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Investigating Effective Teaching Standards for Mooc Academicians of Higher Education Institutions in Sindh, Pakistan: An Application of the Utaut Model

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Abstract

The motive of the article is to investigate the effective teaching standards for MOOC academicians at public universities in Sindh, Pakistan, and the application of the UTAUT model in the new context. This study utilized the UTAUT model to investigate the factors affecting academician intention regarding the acceptance and usage of MOOC in higher institutions. To achieve the research objectives, 497 responses were collected from MOOC academicians through a survey questionnaire to address the suggested hypotheses. Our findings represent the constructs DL, DP, ATM, EE, and FC have a greater impact on BI, which play a significant role in shaping ICT-based teaching and learning outcomes. However, the two constructs PE and SI did not show a significant impact on BI. This research study implication can lead to improved academicians teaching standards that align with the international teaching benchmarks and enhance the technology education landscape at national and international levels.

Keywords: Academician, Teaching standards, MOOC, Distance education, Higher institutions, Sindh Pakistan.

Introduction

The MOOC (Massive Open Online Courses) is the foundation of distance education platforms in collaboration with higher education institutions that purpose to increase the overall accessibility of high-quality education in advanced studies to expedite the landscape of e-learning. In addition, MOOCs play a vital role in the digital age by providing accessible, flexible, and diverse learning opportunities emerging with advanced technologies in education (Sabjan et al., 2021). The MOOC in distance education focuses on enhancing the high-quality educational experience that aligns with the needs of a dynamic and interconnected global society (Castaño-Muñoz et al., 2018). The MOOCs offer to access an internationally certified wide range of courses from well-reputed universities that play a significant role in serving both national and international learners to achieve their educational goals (Qureshi, 2019). The success of MOOCs in distance education depends on academician teaching methods and techniques to instruct professionally in integrating digital literacy and pedagogical methods for clear communication that's strongly influenced by learners' achievements. According to researchers (Khalil et al., 2017; Akram et al., 2021; Shah et al., 2024), an academician is a person or individual who brings deeper knowledge and experience that contributes to the credibility and authenticity of the course learning objectives and attract

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learners who seek guidance from experts in the subject matter. In addition, academicians should be well-prepared in designing learning objectives to help learners understand what they are expected to learn and achieve by the end of the course (Koukis & Jimoyiannis, 2019). The high-quality content and modernized teaching techniques are presented engagingly and interactively to increase learners' motivation and comprehension toward their academic studies for their long-term success emphasized by Perveen, (2018). Primarily, MOOCs as a unique and impactful area within the broader landscape of online education therefore, all the stakeholders especially academicians adopt a new mode of teaching skills that are crucial for effectively navigating and utilizing online teaching tools related to advanced technology and pedagogy principles (Albelbisi et al., 2021; Ho et al., 2023). Sahito et al. (2022), urged that integrating technology and pedagogy skills in online learning platforms empowers academicians to create engaging, personalized, and effective learning experiences that meet the diverse needs of learners, adaptive collaboration and communication, enhance the instructional design, provide valuable data insights, and prepare learners for success in the digital age. Researchers Anthony, (2022), suggested that blending face-to-face instruction with online learning activities allows academicians to combine the benefits of traditional teaching methods with digital tools to accommodate different learning preferences and provide flexibility for learners while maintaining support and guidance from their facilitator. Applying Universal Design for Learning principles ensures that online courses are accessible and inclusive for broad learners to fulfil diverse learning needs.

Past studies revealed (Khalil et al., 2017; Akram et al., 2021; Albelbisi et al., 2021; Ho et al., 2023; Sahito et al., 2022), that research communities contributed to their investigation, the inadequate teaching methods can significantly impact the quality of MOOCs, leading to disengaged learners, and tarnishing the reputation of higher institutions. In addition, consistently low-quality MOOCs can undermine the overall credibility of higher institutions in distance learning programs, leading to a broader questioning of its academic standard. On the other hand (Tømte, 2019; Perveen, 2018; Qureshi, 2019), learners who have experienced insufficient teaching practices of academicians in MOOCs may express lower levels of satisfaction, and negative reviews may cause a reduction its attractiveness in future learning.

By considering the facts, this study aims to investigate effective teaching standards for MOOC academicians in distance education for higher institutions in Sindh, Pakistan. Additionally, this research also focused on understanding the significant factors influencing academicians' intention toward the acceptance of MOOCs. Furthermore, this study needs to be investigated for maintaining high teaching standards that require international teaching benchmarks in online education and protecting the reputation of higher institutions.

