pedagogical relevance of AI-generated content and adapt lesson designs to meet curricular and learner needs. AI literacy enables the teachers to connect lesson plans generated from AI with OBE and SLOs as well as Bloom's level when planning a cognitively demanding activity and assessment [45,46]. Recent evidence suggests that AI tools such as ChatGPT and Khanmigo help teachers create organized lesson plans, differentiated activities and formative assessments in subjects like maths, science and language [31,46]. The effectiveness of AI-generated lesson plans is determined by teachers' capacity to create effective prompts, assess the outputs and adapt the content according to students' needs [8,47]. Teachers with higher AI literacy exhibited greater creativity and pedagogical coherence in AI-assisted lesson planning while teachers with lower AI literacy uncritically accepted AI outputs [48]. The results were consistent with the findings of the Technology Acceptance Model which suggests that perceived ease of using AI operationalised through AI literacy directly influences teachers' use of AI-generated lesson design [48,49]. In light of this theoretical and empirical evidence, the following hypothesis is put forward.

H1. *Teachers' AI literacy positively influences their AI-generated lesson design.*

2.3. AI-Generated lesson design and lesson implementation strategies

Lesson implementation strategies are defined as actions that a teacher undertakes in teaching a lesson in a classroom. These include sequencing of the instruction, activities, assessment and feedback among other things. The structured learning lesson design offered by AI to teachers integrates objectives, activities and assessments and supports coherent implementation in the classroom [50,51]. AI-generated lesson plans have been shown through empirical studies to improve instructional clarity, reduce lesson planning time, and help facilitate higher-order thinking, specifically in contexts with limited resources [52]. In the context of education system enhancement in Pakistan where

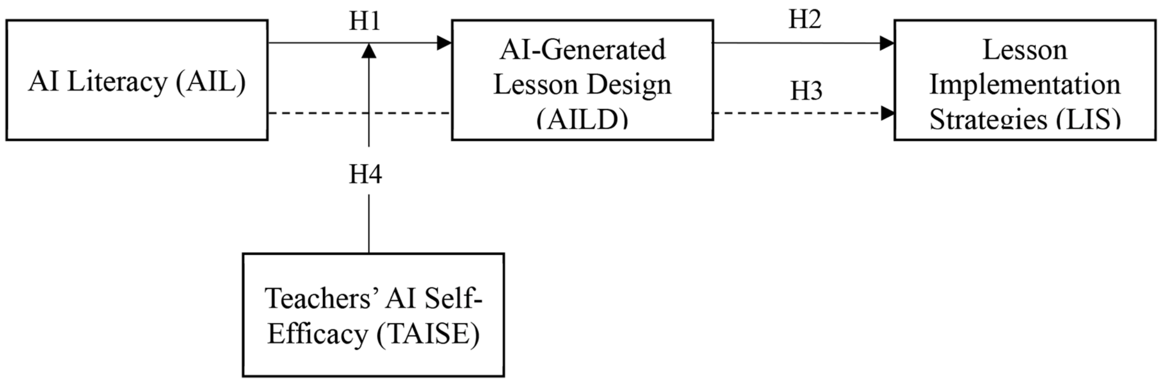

Fig. 1. Research model.

many teachers lack subject-specific pedagogical training and sustained professional development, AI-generated lesson design serves as a compensatory mechanism that boosts educational capacity [2]. Studies carried out in same contexts have revealed that lesson planning that uses AI helps improve the confidence of the teacher, the involvement of the class and the adaptability of the teacher finally helping to contribute to lesson implementation strategies [51,53]. According to the Technology Acceptance Model (TAM), perceived usefulness leads to continuous use of the technology and behavioural integration. As such, it is expected that lesson design by AI will be directly influenced by the lesson implementation strategies of teachers. Therefore, the subsequent hypothesis is proposed.

H2. *Teachers' AI-generated lesson design positively influences their lesson implementation strategies.*

2.4. Mediating role of AI-Generated lesson design

Although AI literacy helps a teacher access AI tool with competence, it is unlikely to directly impact teacher classroom practices. AI-generated lesson design serves as an essential mediating mechanism through which AI literacy is transformed into effective pedagogical strategies. SCT claims that personal capabilities do not dictate behavioral outcomes but rather are mediated by the cognitive artifacts (e.g. lesson plans). Teachers with high AI literacy are more likely to create pedagogically sound AI-assisted lesson plans that enable effective classroom enactment [48]. In technological education, instructional design artefacts play a crucial role by mediating. According to [54], the effects of digital competence on classroom innovation are mediated by AI-supported instructional planning. Likewise, the research of [2] showed that AI-assisted lesson design bridges teachers' technological knowledge and pedagogical practice. These findings highlight the significance of viewing AI-generated lesson design as a mediating variable instead of a direct effect of AI literacy in actual implementation. Thus, the following hypothesis is put forth.

H3. *Teachers' AI-generated lesson design positively mediates the relationship between AI literacy and lesson implementation strategies.*

2.5. Moderating role of teachers' AI self-efficacy

Despite having the same level of AI literacy, teachers differently implement AI-generated lessons in a real classroom context. The SCT states that self-efficacy regulates the application of knowledge to action by influencing persistence, risk-taking and adaptable behaviour. Teachers with a high level of AI self-efficacy are more likely to adapt lesson plans and address classroom contingencies with AI tools and effectively implement them in their classes [55]. Most authors agree that teachers' self-efficacy regarding AI helps them engage more with generative AI tools and experiment more with instruction [56,57]. In contrast, teachers with lower AI self-efficacy may choose not to place trust in lesson designs produced by AI despite being sufficiently literate. This implies that AI self-efficacy intervenes in the AI literacy and AI-generated lesson design relationship strength. As a result, the last hypothesis is written as follows.

H4. *Teachers' AI self-efficacy significantly moderates the relationship between AI literacy and AI-generated lesson design.*

3. Methods

3.1. Research design

The current study aimed to investigate relationships among teachers' AI literacy (AIL), AI-generated lesson design (AILD), lesson implementation strategies (LIS), and teachers' AI self-efficacy (TAISE) in a developing education system. The study specifically focused on government schoolteachers from Sindh, Pakistan, which has faced severe limitations in terms of digital infrastructure, continuous professional development, and pedagogical support. Despite these limitations, recent provincial initiatives have introduced structured programmes for training teachers to employ generative AI tools in lesson preparation and assessment design, thereby enhancing their instructional capacity. Like many previous empirical research studies that investigated technology adoption and instructional practices, this study was also carried out within the positivist research paradigm, which assumes that there are relationships among variables that can be measured and tested empirically by means of statistical techniques [58,59]. In this context, a descriptive cross-sectional survey design was adopted to capture participants' perceptions, competencies, and behavioural tendencies at a specific time, particularly useful in rapidly changing technological contexts (e.g. AI-enhanced education) [60]. This design allowed the researchers to explore teachers' AI literacy influences on AI-generated lesson design and thus on lesson design implementation strategies with a moderation of AI self-efficacy.

3.2. Participants

The study participants consisted of government schoolteachers undergoing an AI-oriented professional training programme conducted at the Provincial Institute of Teacher Education (PITE), Sindh, from October 2024 to June 2025 (See Fig. 2 depicting the complete data collection procedure). The training programme focused on Khanmigo AI tools, which support teachers in lesson planning, teaching activities, assessment design, and feedback generation. All participating teachers completed the training programme and received certification after producing AI-generated lesson plans and classroom activities. A purposive sampling technique was initially employed to select teachers who had completed the AI training programme and demonstrated experience in using AI tools for lesson planning or assessment activities. To ensure

