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INVESTIGATING THE ADOPTION OF AI-BASED MOOCS AS A SMART DIGITAL LEARNING ENVIRONMENT: USING SEM ANALYSIS APPROACH

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ABSTRACT

This study examines the factors influencing the adoption of AI-based Massive Open Online Courses (MOOCs) as a smart digital learning environment for teachers' professional development at university. With the rapid integration of Artificial Intelligence in education, AI-supported MOOCs now provide adaptive learning pathways, personalized feedback, and intelligent content recommendations—significantly transforming traditional online learning. However, in resource-constrained contexts, the adoption of these advanced digital platforms remains limited. Using a survey research design, data were collected from 280 teachers in Sindh university. The instrument was developed by integrating constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Information System Success Model, adapted to reflect AI-driven features within MOOCs. Data were analyzed using Structural Equation Modelling (SEM). The findings reveal that performance expectancy, information quality, system quality, and perceived enjoyment significantly shape teachers' attitudes and intentions to adopt AI-based MOOCs. Conversely, effort expectancy and social influence show limited influence in this context. The proposed AI-MOOC adoption model explains 64% of the variance in behavioral intention and 60% of the variance in actual usage. Importantly, teachers' attitudes emerged as a pivotal determinant influencing behavioral intentions, satisfaction, and actual engagement with AI-supported MOOCs. The study highlights the importance of AI-enhanced content quality, adaptive system design, and user-friendly smart learning environments to improve the acceptance of AI-based MOOCs. These insights offer theoretical contributions to digital learning adoption models and provide practical implications for policymakers and educational institutions aiming to scale AI-enabled professional development.

KEYWORDS: MOOCs, UTAUT, Digital Education, Technology Adoption, Technology-Enhanced Learning.

1. INTRODUCTION

The invention of the Internet has resulted in many technological changes that have affected schools and classrooms in an amazing way. More and more societies are realizing that a proficient teaching workforce is key to national development. Thus, professional development of teachers has become a major priority (Ali & Ahmed, 2022; Bhutta & Rizvi, 2022). Essentially, teachers' actions and effectiveness directly relate to the quality of education and the learning experiences of students. The modern classroom requires continuous upskilling to effectively adapt to the demands of digital literacy, thinking skills and innovations to pedagogy (Gaikhorst et al., 2017). Though in many low-resource contexts, ongoing and high-quality professional development is difficult to achieve. They lack access to training opportunities, which are sporadic.

In Sindh, the lack of access to an organized and continuous professional development programme has been a longstanding issue for thousands of teachers, particularly those working in rural and disadvantaged areas (Jamil, 2004; Singh et al., 2021). Many initiatives geared towards training mostly rely on conventional, physical formats that require high financial and operational input. As a result, only a few teachers can get any substantial training in any year.

Newly recruited teachers often have little training in pedagogy, assessment and classroom management, which aggravates the problem. Even being a graduate and post-graduate, many of these teachers join the teaching profession without a teacher-education qualification like a B.Ed. or ADE degree. The need for professional development of the staff was not met by the school. However, the student learning outcome is persistently low, especially in mathematics, science, and literacy (Dahri et al., 2021; Zubairi et al., 2021).

Sindh lacks sustainable long-term continuous professional development (CPD) models, compounding these challenges. According to a study by Culala & De Leon (2019) and Saqib et al. (2020), training usually relies on donor-funded projects. Also, these projects are short-term and do not have a long-term run. Moreover, centralized training sessions are limited in attendance due to the socio-cultural constraints of especially female trainers. The above statements reveal a dire need for innovative, scalable and cost-effective solutions to improve teacher learning and enhance synergies between educational improvement initiatives and Sustainable Development Goal 4 (SDG4), which calls for inclusive and equitable quality education for all (SESP, 2019)

During these problems globally, when everyone is affected due to the pandemic, MOOCs is now making their mark for digitization and professionalism. According to Khan et al. (2018) and Sayaf et al. (2022), MOOCs are said to be open, flexible, and scalable in nature, allowing thousands of learners to participate together regardless of geographical and financial constraints, as mentioned in the key feature of MOOCs in Figure 1. In the last ten years, the massive MOOC initiative by worldwide institutions like Coursera, edX, and Udacity has managed to open the door for many learners to access quality learning resources and expertise.

The learner is equipped with opportunities to self-pace their acquisition of skills (Raffaghelli et al., 2022). Sindh's local demand for digital platform certificates is evidenced by the millions of certificates issued to users by DigiSkills. In addition, these certificates are also proof of the future potential of MOOCs in teacher-professional development (Dahri et al., 2023).

MOOCs, while contributing significantly to digital learning ecosystems, have now been outdone by a new kid on the block that promises even more personalized, effective solutions. It is an AI-based next-gen intelligent digital learning platform. AI-enabled MOOCs offer intelligent features such as adaptive learning pathways, automated feedback,

Figure 1. MOOCs key features: natural language processing, personalized content recommendations,

predictive learning analytics, and smart tutoring systems (Altikriti & Nemrawi, 2025; Dahri et al., 2025). Through these features, AI-powered MOOCs can customize learning experiences to learners' needs, which increases engagement, efficiency, and learning outcomes.

The use of AI in MOOCs alleviates many limitations which occur during traditional MOOCs. These limitations are: Lack of Personalisation, High Dropout Rate, Lack of Learner Motivation, and Lack of Instructor Interaction. Using AI, assessment can help identify learners' weaknesses, give recommendations in real time and improve helpful sequences to enhance mastery. Chatbots and virtual assistants are intelligent, and they offer assistance 24/7. The assessments on adaptive nature help learners. AI-based MOOCs offer exciting opportunities for teacher professional development, especially in areas like Sindh, where personalized and accessible learning opportunities are badly needed.

AI-powered MOOCS have potential, yet their adoption remains limited in developing countries. Barriers such as limited digital literacy, lack of infrastructure, customer resistance, and low awareness can hinder large-scale implementation (Alamri et al., 2019). In addition, there are very few empirical studies, especially from the teachers' perspective, on AI-enabled MOOCs. Prior Attempts at Understanding Traditional MOOCs. Most prior attempts to understand MOOCs have focused on the informal learning experience (as experienced by learners), using models to present the same. Some of the models used are: 1) Technology Acceptance Model (TAM), 2) Theory of Planned Behaviour (TPB), 3) Expectation-confirmation model of information system, 4) Self-Determination Theory, and 5) Social-Cognitive Learning Theory. Nonetheless, limited studies have incorporated AI-related system dimensions such as perceived intelligence, system adaptivity, and AI trust into adoption frameworks.

In response to this gap in research, the current study aims to address the research question: What predicts Schoolteachers' adoption of the AI-based MOOC in Sindh? Through the integrative constructs of UTAUT and the Information System Success Model, this study planned to investigate the adoption of AI-based MOOCs. Educational change is impossible without teachers, but we know little about how teachers want to engage in AI-supported PD. The usage of Artificial Intelligence-based massive open online course (AI-based MOOC) by teachers is determined by its performance expectancy, effort expectancy, social influence, system quality, information quality, perceived enjoyment and facilitating condition. This study presents new knowledge about teachers' acceptance of AI-based MOOCs in a developing country context characterized by infrastructural constraints, heterogeneous socio-cultural realities, and unequal digital access. The model also incorporates intelligent system characteristics that are distinct to AI-based platforms, thereby extending previous technology acceptance theories. Moreover, the results have practical implications for policymakers, teacher training institutions, and educational technology providers aiming to design scalable, adaptive, and effective AI-driven professional development programmes. AI-based MOOCs are a timely and promising solution to the professional development problems of Sindh. It is important to understand the factors influencing teachers to adopt AI-supported smart learning environments as the government seeks to modernize the workforce, improve teaching, and uplift student learning. This research enhances theoretical comprehension and offers data-driven suggestions to bolster AI-enabled education digitalization through professional development.

2. THEORETICAL BACKGROUND

AI-based MOOCs have become a necessary part of contemporary teacher education in developing and lesser-known educational systems; they must be adopted in all educational systems globally. The effectiveness and scaling-up of intelligent digital learning environments can be improved by understanding what factors teachers accept. Previous research on MOOC adoption extensively relied on established technology acceptance frameworks for explaining users' behavioral intention and actual use, as shown in Figure 2. Previous research has studied conventional MOOCs using models such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT); Task-Technology Fit, Expectation Confirmation Model and Social Cognitive Theory (Alturki & Aldraiweesh, 2023; Qureshi, 2019). The introduction of AI-enabled MOOCs has instigated fresh system features that necessitate broadened theoretical lenses. Past studies demonstrate that user acceptance of MOOCs is influenced by perceptions of usefulness and ease of use, social pressure, and system quality. Wu and Chen (2017), for example, incorporated TAM and Task-Technology Fit and found that perceived usefulness and learner attitude were central to Chinese students' engagement with MOOCs. Fianu et al. (2018), who also employed UTAUT, remarked that performance expectancy, self-efficacy, and system quality had significant predictive effects on MOOC adoption in Ghana. The conclusion is that social influence and performance expectancy determined the decision to adopt MOOCs for workplace training (Hamdan et al., 2018). The studies mentioned show that cognitive, social and technological determinants are important for user acceptance.