Related Work

This section helps researchers to identify challenges or inconsistencies in the current body of knowledge from existing literature (Van Lange Paul, 2015). Therefore, gauging the literature is crucial before conducting the research study. According to researchers (Khan et al., 2018; Albelbisi et al., 2021; Shah et al., 2024), the MOOC platform is a new entrant in the distance learning platform that heavily relies on technological tools and pedagogical knowledge to design effective teaching strategies that align with the required international teaching standards. In a study by researchers Wang et al. (2021), In MOOC, the integration of digital literacy skills and instructional techniques helps and supports academicians in developing high-quality teaching strategies that significantly impact to ensure the learning experience and learners satisfaction. Another study by researchers (Bayne & Ross, 2014; Soyemi et al., 2018; Khalil et al., 2017), recommended that inadequate digital literacy skills and poor pedagogical approach may hinder academicians from creating interactive and effective learning environments that optimize student learning outcomes in online educational settings. Academicians who lack opportunities for professional expertise in online teaching standards may cause the failure of MOOCs and undermine performance in higher institutions (Balula, 2015). Furthermore, another study by researchers Morris & Stommel, (2017), stated that the majority of academicians may hesitate to adopt innovative, modern, and professional teaching strategies in online educational platforms because of a lack of confidence in their ability to incorporate digital tools into their teaching strategies. Along the same lines (Rodés et al., 2021), unclear instructional methods may not create a satisfactory learning environment in MOOCs. He also stated, that clear and structured teaching practices significantly impact the learners' achievement and teachers' efficacy. In past research by (Sabjan et al., 2021; and Khalid et al., 2021), academicians who lack the necessary teaching skills can deliver confusing content with poor course objectives, and a lack of interactive elements leading to questions about the course's academic rigour. Additionally, low-quality teaching strategies can undermine enrolment and trust among learners and institutions' ability to expand their online programs. Other researchers (Marta-Lazo et al., 2019; Morris & Stommel, 2017), asserted that the reputation of higher institutions can promote and compete when academicians set clear course objectives and adopt effective instructional delivery methods using technological tools and pedagogy principles to improve the quality offerings of MOOCs and broader reach for quality education on a global scale. According to researchers (Javed et al., 2023; Qureshi, 2019), although the majority of the researchers have made contributions in their investigations of the problem, still there is a gap concerning the subject of effective teaching strategies adopted by academicians toward the acceptance and use innovative MOOCs in distance education of higher education in Sindh, Pakistan.

Numerous models have been recommended and suggested by researchers to understand the individual's perception and concerns regarding new innovative technology acceptance and utilization such as TPB, TRA, TTF, TAM, Extended TAM, UTUAT, and UATUT2 (Oye et al., 2014). In a study by researcher (Srivastava et al., 2022), UTAUT appears to draw special notice due to its comprehensiveness. In the same line, (Altalhi, 2021), stated that the UTAUT model is widely recognized and measures the acceptance level for various technological contexts such as (e-learning, e-government, e-business, and e-banking platforms). Moreover, (Altalhi, 2021), also asserted the UTAUT is "a model used to determine how the success rate of e-learning users and model aligns well with educational institutions". Moreover, In another study (Samaradiwakara & Gunawardena, 2014), the researchers applied a comparative analysis of the technology acceptance model by considering three parameters of each model likewise constructs, moderators, and explanatory ability (R^2). (Samaradiwakara & Gunawardena, 2014), the researchers found the UTAUT model explanatory power is higher for technology usage intention which is equal to (0.69) rather than others, TAM (0.52), MPCU (0.47), TPB (0.46), and the rest of the models ranging from (0.36-0.40) explained variance (R^2) respectively. The UTAUT model proposes four key integral constructs i.e. performance expectancy, effort expectancy, social influence, and facilitating conditions. Additionally, demographic variables such as gender, age, experience, and voluntariness of use can influence the relationship between these factors and behavioural intentions to the actual usage (Venkatesh et al., 2003).

The current research applies the amended UTAUT model (Unified Theory of Acceptance and Use of Technology) for the successful MOOC setup in distance education of higher institutions in the province of Sindh, Pakistan, understanding the significant factors that influence the effective utilization of MOOCs. The survey data were gathered from academicians or teachers especially those who are engaged and delivered MOOCs from well-reputed public universities located in metropolitan cities in the province of Sindh, Pakistan. Utilizing the quantitative research method, data collection instruments were designed to gather data for this research study. Using SEM (Structural Equation Modelling) the research model with suggested factors' predictive behavior was confirmed.

Research Model

It is very inclusive research in the field of IT/IS behaviour that has been compiled by Venkatesh et al. (2003), which involves pertaining methods and applications of the UTAUT model. This research contribution provided the other researchers with the foundation to further test and validate the research proposed models. The UTAUT model adoption enables researchers to assess the hindrance that occurs while examining online learning platforms like MOOCs. According to (Venkatesh et al. 2003), UTUAT is the chief theoretical model that serves as a valuable tool for researchers seeking to understand the factors influencing individuals' behaviour for acceptance of e-learning-related platforms. The proposed research model which is used to support our findings is illustrated in Figure. 1, in the section. The proposed model integrates certain aspects that were hypothesized as factors to predict the Use of MOOC (UM) for achieving research objectives. The factors included Performance Expectancy (PE), Effort Expectancy (EE), Social Influences (SI), Facilitating Condition (FC), and Behavior Intention (BI), by adding other external factors such as Digital Literacy (DL), Digital Pedagogy (DP), and Attitude towards MOOC (ATM), In addition, demographic or categorical variables likewise Gender, Age, Qualification, and Experience considered in the proposed model with hypothesized relation. The expected theories and models align with the earlier background. We have derived the hypotheses in light of the applied theoretical framework in the following section.