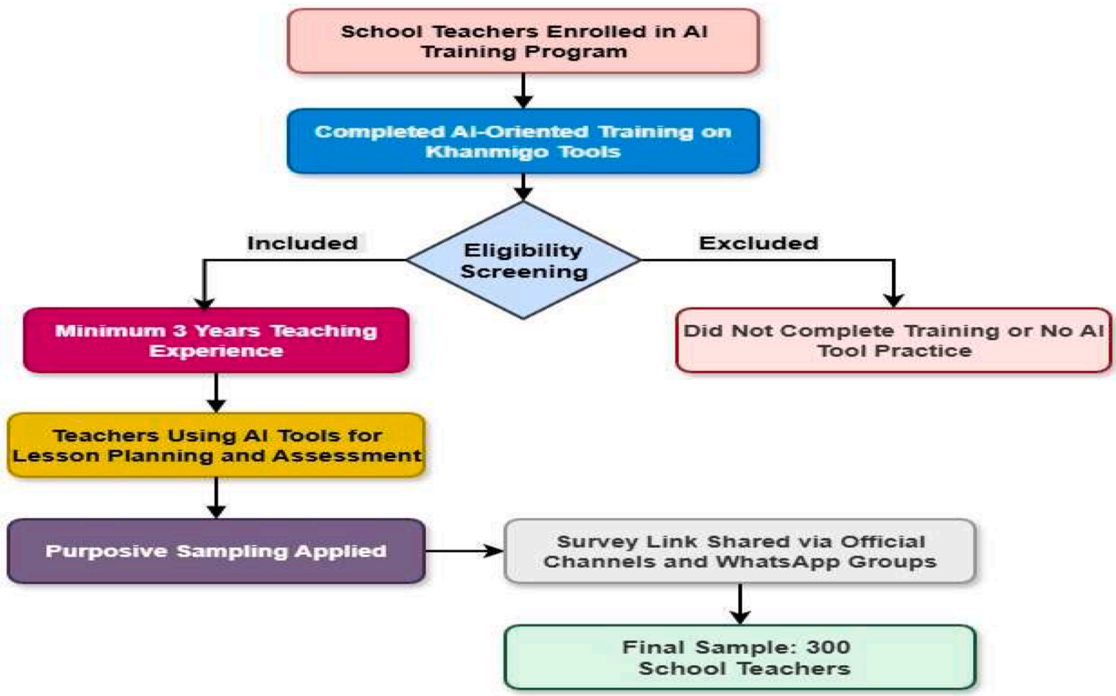

Fig. 2. Participant selection process.

adequate pedagogical exposure, only teachers with a minimum of three years of teaching experience were included in the study. Teachers who had not completed the AI training or lacked practical engagement with AI tools during the programme were excluded. Following purposive selection, convenience sampling was used for questionnaire distribution and response collection. For data collection, an online questionnaire was developed using Google Forms. The survey link was distributed through official training communication channels and dedicated WhatsApp groups created for programme participants. Participation was voluntary, and responses were collected electronically over the data collection period. As a result, the final sample consisted of 300 government schoolteachers with both pedagogical teaching experience and AI-assisted instructional design exposure. The final sample of 300 teachers exceeded the minimum sample size requirements recommended for PLS-SEM analysis. According to Hair et al. [61], PLS-SEM requires adequate sample sizes to ensure statistical power and model stability, while Kock and Hadaya [62] suggested that sample adequacy can be assessed using inverse square root and gamma-exponential methods. Furthermore, the sample size exceeded the commonly recommended 10-times rule for PLS-SEM, thereby supporting the robustness and predictive capability of the structural model.

3.3. Instrumentation

Data collection was carried out through a self-structured administered survey questionnaire designed for AI-equipped teachers. The questionnaire was adapted from established scales and modified to suit the needs of the study, considering the unavailability of a validated instrument to measure AI-generated lesson design and AI-supported lesson implementation strategies among schoolteachers. The questionnaire consisted of two sections. Section one collected demographics like gender, age, qualification, teaching cadre, teaching experience and usage of AI tools. The second section includes four constructs which are AI literacy (AIL), AI-generated lesson design (AILD), lesson implementation strategies (LIS) and teachers' AI self-efficacy (TAISE). A five-point Likert scale was used to measure all the items such that 1 means Strongly Disagree and 5 means Strongly Agree. Initially, a 38-item pool was developed using literature review and expert opinions. The questionnaire which went through a review by five experts in educational technology and teacher education, was piloted with 70 schoolteachers who underwent similar AI training. The 30 items in the final instrument were the result of removing all redundant and double-barreled items based on feedback. Reliability analysis showed all constructs scored higher than 0.70 as shown in Table 2, Constructs, Items numbers, Reliability, sample items and Sources. The relevant value was Cronbach's alpha [63].

Final Data was collected through an online questionnaire using a Google Forms. The link to the questionnaire was disseminated to the participants through official PITE channels, WhatsApp groups, and email. To optimize response rates, 2 reminder messages are sent at one-week intervals. Respondents were willing to fill in the survey at their convenience.

3.4. Data analysis

Analysis of data was carried out in two stages using Jamovi (version 2.6.44) and SmartPLS (version 4.0). For preliminary analyses, data screening and descriptive statistics, reliability analysis, and Pearson correlation, as well as regression-based mediation and moderation checks, Jamovi was used. Before conducting the main analyses, data

Table 2
Constructs, sample items, reliability, and sources.

Construct	Items	α	Sample Items	Sources
AI Literacy (AIL)	7	0.85	I can effectively use AI tools to design lesson plans aligned with learning outcomes.	[22,64]
AI-Generated Lesson Design (AILD)	8	0.87	AI-generated lesson plans help me align activities with Bloom's taxonomy levels.	[22,8]
Lesson Implementation Strategies (LIS)	8	0.88	I confidently implement AI-supported lesson activities in my classroom.	[22,8]
AI Self-Efficacy (TAISE)	7	0.84	I feel confident adapting AI-generated lessons to my classroom needs.	[65,66]

screening and assumption testing were performed to meet all the assumptions of parametric analysis. We found that the missing data were minimal (<1%) and were handled using mean value replacement because no systematic missingness pattern was detected. Normality was assessed using skewness and kurtosis statistics, and all values fell within the acceptable range of ±2, indicating no serious deviation from normality. Homoscedasticity and linearity were examined through residual scatterplots, which indicated acceptable variance distribution across predicted values. Independence of errors was assessed using the Durbin–Watson statistic, which fell within the acceptable range of 1.5–2.5. In addition, multicollinearity was evaluated using Variance Inflation Factor (VIF) values, all of which remained below the threshold of 5, confirming the absence of multicollinearity concerns [61].

Moreover, A Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis was performed on the data using SmartPLS. PLS-SEM is suitable for predictive research models and theory development [61]. The evaluation of the measurement model was performed through factor loading, composite reliability (CR), average variance extracted (AVE), and discriminant validity. Whereas the analysis of the structural model was done to test the direct effects (H1, H2), mediation (H3), and moderation (H4). The significance of various paths was determined through bootstrapping utilizing 5000 subsamples. The results indicate that all constructs were positively and significantly correlated with one another ($p < .001$). Table 3 and Graphical representation of correlation in Fig. 3 suggested that there were significant and positive correlations between AI Literacy and AI-Generated Lesson Design ($r = 0.760$, $p < .001$), AI-generated lesson design and lesson implementation strategies ($r = 0.791$, $p < .001$), and Lesson Implementation Strategies and Teachers' AI Self-Efficacy, $r = 0.818$, $p < .001$. The high correlations amongst the constructs sufficiently support the proposed relationships in the research model and justify proceeding to PLS-SEM analysis.

3.5. Research ethics

The study received ethical approval from the Provincial Education Authority, Sindh, under the Research and Development Wing. All procedures were conducted in accordance with the ethical standards of the institutional research committee and the principles of the 1964 Helsinki Declaration and its subsequent amendments. Written informed consent was obtained from all participants prior to data collection. Participants' anonymity and confidentiality were ensured throughout the study, and all collected data were securely stored and used solely for research purposes. Participants retained the right to withdraw from the study at any stage without penalty.

4. Results

4.1. Demographic information of participants

The Participating teachers ($N = 300$) are presented in Fig. 4. The gender distribution of the sample was fairly balanced with 168 male teachers (56.0%) and 132 female teachers (44.0%). As for age, the majority of respondents were aged between 31 and 40 years ($n = 156$, 52.0%), while equal proportions of teachers were observed for those aged between 25 and 30 years ($n = 72$, 24.0%) and above 40 years ($n = 72$, 24.0%). When it comes to qualifications, almost half of the teachers possessed a bachelor's degree ($n = 138$, 46.0%), which was followed by those with a master's degree ($n = 132$, 44.0%) while those with ($n = 30$, 10.0%) MPhil and PhD were the least qualified. There were primary school teachers (PST) 78 26.0%, junior elementary school teachers (JEST) 66 22.0%, early childhood teachers (ECT) 48 16.0%, high school teachers (HST) 54 18,0%, and educator trainers ($n = 54$ 18,0%), so 6 types of practicum teachers that responded to this research. Regarding teaching experience, it was evident that most of the participants have 6–10 years of experience ($n = 126$, 42.0%). Following them were those who were >10 years ($n = 90$, 30.0%) and 3–5 years ($n = 84$, 28.0%). All teachers reported using Khanmigo ($n = 300$, 100%), and a large proportion also reported experience with ChatGPT ($n = 214$, 71.3%).