The UTAUT (Unified Theory of Acceptance and Use of Technology) is a model that was proposed in 2003 by Venkatesh et al., and it is perhaps the most comprehensive model that looks at acceptance of technology (Venkatesh et al., 2003). The UTAUT model combines and builds from eight other models and includes four main determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. It was originally responsible for 26% of behavioural intention variance. Subsequent additions, such as UTAUT2, improved this explanatory power by adding hedonic motivation and habit (M. Altalhi, 2021). With the help of the UTAUT model, researchers have measured many learners' motivation, readiness and behavioural intentions to take part in technology-based learning within the context of a MOOC.

The researchers argue that traditional UTAUT applications do not explicitly include important features of AI-powered learning environments, including intelligent content personalization, adaptive feedback mechanisms, automated assessment, conversational chatbots, and predictive analytics. The Intelligent Tutoring Systems impact learners' beliefs about the intelligence of the system, trust in automation, and personalization quality. According to recent studies, perceptions of AI capability, algorithmic transparency, trust in AI systems, and adaptive system quality are increasingly relevant in explaining user acceptance of smart learning systems (Holmes et al., 2022). To explore AI-based MOOCs, a theory of the technology acceptance model is necessary, considering the traditional technology acceptance determinants and system intelligence attributes.

To fulfill this need, the present study combines UTAUT and Information System Success Model (DeLone & McLean, 2003), which evaluates digital systems through three main dimensions: system quality, information quality and service quality. In expert literature and research, (AI-based) MOOCs are examined and analyzed from multiple angles, including disciplines. The attractiveness of AI and whose image is beneficial are also debated. Previous research in digital learning environments and LMS (Learning Management System) platforms has confirmed that System Quality and Information Quality influence user satisfaction, intent and continued engagement (Mohan et al., 2020). The IS success factors are especially crucial to teachers who apply AI-powered MOOCs, which would rely on trustworthy, precise, and adaptable AI systems to direct their professional development activities.

Integrating UTAUT and IS Success Model results in a holistic framework to analyse MOOC adoption and analyse them at once. According to UTAUT, teachers who intend to adopt AI-based MOOCs are driven by their perceptions of usefulness, ease of use, influence of other people (social norms) and technological support. On the one side, the Information Systems (IS) model pertains to the impact that characteristics of the Artificial Intelligent (A1)-based MOOC system have on satisfaction and actual use. This integration has been validated in other digital learning research, which proves its strength in predicting user satisfaction and behaviors in technology-enhanced learning research.
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In the case of AI-based MOOCs which incorporate an integrated framework, this becomes of vital importance as AI adds another "intelligence" to the system that operates beyond the digital set-up. The quality of AI-enhanced systems is improved with various types of adaptive algorithms and personalized dashboards, intelligent tutoring systems, and machine-generated feedback. AI-curated resources may involve users being automatically suggested content and personalised learning journeys. The unique characteristics shared by AI tools influence teachers' perceptions of the usefulness, trustworthiness and effectiveness of MOOCs for teachers' continuing professional development. So, this study applies an extended version of UTAUT-IS Success Model towards investigating teachers' acceptance AI driven MOOCS. The model captures both psychological and technological determinants of adoption by examining constructs such as performance expectancy, effort expectancy, social influence, system quality, information quality, perceived enjoyment, attitude, behavioral intention and actual system use. By concentrating on AI-based MOOCs, an area that remains largely underexploited and through a lens that focuses on the teacher population whose professional development is critical for improving educational quality, this theoretical integration fills gaps in literature. In Sindh's smart digital learning environment, teachers' behavioral intention and actual use of AI-based MOOCs will be impacted by UTAUT constructs and IS success dimensions.

Figure 2. Most Common Adoption Models.

Moreover, system, information, and service quality enhancement produces user satisfaction towards MOOC, which will ensure the success of MOOC efforts (Gu et al., 2021). An integrated framework is proposed, which is presented in Figure 3.

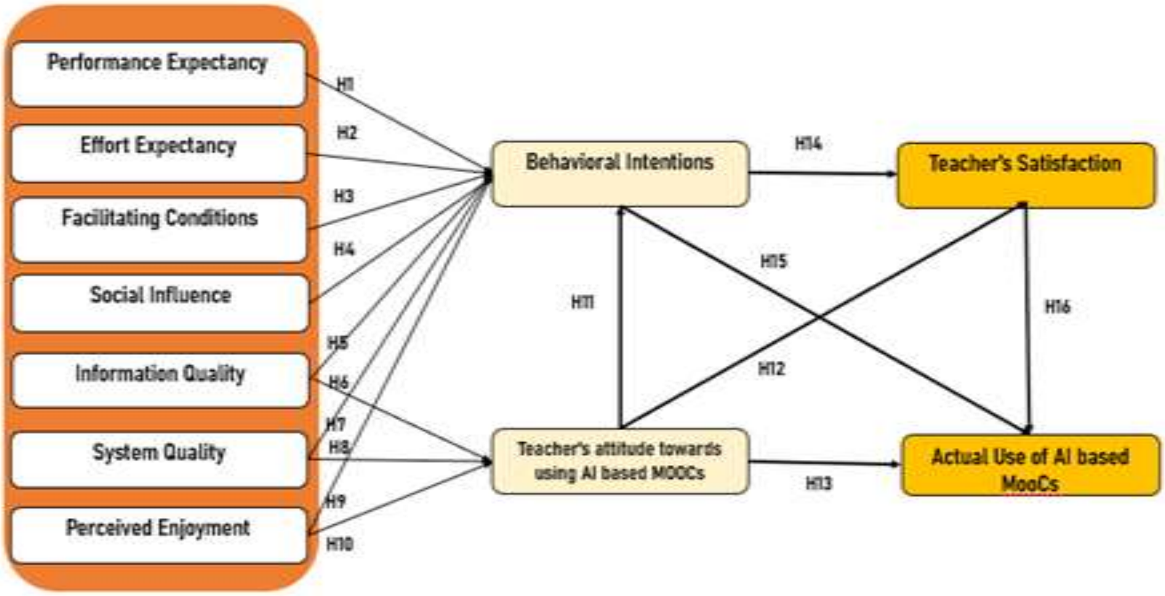


Figure 3. Proposed research model.

2.1. Performance Expectancy (PE)

Performance expectancy (PE) is the extent to which the teacher believes that using the AI-based MOOC platform would enhance his/her instructional performance, professional competencies and teaching ability. The expected improvement in job performance from the use of the technology system (Venkatesh et al., 2003). In the context of AI-supported MOOCs, this expectation goes one step further. We can see that advanced features can be added thanks to artificial intelligence, like adaptive learning pathways, automatic feedback, intelligent tutoring systems, personalized recommendations, real-time analytics and so on. The latest research has shown that learning systems can be more supportive, predictive, and user-centric with the incorporation of AI functionality. Furthermore, learning systems can have higher perceived performance benefits (Troussas et al., 2023; Zahid et al., 2025). For teachers, AI-enhanced MOOCs provide customized professional development experiences such as curated learning content based on teaching gaps, smart dashboards that monitor progress, and AI-generated insights that enhance teaching strategies. Teachers' use of these intelligent tools helps to update their content knowledge, improve their classroom practices, and provides confidence in new technology use. Prior research on MOOCs continuously showed that perceived ease of use (PE) is one of the most prominent indicators of the behavioral intention to adopt educational technology (M. Altalhi, 2021). When it comes to AI-based MOOCs (Massive Open Online Courses), the influencer effect changes because teachers see AI as a tool that can reduce their workload, support them in differentiated teaching, and enhance their professional development by automating learning and personalizing it for students. Supporting evidence further suggests that individuals would adopt smart learning environments for teaching when they feel such systems would improve teaching quality, students' engagement and efficiency of instruction (Alamri et al., 2019; Dahri, Yahaya, Al-Rahmi, Aldraiweesh, et al., 2024). In professional development contexts, especially in underdeveloped areas like Sindh, the performance advantage of AI-based MOOCs, such as flexibility, intelligent support, and real-time, interactive problem assistance, deals with widely discussed challenges of time constraint, access to good training, and personalized mentoring. As a result, teachers' adoption intention of AI-enabled systems would increase with their perception of strong performance gains.

H1: Performance Expectancy has a positive and significant effect on teachers' Behavioral Intention to adopt AI-based MOOCs.

