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Significant Predictors Influencing the Adoption of ChatGPT Usage in the Academia in Sindh, Pakistan: Extension of UTAUT Model

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Abstract

The innovative ChatGPT AI-based application is considered a supplemental tool for learners to assist and guide broader academic information and research opportunities in various domains. This study uses the modified UTAUT model to investigate the significant predictors influencing the learners' intention to adopt ChatGPT in academia in Sindh, Pakistan. The learners' intention to adopt the ChatGPT tool is assessed based on significant predictors such as DS, HCI, PE, EE, SI, and FC as key indicators influencing the ChatGPT adoption. The research model and suggested hypotheses were addressed using a quantitative technique. Data gathered from 497 respondents as learners from top-ranked public institutions in Sindh, Pakistan, was examined using the PLS-SEM approach. This research found that all significant predictors influencing learners' intention to adopt the ChatGPT tool and all predictors have a more significant impact. This research study can help administration and IT experts incorporate the skills and techniques associated with the ChatGPT tool in education in Sindh, Pakistan.

Keywords: Significant predictors, ChatGPT usage, Academia, UTAUT model, Pakistan.

Introduction

Since technology evolved, advanced technology has been considered a valuable tool in modern education due to its ability to enhance teaching and learning experiences, improve educational outcomes, and facilitate access to knowledge to help prepare learners for success in the digital age Aleksic- Maslac & Magzan, (2012). In the context of modern education, a recently launched innovative AI-based application known as ChatGPT. Moreover, ChatGPT is an AI-powered conversational mediator application developed by OpenAI, Grassini (2023). It is based on the GPT (Generative Pre-trained Transformer) architecture, which has to be developed for generating human-like text responses in natural language Bitzenbauer, (2023); Neumann et al. (2023). According to researcher Trương (2023), the ChatGPT tool employs machine learning techniques to generate text-based input received from users and engaging conversations on a variety of topics and provide information on academic and research literature by Fauzi et al. (2023); Baidoo-Anu & Owusu Ansah, (2023).

Additionally, ChatGPT can provide personalized learning support to learners by answering questions, explaining concepts, and offering guidance on various academic content as well as existing research literature, it also interacts to receive instant feedback tailored to their individual needs and learning preferences Korzynski et

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al. (2023). ChatGPT can serve as a supplemental learning resource by providing additional explanations, examples, and resources to complement classroom instruction or course materials that assist learners in deepening their understanding of concepts, exploring related topics, and accessing relevant learning materials in various academic domains Rasul et al. (2023); Strzelecki, (2023); Woithe & Filipec, (2023). For effective use of ChatGPT assistance in academic studies, its operation and navigation depend entirely on digital skills and prompt phrasing input, which is assumed to be essential for clear communication and interaction Stofkova et al. (2022). Researchers suggested Korzynski et al. (2023) and Poola (2023) that digital skills help users to navigate tools and articulate their questions effectively; it can improve the quality of the interaction and the accuracy of ChatGPT's responses. Similarly, ChatGPT relies on text-based communication, so users must be able to phrase their queries and inputs clearly and concisely.

Consequently, Kocoń et al. (2023) and Dalgıç et al. (2024) stated that digital skills and prompt phrasing inputs are essential requirements for using ChatGPT because they facilitate effective communication, enable users to navigate digital interfaces, utilize features effectively, and critically evaluate responses, and adapt to new technologies to enhance academic-related activities in their learning experience for their future success. In the

recommendation by researchers Pirzada & Khan (2013) and Mujahid et al. (2023), by possessing these skills, the learners can maximize their benefits to integrate ChatGPT in their studies to achieve learning outcomes and engage in meaningful interactions with the AI system to understand how technology can be a helpful tool for their long-life career success. Consequently, ChatGPT emerges as a valuable educational tool capable of comprehensively addressing learners' diverse academic needs.