Table 3
Correlation matrix.

Variable	AIL	AILD	LIS	TAISE
AIL	—			
AILD	0.760***	—		
LIS	0.723***	0.791***	—	
TAISE	0.684***	0.786***	0.818***	—

Note. *** $p < .001$.

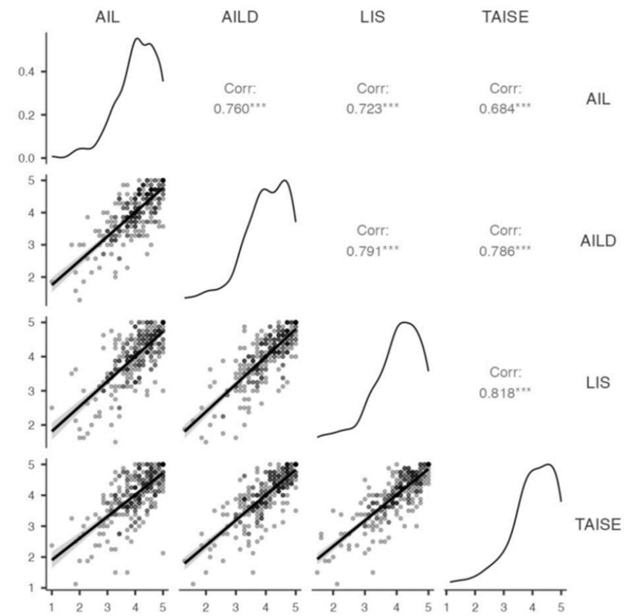

Fig. 3. Correlation results.

Although demographic variables such as age, gender, and teaching experience were collected for descriptive purposes, they were not included as control variables in the structural model analysis. The primary objective of the study was to examine the theoretically driven relationships among AI literacy, AI-generated lesson design, lesson implementation strategies, and AI self-efficacy within a relatively homogeneous group of AI-trained government schoolteachers. Since all participants underwent similar AI-oriented professional training and shared comparable instructional contexts, the study prioritized the predictive relationships among the core theoretical constructs rather than demographic differentiation effects.

4.2. Measurement model assessment

Before assessing the structural relationships postulated, the measurement model was evaluated to ensure the reliability and validity of the latent constructs. In line with the recommended practices in PLS-SEM, the evaluation sought to determine, in terms of indicator reliability, internal consistency reliability, convergent validity and discriminant validity (Joseph F [61]). An assessment of the measurement model confirms whether the constructs of AI literacy, AI-generated lesson design, lesson implementation strategies, and teachers' AI self-efficacy are being measured or not.

The outer loadings of all observed items were examined to assess indicator reliability. As presented in Table 4, the majority of item loadings exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability [61]. However, three indicators (AIL05 = 0.668, AILD02 = 0.683, and LIS01 = 0.682) showed loadings slightly

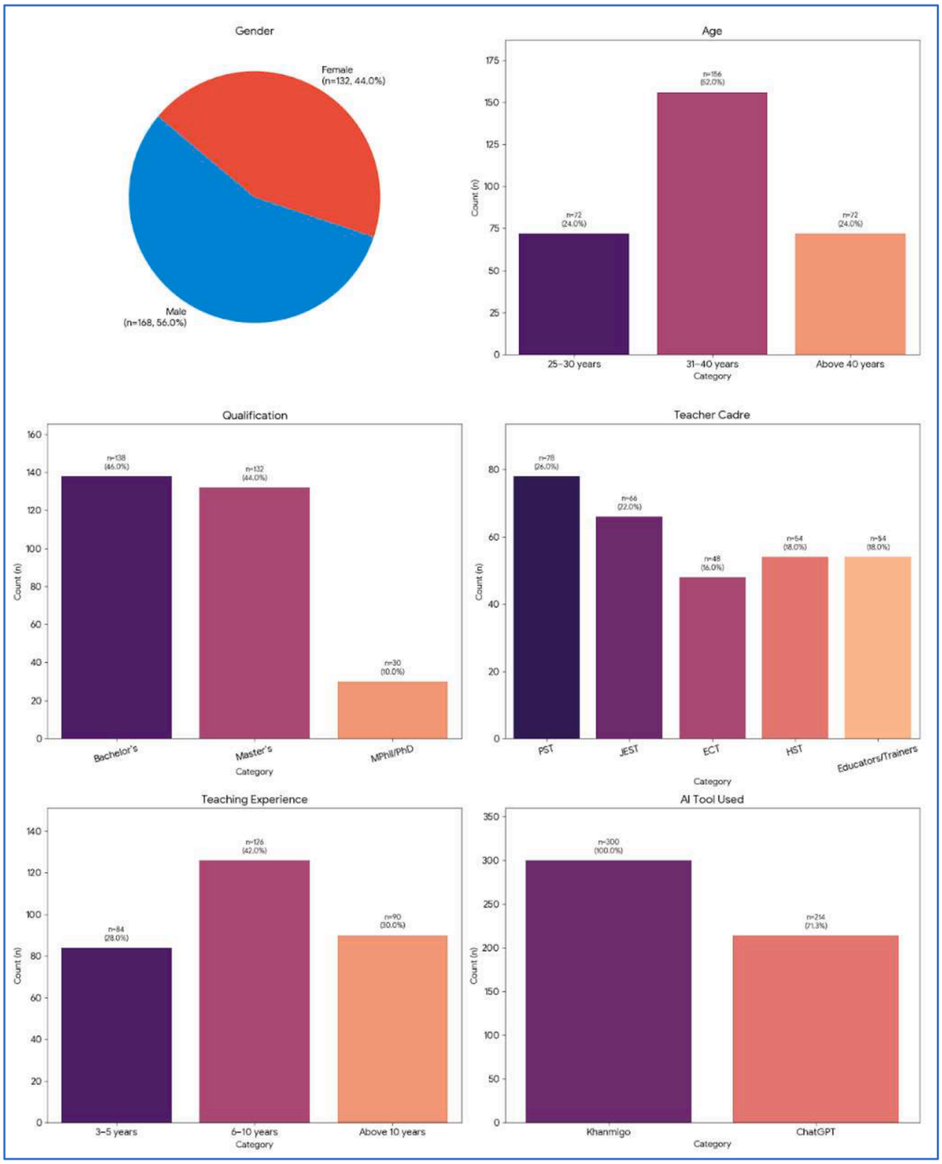

Fig. 4. Demographic characteristics of participants (N = 300).

Table 4
Outer loadings and VIF values.

Items	Loadings	VIF	Items	Loadings	VIF
AIL01	0.731	1.667	**LIS03**	0.77	1.946
AIL02	0.746	2.012	**LIS04**	0.746	2.115
AIL03	0.757	2.076	**LIS05**	0.782	2.458
AIL04	0.726	1.651	**LIS06**	0.755	2.064
AIL05	0.668	1.553	**LIS07**	0.773	2.493
AIL06	0.712	1.743	**LIS08**	0.732	2.215
AIL07	0.743	1.712	**TAISE01**	0.742	2.012
AILD02	0.683	1.549	**TAISE02**	0.733	2.373
AILD03	0.649	1.494	**TAISE03**	0.767	2.341
AILD04	0.782	1.829	**TAISE04**	0.836	2.595
AILD05	0.748	1.905	**TAISE05**	0.778	2.302
AILD06	0.837	2.421	**TAISE06**	0.776	2.178
AILD07	0.801	2.027	**TAISE07**	0.794	2.397
LIS01	0.682	1.629	**TAISE08**	0.765	1.98
LIS02	0.758	2.056			

below 0.70. These indicators were retained because their values remained above the acceptable minimum threshold of 0.60 commonly accepted in exploratory and social science research, particularly when composite reliability and average variance extracted (AVE) values are satisfactory [61]. Moreover, retaining these indicators helped preserve the theoretical comprehensiveness and content validity of the constructs [22]. Since the study relied on self-reported data collected from a single source, common method bias (CMB) was assessed to ensure that the results were not substantially influenced by measurement method variance. Harman's single-factor test was conducted by loading all measurement items into an exploratory factor analysis. The results indicated that the first unrotated factor accounted for 34.72% of the total variance, which is below the recommended threshold of 50%, suggesting that common method bias was not a serious concern [67]. Additionally, all variance inflation factor (VIF) values were below the threshold of 5, further indicating the absence of substantial common method bias and multicollinearity concerns.