2.2. *Effort Expectancy (EE)*

Effort Expectancy (EE) is the perceived ease of use of an information system (Venkatesh et al., 2003). In AI-supported MOOCs, EE is a concept that represents teachers' view of the AI-enhanced platform as simple, clear and usable for professional learning. As highlighted by M. Altalhi (2021) notes that EE (Ease of Use) refers to the clarity of the interface, navigational ease, and lesser mental effort in dealing where dealing is meant for usage of the digital learning tool. Through personalized recommendation, automated feedback, chatbot assistance, voice-based search and adaptive learning pathways, features that further enhance EE can be integrated using AI. These smart supports lessen cognitive load, making the MOOC more accessible, especially for teachers with limited technical skills. The greater the user-friendliness of AI AI-based MOOC environment perceived by an educator, the higher the chances of adoption for continuous professional development. Ease of use is found to be one of the major drivers that affect acceptance of technology. This is especially true in developing environments in which digital illiteracy is rampant (Dahri et al., 2021; So et al., 2012). Thus, the easier the learning process and the less the obstacles to participation, the greater the teacher's behavioral intention towards using AI-enabled MOOCs.

H2: Effort Expectancy has a positive effect on teachers' Behavioral Intention to adopt AI-based MOOCs.

2.3. *Facilitating Conditions* **(FC)**

Facilitating Conditions (FC) are teachers' perceptions of the organizational, technical, and infrastructural support available to effectively use an IS (Venkatesh et al., 2003). In other words, it refers to the availability of reliable internet, appropriate digital devices, technical support, AI-enabled tools, training programs, and institutional policies that support the use of smart learning environments in the context of AI-based MOOCs. As noted by M. According to Altalhi (2020), FC is important in adopting digital learning. Educators are likely to use the system when sufficient support mechanisms are made available to them. MOOCs backed by AI often rely on the availability of a robust technology infrastructure, digital literacy training and ongoing support to help teachers navigate advanced features, including adaptive learning dashboards, AI agents, automated assessment, and intelligence tutor system(Sajja et al., 2024; Zou et al., 2025). When institutions offer these resources, teachers feel more empowered to engage with AI-enhanced professional learning systems. Past studies show that a supportive environment, which has an IT helpdesk, continuous encouragement by administration, and availability of learning resources, positively affects teacher use of digital learning tools (Raffaghelli et al., 2022; Zacharis & Nikolopoulou, 2022). Facilitating conditions are essential for teachers' willingness to adopt AI-based MOOCs for continuous professional development in developing contexts like Sindh (Siddiqui & Qamar, 2018) where technological barriers exist.

H3: Facilitating Conditions have a positive effect on teachers' Behavioral Intention to adopt AI-based MOOCs.

2.4. *Social Influence (SI)*

Social influence (SI) is the degree to which teachers perceived that other important school figures (e.g., school leaders, peers, colleagues and even students) thought they should use the technology. (Venkatesh et al, 2003) In AI-based

MOOCs, SI, or social influence, encompasses advice received from supervisor staff, institutional culture fostering the use of AI, peers' recommendation, and a professional community supporting intelligent learning tools for continued development. According to previous research, teachers' decisions regarding technology adoption are greatly influenced by their networks and the professional context (Mohan et al., 2020). When faculty see peers successfully using AI-supported MOOCs or when administrators stress the benefits of AI-enabled PD, they are more likely to develop positive intentions towards the use of these platforms(Alyoussef et al., 2025; Fakhar et al., 2024). Teachers are also more confident in their use of AI features for intelligent feedback, personalized course pathways, and automated assessment. According to Dahri et al. (2022), social influence is a determinant of teachers' attitudes towards new digital technologies. The strong peer support and leadership support of the teacher could increase the tendency of adopting AI-based MOOC. Thus, SI has significance in the shaping of behavioral intention towards smart digital learning environments.

H4: Social Influence positively affects teachers' Behavioral Intention to adopt AI-based MOOCs.

2.5. Information Quality (IQ)

Information Quality (IQ) refers to the accuracy, relevance, completeness and usefulness of the content that is provided within an information system (DeLone & McLean, 2003). With regard to AI-based MOOCs, IQ covers the clarity of instructional materials, various offerings and their alignment with professional development needs, AI algorithms-generated personalized content, and the reliability of all this AI system-generated data. Essential content influences teachers' trust, satisfaction, and engagement in digital learning (Gu et al., 2021). Artificial Intelligence can deliver tailored content, offer real-time updates while studying, and guarantee quality consistency in MOOCs or massive open online courses(Mahamad et al., 2025; Patil, 2025; Zhang et al., 2025). The usefulness increases of teachers are enhanced because of such modifications to learning results. A person's IQ, and some behavioral functions control the intention and attitude of users towards online learning systems (X. Li & Zhu, 2022). Teachers' perceptions of the information in AI-enabled MOOCs as credible, current, and congruent with their teaching goals will likely lead them to adopt and continue using it.

H5: Information Quality positively influences teachers' Behavioral Intention to adopt AI-based MOOCs

H6: Information Quality positively influences teachers' Attitude toward AI-based MOOCs.

2.6. System Quality (SQ)

According to DeLone and McLean (2003), system quality refers to a digital learning system's technical performance, functionality, and overall reliability. In an AI-based MOOC, SQ consists of navigation ease, interface design and response time, platform failure and accessibility, and the quality of AI-driven features such as intelligent feedback, adaptive dashboard and auto-assessment. The design of AI-supported MOOC Libraries should facilitate the engagement of users to a seamless learning experience and without technical glitches(Fakhar et al., 2024; Yu et al., 2017). Educators are more inclined toward the adoption of the system with a user interface that is intuitive and efficient. According to earlier studies (X. Li & Zhu, 2022), the factors, namely usability, responsiveness and reliability of systems significantly predict acceptance by educators of online study. The integration of AI can further improve SQ by providing intelligent navigation assistance, simplifying technical challenges, and offering real-time support through chatbots or virtual tutors. The better the system quality, the more teachers will intend to adopt AI-based MOOCs. Also, how does it shape teachers' attitudes? Through the positive user experience and less frustration with technical obstacles.

For this reason, SQ is an essential influencer of behavioral and attitudinal outcomes.

H7: System Quality positively influences teachers' Behavioral Intention to adopt AI-based MOOCs.

H8: System Quality positively influences teachers' Attitude toward AI-based MOOCs.

2.7. Perceived Enjoyment (PEN)

Perceived enjoyment (PEN) refers to the degree to which the teachers enjoy the learning experience, feel engaged, and find it satisfying and fulfilling in its own right, aside from performance (Alyoussef, 2023; Zhou et al., 2022). The learning activities and gamified elements of an AI-based MOOC may enhance enjoyment, as well as the use of AI for personalized content(Al-Rousan et al., 2025; Yakubov et al., 2024). Such features enrich the learning environment and encourage teachers to spend more time playing with course materials. Prior studies show enjoyment impacts user attitudes and acceptance of e-learning technologies (Alyoussef, 2023b).. If teachers find AI-based MOOCs fun and stimulating, they are likely to develop a more positive attitude towards their use. Utilising the capabilities of artificial intelligence, like personalized recommendations and automated support—makes learning more interactive and motivating, thus enhancing intrinsic motivation.

With respect to affective factors, perceived enjoyment may be a strong emotional factor influencing teachers' attitudes towards AI-enhanced digital learning environments.

H9: Perceived Enjoyment positively influences teachers' Attitude toward AI-based MOOCs.

2.8. Teacher's Attitude (TA)

The attitude of teachers toward digital learning environments, especially AI-enhanced MOOCs, reflects their overall evaluation of whether such platforms are useful, enjoyable, and appropriate professional development tools. Attitude refers to the positive or negative evaluation of a person regarding the adoption of a new technology in a context. (Ajzen, 1991). According to Davis and his companions (1989), attitude has been recognised in the literature on technological adoption as a primary determinant of behavioural intention. According to the context of AI-supported MOOCs, the teachers' attitude is shaped by the perceived usefulness, ease of use, trust in the AI-generated content, perceived enjoyment, quality of system features like adaptive learning, intelligent feedback, automated assessments(Aldraiweesh & Alturki, 2025; Malakul, 2025). When teachers start believing that AI-based MOOC help build their teaching competencies, save their time, personalizing learning and create engaging learning experiences, their attitudes change. Researchers explored the factors inhibiting secondary school teachers' use of ICT. They found out that the negative attitudes of teachers are the most important barrier. Positive attitude boosts behavioral intention, satisfaction and permanency of usage over a considerable duration of time. As a result of this, teachers' attitude is viewed as a critical mediating construct linking perceptions of platform quality, pleasure and usefulness to behavioural outcomes.

H10: Teachers' Attitude positively influences Behavioral Intention to use AI-based MOOCs (TA $\propto$ BI).

H11: Teachers' Attitude positively influences Teacher Satisfaction with AI-based MOOCs (TA $\propto$ TS).

H12: Teachers' Attitude positively influences Actual Use of AI-based MOOCs (TA $\propto$ AU).

2.9. Behavioral Intentions (BI)

Behavioral intentions (BI) define the teachers' motivational readiness and willingness to use AI-based MOOCs for professional learning. The business intelligence (BI) is a primary determinant of actual technology use in many theoretical models, including UTAUT, TAM, TPB, and IS continuance models (Venkatesh et al., 2003; Meet et al., 2022). In the digital world and in the era of the integration of AI in education, BI reflects the teacher's own engagement with an online course, interaction with AI, and professional development through MOOC. When teachers see MOOCs as useful, easy to use, nice to use, and supported by institutional and peer networks, their intention to use these platforms strengthens. If the intention is strong, it means that teachers are willing to use MOOCs on a regular basis. Past research revealed that behavioral intention is one of the strongest predictors of both satisfaction and actual use of the system in digital learning environments (Almogren et al., 2024). More BI leads to higher acceptability, higher usage, and higher sustainability of AI-based MOOCs in the long run.