Digital Literacy (DL)

Digital literacy is also referred to as "Information Literacy", Computer literacy", and "Technology Literacy" which involves proficiency in basic digital skills such as using computers and operating software applications considered to be essential skills in the digital age (Pasha, 2016). Digital literacy skills enable academicians to use various features and navigate the MOOC platform to create engaging content, facilitate interactions, and assess learners' progress confidently. According to research by (Soyemi et al., 2018; AlQaidoom & Shah, 2019). inadequate use of digital literacy using MOOC platforms may hinder academicians' ability to facilitate interactive learning experiences which decreases learners' participation and satisfaction. A study by McAuley (2010), also stated that academicians lacking digital skills may produce inappropriate outcomes that are perceived as outdated, unengaging, and potentially damaging to the reputation of the higher institution and undermine the quality performance of MOOC in distance education. Additionally, academicians who lack digital literacy may struggle to navigate these platforms efficiently, leading to frustration and inefficiency in course management (Pasha, 2016; Mailizar et al., 2022).

Digital pedagogy (DP)

Pedagogy principles refer to the fundamental theories and guidelines that inform the practice of teaching and learning. In addition, the pedagogy principles guide academicians in designing high-quality instructional strategies, creating learners-centric knowledge, and facilitating meaningful learning experiences for learners' engagements (Wadmany & Kliachko, 2014). Since technology emerged with education it has become renamed by digital pedagogy which encompasses the methods, strategies, and approaches that are essential for academicians to engage learners with high-profile international teaching standards (Nanjundaswamy et al., 2021). Moreover, digital pedagogy equips academicians with the necessary digital literacy skills and the ability to integrate them into their professional teaching techniques required to align with the teaching benchmarks which is most important for clear content delivery and learner satisfaction. The past study revealed (Irfan et al., 2021; Abid et al., 2021) asserted that academicians who undermine knowledge of digital pedagogy may inadvertently create barriers to accessibility for learners with diverse learning needs and fail to achieve course objectives with convenience features such as closed captions, alternative text, or ordered presentations can exclude learners with incapacities from their ability to fully participate in the MOOC platform. On the other hand (Nanjundaswamy et al., 2021; Rodés et al., 2021; Ho et al., 2023), asserted that academicians without effective digital pedagogy can lead to inefficiencies in course delivery and incompetence in the use of technological tools creating confusion among learners which can be frustrating for both academics and learners.

Attitude towards MOOC (ATM)

The academician attitude toward MOOCs in distance education platforms can vary depending on their experiences and personal preferences which may embrace online platforms as opportunities to innovate in their teaching practices and reach broader learners at the national and international levels (Ab Jalil et al., 2019). According to the recommendation by researchers (Bakogianni et al., 2020), a positive academician attitude has a significant impact on effective teaching delivery in online teaching and an enthusiastic attitude can inspire learners to engage actively in learning whereas a negative or indifferent attitude may dampen learners' motivation and enthusiasm for learning. According to the researchers (AlQaidoom & Shah, 2019), a proactive and positive attitude toward online class management promotes consistency, fairness, and clear expectations, minimizing disruptions and maximizing instructional time.

Performance Expectancy (PE)

The performance expectancy concept describes the degree to which a person thinks that utilizing a specific technology will enable them to perform better at work (Altalhi, 2021; Haron et al., 2021). Academicians who are engaged in delivering MOOC, performance expectancy relates to their belief that incorporating effective teaching methods enhances learners' learning outcomes (Wang et al., 2021). Academics who perceive MOOCs as effective tools for delivering content, engaging learners, and promoting learning are more likely to integrate them into their teaching practices.

Effort Expectancy

Effort expectancy refers to the degree of ease associated with the use of a technology. In the context of MOOCs in distance education, effort expectancy relates to academicians' perceptions of how easy or difficult it is to use MOOC platforms for higher institutions and incorporate them into their teaching principles (Irianto et al., 2023; Srivastava et al., 2022). Academicians who perceive MOOCs as user-friendly and intuitive are more likely to adopt them as effective teaching tools (Alotaibi, 2023).

Social Influence

Social influence refers to the influence of social factors such as norms, opinions, and support from peers, colleagues, or administrators on individuals' acceptance and use of technology (Wang et al., 2021; Altalhi, 2021). In the context of MOOCs, social influence may manifest through support from colleagues, peer recommendations, or professional development opportunities related to academicians' online teaching. Positive social influence can encourage academicians to deliver effective teaching techniques and provide them with the necessary support and resources to do so (Wan et al., 2020).

Facilitating Condition

Facilitating conditions refer to the extent to which individuals perceive that organizational technical support is available to facilitate the appropriate use of technology (Alotaibi, 2023; Li, Yalin, and Min Zhao, 2021). In the context of MOOCs, facilitating conditions may include access to technical support and infrastructure that support the integration of MOOCs academicians into best teaching practices. Adequate facilitating conditions can reduce barriers to adoption and enable academicians to successfully implement MOOCs in their teaching principles (Irianto et al., 2023).