The evaluation of internal consistency reliability was performed using composite reliability (CR) and convergent validity was done using AVE. Table 5 shows that all the constructs had a composite reliability that was greater than 0.70. So, the constructs are reliable. Likewise, all constructs' AVE values exceeded 0.50, confirming that every construct accounts for more than half of the variance in its respective indicators [22,61]. The results show that the measurement model has adequate

Table 5
Construct reliability and convergent validity.

	Composite reliability	Average variance extracted (AVE)
AIL	0.8870	0.5280
AILD	0.8860	0.5670
LIS	0.9110	0.5630
TAISE	0.9230	0.6000

reliability and convergent validity.

Moreover, the Fornell–Larcker criterion and Heterotrait–Monotrait ratio of correlations (HTMT) were used to establish discriminant validity [68]. Discriminant validity was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT) to ensure a rigorous evaluation of construct distinctiveness within the measurement model. The Fornell–Larcker criterion remains one of the most widely applied traditional approaches in PLS-SEM because it compares the square root of the Average Variance Extracted (AVE) with inter-construct correlations to establish discriminant validity [69]. However, recent methodological literature has highlighted that the Fornell–Larcker criterion may not always detect discriminant validity issues effectively, particularly in conceptually related or complex constructs (J F [70,71]). Consequently, HTMT has been recommended as a more sensitive and reliable criterion for identifying discriminant validity problems in SEM research [72]. Recent Scopus-indexed studies in educational technology and AI adoption research further recommend the combined application of both methods because of their complementary strengths and their ability to enhance methodological rigor and robustness in PLS-SEM measurement assessment [73,74]. Based on the Fornell–Larcker criterion, the construct's AVE for the square root should be greater than the correlation with any other construct. As displayed in Table 6, the diagonal values (the square roots of AVE) were higher than the inter-construct correlations, which satisfies this criterion for every construct.

The discriminant validity of the constructs was further assessed using the Heterotrait–Monotrait ratio of correlations (HTMT), which is considered a most common criterion for evaluating discriminant validity in PLS-SEM [68]. As presented in Table 7, most HTMT values were below the conservative threshold of 0.85. However, the HTMT value between teachers' AI self-efficacy (TAISE) and AI-generated lesson design (AILD) was 0.895, slightly exceeding the conservative criterion. Nevertheless, this value remained below the more liberal threshold of 0.90 recommended for conceptually related constructs in exploratory research [61,68]. Given the theoretical closeness between teachers' confidence in using AI tools and their engagement in AI-generated lesson design, discriminant validity was considered acceptable. This combined evidence from the Fornell–Larcker criterion and HTMT analysis supports the empirical distinctiveness of the constructs.

4.3. *Structural model assessment and hypothesis testing*

After confirming the measurement model, the proposed structural model was evaluated through SmartPLS to test the hypothesized relationships among the constructs. The consideration of the path coefficients (β), t-values, p-values, f^2, and R^2 was considered Bootstrapping with 5000 resamples was done to access significance. Robustness and cross-validation of mediation and moderation analyses were further verified using Jamovi.

Table 6
Fornell–Larcker criterion.

Construct	AIL	AILD	LIS	TAISE
AIL	0.727			
AILD	0.744	0.753		
LIS	0.726	0.799	0.750	
TAISE	0.684	0.785	0.818	0.774

Table 7
HTMT value.

	AIL	AILD	LIS	TAISE
AIL				
AILD	0.8430			
LIS	0.8300	0.8170		
TAISE	0.7780	0.8950	0.8110	
TAISE x AIL	0.5020	0.4560	0.4390	0.4480

4.3.1. *Direct effects (H1 and H2)*

The first hypothesis states that teacher AI literacy has a positive influence on the design of AI-generated lessons. The data indicated a robust and significant impact of AIL on AILD ($\beta = 0.382$, $t = 7.870$, $p < .001$). The results are presented in Table 10, and a graphical presentation of the structural model is shown in Fig. 7. The findings imply that teachers with a higher AI literacy level are capable of producing effective AI-enabled lesson plans, thereby supporting H1. Hypothesis 2 states that lesson design based on AI positively influences lesson implementation strategies. The findings revealed that AILD posted a strong enhancement of LIS ($\beta = 0.579$, $t = 10.342$, $p < .001$), which offered substantial empirical support for H2. Well-designed AI-generated lesson plans are of great help to teachers for effective lesson implementation in classrooms. The capacity to explain the model was high. The combination of AI literacy and AI self-efficacy accounted for nearly seventy percent (69.8%) of the variability in AI-generated lesson design ($R^2 = 0.698$). Furthermore, AI-generated lesson design and AI literacy accounted for sixty-seven percent (67.7%) of the variability in lesson implementation strategies ($R^2 = 0.677$). These R^2 values point towards good predictive accuracy in the benchmarks.

4.3.2. *Mediating effect of AI-Generated lesson design (H3)*

Hypothesis 3 sought to find out if the AI-designed lesson planning would mediate the relationship AI literacy and lesson implementation strategies. The mediation was analyzed in SmartPLS and Jamovi with the same results. The statistically significant indirect effect between the AIL and LIS through AILD (Estimate=0.439, p<.001, 95% CI [0.329, 0.551]) as shown in Table 8 and graphical representation is shown in Fig. 5. Moreover, Table 8 demonstrates the results of SmartPLS that the direct effect of AIL to LIS is still significant (Estimate = 0.291, $p < .001$). The notable direct and indirect effects suggest partial mediation, which points out that AI literacy does indeed contribute directly to lesson implementation strategies, but a large part of this impact comes from AI-generated lesson designs. The finding of H3 highlights the involvement of AI-generated instructional planning as a mechanism, linking skills of teachers to classroom practices.

4.3.3. *Moderating effect of teachers' AI self-efficacy (H4)*

According to Hypothesis 4, teachers' self-efficacy regarding AI shapes the relationship between AI literacy and AI-generated lesson design. Both SmartPLS and Jamovi were used to investigate the interaction term (AIL × TAISE). The interaction effect was not statistically significant in our analysis of the data set ($\beta = -0.015$; $t = 0.622$; $p = 0.534$) and (Estimate=0.3038, SE=0.204, 95% CI [0.355, 0.5052]) as shown in Tables 9 & 10, and graphical representation is shown in Fig. 6. The finding suggests that teachers' AI self-efficacy does not significantly change the strength of the relationship between AI literacy and AI-generated lesson design. This means H4 was not supported. The lack of significant moderation indicates that just AI literacy may suffice for teachers to tailor AI-generated lessons effectively, particularly in a context where all participants received organized AI training and were generally confident in AI.

5. Discussion

The study aims to examine the influence of teachers' AI literacy on

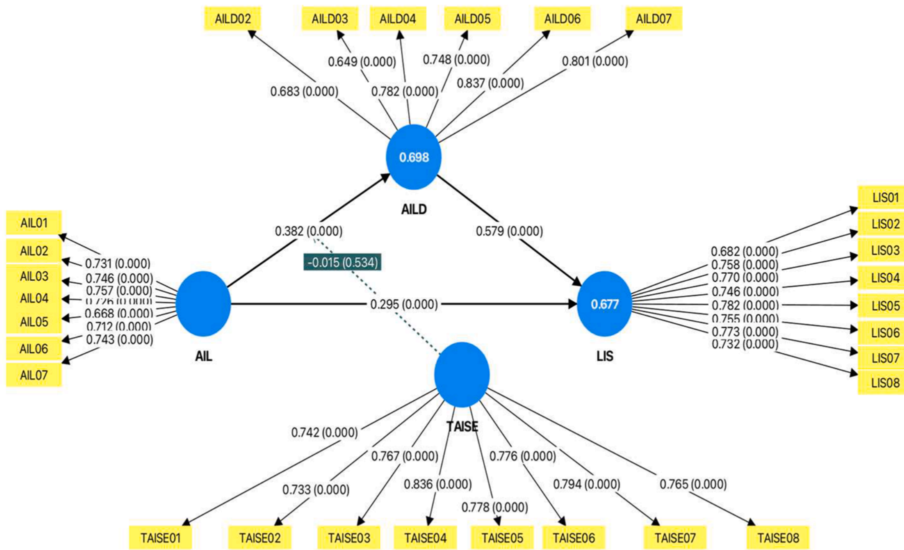

Fig. 7. Structural model results.