H13: Behavioral Intention positively influences Teacher Satisfaction with AI-based MOOCs (BI $\propto$ TS).

H14: Behavioral Intention positively predicts the Actual Use of AI-based MOOCs (BI $\propto$ AU).

2.10. Teacher's Satisfaction (TS)

Teacher satisfaction (TS) is defined as the degree to which it refers to the contentment and positive perception of educator experiences while using digital learning platforms (Al-Maatouk et al., 2020). When talking about AI-based MOOCs, satisfaction indicates the perception of teachers about how effective the platform is, the relevance of the content, the quality of AI-enabled personalizing, and overall learning experience. The platform users are highly satisfied that their professional development needs were met, learning improved, and engagement through intelligent capabilities, which include adaptative content, automated feedback, and AI-assisted learning pathways. Research consistently shows that happy learners are more active, persistent, and successful (DeLone & McLean, 2003). As a result of system and content quality, in AI-enhanced digital learning environments, satisfaction is not only an outcome, but it is also a driver of use and adoption. Those teachers who consider AI-based MOOCs enjoyable, effective and responsive are more likely to use them in their practices.

H15: Teacher Satisfaction positively influences the Actual Use of AI-based MOOCs (TS $\propto$ AU).

2.11. Actual Use Of MOOCs (AU)

Actual Use (AU) refers to the extent of engagement of the teachers with the AI-based MOOC, both for professional development and instructional improvement (Venkatesh, 2022). It shows measurable behavioral outcomes like how often students take the course, finish modules created by AIs, use smart assessments, and so on. MOOCs based on artificial intelligence increase their actual use by providing easy, flexible, personalized learning. Features including intelligent tutoring, collaborative learning tools, and adaptive learning paths engage and motivate students with real-time feedback. Also, their open nature allows teachers to use high-quality resources from top-ranking world institutions and continue learning from other teachers while sharing knowledge (Altalhi, 2021; Dahri et al., 2021). With this platforms, self-driven learning and the use of AI as a guide let the teachers learn effectively and continue growing. Actual use is thus an important outcome that indicates the effectiveness of AI-based MOOCs in quality teaching improvement and professional development.

3. RESEARCH METHODOLOGY

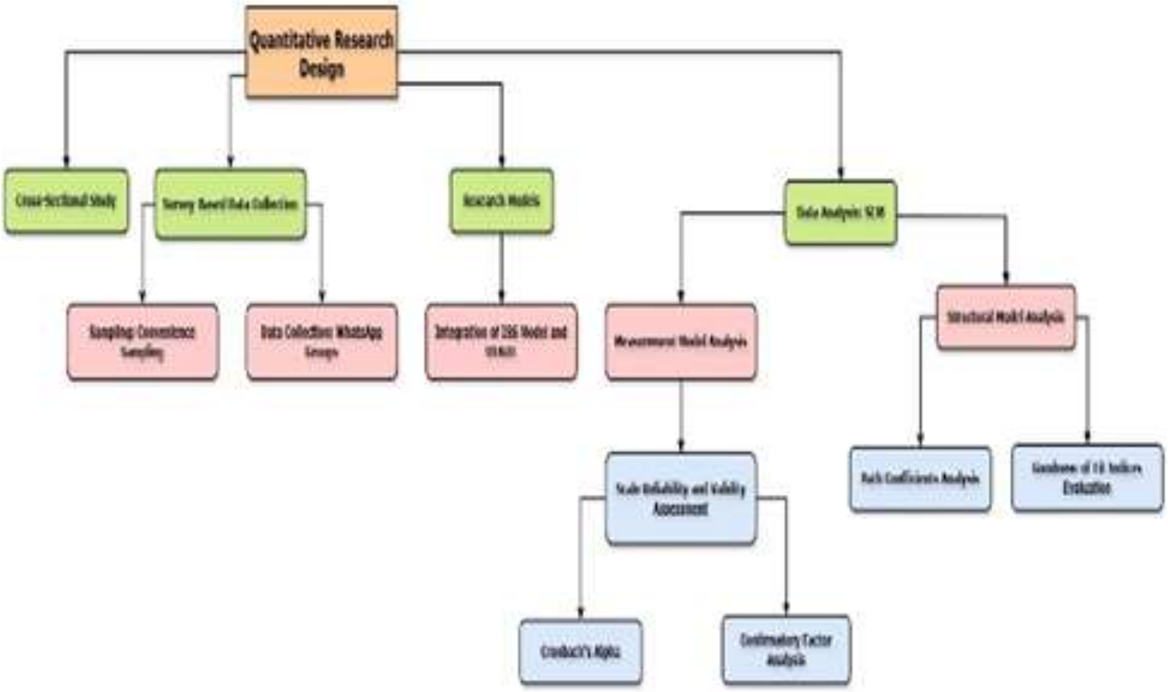


Figure 4: Proposed Research Design.

This research study utilised a quantitative design to investigate the factors influencing teachers' adoption and use of AI-based MOOCs as smart digital learning environments for professional development (see Figure 4 for the overall research design). The researchers used a cross-sectional design to gather data once on relationships among constructs (Olsen & St George, 2004). Cross-sectional designs are effective at determining the prevalence and associations between different variables within a population. In this respect, they can offer a snapshot of the adoption of practices or technologies. A survey-based approach was used to collect data from teachers with experience/exposure to AI-supported MOOCs. The sampled teachers were those engaging in professional development using digital platforms. The questionnaire was developed to measure the performance expectancy, effort expectancy, social influence, facilitating conditions, information quality, system quality, perceived enjoyment, attitude, behavioural intention, satisfaction, actual use and demographic information for control purposes. Structural Equation Modeling (SEM) was applied in the research to analyse the data. SEM allows the simultaneous evaluation of the measurement model and structure model (Joe F Hair et al., 2014). The measurement model was used to assess the reliability and validity of the scale. The Cronbach Alpha, composite reliability and CFA were used to test for construct validity and internal consistency (J. Hair et al., 2017). Afterwards, the structural model was assessed for evaluating hypothesised relationships among constructs. The path coefficients, t-values and goodness-of-fit indices were used for determining the strength, direction and statistical significance of the proposed relationship (Hair Jr et al., 2021). This methodology offers empirical insights that can help to understand the adoption and use of AI-based MOOCs in addition to the factors that drive teachers' engagement with smart digital learning environments within professional development contexts.

3.1. Sampling And Data Collection

The current research data were collected from the newly appointed teachers of primary and secondary schools of the Sindh region, under the School Education and Literacy Department, Government of Sindh, from 2024-25. The participants were selected based on their knowledge and involvement in professional development MOOCs which are based on AI. The study included teachers who were already using MOOC courses. The survey employed a 5-point Likert scale system for the constructs of MOOC (massive open online course) adoption, attitudes, behavioral intentions, system satisfaction and actual use, together with the demographic features. A total of 300 questionnaires were shared through WhatsApp groups. A total of 20 responses were removed during the data screening, as given in the next section. Ten responses were dropped because they were incomplete. The other 10 responses were dropped because there was missing data or an outlier, which was later confirmed with manual inspection. After removing invalid responses, the final dataset consisted of 280 valid responses, which meets the minimum sample size required for SEM analysis (Joseph F Hair et al., 2012). The sample is considered adequate for estimating path coefficients, model fit indices, and construct relationships in the proposed AI-based MOOC adoption model.

3.3. Measurement Instruments

The questionnaire comprised two main sections. The beginning part has information which includes gender, age, and educational level. The technology acceptance model will be explained in the next section. The section having 48 items taken from earlier research provides the assurance of content validity. To test the reliability of the questionnaire, a preliminary test was conducted by 60 teachers before the main analysis. The data were claimed to be reliable following the established research, with the result of Cronbach's alpha method at the preferred score of 0.7 (Joseph F Hair et al., 2006). All constructs revealed a reliability of "Cronbach's alpha values" that exceeded this benchmark. This was indicative of the reliability of the data for subsequent SEM analysis. Data analysis was done making use of the software package 'Statistical Package for the Social Sciences (SPSS)'. The structural modeling phase of the analysis was conducted using Smart PLS 4.0 through the recommended two-step approach (F. Hair Jr et al., 2014). The first step of the study focused on developing, determining convergence and assessing the discriminant validity of the measures. The second step of the research was the structural analysis of the model.

4. FINDINGS AND RESULTS ANALYSIS

4.1. Participants Data Analysis

The participant sample (N = 280) was generally youthful, as shown in Table 1. This is evident from the numbers, which show 88% in the 20 – 30 group, 11% in the 31 – 40 group, with a low number in other higher age groups. The sample consisted of 88 % males and 12 % females, indicating significant gender imbalance. Most of the respondents (71%) hold bachelor's degrees, while 25% hold master's degrees. Some percentage hold a PhD/Doctorate degree. A better understanding of the age, gender, and differing levels of education among participants can help clarify findings regarding the acceptance and use of AI-based MOOCs for teacher professional development.