Behavior Intention

Behavioural intention reflects individuals' plans to use technology in the future (Chen et al., 2023). In the MOOC context, behavioural intention is used as a dependent or direct predictor of actual technology usage. Behaviour intention is a key determinant of understanding how and why academicians engage and deliver MOOCs. By addressing the determinant of BI (Srivastava et al., 2022; Li, Yalin, and Min Zhao, 2021; Chen et al., 2023). In addition, BI is the strongest predictor of actual user behaviour which reflects the academician willingness and intention to use of MOOC platform.

Use of MOOC

This refers to the observable action of the users when interacting with a technology. The actual use of MOOCs in the UTUAT model is a vital component of understanding the practical application and effectiveness of MOOCs by focusing on the prediction of Behavioural intention (Wan et al., 2020; Srivastava et al., 2022; Li, Yalin, and Min Zhao, 2021).

Based on the above hypotheses, we have validated the study of the research model below, creating our research model based on the amended UTAUT model as shown in Figure 1.

Relationship of Suggested Hypotheses

H$_{1:}$ Digital literacy has a significant impact on the behaviour intention towards the acceptance and use of MOOCs.

H$_{2:}$ Digital pedagogy has a significant impact on the behaviour intention towards the acceptance and use of MOOCs.

H$_{3:}$ Attitude toward MOOCs has a significant impact on the behaviour intention towards the acceptance and use of MOOCs.

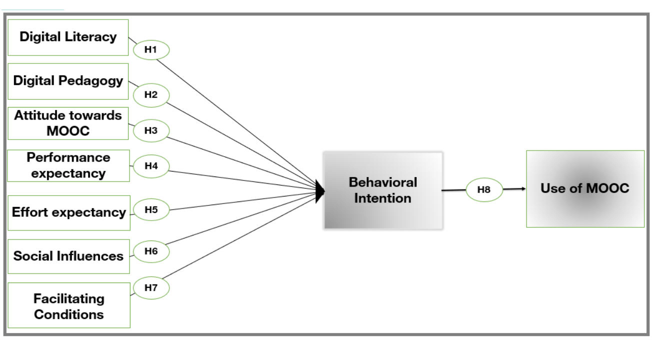


Fig. 1: Research Model

H$_{4:}$ Performance expectancy has a significant impact on the behaviour intention towards the acceptance and use of MOOCs.

H$_{5:}$ Effort expectancy has a significant impact on the behaviour intention towards the acceptance and use of MOOCs.

H6: Social influence has a significant impact on the behaviour intention towards the acceptance and use of MOOCs.

H7: Facilitating conditions have a significant impact on the behaviour intention towards the acceptance and use of MOOCs.

H8: Behavior intention has a significant impact on the actual use of MOOCs.

Research Methodology

Development of Data Collection Instrument

The data instrument is comprised of academicians who delivered MOOCs in distance education from well-reputed public institutions. For the quantitative approach method (Nakagawa et al., 2023), a survey questionnaire was issued to validate the hypotheses to determine the significant impact of constructs under investigation and to serve the research purpose (Altalhi, 2021; Wadmany & Kliachko, 2014). The survey questionnaire was designed and composed of a total of 39 items considering from past studies (McAuley et al., 2010; Bakogianni et al., 2020; Wang et al., 2021). The initial part of the questionnaire contained demographic information of all participants such as gender, age, experience in delivering MOOC, etc. The second part addresses the importance of constructs likewise Digital literacy (DL, having four items), Digital Pedagogy (DP, having five items), Attitude toward MOOC (ATM, having three items), Performance Expectancy (PE, having three items), Effort Expectance (EE, having three items), Social Influence (SI, having three items), Facilitating Condition (FC, having three items), Behavior Intention (BI, having four items), and Use of MOOC (UM, having three items). All of the elements had an impact on behaviour intention toward the impactful usability of the MOOC platform. The survey questionnaire included a five-point Likert scale starting with (1-strongly disagree) and ending with (5-strongly agree) (Tseng et al., 2022). The survey questionnaire form was designed in Google form format and shared a link to the targeted audiences through official emails and WhatsApp groups of faculties to collect valuable thoughts. Using the collected responses, the researchers examine the assessment of the (Measurement Model and Structural path estimation) using the Partial Least Square-Structure Equation Modelling (PLS-SEM) techniques (Sadriddinovich, 2023; Purwanto, 2021).

Participants

This research study collected 497 responses from academicians who are teaching at six public universities that designed MOOCs in Sindh province, Pakistan. The targeted public universities are the University of Karachi, Sindh Madarsatul Islam University, the University of Sindh, Sukkur IBA University, and Shah Abdul Latif University. The selected universities have existed in highly populated cities such as Karachi, Hyderabad, and Sukkur in the province of Sindh, Pakistan. Based on collected responses, the study analyzed the research model using SPSS and SmartPLS4 and managed the digitized survey instrument to not allow missing values and outliers (Templ, 2023; Purwanto, 2021). The data was examined concerning the structural equation model by the researchers to determine the sample size.