In this Modern era, technology holds the potential to bolster academic learning experiences. In lighting, ChatGPT's previous literature Bodani et al. (2023); Ansari et al. (2023); Menon & Shilpa (2023), several researchers have investigated various models for understanding key indicators influencing its limited acceptance and usage within academia, particularly in underdeveloped countries like Pakistan. According to recommendations by researchers Ashraf et al. (2022) and Rasul et al. (2023) have emphasized the significance of digital skills, highlighting that insufficient proficiency in this area may hinder the adoption of ChatGPT because it functions using artificial intelligence (AI) technology, which may be intimidating to learners without adequate digital literacy. Such deficiencies in digital skills pose challenges for learners and potentially lead to disengagement.

Conversely, other studies by Emon et al. (2023), Woithe & Filipec (2023); Ge & Wu (2023), have noted that steering conversations on ChatGPT interfaces toward specific topics can be difficult. The slight variations in phrasing may yield inconsistent responses, thereby compromising accuracy. However, ChatGPT's responses are observed to be sensitive to how questions are phrased and the adeptness with which prompt inputs are provided to ensure accuracy. Hence, considering all the facts, this research focuses on examining the predictors influencing the adoption of ChatGPT usage in academic settings, specifically in developing countries like Pakistan, and particularly in summarizing information across a broad spectrum of educational and research domains. This study aims to shed light on ChatGPT's role as a supplementary tool in educational endeavours; through its exploration, the research seeks to contribute to the learners' intention to adopt ChatGPT tools in academia and understand how advanced technology supports their academic needs and research activities.

Literature Review

This section assists scholars in identifying gaps or contradictions in the present body of knowledge from the available literature. Therefore, it is crucial to review the existing literature before conducting research. According to Bitzenbauer (2023); Neumann et al. (2023), urged that ChatGPT is an advanced technological AI-based text-generating tool that requires digital skills to operate and navigate the tool effectively. In the same way, clear command phrasing input is an essential skill for ChatGPT usage that helps and supports the individual's intention accurately. In addition, digital skills and precise phrasing as input are vital for ChatGPT usage because they facilitate effective communication, improve response quality, streamline interaction, minimize misunderstandings, maximize utility, and enhance learning experiences Korzynski et al. (2023). The individuals are developing these skills which can make the most of their interactions with ChatGPT and achieve their objectives more efficiently.

In light of ChatGPT literature by Bodani et al. (2023), Ansari et al. (2023), Mujahid et al. (2023), many researchers determined several theories and models by investigating their research contribution and suggested, despite ChatGPT being a valuable tool for learners in their academic and research studies but the majority of underdeveloped countries like Pakistan failed to adopt ChatGPT as a useful tool by lacking digital skills and phrasing for clear communication. Considering all these facts, this research intends to examine the significant predictors influencing learners' attitudes to adopt ChatGPT in academia in Sindh, Pakistan. According to Ashraf et al. (2022), Pirzada & Khan (2013) asserted that users with inadequate digital skills may need help to formulate clear and concise queries or prompts when interacting with ChatGPT, which can lead to misunderstandings or irrelevant responses from the AI On the other hand, according to Strzelecki (2023) and Woithe & Filipec (2023), learners who lack digital skills may have difficulty navigating and interpreting the responses generated by ChatGPT; this may cause misinterpretation of the information provided, which leads to confusion for learners. Although several researchers, Bibi & Atta (2024), have contributed to the overall research on the topic of ChatGPT, it is still a challenging tool for learners in developing countries like Pakistan.

Researchers have encouraged and suggested numerous models to predict the individual's views and concerns surrounding the acceptance and use of new innovative technologies by adapting well-known models such as TPB, TRA, TTF, TAM, Extended TAM, UTUAT, and UATUT2 Oye et al. (2014). This research study uses the modified UTAUT model, which is well recognized and used to predict users' adoption and usage of innovative technology applications in different situations, including educational settings like the ChatGPT tool Hewage, (2023); Emon, (2023). In the recommendation by researchers Venkatesh et al. (2003), the UTAUT model takes into account (70%) of the variance in usage intentions. Consequently, the UTAUT model posits and associates four important integral constructs: PE, EE, SI, and FC factors.