Table 1: Demographic Information Of Schoolteachers Items.

Characteristics	Characteristic	Count	%
Age (years)	- 20 to 30	245	84.25
	- 31 to 40	32	11.01
	- 41 to 50	3	1.03
	- 51 to 60	0	0.00
Gender	- Male	247	88.61
	- Female	33	11.89
Educational Qualification	- Bachelor's degree	200	72.46
	- Master's degree	70	25.36
	- PhD/Doctorate	5	1.81
	- Other	5	1.81

4.2. Measurement Model Analysis

To evaluate convergent validity, we assessed the factor loadings, average variance extracted (AVE), and composite reliability (CR) according to Hair et al. (2019). Acceptable levels are factor loadings of greater than 0.70, CR of greater than 0.70 and AVE of greater than 0.50. In the table 2, the outcomes of SEM analysis were detailed, which showed the measurement model results (Hair et al., 2017). The Cronbach's alpha showed internal consistency of the scale items ranging from 0.81 to 0.88, which is greater than 0.70 (Nunnally & Bernstein, 1994). The more accurate reliability measure CR (Raykov, 1997), which takes into account factor loadings, was also greater than 0.70 for all constructs, supporting the reliability and internal consistency of the measurement model (Alwakid et al., 2025; Joseph F Hair et al., 2019).

Table 2: Convergent Validity Results (Cronbach's Alpha, AVE, And CR).

Constructs	Coding	Factor Loading	Alpha	CR	AVE
Performance Expectancy	PE1	0.77	0.810	0.810	0.570
	PE2	0.82			
	PE3	0.78			
	PE4	0.74			
	PE5	0.64			
Facilitating Conditions	FC1	0.71	0.830	0.840	0.600
	FC2	0.83			
	FC3	0.81			
	FC4	0.75			
	FC5	0.77			
Effort Expectancy	EE1	0.77	0.870	0.990	0.700
	EE2	0.86			
	EE3	0.9			
	EE4	0.79			
Social Influence	SI1	0.74	0.850	0.890	0.690
	SI2	0.82			
	SI3	0.88			
	SI4	0.88			
Information Quality	IQ1	0.77	0.870	0.870	0.650
	IQ2	0.78			
	IQ3	0.88			
	IQ4	0.83			
	IQ5	0.77			
System Quality	SQ1	0.79	0.870	0.870	0.650
	SQ2	0.78			
	SQ3	0.81			
	SQ4	0.84			
	SQ5	0.81			
Perceived Enjoyment	PEN1	0.83	0.880	0.890	0.680
	PEN2	0.84			
	PEN3	0.85			
	PEN4	0.82			
	PEN5	0.8			
Teacher's attitude	TA1	0.86	0.890	0.890	0.750
	TA2	0.86			
	TA3	0.88			
	TA4	0.87			
Actual Use of AU based MOOCs	AU1	0.82	0.860	0.860	0.700
	AU2	0.85			
	AU3	0.84			
	AU4	0.84			
Behavioral Intentions	BI1	0.85	0.820	0.820	0.730
	BI2	0.85			
	BI3	0.86			
Teachers' Satisfaction	AU1	0.84	0.870	0.870	0.720
	AU2	0.87			
	AU3	0.83			
	AU4	0.85			

AVE refers to the variation explained by a construct, as opposed to measurement error (Fornell & Larcker, 1981). The AVE values ranged from 0.49 to 0.74, which showed strong composite reliability and factor loadings, thus supporting excellent convergent validity (Hair et al., 2017). The results show that the items adequately explain their respective constructs' variances. As per the study (Al Shamsi et al., 2022), the higher loading value (.70 or above is acceptable) of the observed items depicted a good relation with their constructs. This means that each item adds significantly to the variance of its own construct. Overall, these results support the reliability and appropriateness of the measurement model of the study framework.

4.2.1. Common Method Bias (CMB)

There is a possibility of CMB since the dependent and independent variables were both obtained from the same respondent (Schwarz et al., 2017). To counter this, a single-factor test by Harman was performed in SPSS using exploratory factor analysis with all scale items. As recommended by Podsakoff et al. (2003), the first factor with 34.16% of the total variance is far less than 50%. This shows that no factor predominated, which indicates that CMB is not have a significant influence on the study (Chaudhuri et al., 2024).

4.2.2. Analysis Of Effect Sizes f2

The f^2 effect sizes show the strength of the correlations between the constructs examined in the research related to adopting AI-based MOOCs for teachers' professional development. According to Cohen (1988), effect sizes can be classified into weak, medium, or large (see Table 3). The suggested model indicates that the effect of Behavioural Intention on Actual Use (AU) of AI-based MOOCs is 0.110 (medium effect) whereas the effect of Behavioural Intention on Teacher Satisfaction (TS) with AI-based MOOC is 0.370 (large effect). The desire for human-like conversation between teacher and robot leaves teachers unhappy, survey shows - this shows that even the people who use them are confused. High effect on satisfaction may derive from perceived added value of AI features such as adaptive learning paths, personalized feedback, and intelligent assessments, which enhance perceived usefulness and engagement. On the other hand, Effort Expectancy (EE) has a negligible influence on BI, with an effect size of 0.000 (weak). This means that they do not think too much about how carrying out the intention to use Microsoft or other platforms is made easier with AI features. This is probably because, with the sampled teachers having more experience with online platforms, the design of the AI features is intuitive.

The effect sizes of Facilitating Conditions (FC) and Information Quality (IQ) towards BI are

0.020 and 0.050 respectively. Having access to supportive infrastructure and quality AI-enhanced content helps improve teachers' intentions only to a modest extent, as they were not perceived as having a greater impact than more motivational and attitudinal ones like performance expectancy or perceived enjoyment. These findings highlight that for AI-based MOOCs, it is the motivational factors and teachers' attitudes towards the AI-based functionalities that play a more important role in predicting adoption and engagement than ease-of-use or supportive conditions.

Table 3. Analysis of Effect Sizes f2.

Path	Effect Size (f^2)	Classification	Benchmark
BI -> AU	0.110	Medium	The following threshold values for effect sizes are based on (Cohen, 1988) Small (S): f2=>0.02 Medium (M): f2=>0.15 Large (L): f2=>0.35
BI -> TS	0.370	Large	
EE -> BI	0.000	Small	
FC -> BI	0.020	Small	
IQ -> BI	0.050	Small	
IQ -> TA	0.100	Medium	
PE -> BI	0.020	Small	
PEN -> TA	0.110	Medium	
SI -> BI	0.010	Small	
SQ -> BI	0.040	Small	
SQ -> TA	0.020	Small	
TA -> AU	0.020	Small	
TA -> BI	0.100	Medium	
TA -> TS	0.230	Medium to Large	
TS -> AU	0.130	Medium	

According to the authors, the R-squared (R^2) values shown in Table 4 refer to the amount of variance in the dependent variable that the independent variables explain when fitted into a regression model (Hair et al., 2019). The R^2 of a model quantifies the extent to which the observed data is in line with the hypothesised data. An R^2 of 0.60 for Actual Use (AU) indicates that 60% of the variance in teachers' use of AI-based MOOC is explained by the independent variables of the model, which has a strong effect. The coefficient of determination (R2) of Behavioural Intention (BI) is 0.64, which indicates that 64% of the teachers' intention to use AI-supported MOOCs has been explained. It also indicates a considerable impact. Also, teacher attitude (TA) has an R^2 of 0.52, and teacher satisfaction (TS) has an R^2 of 0.65, highlighting how much the exogenous constructs affect teachers' adoption and use of AI-enhanced digital learning environments.

Table 4: R2 of the Endogenous Latent Variables.

Factors	R-square	Effect	Benchmark
AU	0.60	Moderate	"0.75 => Substantial 0.50 => Moderate 0.25 => Weak (Hair et al. 2017)"
BI	0.64	Moderate	
TA	0.52	Moderate	
TS	0.65	Moderate	

According to Discriminant Validity (DV), the definitions and measures must be distinct from one another, and the constructs measured must have low overlap with one another measuring different latent concepts in line with the research assumptions (Fornell & Larcker, 1981). HTMT is a stringent method specifically used to test DV. The calculation of the ratio of the correlations of the different traits (heterotrait-heteromethod) to the correlations of the same trait (monotrait-heteromethod). HTMT values that are lower than 0.85 signify discriminant validity (DV). A score that exceeds this threshold value indicates lesser DV, which indicates the constructs may not be dissimilar (Henseler et al., 2015). The HTMT ratio method, as shown in Table 5 validates DV, where all the off-diagonal values are much lower than 0.85 (Fornell & Larcker, 1981).

Table 5: Discriminant Validity (HTMT Ratio).