Findings and Discussion

Descriptive Statistics

The demographic variables were adopted to classify the responses in the survey instrument. These factors included gender, age, qualification, and experience for MOOC usage in distance education. The sampling size considered for this purpose was 310 males and 187 females out of a total of 497 academicians representing in percentage (62.4%) and (37.6%) respectively. The majority of these academicians 133 numbers were aged between 31-35 in percentage (26.8%) remaining the second highest 83 numbers were aged between 26-30 in percentage (16.7%), 80 number were aged between 18-25 in percentage (16.1%), 73 number were aged between 41-45 in percentage (14.1%), 63 number were aged between 36-40 in percentage (12.7%), 35 number were aged between 46-50 in percentage (7.1%), and 29 number were aged 50+ in percentage (5.8%). The academicians' qualifications were 96 Ph. D's. per cent (19%), 320 Master's in per cent (64.4%), and 80 Bachelor's in per cent (16.6%). The MOOC academicians 260 experienced less than a year per cent (54.4%), number of academicians 143 experienced between 1-2 years per cent (28.8%), number of academicians 30 experienced between 3-4 years per cent (6%), number of academicians 22 experienced more than five years percentage (4.4%), number of academicians 21 experienced between 2-3 years per cent (4.2%), number of academicians 10 experienced between 4-5 years per cent (2%). According to our demographic findings, we are not considering gender and age as important because any gender and age group can be engaged in delivering MOOC, the targeted focus is on the academicians' qualifications and experience the results indicate that the majority of academicians are highly qualified Ph.D. and Master (96 + 320 = 416 percent in total 83.4%) engaged in MOOC classes, Similarly, majority of the academicians involved less than a year and between 1-2 years experiences (260 + 143 = 403 percent in total 80.1%) were assumed having less experienced delivering MOOC. The bulk of the responses were collected from the cities likewise 245 were from Karachi (49.8%), 124 from Hyderabad (24.8%), 62 from Sukkur (12.6%), and 66 were collected from Khairpur (14%).

Reliability Analysis (Pilot Study)

Pilot studies provide an opportunity to test the validity and reliability of data instruments such as surveys, questionnaires, or measurement tools before conducting a final research survey. In this regard, 36 participants from targeted responses were randomly selected for the initial test. The Cronbach's Alpha test was applied to the construct items for measuring reliability. The acceptable and sufficient Cronbach's Alpha reliability coefficient is set at equal to or higher than **0.7** (Alshahrani & Walker, 2017). All the constructs' significance values are higher than 0.7 as shown in (Table 1). For the final study, the researchers decided to conduct since all the constructs' significance values could be regarded as reliable (Table 1).

The nine measurement scales of the questionnaire can be utilized in the current investigation because they are considered reliable as shown in the above table.

Measurement Model Analysis

SmartPLS is specifically designed for Partial Least Squares Structural Equation Modeling (PLS-SEM) which is well-suited for analyzing complex models with latent variables (Ramayah et al., 2018). Researchers (Ramayah et al., 2018), also stated PLS-SEM can combine factor loadings, regression analysis, and path analysis into a single comprehensive model, providing a holistic approach to data analysis. In this context, this research study utilized PLS-SEM to examine the assessment of the structural model and measurement

Table 1: Cronbach's Alpha survey measurement scale

No.	*Constructs*	*Items*	*Cronbach α*
1	Digital Literacy	04	0.883
2	Digital Pedagogy	05	0.896
3	Attitude towards MOOC	03	0.893
4	Performance Expectancy	03	0.877
5	Effort Expectancy	03	0.871
6	Social Influence	03	0.818
7	Facilitating Condition	03	0.807
8	Behaviour Intention	04	0.904
9	Use MOOC	03	0.844

model (Al-Mekhlafi et al., 2022). The measurement model (outer model) is described as the relation between indicators themselves, whilst the relationship between latent constructs themselves is referred to as a structural model. According to Edeh et al. (2023), the highest probability technique was used to measure the suggested research model using SEM-PLS. Reliability and convergent validity were determined by a variety of metrics including Factor Loadings, Composite Reliability, and Average Variance Extracted. A higher load number helps to indicate the dimensionality of the factors. For assessing reliability, the Composite Reliability (CR) metric is a helpful tool. By providing a correct value through factor loadings in the created formula, CR performs a similar job. The average amount of variation found in a particular variable that describes the latent construct is known as Average variation Extracted or AVE. When the discriminate validity is greater than one factor, AVE can be used to assess the convergence of each factor. Table 1, shows that our experiment's results for data instrument reliability and convergent validity exceed the necessary criteria for these concepts. Table 2 summarizes the data instrument validity and reliability and shows the evaluation findings for each factor as a function of the variable that was obtained from the data instrument.

Assessment of Measurement Model (Outer Model)