Table 8
Mediating effect.

Effect	Estimate	SE	Lower (95% CI)	Upper (95% CI)	Z	p
Indirect	0.439	0.0566	0.329	0.551	7.76	< .001
Direct	0.291	0.0676	0.161	0.427	4.30	< .001
Total	0.730	0.0489	0.632	0.824	14.93	< .001

AI-generated lesson design. Moreover, the study also examines how that design further shapes the lesson implementation strategies of the school classroom and the mediation of AI-generated lesson design and the moderation of AI self-efficacy. This study only focused on the teachers who are using GPT based Artificial Intelligence (AI) tools for pedagogical activities in under-resourced contexts (that is, classrooms with limited resources) in developing countries context and This study is firmly designed in the Technology Acceptance Model and social-cognitive perspectives. It seeks to respond to calls for researchers to broaden the scope of student-centred AI research and engage in empirical investigations of teachers' use of generative AI for pedagogical activities.

Furthermore, the results on H1 show that teachers' AI literacy tends to have a positive and significant effect on AI-assisted lesson design. This suggests that teachers' conceptual and procedural understanding of AI tools enables them to engage meaningfully in pedagogical design tasks

Table 9
Moderation effect.

Variable	Estimate	SE	Lower (95% CI)	Upper (95% CI)	Z	p
AIL	0.3038	0.0524	0.204	0.4095	5.799	< .001
TAISE	0.5943	0.0517	0.490	0.6955	11.505	< .001
AIL * TAISE	−0.0153	0.0422	−0.114	0.0541	−0.362	0.717

Table 10
Summary of hypothesis results.

Relationships	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIL -> AILD	0.3820	0.3820	0.0480	7.8700	0.0000
AIL -> LIS	0.2950	0.2970	0.0600	4.9110	0.0000
AILD -> LIS	0.5790	0.5790	0.0560	10.3420	0.0000
TAISE -> AILD	0.5160	0.5170	0.0480	10.6430	0.0000
TAISE x AIL -> AILD	−0.0150	−0.0140	0.0240	0.6220	0.5340

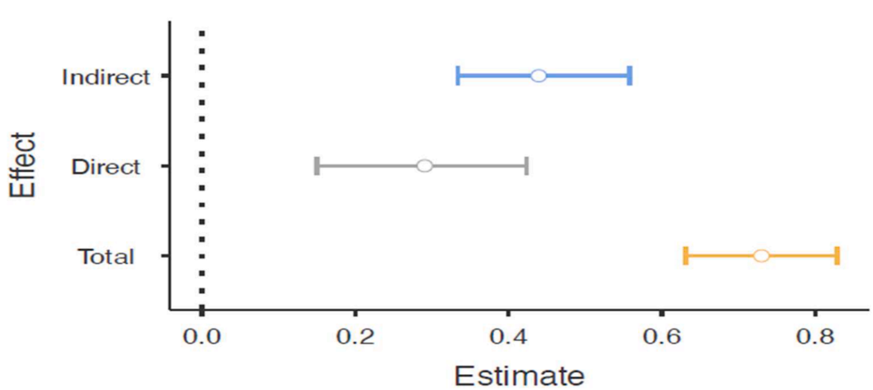

Fig. 5. Mediation effect.

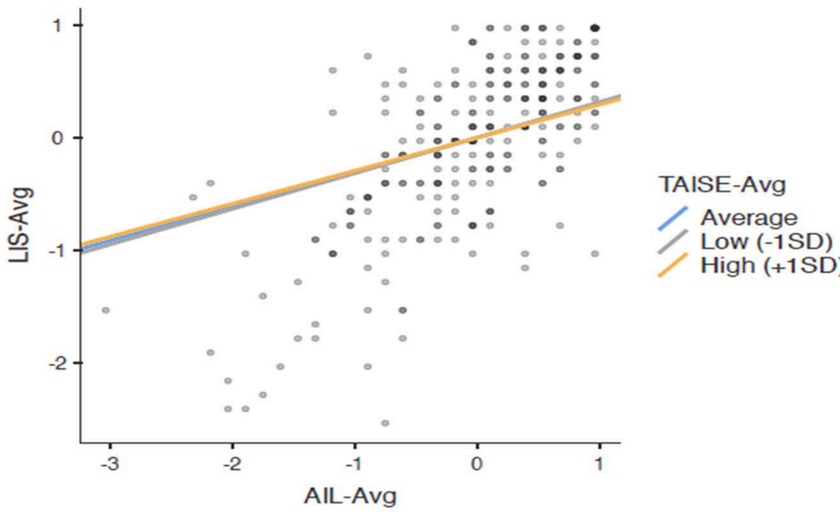

Fig. 6. Moderation effect.

instead of just normal use of AI [75]. Similar to previous research, teachers who understand AI are better able to relate AI-generated materials to curriculum expectations, learner goals and Bloom's taxonomy [76]. In Sindh, where many teachers lack pedagogical training in subject-specific instruction, there are issues with instructional design knowledge. It is believed that AI literacy can fill that gap, aiding in lesson planning and structuring activities. The evidence suggests that literacy in AI is not only a technical competence but also an instructional competence that must enable pedagogical quality [77]. This finding aligns with recent educational AI adoption studies showing that AI literacy enhances teachers perceived usefulness, confidence, and pedagogical readiness to integrate generative AI tools into classroom practices [32]. Recent studies further argue that AI literacy reduces technological uncertainty and improves teachers' ability to critically evaluate AI-generated instructional content [78].

Furthermore, H2 findings show that AI-generated lesson design greatly impacts teachers' lesson implementation strategies. The finding is consistent with earlier research, which suggests that effective lesson plans can enhance teachers' confidence, classroom organisation, and adaptive teaching behaviours [2,12]. According to Holmes and Miao [79], Generative AI tools such as ChatGPT and Khanmigo help teachers create differentiated activities, formative assessment, and higher-order questioning strategies, enabling more interactive and student-centred classroom practices [31,80]. In Sindh's public-school system characterised by large class sizes, limited instructional resources and on-the-job pedagogical support that is minimal AI-generated lesson designs appear to function as a cognitive scaffolding tool that translates abstract curriculum intentions into performable teaching behaviour [32, 81,82].

The mediation analysis for H3 established that the relationship between teachers' AI literacy and lesson implementation strategies is partially mediated by AI-generated lesson design. This finding enhances the Technology Acceptance Model framework (TAM) by establishing that having AI literacy does not by itself translate into improved learning and teaching practices unless it is operationalised by pedagogical artefacts such as lesson plans and assessments. The recent literature suggests that the mechanisms through which AI artefacts (e.g., system-driven recommendations) impact learning are very much contingent on the persistence of instructional design practices [22,83]. In other words, the teachers use AI-generated lesson plans to fill the gaps in mastery of content, the sequencing of instruction and the design of assessments, especially in maths, science and language subjects, this mediation effect becomes more meaningful in the context of Sindh.

The moderation analysis revealed that teachers' AI self-efficacy did not significantly moderate the relationship between AI literacy and AI-generated lesson design (H4). Although teachers' AI self-efficacy showed a significant direct effect on AI-generated lesson design, the interaction effect was statistically insignificant. Therefore, H4 was not supported. This finding suggests that teachers with higher AI literacy may already possess sufficient competence to effectively engage with AI-generated lesson design regardless of differences in self-efficacy levels. The result partially contrasts with Social Cognitive Theory, which emphasizes self-efficacy as an important determinant of technology-enabled behaviour [84,85]. However, the finding is consistent with studies showing that AI literacy and technological competence may independently predict teachers' AI-supported instructional practices, even when moderating effects of self-efficacy remain weak [48,53]. In Sindh, recent AI training initiatives may have increased teachers' baseline confidence in using AI tools such as ChatGPT and Khanmigo, thereby reducing the moderating influence of self-efficacy. Teachers who trust their ability to use AI tools will be far more likely to try advanced prompts; edit AI-provided outputs; and critique lesson content rather than take it at face value [23]. In Sindh, recent government and donor-led AI trainings have led to teachers feeling more confident using tools like ChatGPT and Khanmigo, thereby, increasing the teaching potential of AI literacy. However, the moderating effect also indicates that in the absence of adequate self-efficacy, AI literacy may not translate into quality lesson design, indicating the need for more professional development rather than one-off training.

