P-ISSN: 2790-6795	Annals of Human and Social Sciences	Apr-June 2024,Vol. 5, No. 2
O-ISSN:2790-6809	http://doi.org/10.35484/ahss.2024(5-II)64	[699-705]

Annals of Human and Social Sciences
www.ahss.org.pk

RESEARCH PAPER

The Future of Learning: Integrating ChatGPT in Pakistan's Higher Education

[1]Maryam Buriro, [2]Dr. Waqar Ahmed Sethar and [3]Amanullah Parhyar*

1. Ph.D scholar, institute of Business Administration University of Sindh, Jamshoro, Sindh, Pakistan
2. Assistant Professor, Mehran University Institute of Science & Technology Development, Mehran University of Engineering & Technology, Jamshoro, Sindh. Pakistan.
3. Lecturer, Department of Business Administration, Government College University Hyderabad, Sindh, Pakistan

Corresponding Author Amanullah.parhyar@gcuh.edu.pk,

ABSTRACT

The aim of this study is investigate the causes of using Generative AI Tools. GPT is a generative AI has started making inroads into higher education around the world, however, there is a debate around these AI tools special Generative -AI tools like ChatGPT. Using questionnaire survey the data was collected (b=151) from three universities located in Jamshoro, Sindh,. The finding shows the positive significant effect of behavioral intentions on the ChatGPT usage of the students with 78% variance explained by constructs like performance expectancy, effort expectancy, social influence, information quality, source trustworthiness, technical knowledge, facilitating conditions, however, behavioral intentions was not found to lead to actual usage of ChatGPT by the students with only weaker variance (14%) by behavioral intentions. This study recommends that while ChatGPT use cannot be stopped at the campus, it is recommended that this may complemented and integrated in the higher education Institutions.

Key words: ChatGTP, Generative AI, LLM, Higher Education

Introduction

Recently developed by OpenAI, ChatGPT is a conversational AI interface that falls under the LLMs category. It can respond to natural language inputs and produce responses that resemble those of a person (OpenAI, 2023). ChatGPT is a member of a new class of AI algorithms, as opposed to earlier AI interfaces, which were mostly Deep Learning (DL) models that recognized and kept patterns in data (Rospigliosi, 2023). Based on the context of the words that came before it, ChatGPT is trained to predict the likelihood of a particular word sequence (Naseem et al., 2021)The main purpose of ChatGPT is to facilitate human-like communication. But it can do much more than that. It is proficient at producing unique works of literature, including novels, poetry, and stories, and it can emulate a wide range of actions (Tlili et al., 2023).

In order to address any difficulties, the questioner may raise, ChatGPT offers follow-up inquiries that expand and improve the responses. Additionally, ChatGPT can improve research abilities, critical thinking, problem-solving, constructive writing assignments, and academic research Additionally, it can point up undiscovered facets and hot research subjects, assisting students in developing a deeper comprehension and critical analysis of a certain subject (Kasneci et al., 2023)Still, once ChatGPT was made available to the public in November 2022, the conversation over using AI-based models in higher education came to a crucial halt.

Literature Review

Yilmaz et al. (2023) have studied impact of ChatGPT on computational skills, self-efficacy, motivation of undergraduate students in Bartin University Turkey, he used experimental design of control group and post and pre-test. The 45 participants were part of the study , experimental group used CharGPT and control group did not used ChartGPT for programming task. The findings suggest that students has a positive effect on self efficacy, computational skills and motivation. Study shows the potential benefits of using generative AI in education which may increase the productivity of the study students. However, the sample data is not sufficient to conclude sufficiently about generalizing the results.

Essel et al., (2024) have investigated the effects of ChatGPT on the cognitive skills of undergraduate students. Using quantitative students with 125 students, the study also used experimental design with experimental and control group. The study showed that LLM model like ChatGPT have increased the creative, reflective and critical thinking skills of the students . This study highlights the use of AI tools in education with positive results. However, the sample size is again 125 students, which should have been increased sufficiently to 300 students divided into 150/150, which would have increased the generalizability of the research findings.

The authors have used knowledge perceived ethics, attitudes regarding us of ChatGPT (Acosta-Enriquez, 2024). Some members of the academic have started using ChatGPT for academic advice some authors have mapped the global usage of ChatGPT in higher education, others have measured the performance of medical students in higher education (Bharatha, 2024), some authors have assessed the impact of ChatGPT on digital literacy of the students. (Gong, 2023). It is concluded from the literature that academic circles as well as students have realized the importance of LLM or generative AI in higher education, however, the perception , intentions and other expectancies, information quality, social influence and impact of source trustworthiness is still understudied area for usage of ChatGPT, therefore, therefore, this studies tries the fill this gap.