The current study uses a modified UTAUT model (Unified Theory of Acceptance and Use of Technology) to understand and predict the significant factors influencing learners' intention toward adopting ChatGPT usage in higher education institutions in Sindh, Pakistan. The survey responses were obtained from learners who engaged in their studies at top institutions in big cities, such as Karachi, Hyderabad, Nawabshah, and Sukkur in the province of Sindh, Pakistan. Using a quantitative research approach, data-gathering instruments were designed to collect responses for this research investigation to achieve research outcomes. The research model's predictive behaviour using recommended parameters was confirmed using SEM (Structural Equation Modeling).

Research Model

A comprehensive study of IT/IS behaviour has been compiled by Venkatesh et al. (2003), which includes UTAUT model-related approaches and applications. This research work provides the foundation for other researchers to verify and evaluate the presented models. The adoption of the model enables researchers to assess the advantages and consequences of examining technological tools integrated into their academics. According to Venkatesh et al. (2003), UTUAT is the primary theoretical model researchers can use to understand better and predict the factors that influence the acceptability of ChatGPT in higher institutions. Figure 1 illustrates the proposed research model that will be utilized to support our findings. The suggested research model includes critical aspects hypothesized to predict the behaviour intention of ChatGPT usage (BI) for achieving research objectives. The independent factors included Digital Skills (DS), Human-ChatGPT Interaction (HCI), Performance Expectancy (PE), Effort Expectancy (EE), Social Influences (SI), and Facilitating Condition (FC). In contrast, Behavior Intention (BI) is considered as a dependent variable. The expected theories and models are consistent with the previous background. The following section will generate the hypotheses based on the applied theoretical framework.

Digital Skills

Digital Skills are the cornerstone of basic computer processes, allowing users to interact with the computer and its applications Ge & Wu, (2023). In addition, learners must be able to use the online version of the web browser applications, particularly when utilizing advanced technological tools for their academic purposes. According to Khan et al. (2021) and Stofkova et al. (2022), the learners' inadequate familiarity with technological tools like ChatGPT posed challenges to their integration into academic settings. Similarly, Soroya & Ameen (2020)., emphasized the importance of digital skills for learners to effectively utilize AI-powered tools like ChatGPT in the digital classroom setting. Furthermore, a study by Soomro et al. (2020) examined the factors influencing the adoption of AI technologies in education and identified digital skills as a critical determinant. They found that the learners who needed more proficiency in digital skills were less inclined to adopt ChatGPT tools due to perceived barriers to usage. Therefore, the hypothesis posits:

H_1: Digital skills have positive effects on behaviour intention of ChatGPT usage.

Human-ChatGPT Interaction

Human-ChatGPT interaction refers to interactions between a user and the ChatGPT language model. Furthermore, Human-ChatGPT interaction entails exchanging information, inquiries, and generate responses in natural language to obtain academic topic explanations, research material, complex mathematical solutions, and existing research literature Shaengchart et al. (2023). According to Emon et al. (2023) and Menon & Shilpa (2023), Inappropriate command phrasing input in ChatGPT can lead to inaccurate academic explanation responses because the effectiveness of ChatGPT responses is highly dependent on the clarity and specificity of the feedback provided by learners. In a study conducted by Foroughi et al. (2023), it was observed in the literature that understated variations in input phrasing could significantly impact the quality and accuracy of ChatGPT-generated responses. Furthermore, research by Bibi & Atta (2024) **and** Woithe & Filipec (2023) highlighted that beginners must provide prompt and contextually relevant input to ChatGPT for generating accurate academic explanations. They emphasized the need for users to structure their queries to align with the system's capabilities and limitations, thereby enhancing the likelihood of obtaining meaningful responses. Therefore, the hypothesis posits:

H_2: Human-ChatGPT interaction has positive effects on behaviour intention of ChatGPT usage.

Performance Expectancy

Performance Expectancy is the degree to which an individual believes that employing proper technologies will help them improve their relevant performance in their academic activities. It refers to the perceived utility of the ChatGPT language model by enriching the learners' academic progress and research experiences Venkatesh et al. (2003); Choudhury & Shamszare (2023). Therefore, the hypothesis posits:

H_3: Performance expectancy has positive effects on behaviour intention of ChatGPT usage.