	AU	BI	EE	FC	IQ	PE	PEN	SI	SQ	TA	TS
AU											
BI	0.85										
EE	0.04	0.06									
FC	0.75	0.77	0.08								

IQ	0.85	0.83	0.06	0.76							
PE	0.68	0.78	0.05	0.82	0.78						
PEN	0.79	0.78	0.05	0.73	0.79	0.73					
SI	0.15	0.11	0.07	0.07	0.09	0.05	0.05				
SQ	0.78	0.78	0.09	0.73	0.78	0.69	0.74	0.08			
TA	0.73	0.8	0.04	0.65	0.75	0.68	0.73	0.1	0.66		
TS	0.85	0.89	0.1	0.8	0.83	0.73	0.86	0.06	0.78	0.82	

4.2. PLS-SEM Estimation and Hypothesis Testing

A total of 15 hypotheses were tested in the study on adoption of AI-based MOOCs for teacher's professional development. The results, found in Tables 7 and figure 5, supported H1, H3, H5-H7, H9-H11 and H13-H15, while H2, H4, H8 and H12 were not supported.

Performance Expectancy (PE) has a positive impact on the Behavioral Intention (BI) (T = 2.28, p = 0.02) suggesting that the usefulness of AI-enhanced MOOC platform is likely to encourage the teachers' intention to adopt them. The research findings indicate that Information Quality (IQ) (T = 2.96, p < 0.001) and System Quality (SQ) (T = 3.28, p < 0.001) have significant positive and strong effects on BI. This shows that teachers are likely to adopt AI supported MOOCs for quality and reliable content, as well as being technically sound.

TA (Teachers' Attitude) is crucial movement of BI, (T=3.71, p<0.001) and TS (T=4.51, p<0.001) Perceptions and attitudes towards the MOOC (Massive Open Online Course) are likely to enhance intention to use the platform and satisfaction with learning. Additionally, the results showed that the BI significantly predicted TS (T = 6.41, p < 0.001) and Actual Use (AU) (T = 4.53, p < 0.001). It means teachers' intention is a strong predictor of TS and AU. The impact of the TS on AU was also significant (T = 4.21, p < .001). This suggests satisfaction can play an important role on sustained use of AI-based MOOCs for professional development.

The findings revealed how technical factors, motivational factors, and attitudinal factors are interconnected in their influence on the teachers' adoption of AI-enhanced MOOCs. Thus, the result gives insights for the policymakers, educators, and platform designers to improve engagement and learning outcomes.

Table 7: Hypothesis Testing Results.

Relationships	Original sample (O)	T Value	P values	Decision
H1=PE -> BI	0.14	2.28	0.02	accepted
H2=EE -> BI	-0.02	0.49	0.62	Not accepted
H3=FC -> BI	0.14	1.97	0.05	accepted
H4=SI -> BI	-0.05	1.16	0.24	Not accepted
H5=IQ -> BI	0.22	2.96	0.00	accepted
H6=IQ -> TA	0.33	3.42	0.00	accepted
H7=SQ -> BI	0.19	3.28	0.00	accepted
H8=SQ -> TA	0.14	1.84	0.07	Not accepted
H9=PEN -> TA	0.34	2.76	0.01	accepted
H10=TA -> BI	0.27	3.71	0.00	accepted
H11=TA -> TS	0.39	4.51	0.00	accepted
H12=TA -> AU	0.13	1.39	0.17	Not accepted
H13=BI -> TS	0.49	6.41	0.00	accepted
H14=BI -> AU	0.33	4.53	0.00	accepted
H15=TS -> AU	0.39	4.21	0.00	accepted

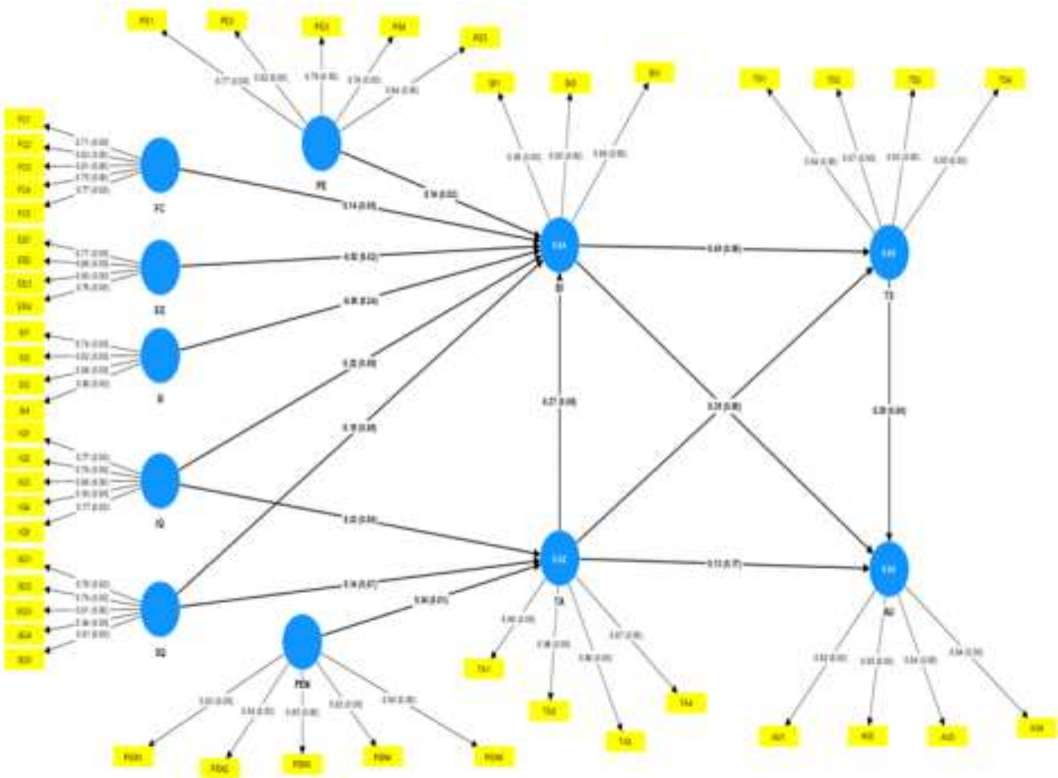


Figure 5: Structural Model.

4.3. Discussion

AI-based MOOCs have attracted significant interest as a smart digital learning environment for teacher professional development in recent years. AI-Based MOOCs are a promising tool for continuous professional development (CPD) and offer better accessibility, personalization and adaptive learning opportunities. There remain a lack of studies analyzing the factors affecting teachers' acceptance and actual use of such AI-based learning environments. This article examines the major factors affecting teachers' adoption and usage of Artificial Intelligence-based MOOCs to facilitate professional development of teachers. The results are hypothesis by hypothesis and begin with the H1 hypothesis which is the Performance Expectancy and Behavioral Intention (BI) to use AI-based MOOCs. After which, comprehensive results of all 15 hypotheses are presented (H1–H15).

4.3.1. Performance Expectancy (PE) Dan Behavioral Intention (BI).

The study found a significant positive relationship between performance expectancy (PE) and behavioral intention (BI) to use AI-based MOOCs for professional development or BI $\propto$ PE. This indicates that teachers' belief that AI-enhanced MOOCs can help them to perform their job better influences their intention to use them. The finding is consistent with past studies showing that PE is a vital predictor of BI in technology adoption (M. Altalhi, 2021; Meet et al., 2022). Teachers have greater chances of participating in AI-based MOOCs that they consider to enhance their teaching skills, teaching strategies and knowledge acquisition. This shows that Behavioural and operational force, independence, assesses usefulness and efficacy. The application can be used by UTAUT and TPB theories (Ajzen, 1991; So et al., 2012). In addition, these findings support the work of Arain et al. (2019) and Dahri et al. (2021), confirming that PE is a strong determinant of behavioral intention in diverse educational technologies, including AI-supported learning setups.

H2: Effort Expectancy (EE) and Behavioral Intention (BI)

The finding in this research indicates that the relationship between Effort Expectancy (EE) and Behavioral Intention (BI) to use AI-based MOOCs for professional growth is not significant. In brief, BI $\propto$ EE. This means the teachers' perception of the ease or difficulty of using an AI-enhanced MOOC does not affect the intention to adopt. This finding is different from those of earlier studies, which found EE to be a significant predictor of behavioural intention in the case of mobile learning (Arain et al., 2019) and e-learning (Zacharis & Nikolopoulou, 2022). One explanation may be that the teachers consider AI-based MOOCs convenient and easy to use. Thus it may lessen the impact of perceived effort. One more issue is that EE operationalization may not precisely reflect ease of use in the context of AI in this study To assess the potential impact of EE on behavioral intention on AI-supported education, future studies should refine its measure. Although the finding is not statistically significant this adds to the literature on EE in technology adoption. It also indicates that perceived usefulness and system quality may be more important for the case of AI-based MOOC adoption than perceived effort.