This research theoretically enriches TAM by expanding it into a teacher-centric generative AI framework that encompasses AI literacy, pedagogical design, and classroom implementation in a developing country context. The findings indicate that teacher training on AI in Sindh should focus on pedagogy, lesson delivery, and boosting confidence instead of just being familiar with tools. By doing gone, generative AI can be a gamechanger in improving instruction and learning in resource-constrained educational systems.

6. Conclusion

The aim of the study was to identify and analyze the problems being faced by the school education system, primarily located in developing regions (Sindh Pakistan). Teachers with fewer pedagogical training opportunities often teach with fewer teaching resources and without on-the-job support. The rapid appearance of generative AI tools like ChatGPT and Khanmigo has provided many opportunities for teachers in lesson design, assessment design, and teaching in the classroom. Nonetheless, there remains a deficient amount of empirical evidence accounting for teachers' AI capabilities. In response to this gap, we developed and tested a theory-driven model using structural equation modelling to investigate the relationships between teachers' AI literacy, AI-generated lesson design, lesson implementation strategies, and AI self-efficacy. The research shows that teachers' AI literacy is vital for AI-generated lesson design, which influences lesson implementation strategies in the classroom considerably. According to the findings, the teaching of AI literacy is not just a technical skill but a pedagogically significant competence through which teachers can transform curriculum, outcome-based education (OBE) principles and Bloom's taxonomy into lesson plans. The findings of the mediation analysis further suggest that AI-enabled lesson design serves as an important explanatory mechanism between AI literacy and instructional practice. In other words, pedagogical artefacts matter for reaping the benefits of AI in teaching. Moreover, AI self-efficacy as a moderator shows that the teacher's confidence to work with AI tools strengthens the relationship between AI literacy and AI-generated lesson design. Teachers who think they are able to make effective use of AI are more likely to adapt, refine, and contextualize AI-generated content than simply adopt it. As a whole, these findings extend the Technology Acceptance Model and Social Cognitive Theory to generative AI in school education. Further, they showed that behavioural outcomes depend not only on perceived usefulness and skills but also on confidence and pedagogical enactment. In light of the realities of schooling in Sindh, the study establishes generative AI as a technology capable of transformative use, provided teachers are sufficiently literate, confident, and pedagogically engaged.

6.1. Limitations and future directions

This study has several limitations, which should be acknowledged. Within a single geographical and administrative context of Sindh, Pakistan data were collected from schoolteachers which limits the generalizability of the findings to other provinces or countries with different policy environments, technological infrastructures, and teacher training systems. For the purpose of testing the robustness of the findings, a repeat of the model in different regions or comparison. In addition, this study only looked at lesson design and lesson implementation strategies and no other important instructional dimensions, such as assessment practices, feedback quality, student engagement, and learning outcomes. As to generative AI used for formative assessment, personalization, and adaptive learning, future works should extend the model to incorporate these pedagogic components in education.

Furthermore, although this study integrated TAM and SCT to explain teachers' AI-supported instructional practices, future research may extend the theoretical framework by incorporating additional models such as Task-Technology Fit (TTF), UTAUT, or UTAUT2 to better understand the contextual, technological, and task-related dimensions of generative AI adoption in education. The inclusion of these frameworks may provide deeper insights into how AI tools align with subject-specific instructional needs, pedagogical tasks, and classroom environments.

Third, even though the AI self-efficacy significantly moderates the relationship between AI literacy and lesson design, the moderation effect is quite strong, suggesting that other psychological and contextual variables are evidently the case.

Future studies should therefore examine additional moderating variables such as subject specialization, institutional support, digital infrastructure, prior AI experience, and pedagogical beliefs to establish stronger contextual rigor and benchmarking of AI-supported teaching practices across diverse educational settings.

Another limitation of the study is that demographic variables such as age, gender, and teaching experience were not included as control variables in the structural model analysis. Although the study focused primarily on theory-driven relationships, demographic characteristics may still influence teachers' adoption and implementation of AI-supported instructional practices. Future research should incorporate demographic and contextual control variables to explore potential differences across teacher groups and educational settings. The research used a quantitative cross-sectional design. Longitudinal or mixed-methods research that includes classroom observations and qualitative interviews could shed light on how teachers interact with AI-generated lesson plans. Future studies may also employ benchmarking approaches, longitudinal validations, and comparative multi-group analyses to further validate the stability and generalizability of the proposed model across educational contexts and subject domains.

6.2. Implications for theory, practice, policy, and sustainability

This research has several key theoretical implications. The first contribution is that it expands on TAM by embedding AI-generated lesson design as a pedagogical mediator allowing us to move beyond intention-models towards instructional practice outcomes. The study enriches Social Cognitive Theory, as it gives an empirical account of how AI self-efficacy strengthens techno-pedagogical design. When put together, they advance the emerging theoretical discourse of generative AI adoption in education, especially in under-researched school-level contexts. Based on the findings above, teacher professional development programmes should focus on AI literacy and pedagogical application, rather than merely training on tools. Efforts in Sindh to train subject specialists in the use of generative Artificial Intelligence (AI) for OBE aligned lesson planning, activity designing and assessment development in mathematics, science, language and other subjects. It's equally important to strengthen teachers' AI self-efficacy with continuous mentoring, peer learning communities, and classroom support. The findings provide support at the policy level for the formulation of institutional and provincial policies that would formally embed generative AI into teacher training frameworks and CPD programmes. It is vital to have clear guidelines on ethical, responsible, and pedagogically sound use of AI for sustainability and trust. By embedding instructional design powered by AI within broader education reform agendas, policymakers can harness generating AI to enhance teaching quality and address long-standing learning outcome disparities in the school system in Sindh. Ultimately, developing teacher AI literacy and confidence has sustainability benefits for long-term resilience in teaching and learning. Generative AI is a capacity-building tool that boosts creativity, critical thinking and adaptability of instruction rather than a replacement for teachers. And it can facilitate sustainable pedagogical transformations even in resource-challenged settings.