Effort Expectancy

Expert Expectancy refers to the approval of the language model by those who are regarded domain experts in the context of ChatGPT. It reflects how expert opinions influence the learners' desire to achieve learning expectations in their academic domains by utilizing and accepting the ChatGPT language model Venkatesh et al. (2003); Shahsavar & Choudhury, (2023); Tiwari et al. (20203). Therefore, the hypothesis posits:

H_4: Effort expectancy has positive effects on behaviour intention of ChatGPT usage.

Social Influence

Social influence in ChatGPT usage refers to the impression of others' attitudes, opinions, and expectations around the use of the language model in academic domains. It refers to the effect of friends, coworkers, or online groups on a person's decision to use ChatGPT to enhance their learning experience and understand how ChatGPT is a valuable tool in their studiesVenkatesh et al. (2003); Sallam et al. (2023); Kim, (2023). Therefore, the hypothesis posits:

H_5: Social Influence has positive effects on behavior intention of ChatGPT usage.

Facilitating Condition

Facilitating conditions for ChatGPT acceptance include the perceived availability of technology resources and technical infrastructure to enable learners to use the ChatGPT language model efficiently in their academic activities. It includes things like user-friendly interactions and dependable technical assistance that should be compact in the learning experience emphasized by Venkatesh et al. (2003), Yang et al. (2023), Sallam et al. (2023). Therefore, the hypothesis posits:

H_6: Facilitating Conditions have positive effects on the behavior intention of ChatGPT usage.

Behavior Intention of ChatGPT Usage

Behaviour intention to adopt ChatGPT refers to an individual's or learners' willingness and readiness to adopt ChatGPT conversational agent for various purposes such as academic assistance and research information retrieval. It is a critical construct in understanding technology adoption and is often studied within the framework of the UTAUT model Venkatesh et al. (2003); Choudhury & Shamszare (2023); Kim (2023); Tiwari et al. (20203).

By considering the above hypotheses, we validated the study of the research model below, developing our research model using the modified UTAUT illustrated in Figure 1.

Methodology

Procedure

The data-gathering team consists of registered learners from top-ranked public institutions. For the quantitative approach method by Stanley et al. (2005), a survey questionnaire was designed for data collection to validate the research model and test the suggested hypotheses to fulfil study objectives and determine the significant influence of constructs under investigation. The survey questionnaire was made of 35 items to serve the purpose of the study. The first part of the

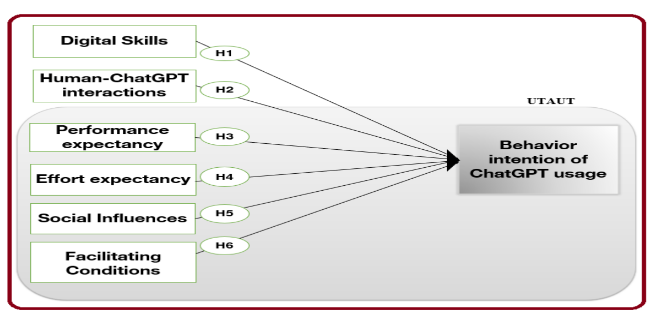

Fig. 1: Research Model

questionnaire was related to the demographic information of the respondents, such as gender, age, academic year, institution name, etc. The second part was composed to address the constructs items such as Digital Skills (DS, having four items), Human-ChatGPT Interaction (HCI, having five items), Performance Expectancy (PE, having four items), Effort Expectancy (EE, having four items), Social Influences (SI, having four items), Facilitating Condition (FC, having four items) influencing the to the behavioural intention (BI, having four items). A cross-sectional survey methodology was employed to gather data and investigate the influences between independent and dependent variables. A survey instrument utilizing a five-point Likert scale, ranging from strongly disagree to agree strongly, was developed to capture insights from the target population (Chen et al., 2023). The data collection tool was designed using Google Forms and disseminated to participants through email and WhatsApp. The measurement instrument administered the collected responses without missing data or outliers Kwak et al. (2017). Using the responses, the study assesses the proposed research model with SPSS and SmartPLS4, the latest and modern statistical tools for data analysis (Sadriddinovich, 2023; Purwanto, 2021). The researchers examined the data for the structural equation model (Measurement Assessment Model) to determine the sample size.