Convergent Validity

The application of indicators such as factor loadings, variance extraction, and reliability, which comprise Cronbach's Alpha and composite reliability determines the relative degree of convergent validity. According to Goretzko et al. (2024), when a construct's composite reliability (CR) and reliability coefficient for all constructs are greater than 0.7, it indicates that there is internal consistency across many construct measures. Table 2 provides evidence by showing that the constructs Cronbach's alpha scores are greater than 0.7 ranging between **0.807 and 0.904,** respectively (Alshahrani & Walker, 2017). For each construct, composite reliability (C.R) is computed and compared to the cut-off value of 0.6 by (West et al., 2023). The (C.R) composite reliable values for Performance expectancy were (0.842), attitude towards MOOC was (0.791), effort expectancy was (0.782), social influence was (0.774), facilitating condition was (0.727), digital literacy was (0.793), digital pedagogy was (0.847), behaviour intention was (0.914), and Use of MOOC was (0.772), ranges between **0.727-0.916** respectively, to achieve the concepts of convergent validity. Moreover, it is expected that the concepts of average extracted variance will exceed the minimum criterion of 0.5. However, this condition may only apply to the constructs facilitating condition since its AVG is 0.487. According to Cheung et al. (2023), when AVG is below 0.5 and composite reliability is above 0.6, the convergent validity of the constructs is sufficient. Moreover, the researchers suggested (Alshahrani & Walker, 2017; Muhamad Safiih & Azreen, 2016), that when the significance of AVG is lower than 0.5 and CR is higher than 0.6, the construct is valid because this situation may occur during biased insight from respondents. In our findings, the AVG obtained values for performance expectancy was (0.641), attitude towards MOOC was (0.558), effort expectancy was (0.0.546), social influence was (0.544), facilitating condition was (0.487), digital literacy was (0.501), digital pedagogy was (0.527), behaviour intention was (0.733), and Use of MOOC was (0.541) ranging between **0.487-0.733** respectively. Convergent validity was demonstrated as evidenced by the composite reliability values, which were greater than 0.6 for every construct, Table 2. Shown the convergent validity findings.

Discriminant Validity

Table 2, demonstrates that all requirements for the discriminating validity are met because the AVE values are greater than the squared correlation between the constructs in the measurement model. As discussed in section 5.2.1.1, the construct should identify at least 50% for the measurement variance if an AVE value is more than 0.5 (Cheung et al., 2023). Partial Least Squares were used to determine the discriminant value using (SmartPLS). Table 2, displays the loadings and cross-loadings which seems a careful analysis, loadings and cross-loadings reveal that each measurement item is broadly loaded on its own latent constructs as opposed to loading on other constructs. Table 3, shows the results of the AVE analysis. The table's bold diagonal parts indicate the square root of the AVE scores. On the other hand, off-loading diagonal elements show the correlation between the constructions. The data indicates that the square root of the AVE values is present and exceeds the usual value of 0.5, falling between the ranges of **0.697-0.856**. The AVE appears to be larger than all other correlations for each construct, indicating that the variance of each construct with its own measures is larger than that of the other constructs in the model emphasizing the discriminate validity.

The Structural Path Assessment (Inner Model)

Coefficient of determinant -R^2

The coefficient of determination (R^2 value) measure is essentially utilized by analyzing the structure model (Verhulst

Table 2: Convergent validity acceptable results

Constructs	Items	Loading	Cronbach's	CR	AVG
Performance expectancy	PE1	0.817	0.839	0.842	0.641
	PE2	0.811			
	PE3	0.773			
Attitude towards MOOC	ATM1	0.786	0.804	0.791	0.558
	ATM2	0.708			
	ATM3	0.753			
Effort Expectancy	EE1	0.789	0.875	0.782	0.546
	EE2	0.654			
	EE3	0.767			
Social Influence	SI1	0.867	0.771	0.774	0.544
	SI2	0.783			
	SI3	0.518			
Facilitating Condition	FC1	0.847	0.743	0.727	0.487
	FC2	0.449			
	FC3	0.742			
Digital Literacy	DL1	0.791	0.795	0.793	0.501
	DL2	0.792			
	DL3	0.447			
	DL4	0.741			
Digital Pedagogy	DP1	0.701	0.846	0.847	0.527
	DP2	0.739			
	DP3	0.829			
	DP4	0.681			
	DP5	0.673			
Behavior Intention	BI1	0.838	0.916	0.914	0.733
	BI2	0.834			
	BI3	0.849			
	BI4	0.902			
Use of MOOC	UM1	0.805	0.767	0.772	0.541
	UM2	0.849			
	UM3	0.507			

Table 3. Fornell and Larcker Scale

	BI	PE	ATM	EE	DP	DL	SI	FC	UM
BI	0.856								
PE	0.845	0.801							
ATM	0.777	0.781	0.747						
EE	0.666	0.543	0.501	0.739					
DP	0.791	0.739	0.696	0.631	0.726				
DL	0.552	0.553	0.522	0.515	0.646	0.707			
SI	0.416	0.352	0.334	0.417	0.406	0.343	0.737		
FC	0.571	0.551	0.475	0.426	0.523	0.455	0.504	0.697	
UM	0.666	0.543	0.507	0.469	0.551	0.333	0.631	0.583	0.736

& Neale, 2021). This coefficient also supports the assessment of the predicted accuracy of the model (Sarstedt et al., 2022). It is expressed as the squared correlation between the actual and expected values of a certain endogenous construct. The coefficient represents the combined effect of exogenous latent factors on an endogenous latent variable. Every recognized exogenous construct protects the extent of the variance of the endogenous constructs since the coefficient presents the squared correlation between the actual and expected values of the variables. According to (Wong, 2013; Sarstedt et al., 2022), high power is indicated by values greater than 0.67, whereas direct qualities are found between 0.33 and 0.67, and weak qualities are found between 0.19 and 0.33. A value of less than 0.19 is deemed ineligible. Figure 2 shows that the model has high predictive power which supports the higher percent as per the concepts of coefficient of determination. Table 4, illustrates the excellent predictive value of the model, which accounts for approximately 92% and 67% of the variance in the behavioral intention and use of MOOC, respectively.