H3: Facilitating Conditions (FC) and Behavioral Intention (BI)

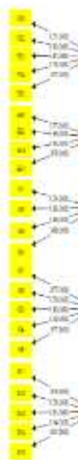
According to the research, there was a substantial relationship between Facilitating Conditions (FC) and Behavioural Intention (BI) to use AI-based MOOCs for professional development (BI ∝ FC). This shows that the option of having supporting infrastructure, technical help, and requisite resources prompts the teacher community to use AI-enhanced MOOCs. Such findings support earlier studies, which have found that FC is a significant predictor of technology adoption intention (M. M. Altalhi, 2021; Sattari et al., 2017). Conditions that facilitate teachers' perceptions toward the ease of use (PEOU) and perceived usefulness (PU) of AI-based MOOCs will enhance their intention to use (Dahri et al., 2024).

H4: Social Influence (SI) and Behavioral Intention (BI)

The findings revealed that the relationship between Social Influence (SI) and Behavioral Intention (BI) to use AI-based MOOCs for professional development is not significant (BI ∝ SI). Based on the analysis, it can be inferred that teachers' willingness to adopt AI-enhanced MOOCs is not greatly influenced by the views, support and actions of colleagues, peers and supervisors. The finding here contradicts those of previous studies where SI was a significant precursor of BI of mobile learning (M-learning) and social media adoption (Dahri et al., 2023). One possible explanation is that teachers place their personal motivations, perceived benefits, and practical utility of AI-based MOOCs over peer influence. Learning platforms equipped with AI that provide personalized content and develop adaptive learning features are likely to reduce the impact of social cues on the decision to interact with the system. Even though it does not mean much, this result does add to the literature on the relevance of SI in the context of the adoption of technology. It emphasizes the need to consider contextual and individual factors which can moderate the influence of social networks on teachers' adoption intentions. Future studies ought to investigate situations in which social influence might turn out to be a more vital driver of adoption of AI-based MOOCs.

H5 and H6: Information Quality (IQ) and Its Impact on BI and TA

Our study detected a significant positive relationship of Information Quality (IQ) with Behavioural Intention (BI) to use AI-based MOOCs for professional development (BI ∝ IQ). Besides, Information Quality (IQ) significantly positively impacts Teachers' Attitude (TA) to use AI-based MOOCs (TA ∝ IQ). According to H5, teachers are more likely to intend to adopt AI-enhanced MOOCs that they perceive as accurate, relevant, comprehensive, and timely. The findings of the study showed that high-quality information offered in the system increases the confidence of teachers in the system's usefulness in enhancing their professional development. Both of these results corroborate past findings on the significant role of IQ as a predictor of BI in technology-supported teacher training (Al-Rahmi et al., 2021). The results on H6 indicate that high-quality information also positively affects teachers' attitude towards AI-based MOOCs. When instructors regard AI content as useful, reliable, and accurate, they feel more positively towards the intention to use this type of platform. Thus, which supports the Theory of Planned Behavior (TPB) whereby attitudes and perceived behavioural control cause behavioural intention (So et al., 2012). Further, the findings seem to conform with the Technology Acceptance Model (TAM) where perceived usefulness and ease of use (both of which are driven by IQ)are essential to adopting the technology (Viswanath, 2003). Including AI features in MOOCs enhances the perceived quality of information available in MOOCs and strengthens both intention and attitude towards the adoption of MOOCs.



H7 and H8: System Quality (SQ) and Its Impact on BI and TA

The findings reveal a significant positive connection between System Quality (SQ) and Behavioral Intention (BI) to utilize AI-enhanced MOOCs for professional development (BI ∝ SQ). Furthermore, the research confirms that SQ positively impacts Teacher's Attitude (TA) (TA ∝ SQ). According to H7, users' perception of the platform's trustworthiness and user-friendliness contributes to a higher likelihood of teachers' intention to adopt AI-based MOOCs. When the system is of high quality, it builds trust in the technology and enables teachers to use the MOOC freely. This coincides with the findings of previous studies that SQ is a strong predictor of behavioural intention (Ohanu et al., 2023). The finding on H8 indicates that system quality positively influences teachers' attitudes toward artificial intelligence MOOCs. When teachers experience exceptional navigation, quick response, and strong technical functionality from a platform, their perception of its value increases. This assertion is aligned with 'Theory of Planned Behavior' and 'Technology Acceptance Model' (TAM). Both theories underline that perceived usability and functionality affect attitude and behavioural intention (Dahri et al., 2024). These results may remind us of the importance of high system quality in AI-driven MOOCs to improve intention & attitude to promote further adoption & effective integration for teacher professional development.

H9: Perceived Enjoyment (PEN) and Teacher Attitude (TA)

According to our study, the more an individual found the use of artificial intelligence (AI) in MOOCs enjoyable, the more favourable their attitude towards it. Teachers who find engaging and enjoyable AI-based MOOCs have more likelihood of developing favourable attitude toward their use for professional development. The perception of enjoyment is a significant predictor of attitude toward adopting technology according to past studies (Khalid, 2014; Teo & Noyes, 2011). When students enjoy learning, their inner motivation rises. They will engage more with digital learning. MOOCs powered by Artificial Intelligence (AI) must be designed to be interactive, gamified, and personalized to increase enjoyment. Features like adaptable learning paths, real-time feedback, interactive simulations, and game and collaborative features can make learning more engaging, helping to positively impact teachers. These findings indicate that MOOC providers and educational institutions must also focus on user engagement and satisfaction along with quality content and reliable systems. As learners enjoy their experiences more, they develop more positive attitudes, driving greater adoption and use – and sustained use – of AI-based MOOCs for teacher professional development.

H10, H11, and H12: Teacher Attitude (TA) and Its Impact on BI, TS, and AU

Teacher Attitude (TA) had a significant positive relationship towards Behavioural Intention (BI) to use AI-powered MOOCs for professional development as the notation suggest that $BI \propto TA$. Similarly, TA had a significant positive effect on Teacher Satisfaction (TS) $TS \propto TA$) and Actual Use of MOOCs ($AU \propto TA$). The results for H10 suggest that teachers with a more positive attitude towards AI-enhanced MOOCs are more likely to have intention to use such resources for professional development. The findings are consistent with earlier research, which has pointed out the importance of attitude as a determining factor for intentions in the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB) (Ajzen, 1991; Viswanath, 2003). When teachers acknowledge the benefits of AI-powered learning tools, their positive attitudes motivate their adoption of them. The finding on H11 indicated that teachers who were positively inclined towards the use of MOOCS are more likely to find them satisfying, according to the study of C. Li & Phongsatha (2022) and Yang et al. (2022), prior attitudes towards technology had a strong effect on user satisfaction. The teachers feel satisfied with the user experience that the personalized learning paths and adaptive feedback that interactive content offers. According to the findings on H12, positive teacher attitudes are significantly associated with actual use of MOOCs for CPD. Teachers with positive perception for AI-based MOOCs will continuously engage with the platform, use content in practice, and effectively make use of ones that are AI-supported platforms (Abu-Al-Aish & Love, 2013; Akgunduz & Akinoglu, 2016). Overall, these findings support the TPB and TAM frameworks. Thus, encouraging a more positive teacher attitude toward AI-enabled MOOCs is essential to enhance intention, satisfaction, as well as actual usage. Educational institutions and providers of MOOCs should make use of engagement strategies that generate positive perceptions of the features of AI used for ensuring its adoption, satisfaction, and sustained professional development outcome.

H13 and H14: BI and Its Impact on TS and AU

According to the research study, the relationship between Behavioral Intention (BI) and Teacher Satisfaction (TS) was positive and significant in an AI-powered MOOC, and so was the relationship between BI and Actual Use (AU) of MOOC for professional development ($AU \propto BI$). Teachers' intention to use AI-enhanced MOOCs for professional development will lead them to be satisfied with such courses, according to the finding on H13. This shows that the stronger the teacher's intention to use learning tools based on AI the higher their satisfaction with learning. According to Alqahtani et al. (2022) and Goh et al. (2017), personalized recommendations, adaptive learning paths, and automated feedback of AI features lead to a more engaging and satisfying experience. This suggests that intended purpose is important in actualizing satisfaction. The results on H14 showed that teachers with higher behavioral intention to use AI powered MOOCs are more likely to use them for their professional development. The paper supports the existing literature which finds that behavioural intention is a strong predictor of using technology, especially as per Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB) (Ajzen, 1991; Viswanath, 2003). Teachers who intend to engage in MOOCs are more likely to engage in them. These represent a wide variety of tools, notably supported by AI, that enhance teachers' skills or professional knowledge of them. These findings suggest that behavioral intention is an important factor in teacher satisfaction and actual use of AI-powered MOOCs. Strategies that enhance teachers' intention, like showing the benefits of AI, making content interactive and adaptive, or assisting in skill development, can enhance satisfaction and engagement with MOOCs, for MOOC providers, and educational institutions.