Participants and Descriptive Statistics

This study gathered 497 targeted responses from learners who are under study at top universities located in highly populated cities in the province of Sindh, Pakistan. The collected responses were employed to ascertain the research findings concerning validating the proposed research model and suggested hypotheses to achieve research outcomes.

The demographic information used to categorize survey responses collected from the learners included gender, age, qualification, and academic year. The sample size evaluated for this purpose was 310 males and 187 females from a total of 497, representing in per cent 62.4% and 37.6%, respectively. The majority of these learners, 133, were between the ages of 31 and 35 (26.8%), with the second highest being 83 between the ages of 26 and 30 (16.7%), 80 learners between the ages of 18 and 25 (16.1%), 73 learners between the ages of 41 and 45 (14.1%), 63 learners between the ages of 36 and 40 (12.7%), 35 learners between the ages of 46 and 50 (7.1%), and 29 over the age of 50 (5.8%). The learners' qualifications included 96 Ph. D.s (19%), 320 Master's degrees (64.4%), and 80 Bachelor's degrees (16.6%). The majority of the learners' academic years included 286 between 2-3 years (53.6%), 130 between 1-2 years (27.8%), 80 between 2-3 years (16.6%), and between 3-4 years students have not participated in the survey. The bulk of the responses, 250 were collected from Karachi (49.6%), 150 were collected from Hyderabad (48.8%), 75 were collected from Sukkur (14.2%), and 72 were collected from Nawabshah (13.2%) in Sindh Pakistan.

Findings and Discussion

Reliability Test (Pilot Study)

Pilot studies allow you to test the reliability of data instruments like questionnaires and measuring tools before performing a final research study. In this regard, 49 volunteers from targeted answers were randomly chosen for the initial test. The Cronbach's Alpha test was used to determine the dependability of the construct items. Cronbach's Alpha reliability coefficients of **0.7** or higher are considered satisfactory and appropriate by Hair et al. (2013). All constructs have significance values of more than 0.7, as represented in Table 1. The researchers chose to undertake the final investigation because the significant values for all constructs were reliable.

The questionnaire's six measuring scales can be used in this study because they are considered reliable, as shown in Table 1 below.

Measurement Model Analysis

SmartPLS is explicitly built for (PLS-SEM) Partial Least Squares Structural Equation Modeling, which is ideal for assessing complex models with latent variables Ramayah et al. (2018). In addition, this work used PLS-SEM to investigate the structure model and measurement analysis. The (outer model) measurement is defined as the relationship amongst the indicators, whereas the link between latent components is known as a structural model. According to Hubona (2009), the highest probability technique was employed to assess the proposed research model utilizing PLS-SEM. Various measures were used to determine reliability and convergent validity, including factor loadings, composite reliability, and the extracted average variance. A more significant load

Table 1: The data instrument relies on Cronbach's Alpha survey measurement scale

Constructs	*No of Items*	*Alpha ($\alpha \geq 0.7$)*
BI	04	0.902
Digital Skills	04	0.883
Human-Computer Interaction	05	0.896
Performance Expectancy	04	0.877
Effort Expectancy	04	0.871
Social Influence	04	0.818
Facilitating Condition	04	0.807

number indicates the dimensionality of the factors. The Composite Reliability (CR) metric is a supportable tool for evaluating reliability. (CR) does a similar function by supplying the correct value using factor loadings in the generated formula. The average amount of variation identified in a particularvariable that defines the latent construct is called the Average Variance Extracted (AVE). When the discriminate validity exceeds one factor, AVE can be used to evaluate the convergence of each factor. Table 1 demonstrates that our experiment's data instrument reliability and convergent validity outcomes exceed the required criteria for these concepts. Table 2 outlines the data instrument's validity and reliability and displays the evaluation findings for each factor as a function of the variable acquired from the data instrument.