Table 4. The endogenous latent variable R^2

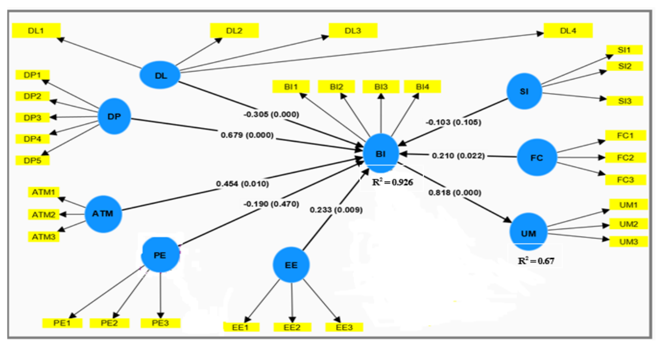
	R2	Results
BI	0.926	High
UM	0.670	High

Path Coefficient - Test of the Hypotheses

To evaluate the relationship between the structural model's theoretical constructs to analyze the suggested hypotheses, a structural equation modeling with the maximum likelihood estimation (MLE) was implemented using (Smart PLS Ver. 4) (Ramayah et al., 2018; Wong, 2013). In addition, in SEM, MLE is used to estimate the parameters by both the measurement model and structural model. Table 5 and Figure 2 represent the summary of the results related to the structural model; therefore, it is evident that six hypotheses were determined to be significant except for two hypotheses. Digital Literacy (DL) ($b = -0.305$, $P < 0.001$) was found negatively but supported, Digital Pedagogy (DP), Attitude towards MOOC (ATM), Effort Expectancy (EE), Facilitating Condition (FC), Behavior Intention (BI) ($b = 0.679$, $P < 0.001$), ($b = 0.454$, $P < 0.001$), ($b = 0.233$, $P < 0.009$), ($b = 0.21$, $P < 0.022$), and ($b = 0.818$, $P < 0.001$) respectively. The finding shows that DL, DP, ATM, EE, and FC have significant effects on BI. Hence, hypotheses H1, H2, H3, H5, and H7 were supported by the empirical data, similarly, H8 had a significant impact on UM accepted. While Performance Expectancy (PE) ($b = -0.19$, $P < 0.470$) and Social Influence (SI) ($b = -0.103$, $P < 0.105$), the effect of PE and SI on BI were found negative and not supported. The suggested research hypotheses were evaluated with the help and support of partial least squares structural equation modeling (PLS-SEM). Performance analysis was used to carefully evaluate the structural model by looking at the variance explained (R-squared value), structural routes, and t-statistics. The structural model is illustrated in Figure 2, and the results of the data analysis are stated in Table 5. Each hypothesis in the research model has a path significance and variance explained (R2) component, each of which was examined to verify the theories put forth.

Table 5: Structural Model Results: Research Hypotheses Significant

	Path	t - value	P val-ues	Direc-tion	Decision
BI → UM	0.818	27.261	0.001	Positive	Supported
DL → BI	-0.305	4.008	0.001	Negative	Supported
DP →BI	0.679	4.404	0.001	Positive	Supported
ATM → BI	0.454	2.568	0.001	Positive	Supported
EE → BI	0.233	2.62	0.009	Positive	Supported
FC → BI	0.210	2.297	0.022	Positive	Supported
PE → BI	-0.190	0.722	0.470	Negative	Not supported
SI → BI	-0.103	1.619	0.105	Negative	Not supported



Note: ($p^{**} < = 0.01$, $p^{*} < 0.05$)

Figure 2. Path coefficient values

Based on our analysis, we obtained three effects likewise (path coefficient is positive and hypotheses accepted), (path coefficient is negative and hypotheses accepted), and (path coefficient is negative and hypotheses rejected) respectively that need to be explained and discussed.

The first effect, digital pedagogy refers to hypothesis H2, DP to BI suggests that academicians who have a strong understanding and proficiency in digital pedagogical knowledge are more likely to intend to use MOOCs in their effective teaching practices. This relationship may be explained by the perception that effective pedagogical knowledge enhances the quality of instructional methods with the integration of ICT tools to promote the online learning experience of broad learners and achieve learning outcomes. The finding of H2 is presented in the past study concluded by researchers (Nanjundaswamy et al., 2021; Rodés et al., 2021; Susanto et al., 2020). Attitude towards MOOC refers to hypothesis H3, ATM to BI indicates that academicians who hold positive attitudes towards MOOCs are more likely to intend to use them in their teaching practices. This relation may be attributed to the perception that MOOCs offer valuable opportunities for expanding access to education and enhancing teaching effectiveness. The H3 findings related to a study by Virani et al. (2023), investigated the same significant impact in their study. The effort expectancy refers to hypothesis H5, EE to BI suggests that academicians who perceive MOOCs as easy to use and integrate into their teaching techniques are more likely to intend to use them. This relationship may be driven by the belief that user-friendly and accessible MOOC platforms in distance education of higher institutions facilitate the acceptance of online teaching methods effectively. The finding of H5 is reported in the previous study conducted by the researcher (Tsang et al., 2022), Facilitating conditions refer to hypothesis H7, FC to BI, emphasizing the importance of institution investment in providing resources and support to facilitate effective online teaching and enhance the quality performance of MOOC offerings (Khalid et al., 2021). Behavior intention refers to hypothesis H8, this relationship indicates that behavioral intentions translate into actual behavior meaning that academicians who intend to use MOOCs are motivated and more likely to take concrete steps integrating them into their effective teaching practices. Academicians' intentions to use MOOCs are influenced by various factors, such as their perceptions of MOOCs' utility, their attitudes toward using digital technologies, and the corporate support and resources available to them. The relevant finding of H8 was reported in a previous study (Khalid et al., 2021).