CRediT authorship contribution statement

Nisar Ahmed Dahri: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Akhtar Hussain:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition. **Amjad Islam Amjad:** Visualization, Validation, Software, Methodology, Investigation. **Muhammad Hafidz Fazli Bin Md Fauadi:** Writing – review & editing, Supervision, Formal analysis, Data curation. **Raheem Bux Soomro:** Writing – review & editing, Visualization, Software, Formal analysis.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Pakistan Institute of Education, National Achievement Test 2023, 2023. https://pie.gov.pk/SiteImage/Downloads/NAT.2023.Findings.Report.06.03.2024-Final-v6.pdf.
[2] W.N. Alwakid, N.A. Dahri, M. Humayun, G.N. Alwakid, Exploring the role of AI and teacher competencies on instructional planning and student performance in an outcome-based education system, Systems 13 (7) (2025) 517.
[3] K. Ahmed, I. Nazish, T. Hussain, Y. Abbas, M. Haseeb, Identifying gaps in science curriculum student learning outcomes and grade V students' achievement, Indus J. Soc. Sci. 3 (2) (2025) 243–258.
[4] S. Tayyaba, Rural-urban gaps in academic achievement, schooling conditions, student, and teachers' characteristics in Pakistan, Int. J. Educ. Manag. 26 (1) (2012) 6–26.
[5] W. Strielkowski, V. Grebennikova, A. Lisovskiy, G. Rakhimova, T. Vasileva, AI-driven adaptive learning for sustainable educational transformation, Sustain. Dev. 33 (2) (2025) 1921–1947.
[6] Owen, A., & Funk, L. (2025). Beyond ChatGPT: a comparative study of generative AI tools in curriculum design and personalized learning.
[7] M. Penn, U. Ramnarain, Creating adaptive learning pathways for inquiry-based learning in school science using generative AI large language models, Int. J. Sci. Educ. (2025) 1–25.
[8] N. Aslam, G. Qureshi, S.M. Hassan, AI in the Classroom: A Rapid Evaluation of AI-generated Lesson Plans in Islamabad's Public Schools, EdTech Hub., 2025.
[9] D. Feng, N. Naprathansuk, Outcome Based Education System Inguizhou Vocational College Ofindustry and Commerce, Guizhou, China, Maejo University, 2025.
[10] S. Shaheen, Theoretical perspectives and current challenges of OBE framework, Int. J. Eng. Educ. 1 (2) (2019) 122–129.
[11] H. Akdeniz, T. Clark, J.L. Roberts, Can AI generate questions aligned with Bloom's taxonomy? A framework for gifted education to support teachers, J. Adv. Acad. 36 (2025) 1932202X251349917.
[12] S. Belloula, Empowering educators: leveraging AI to revolutionize lesson planning, Int. J. Res. Educ. Sci. 11 (2) (2025) 264–280.
[13] L.W. Anderson, D.R. Krathwohl, A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives: Complete Edition, Addison Wesley Longman, Inc., 2001.
[14] M.T. Leinenbach, M.L. Corey, Universal design for learning: theory and practice, in: Society for Information Technology & Teacher Education International Conference, 2004, pp. 4919–4926.
[15] T.J. Gurl, M.P. Markinson, A.F. Artzt, Using ChatGPT as a lesson planning assistant with preservice secondary mathematics teachers, Digit. Exp. Math. Educ. 11 (1) (2025) 114–139.
[16] A. ElSayary, An investigation of teachers' perceptions of using ChatGPT as a supporting tool for teaching and learning in the digital era, J. Comput. Assist. Learn. 40 (3) (2024) 931–945.
[17] G.-G. Lee, X. Zhai, Using ChatGPT for science learning: a study on pre-service teachers' Lesson planning, IEEE Trans. Learn. Technol. 17 (2024) 1643–1660.
[18] G. Wang, F. Sun, A review of generative AI in digital education: transforming learning, teaching, and assessment, Int. J. Inf. Commun. Technol. 26 (19) (2025) 102–127.
[19] S.U. Khan, A. Mukhtar, A.K. Suhag, Exploring the teachers' Perspective regarding the use of AI for the improvement of the educational system in public secondary schools of Clifton, Karachi, J. Polit. Stab. Arch. 3 (3) (2025) 1174–1209.
[20] H. Fan, G. Chen, X. Wang, Z. Peng, LessonPlanner: assisting novice teachers to prepare pedagogy-driven lesson plans with large language models, in: Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology, 2024, pp. 1–20.
[21] K. Karpouzis, D. Pantazatos, J. Taouki, K. Meli, Tailoring education with GenAI: a new horizon in lesson planning, in: 2024 IEEE Global Engineering Education Conference (EDUCON), 2024, pp. 1–10.
[22] A.I. Amjad, B.S. Sheikh, Trusting the machine: how AI assessment feedback and AI literacy shape students' Idea implementation skills, Eur. J. Educ. 61 (1) (2026) e70457.
[23] Y. Walter, Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education, Int. J. Educ. Technol. High. Educ. 21 (1) (2024) 15.
[24] S. Salih, O. Husain, M. Hamdan, S. Abdelsalam, H. Elshafie, A. Motwakel, Transforming education with AI: a systematic review of ChatGPT's role in learning, academic practices, and institutional adoption, Results Eng. 25 (2025) 103837.
[25] E. Molina, J.C. Cobo Romani, J.A. Pineda, H. Rovner, The AI Revolution in Education: What You Need to Know, 2024.
[26] D. Uygun, Teachers' perspectives on artificial intelligence in education, Adv. Mob. Learn. Educ. Res. 4 (1) (2024) 931–939.
[27] S. Varsik, L. Vosberg, The Potential Impact of Artificial Intelligence on Equity and Inclusion in Education, OECD Publishing., 2024.
[28] Kong, B., Li, Z., Ratner, S., Hemberg, E., & Haque, S. (2024). Artificial intelligence for education in Bangladesh: insights from the first small-scale artificial intelligence needs assessment and training for primary education teachers.
[29] U. Natarajan, K.Y.T. Lim, K. Laxman, A national vision for information and communication technologies in education: reflections on Singapore's ICT technologies masterplans, Int. J. Educ. Manag. 35 (5) (2021) 943–954.
[30] UNESCO. (2023). Technology in education. In Global Education Monitoring Report 2023: Technology in education–A tool on whose terms?
[31] K. Academy, Khanmigo for Teachers, 2025. https://khanacademypakistan.org/.
[32] A.M. Al-Abdullatif, Modeling teachers' acceptance of generative artificial intelligence use in higher education: the role of AI literacy, intelligent tpack, and perceived trust, Educ. Sci. 14 (11) (2024) 1209.
[33] A.A. Aldraiweesh, U. Alturki, The influence of social support theory on AI acceptance: examining educational support and perceived usefulness using SEM analysis, IEEE Access 13 (2025) 18366–18385.
[34] L. Xue, J. Mahat, N. Ghazali, X. Shi, Technology acceptance model (TAM) in artificial intelligence in higher education (AIHEd): a systematic literature review, J. Institutional Res. South East Asia 23 (1) (2025) 355–375. https://www.scopus.com/inward/record.uri?eid=2-s2.0-105010921309&partnerID=40&md5=e8df9e9e164821817d4b11f2d0483f7b.
[35] E.J.G. Eusebio, P.R. Baldera, A.M.C. Patiam, E.F. Villanueva, N.A. Gaa, A.M. F. Solis, M.L.C. Soriano, A.L. Ribon, AI in the classroom: a systematic review of barriers to educator acceptance, Int. J. Learn. Teach. Educ. Res. 24 (9) (2025) 126–147, https://doi.org/10.26803/ijlter.24.9.7.
[36] G.A. Murshidi, A.E. Sayary, K. Ragab, A.A. Zaabi, Understanding teachers' ADOPTION of ai: insights from innovation diffusion and social cognitive theories, J. Inf. Technol. Educ.: Res. 24 (2025) 035, https://doi.org/10.28945/5643.
[37] R. Scherer, T. Teo, Unpacking teachers' intentions to integrate technology: a meta-analysis, Educ. Res. Rev. 27 (2019) 90–109, https://doi.org/10.1016/j.edurev.2019.03.001.
[38] R. Scherer, F. Siddiq, J. Tondeur, The technology acceptance model (TAM): a meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education, Comput. Educ. 128 (2019) 13–35.
[39] S. Zaineldeen, L. Hongbo, A.L. Koffi, B.M.A. Hassan, Technology acceptance model' concepts, contribution, limitation, and adoption in education, Univers. J. Educ. Res. 8 (11) (2020) 5061–5071, https://doi.org/10.13189/ujer.2020.081106.
[40] A. Ashoori Tootkaboni, M. Maghsoudi, Pre-service teachers' behavioral intentions toward AI integration: un extension of the technology acceptance model, Rev. Interuniv. Form. Profr. 39 (3) (2025) 219–237, https://doi.org/10.47553/rifop.v39i3.115994.
[41] J. Biggs, C. Tang, Train-the-trainers: implementing outcomes-based teaching and learning in Malaysian higher education, Malays. J. Learn. Instr. 8 (2011) 1–19.
[42] G. Al Murshidi, A. Elsayary, K. Ragab, A. Al Zaabi, Understanding Teachers' adoption of AI: insights from innovation diffusion and social cognitive theories, J. Inf. Technol. Educ.-Res. 24 (2025) 035, https://doi.org/10.28945/5643.
[43] D.T.K. Ng, J.K.L. Leung, X. O'Dea, S.K.W. Chu, From AI literacy to generative AI literacy: conceptualization and frameworks. From AI Literacy to Generative AI Literacy: Theory, Policy and Practice, Springer, 2026, pp. 21–38.
[44] K.-S. Tang, G. Cooper, N. Rappa, J. Edwards, Critical questioning with generative AI: developing AI literacy in secondary education, Think. Ski. Creat. (2025) 102043.
[45] B. Ng, A.N. Lee, Connecting lifelong learning and 21st century competencies to career success. Future-oriented Learning and Skills Development for Employability: Insights from Singapore and Some Asia-Pacific Contexts, Springer, 2024, pp. 85–99.
[46] K.V. Nguyen, The use of generative AI tools in higher education: ethical and pedagogical principles, J. Acad. Ethics (2025) 1–21.
[47] N.A. Dahri, N. Yahaya, W.M. Al-Rahmi, M.S. Vighio, F. Alblehai, R.B. Soomro, A. Shutaleva, Investigating AI-based academic support acceptance and its impact on students' performance in Malaysian and Pakistani higher education institutions, Educ. Inf. Technol. (2024) 1–50.
[48] M. Dilek, E. Baran, E. Aleman, AI literacy in teacher education: empowering educators through critical co-discovery, J Teach Educ 76 (3) (2025) 294–311.
[49] S. Choi, S. Jeong, S. Park, Y. Kim, I. Han, Analyzing teacher–AI interaction patterns across teacher experience and AI proficiency in student-centered lesson design, Teach. Teach. Educ. 169 (2026) 105266.
[50] O. Filiz, M.H. Kaya, T. Adiguzel, Teachers and AI: understanding the factors influencing AI integration in K-12 education, Educ. Inf. Technol. (2025) 1–37.
[51] J. Kim, H. Lee, Y.H. Cho, Learning design to support student-AI collaboration: perspectives of leading teachers for AI in education, Educ. Inf. Technol. 27 (5) (2022) 6069–6104.
[52] M. Dervić, S. Bećirović, E. Polz, Revolutionizing pedagogy: the transformative influence of artificial intelligence on educators' practices. Artificial Intelligence and Human Agency in Education: Volume One: The Nexus Between AI and Human Agency in Educational Contexts, Springer, 2025, pp. 193–212.
[53] H. Du, Y. Sun, H. Jiang, A.Y.M.A. Islam, M. Agyemang Adarkwah, Improving the quality of AI-supported K–12 teaching: the effects of teachers' AI-TPACK and self-efficacy, Interact. Learn. Environ. (2025) 1–22.
[54] Y. Zhao, L. Huang, Promoting teaching innovation among university teachers through AI literacy from the perspective of planned behavior: the moderating effects of three perceived supports, Front. Psychol. 16 (2025) 1699174.
[55] C. Rajapakse, W. Ariyarathna, S. Selvakan, A self-efficacy theory-based study on the teachers' readiness to teach artificial intelligence in public schools in Sri Lanka, ACM Trans. Comput. Educ. 24 (4) (2024) 1–25.
[56] Q. Liu, J. Chou, H. Feng, Effect of teachers' self-efficacy with generative AI and reflection on students' second language achievement, Comput. Assist. Lang. Learn. (2025) 1–22.
[57] J. Lu, R. Zheng, Z. Gong, H. Xu, Supporting teachers' professional development with generative AI: the effects on higher order thinking and self-efficacy, IEEE Trans. Learn. Technol. 17 (2024) 1267–1277.
[58] T. Calzolari, A. Genovese, A. Brint, S. Seuring, Unlocking circularity: the interplay between institutional pressures and supply chain integration, Int. J. Oper. Prod. Manag. 45 (2) (2025) 517–541.