Measurement Model Assessment (Outer Model)

Convergent Validity

Indicators such as factor loadings, variance extraction, and reliability, including Cronbach's Alpha and composite reliability, determine the relative degree of convergent validity. According to Hair et al. (1998). When a construct's composite reliability (CR) and reliability coefficient exceed 0.7, it implies internal consistency across several construct measures. Table 2 shows evidence that the constructs' Cronbach's alpha scores are more significant than 0.7, with values ranging from 0.807 to 0.904 Nunnally & Bernstein, (1978); Hair et al. (2013). Each construct's composite reliability (C.R) is calculated and compared to the cut-off value of 0.6 by Bagozzi and Youjae (1988). The (C.R) composite reliable values for performance expectancy were (0.842), effort expectancy was (0.782), social influence was (0.774), facilitating condition was (0.727), the digital skill was (0.793), human-ChatGPT interaction was (0.847), behaviour intention was (0.914), ranging from **0.727 to 0.916**, respectively, to achieve the concepts of convergent validity. Furthermore, the ideas of average extracted variance are supposed to exceed the minimum criteria of 0.5. However, this condition may only apply to the enabling facilitating condition as its AVG is 0.488. Fornell and Larcker (1981) found that when AVG is less than 0.5 and composite reliability (CR) is more significant than 0.6, the constructs' convergent validity is sufficient. In addition, researchers suggested by Hair et al. (2013) and Muhammad Safiih & Azreen (2016) that when the AVG of the constructs is below then its significance and CR is higher than 0.6, the construct is valid because sometimes the response can be biased. The AVG obtained values for performance expectancy were (0.641), effort expectancy was (0.546), social influence was (0.544), facilitating conditions were (0.487), digital skills were (0.501), human-ChatGPT interaction was (0.527), and behaviour intention were (0.733), ranging from **0.488 to 0.733.** Convergent validity was proven by composite reliability values better than 0.6 for all constructs. The findings on convergent validity are shown in (Table 2).

Discriminant Validity

Table 2 shows that all of the prerequisites for discriminating validity are met, as the AVE values exceed the squared correlation between the constructs of the measuring model. As described in section 5.2.1.1, if the AVE value is more than 0.5, the construct should account for at least a partial (50%) of the extent variance. The discriminant value was evaluated by utilizing partial least squares (SmartPLS). Table 2 shows the loadings and cross-loadings, which appear to be a thorough investigation. The loadings and cross-loadings indicate that each measurement item is primarily loaded on its latent constructions rather than other constructs. Table 3 displays

Table 2: The acceptable result for Convergent validity (Factors loading, Cronbach's Alpha ≥ 0.7, C.R ≥ 0.6, AVG ≥ 0.5)

Constructs	*Items*	*Factor Loading*	*Cronbach's Alpha*	*CR*	*AVG*
Performance expectancy	PE1	0.817	0.839	0.842	0.641
	PE2	0.811			
	PE3	0.773			
	PE4	0.737			
Effort Expectancy	EE1	0.789	0.875	0.782	0.546
	EE2	0.654			
	EE3	0.767			
	EE4	0.675			

Constructs	*Items*	*Factor Loading*	*Cronbach's Alpha*	*CR*	*AVG*
Social Influence	SI1	0.867	0.771	0.774	0.544
	SI2	0.783			
	SI3	0.718			
	SI4	0.693			
Facilitating Condition	FC1	0.647	0.743	0.727	0.488
	FC2	0.719			
	FC3	0.742			
	FC4	0.686			
Digital Skills	DS1	0.791	0.795	0.793	0.501
	DS2	0.792			
	DS3	0.747			
	DS4	0.741			
	HCI1	0.701	0.846	0.847	0.527
	HCI2	0.739			
Human-ChatGPT Interaction	HCI3	0.829			
	HCI4	0.781			
	HCI5	0.671			
Behavior Intention	BI1	0.838	0.892	0.914	0.733
	BI2	0.834			
	BI3	0.849			
	BI4	0.902			

the findings of the AVE analysis. The bold diagonal parts of the table represent the square root of the AVE scores. On the other hand, off-loading diagonal elements demonstrate the construction's relationship. The data clearly shows that the square root of the AVE values exists and surpasses the expected value of 0.5, lying between the ranges of **0.697 and 0.856.** The AVE appears to be larger than all other correlations for each construct, implying that the variance of each construct with its measures is greater than that of the different constructs in the model, highlighting discriminating validity.