The second effect, Digital literacy referred to as hypothesis H1 was supported and found to be negatively related to BI, the relation DL to BI suggests that academicians with higher levels of digital literacy have lower behavioral intentions to use MOOCs in their teaching methods. Highly digitally literate academicians may have concerns about the effectiveness or relevance of technology in enhancing teaching and learning outcomes. They may perceive traditional teaching methods as more effective or suitable for their teaching context, resulting in lower intentions to use technology like MOOCs. Consequently, despite their digital literacy skills, academicians may perceive the integration of technological tools towards MOOC platforms as complex or time-consuming. They may be hesitant to invest the effort required to learn and adapt to new technologies leading to lower behavioral intentions to use online learning platforms like MOOCs. The same findings in H1 represented to support the previous study investigations by researchers (Khalil et al., 2017; Alanoglu et al., 2022; Mailizar et al., 2022).

The third effect, performance expectancy refers to hypothesis H4, A negative path coefficient from PE to BI was found rejected suggesting that academicians who perceive MOOC platforms as less effective for their teaching purposes are less likely to have intentions to use them. Academicians may face resistance or doubts about the adoption of MOOC platforms due to concerns about their effectiveness, relevance, or alignment with traditional teaching practices. This resistance to change may lead to negative perceptions of the usefulness of MOOCs and decrease intentions to use them. In addition, as a result, they may not see a direct connection between the technological teaching performance benefits and their intentions to use it. On the other hand, social influence refers to hypothesis H6, A negative path coefficient from SI to BI was found rejected, the finding implies that external pressures from social networks and institutional contexts do not positively impact academicians' intentions regarding the acceptance and use of MOOC platforms for teaching purposes. Organizational norms and culture may not align with the acceptance and use of MOOC platforms for teaching purposes leading to negative social influence on academicians' intentions. Overall, the negative paths from Performance Expectancy and Social Influence to Behavioral Intention suggest that perceived usefulness and social support do not positively influence academicians' intentions to use MOOC platforms for teaching purposes. The same findings in H1 represented to support the previous study investigations by researchers (Wang et al., 2021; Oye et al., 2014; Sewandono et al., 2023; Bag et al., 2022; Šumak et al., 2010).

Conclusion

Based on our investigation, the performance expectancy (PE) and social influence (SI) were not supported. PE suggested the academician may not see a direct connection between the technological teaching performance benefits and their intentions to use MOOC because academicians with high technological self-efficacy may not see the expected performance benefits from technology adoption. While SI finding implies that external pressures from social networks and institutional contexts do not positively impact academicians' intentions regarding the acceptance and use of MOOCs. Academicians teaching MOOCs, particularly focused on digital literacy DL, digital pedagogical DP, and positive attitudes ATM were considered crucial indicators to enhance effective teaching techniques towards online-related learning platforms like MOOCs in distance education programs initiated by higher institutions in Sindh, Pakistan. Moreover, the effort expectancy EE and facilitating conditions FC also play a pivotal role in academician teaching practices ensuring the MOOC platform is user-friendly and providing institutional support were key factors in enhancing the quality of MOOCs and the overall educational experience. These elements collectively play a significant role in maintaining high teaching standards, which in turn contribute to the strong reputation and success of distance learning programs of higher institutions in the province of Sindh, Pakistan. In addition, MOOCs attract learners from around the world and increase the institution's visibility on a global scale.

The behavior intention BI was tested using an eminent variance R-squared, and the result was 92% ($R^2 = 0.926$) and the variance of factor use of MOOC UM was 67% ($R^2 = 0.67$). This validates the significance of relevance and explanatory power of the research model.

Limitations and Future Work

Similar to all empirical studies, certain limitations to this research should be noted and addressed. In this research context, the selected few public universities from a particular province may limit the applicability of the study findings such as unique cultural, socio-economic, and educational contexts to the broader populations or settings. Additionally, the inclusion of a limited number of institutions within the selected province may restrict the representativeness of the study sample.

Future research endeavors should explore additional factors influencing acceptance such as evaluation mechanisms and learner engagement strategies to further enhance our understanding of MOOC platforms and include multiple provinces or regions to enhance generalizability and capture diverse perspectives for distance education in higher institutions. Ultimately continued collaboration and innovation in this field are essential to meet the evolving needs of academicians and learners in today's dynamic educational landscape.

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