H15: TS and AU

There is a positive relationship between Teacher Satisfaction (TS) and AU, that is, AU $\propto$ (TS) of AI-powered MOOCs for professional development. Teachers who are satisfied with their experiences on AI-enhanced MOOCs are more likely to engage with these platforms for their professional development. Artificial Intelligence (AI)-based features enhance user satisfaction. Some examples are personalized learning path, adaptive assessment, automated feedback, and intelligent recommendations. Teachers' perceived value and perceived effectiveness of the AI-powered MOOC enhance in motivation and willingness to use the MOOC and leads to actual usage (Yang et al., 2022). According to the Technology Acceptance Model (TAM), user satisfaction is an effective predictor of continued use of technology (M. Altalhi, 2021). Also, the finding validates previous studies that highlighted technology use, satisfaction and engagement in education context. For MOOC providers and educational institutions designing AI-enabled MOOCs should be based on users' satisfaction according to this finding. To encourage teachers to use the platform often, providers must make it easy to use. It must be intuitive, interactive, and responsive to individual learning needs.

4.4. Theoretical Implications

This research shows significant contributions to theory especially towards teachers' adoption of MOOCs as AI-enhanced digital learning environments. In this study, the Information System Success (ISS) model has been integrated with the Unified Theory of Acceptance and Use of Technology (UTAUT) in order to offer an elaborate and nuanced research framework for study of teacher's adoption of MOOCs for professional development. The findings suggest that performance expectancy, information quality, system quality, perceived enjoyment, teacher attitude greatly influences behavioral intention, satisfaction, and actual use. According to the findings of the study, where teachers rated an artificially intelligent educational platform high; the technology acceptance model can be applied in the context of an artificially intelligent educational platform. Besides, the paper bears testimony to the relevance of technical as well as user-oriented factors for predicting the adoption of MOOCs. Thus, it bridges theories from the IS area and EdTech literature. This integration adds to the literature by demonstrating how specific features of digital learning environments powered by AI impact perceptions of usefulness and satisfaction, enhancing adoption behaviours. In addition, the findings add to the ongoing theoretical discussions surrounding the impact of facilitating conditions, social influence, and perceived enjoyment on technology acceptance. The study improves the existing models and sets the stage for future studies on different types of AI-powered educational technologies in a range of educational contexts by indicating which factors significantly predict both behavioural intention and actual use.

4.5. Practical Implications

In practical terms, the findings offer recommendations to educational institutions, MOOC providers, and policymakers who wish to facilitate effective professional development through online learning environments. The research shows that educational content, system functionality, and user experience are important for teachers to adopt MOOCs. AI features like personalised recommendation systems can motivate teachers to take up online courses. Adaptive learning paths can help teachers get a better outcome as well. MOOC providers and institutions should also put efforts toward making the learning experience enjoyable and interactive, as perceived enjoyment is significantly related to teacher attitude and behavioural intention. Having adequate technical support, simplifying platform navigation, and providing structured guidance can ease the barriers to adoption and enhance user confidence. Creating content and learning modules that are localised and culturally appropriate is another way to support engagement and ongoing use by teachers. The study highlights the significance of investment in infrastructure and the creation of enabling conditions like internet connectivity, devices, and professional development incentives to orient teachers for engagement with AI-driven MOOCs. By tackling technical and pedagogical issues, stakeholders can get the results of improved quality of education, continuous learning, and improved teaching practices in the learning ecosystem. The findings of this study will not only contribute to theory but also offer practical methods for better utilizing AI-based MOOCs for the professional development of teachers. Similarly, they set a fine example of how digital learning environments can be effectively used in education to support lifelong learning.

5. CONCLUSION

In recent years, the educational setup has gone through significant changes, thanks to the growth and increased use of AI-enabled digital learning environments, e.g. MOOCs. The purpose of this study was to investigate what educators think about the adoption and use of AI-driven MOOCs for professional development. According to the study, further investigation is needed into the key variables that determine acceptance. The researchers used UTAUT and ISS in a combination way to understand the behavioural as well as system usage determinants of the adoption of Al applications in education. The findings reveal the major factors that influence teachers' attitudes and intentions to use AI-supported MOOCs. According to the study's findings, performance expectancy (PE), information quality (IQ), system quality (SQ), and perceived enjoyment (PEN) were significant predictors. This suggests that the teachers' useful perception, content usefulness, system reliability and enjoyable experience were strong determinants of their attitude and intention. Furthermore, teacher attitude (TA) was found to be a key construct that enhances behavioural intention (BI), teacher satisfaction (TS) and actual use (AU) of AI-enabled MOOCs. The findings suggest that the design of digital learning environments must optimize not only the content but also AI tools to personalize learning and adaptively provide feedback while constantly engaging the teacher. The study further revealed that effort expectancy (EE) and social influence (SI) had a limited effect on teachers' intention to adopt AI-supported MOOCs. Teachers, in general, find these platforms easy to use and do not find peer or social pressures as decisive factors in their decision-making. MOOCs were instead impacted more by the perceived benefit, system quality and engagement feature. The findings highlighted the importance of intrinsic motivation and system performance to promote professional development using digital learning. This study, overall, provides evidence for theory and practice in the factors determining the adoption of AI-enhanced MOOCs by teachers. It shows how the use of AI in digital learning spaces can improve teachers' engagement, satisfaction and actual use, which supports their continuous professional development. The findings are useful for MOOC designers, institutions, and policymakers interested in the effective adoption and sustainable use of an AI-powered learning environment in education.

5.1. Limitations And Future Work

Although the study has important implications, it has limitations that should be considered and that also offer suggestions for future research and interpretation of results.

5.1.1. Model Limitations

The integrated model of UTAUT and ISS constructs explained 60% variance in AU and 64% variance in BI, but there is still substantial variance left unexplained in AU and BI. Future studies could integrate predictors like self-efficacy, confirmation, perceived risk, trust in AI, adaptive learning features, digital literacy, or organizational support to improve model predictive power in understanding AI-supported MOOCs adoption among educators, which would enhance our understanding. Adding such tools may also shed light on how personalization AI, recommendation systems, and interactive feedback impact users' adoption and satisfaction.

5.1.2. Sample And Context Limitations

The respondents were only newly appointed teachers in the province of Sindh. Therefore, the findings may not be generalizable to other geographical locations, educational contexts, and levels of teaching experience. Future research should include samples from various provinces, countries, and educational levels to obtain the contextual and cultural differences impacting MOOC adoption. Having teachers with different types of experience in digital technologies and MOOCs can also add to the understanding of adoption patterns.

5.1.3. Cross-Sectional Design

A cross-sectional survey design was used for this study at a particular point in time. While you will learn about perception and behavior with this approach, it does not allow for an understanding of cause and effect, and it cannot help you understand how something changes over time. The future research can use longitudinal or experimental designs to follow-up changes in teachers' adoption, engagement, satisfaction and learning outcomes over time with AI-supported MOOCs. This deep dive would elucidate how initial intentions get translated into prolonged use and professional growth.

5.2. Measurement Limitations

The research depends on self-reported survey data, which can introduce issues of social desirability, recall, and overestimation of usage behaviours. Future studies can enhance the findings of a survey with the use of learning analytics, AI tracking metrics, and logs of objective system usage to yield better assessments of real engagement and learning outcomes.

5.3. Technological Limitations

The study examined MOOCs as a generic digital learning platform without consideration of the design variations, the use of AI, content types, or different levels of interactivity. In future research, specific AI-enhanced MOOC platforms may be examined, where features such as adaptive learning, personalized feedback, gamification, or AI tutoring may be compared to check which features enhance adoption, satisfaction and learning outcomes.

5.4. Behavioral and Psychological Limitations

Although other psychological or motivational constructs, such as intrinsic motivation, professional identity, perceived competence, or cognitive load, were not analyzed, constructs such as attitude, behavioral intention, and satisfaction were. The future studies should receive attention of the various dimensions that will help in unravelling the cognitive and affectives mechanism.

5.5. Organizational And Policy Limitations

The study ignored broader institutional, administrative, or policy-level issues, such as demands for professional development incentives, digital infrastructure, leadership support, or compulsory training requirements. Inclusion of that in future studies may shed light on how organizational and policy contexts interact with individual perceptions to influence the adoption of AI-supported MOOCs.

5.6. Learning Outcomes And Effectiveness

In the end, the focus of the study was on adoption, intention and satisfaction. They did not measure anything relating to the actual learning or skills improvement in participants and professional growth which happens due to participation in AI-supported MOOC. Future studies must make use of a performance assessment, knowledge tests or classroom application metrics to evaluate the efficacy of MOOCs in enhancing teachers' professional development.

5.7. Future Directions

Based on these limitations, future research could. Include additional technological, psychological, and organizational factors in the conceptual model.

- Conduct site-appropriate cross-cultural studies for broader generalizability.
- Use experimental designs to exhibit enhanced positive impacts and lasting participation in ICT use.
- Use AI-driven analytics to integrate objective usage and learning outcome data.
- Explore and investigate selected features of MOOCs driven by AI to unveil effective professional development opportunities.
- Understand how multiple factors, including cognitive and behavioral, motivate farmers to adopt an innovation.
- Experts would assess what changes AI-supported MOOCs will bring in the long term to teachers' professional development and classroom transaction.
- Future research could help us understand how AI-supported MOOC adoption affects teacher professional development in a comprehensive, generalizable, and actionable manner. It can impact the implementation of educational technology in other contexts as well.

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