Table 3: Fornell and Larcker Scale

	BI	*PE*	*EE*	*DS*	*HCI*	*SI*	*FC*
BI	0.856						
PE	0.845	0.801					
EE	0.666	0.543	0.738				
DS	0.791	0.739	0.631	0.707			
HCI	0.552	0.553	0.515	0.646	0.725		
SI	0.416	0.352	0.417	0.406	0.343	0.737	
FC	0.571	0.551	0.426	0.523	0.455	0.504	0.697

The Structural Model (Inner Model) Assessment

Path Coefficient - Test of the Hypotheses

To assess the relationship between the structural model's theoretical constructs and to test the suggested hypotheses, a structural equation model with the highest probable estimation (Smart PLS ver. 4) was used by Wong (2013) and Ramayah et al. (2018). Table 4 and Figure 2 summarize the results; hence, it is indicated that all hypotheses were found to be significant. Considering the data analysis hypotheses, H1, H2, H3, H4, H5, and H6 were significantly supported,

The study found that Digital skills (DS) ($b = 0.305$, $P < 0.00$), Human-ChatGPT Interaction (HCI) ($b = 0.679$, $P < 0.00$), Effort Expectancy (EE) ($b = 0.233$, $P < 0.009$), Facilitating Condition (FC) ($b = 0.210$, $P < 0.022$), Performance Expectancy (PE) ($b = 0.190$, $P < 0.004$), Social Influence (SI) ($b = 0.103$, $P < 0.009$). The findings indicate that all the independent factors, likewise DS, HCI, EE, FC, PE, and SI, have a significant impact on the dependent variable BI. Consequently, the hypotheses H1, H2, H3, H4, H5, and H6 were validated and had a considerable effect. The hypotheses

Table 4: Structural Model Results: Research Hypotheses Significant (p=<0.01, p* <0.05)**

	Path	*t - value*	*P values*	*Direction*	*Decision*
DS -> BI	0.305	4.008	0	Positive	Supported
HCI -> BI	0.679	4.404	0	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	2.722	0.004	Positive	supported
SI -> BI	0.103	3.619	0.009	Positive	supported

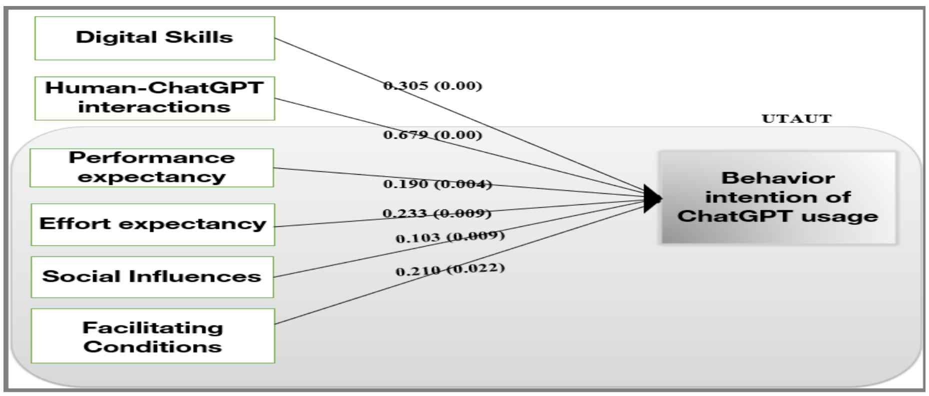

Figure 2: Path coefficient values (significant p** < = 0.01, p* < 0.05)

test findings are represented in Table 4.

Conclusion

The current research study uses the modified UTAUT model to investigate the assessment of significant predictors influencing the adoption of ChatGPT usage in the academia in the province of Sindh, Pakistan: The factors that determine the considerable impact on individuals' intention to adopt ChatGPT usage in institutions were investigated using the (UTAUT) model. DataData was obtained through a survey approach to produce results to achieve a quantitative study outcome for a quantitative study outcome. The responses were gathered from learners currently engaged in their academic studies from top institutions in the province of Sindh, Pakistan. Structural Equation Modeling was used to test the research model's predicted stimulants for their ability to predict study outcomes. The influential factors drive PE, EE, SI, and FC, with ChatGPT mindset, digital skills, and human-ChatGPT interaction—all of the components that influence behavior intention toward the effective adoption and use of ChatGPT in education. One probable explanation is UTAUT's adaptation to an effective ChatGPT tool in this specific scenario. The significant predictors have been shown statistically to influence the learners' attitudes and intentions regarding the adoption and usage of the innovative ChatGPT tool in top institutions in Pakistan.