[59] R.B. Soomro, W.M. Al-Rahmi, N.A. Dahri, L. Almuqren, A.S. Al-Mogren, A. Aldaijy, A SEM–ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs, Sci. Rep. 15 (1) (2025) 5438.
[60] P. Villamin, V. Lopez, D.K. Thapa, M. Cleary, A worked example of qualitative descriptive design: a step-by-step guide for novice and early career researchers, J. Adv. Nurs. 81 (8) (2025) 5181–5195.
[61] J.F Hair, J.J. Risher, M. Sarstedt, C.M. Ringle, When to use and how to report the results of PLS-SEM, Eur. Bus. Rev. 31 (1) (2019) 2–24.
[62] N. Kock, P. Hadaya, Minimum sample size estimation in PLS-SEM: the inverse square root and gamma-exponential methods, Inf. Syst. J. 28 (1) (2018) 227–261.
[63] T. Bayır, G. Akel, Gamification in mobile shopping applications: a review in terms of technology acceptance model, Multimed. Tools Appl. 83 (16) (2024) 47247–47268.
[64] T.K.F. Chiu, Y. Chen, K.W. Yau, C. Chai, H. Meng, I. King, S. Wong, Y. Yam, Developing and validating measures for AI literacy tests: from self-reported to objective measures, Comput. Educ.: Artif. Intell. 7 (2024) 100282.
[65] T. He, J. Huang, Y. Li, L. Wang, J. Liu, F. Zhang, S. Fu, S. Gong, The mediation effect of AI self-efficacy between AI literacy and learning engagement in college nursing students: a cross-sectional study, Nurse Educ. Pr. 87 (2025) 104499.
[66] Y.-Y. Wang, Y.-W. Chuang, Artificial intelligence self-efficacy: scale development and validation, Educ. Inf. Technol. 29 (4) (2024) 4785–4808.
[67] P.M. Podsakoff, S.B. MacKenzie, J.-Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies, J. Appl. Psychol. 88 (5) (2003) 879–903.
[68] J. Henseler, C.M. Ringle, M. Sarstedt, A new criterion for assessing discriminant validity in variance-based structural equation modeling, J. Acad. Mark. Sci. 43 (2015) 115–135.
[69] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, J. Mark. Res. 18 (1) (1981) 39–50.
[70] J F Hair, M. Sarstedt, C.M. Ringle, P.N. Sharma, B.D. Liengaard, Going beyond the untold facts in PLS–SEM and moving forward, Eur. J. Mark. 58 (13) (2024) 81–106, https://doi.org/10.1108/EJM-08-2023-0645.
[71] L. Radomir, O.I. Moisescu, Discriminant validity of the customer-based corporate reputation scale: some causes for concern, J. Prod. Brand Manag. 29 (4) (2019) 457–469, https://doi.org/10.1108/JPBM-11-2018-2115.
[72] E. Roemer, F. Schuberth, J. Henseler, HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling, Ind. Manag. Data Syst. 121 (12) (2021) 2637–2650, https://doi.org/10.1108/IMDS-02-2021-0082.
[73] P. Jarial, H. Aggarwal, B.S. Singla, The effectiveness of MOOCs in Technical education: an Indian perspective, Sci. Rep. 15 (1) (2025), https://doi.org/10.1038/s41598-025-09405-0.
[74] P. Singh, L. Anthonysamy, Development and validation of an instrument to assess instructors' usage, acceptance, and confidence towards ChatGPT: a reliability and discriminant validity analysis, Educ. Inf. Technol. 30 (17) (2025) 25251–25271, https://doi.org/10.1007/s10639-025-13773-5.
[75] X. Xie, M.F. Teng, L.J. Zhang, A. Alamer, Exploring AI literacy and AI-induced emotions among Chinese University English language teachers: the partial least square structural equation modeling (PLS-SEM) approach, Int. J. Appl. Linguist. 35 (2025) 1897–1911.
[76] L. Kohnke, B.L. Moorhouse, D. Zou, ChatGPT for language teaching and learning, Relc. J. 54 (2) (2023) 537–550.
[77] A.I. Amjad, S. Aslam, U. Tabassum, Tech-infused classrooms: a comprehensive study on the interplay of mobile learning, ChatGPT and social media in academic attainment, Eur. J. Educ. 59 (2024) e12625.
[78] V. Milutinović, Unpacking the relationship between AI competences, intelligent ethical TPACK, and factors influencing AI adoption in pre-service teachers: a comprehensive model, Educ. Inf. Technol. 30 (18) (2025) 26261–26299, https://doi.org/10.1007/s10639-025-13786-0.
[79] W. Holmes, F. Miao. Guidance for generative AI in education and research, UNESCO Publishing, 2023.
[80] M.M. Asad, A. Aijaz, Influence of ChatGPT and generative AI on continuous learning and skill enhancement in Education 4.0: contextual insights from the higher education of Pakistan, TQM J. (2025).
[81] J. Cabero-Almenara, J. Barroso-Osuna, F.D. Guillén-Gámez, A. Palacios-Rodríguez, Teachers' pedagogical beliefs and their acceptance of artificial intelligence in higher education: a comparative study between countries, Aula Abierta 54 (3) (2025) 257–268, https://doi.org/10.17811/rifie.21273.
[82] G. Geng, J. Chen, An empirical longitudinal study of AI integration in transforming teachers' pedagogical content knowledge: insights from language educators in rural China, Educ. Technol. Res. Dev. 74 (2026) 1149–1185, https://doi.org/10.1007/s11423-026-10602-5.
[83] M.R. Karaman, Are lesson plans created by ChatGPT more effective? An experimental study, Int. J. Technol. Educ. 7 (1) (2024) 107–127.
[84] D. Nababan, A.N. Hidayanto, B. Hardian Syahbuddin, S. Setiawan, D.M. Sihotang, Analysing the factors that influence the intention in utilising ChatGPT as a lecture support tool based on social cognitive theory perspective, in: 2025 16th International Conference on E-Education, E-Business, E-Management and E-Learning, IC4e 2025, 2025, pp. 602–606, https://doi.org/10.1109/IC4e65071.2025.11075345.
[85] A. Shata, K. Hartley, Artificial intelligence and communication technologies in academia: faculty perceptions and the adoption of generative {AI}, Int. J. Educ. Technol. High. Educ. 22 (14) (2025), https://doi.org/10.1186/s41239-025-00511-7.