This research is intended to understand the elements that influence Pakistani learners' perceptions and concerns regarding adopting ChatGPT and predict how innovative technology will be useful in their academic studies. The behaviour intention can be investigated in the ChatGPT adoption and usage in Pakistan with the support of the research model along with suggested hypotheses to achieve research objectives is the suitable option for this purpose. The proposed hypotheses were examined with the help of Structure Equation Modeling (PLS-SEM). Performance analysis was used to analyze the structural model, including R-squared values, structural pathways, and t-statistics. Figure 2 depicts the structural model, while Table 4 summarises the results of the analysis. The study model examined path significance and variance explained (R^2) for each hypothesis to validate its stated validity.

The study indicated that learners' intentions to adopt and use the ChatGPT tool in academia in Sindh, Pakistan, were positively influenced by (PE), (EE), (SI), (FC), (DS), and (HCI) predictors. This outcome aligns with H1, H2, H3, H4, H5, and H6 have a greater influence. These data demonstrate that Proficiency enables learners to engage effectively with the

ChatGPT tool to enhance their learning experience and that they have greater intention to utilize ChatGPT as a valuable tool for educational purposes in the academia of Sindh, Pakistan. Previous research has found a beneficial impact on learners' intent to use ChatGPT Bibi & Atta, (2024). Choudhury & Shamszare, (2023). Gulati et al. (2024).

Moreover, HI and H2 hypotheses are considered significant indicators by adding H3, H4, H5, and H6 in this research that influence the learners' intention to adopt the CHATGPT tool by integrating it with their academic needs. Learners with higher levels of digital skills, denoted (H1) hypothesis, are generally more adept at learning and using new technologies. Proficiency in digital skills, such as familiarity with software interfaces, online communication tools, and information retrieval techniques, can lower barriers to adopting novel technologies like ChatGPT. In addition, by possessing digital skills, the learners are better equipped to understand, utilize, and integrate ChatGPT into their academic activities. This can lead to a positive intention for learners to use ChatGPT as a valuable tool for problem-solving and knowledge enhancement in their academic institutions in Sindh, Pakistan Livingstone et al., (2023).

On the other hand, (H2), by engaging clear and specific phrasing input, helps ChatGPT understand the learner's intent or query accurately. Phrasing input effectively is crucial for learners to receive accurate and meaningful responses from ChatGPT in their academic pursuits, driven by their familiarity related to performance expectancy, effort expectancy, social influences, and facilitating conditions Radford et al., 2019; Svenningsson & Faraon, (2019). Our study findings revealed and addressed that institute administration and educators can promote the adoption of ChatGPT among learners and facilitate its integration into academic settings effectively by providing support, training, and resources to learners, which can also enhance their confidence and proficiency in using ChatGPT for educational purposes. Furthermore, the institutes' administration and IT experts should prioritize characteristics that improve learners' competency associated with ChatGPT applications and ensure ChatGPT adoption in academia in Sindh, Pakistan.

The R-squared value of 68% (R^2 = 0.68) validates the variance of model accuracy power in learners' intention to adopt the ChatGPT tool in education. The study used PE, EE, SI, FC, DS, and HCI to predict the variable. A nominal R-squared value was calculated for user behavioural intentions. According to (Chin, 1998), ratings above 0.67 indicate a high value, while characteristics between 0.33 and 0.67 are direct and ranging between 0.19 and 0.33 are considered weak. Those below 0.19 are inadmissible. The overall variance of these covariates was 68% (R^2 = 0.68).

Future Direction

In the future, research endeavours may investigate the adoption of the ChatGPT tool within diverse cultural contexts. Additionally, while this research applied a quantitative survey approach, employing in-depth focus group interviews could offer deeper insights into ChatGPT adoption. Furthermore, forthcoming research could conduct comparative analyses involving technology acceptance models, including TAM, TOE, and Diffusion of Innovation at teachers' levels. These efforts aim to enhance our comprehension of ChatGPT adoption for the education sector.

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