Material and Methods

This study is cross sectional , and was conducted at Jamshoro,Sindh, Pakistan from the undergraduate students during the month of May, 2024. The participants who are studying in different undergraduate program were the main focus of this study ,and the postgraduate students were not the focus, so they were excluded from the study. The study initial target 300 students for the data collection, however , the response rate was very low as 50%. The students were selected randomly , by visiting different department as well as online version of the questionnaire was also distributed. This study employed questionnaire survey for collection of the data. SPSS and Excel were used to enter the data and preliminary statistics. For latent variable analysis we used Partial Least Square structural Modeling was used in R statistical computing software with SeminR package. The model was examined using PLS-SEM measurement model and assessment of Structural Model, bootstrapping with 5000 subsample as used to estimate the hypothesized relationships.

Results and Discussion

The data was collected from three universities located in Jamshoro i.e. Mehran University of Engineering and Technology, Liaquat University of Medical and Health Sciences, University of Sindh the achieved response is *n= 151* mostly undergraduate students.This section shows the findings of the data collected from the undergraduate students, the section shows the assessment of measurement model, structural model and hypothesis results, PLS SEM model is evaluated based on reliability using Cronbach's alpha, composite reliability, indicator reliability and convergent validity using average variance extracted, while hypotheses are tested using Bootrapping performed in Smarts 4. Structural model is assessed based on coefficient of determination.

Research Hypothese

H1: Information Quality has positive relationship weith behaviorial intetnions
H2: Facilitating conditions have positive relationship with behaviorial intentions
H3: Source Trustworthiness have positive relationship with behaviorial intentions
H4: Social Influence has positive relationship with behaviorial intentions
H5: Effort Expectancy has positive relationship with behaviorial intentions
H6: Performance Expectancy has positive relationship with behaviorial intentions
H7: Technical Knowledge has positive relationship with behaviorial intentions
H8: Perciepved Interactivity has positive relationship with behaviorial intentions
H9: Behaviorial Intetions has positive relationship with ChatGPT Use

Assessment of Measurement Model

It is important for researchers to understand that the explanation of reflective and formative measures above pertains to the measurement theory's presumption of an epistemic relationship between indicators and conceptions (Sarstedt et al., 2016). To describe the concepts in the statistical model, PLS-SEM, which includes the CCA technique, computes composites from linear combinations of sets of indicators. When estimating a composite using correlation weights, the arrows usually point in the direction of the indicators rather than the construct. This measurement type is commonly known as reflective. However, the arrows usually point from the indicators to their construct when a composite is composed using regression weights. Many times, this is called a formative measurement (Nitzl & Chin, 2017). These PLS-SEM reflective measurement model calls for assessment of construct reliability with Cronbach's alpha , composite reliability , convergent validity, discriminant validity use HTMT ratio of Fornell Larcker Criterion.

The criteria for assessing construct validity is to use Cronbach's alpha and composite reliability (See Table) , where all latent constructs have composite and alpha values >0.70, these values suggest attaining the maximum threshold for construct validity of the constructs in PLS-SEM path model, therefore, the construct is reliable (Hair et al., 2019). The convergent validity is measured by average variance extracted that should >0.50, all constructs show meeting the minimum threshold of 0.50 thus achieving the convergent validity which measures at least 50% variation introduced by its indictors.

Table 1
Construct Reliability

Construct	Original	Outer loadings	Alpha	rhoC	AVE	rhoA
Performance Expectancy	PE1	0.816	0.832	0.833	0.555	0.836
	PE2	0.706				
	PE3	0.739				
	PE4	0.714				
Effort Expectancy	EE1	0.609	0.816	0.811	0.52	0.819
	EE2	0.756				
	EE3	0.702				
	EE4	0.803				
Facilitating Conditions	FC1	0.761	0.758	0.768	0.568	0.805
	FC2	0.760				
	FC3	0.759				

	FC4	0.375				
Social Influence	SI1	0.814	0.906	0.906	0.764	0.91
	SI2	0.87				
	SI3	0.935				
Perceived Interactivity	PI1	0.967	0.803	0.825	0.708	0.866
	PI2	0.693				
Information Quality	IQ1	0.765	0.757	0.758	0.61	0.758
	IQ2	0.797				
Source Trustworthiness	ST1	0.842	0.788	0.789	0.652	0.792
	ST2	0.772				
Technical Knowledge	TK1	0.790	0.872	0.872	0.695	0.877
	TK2	0.795				
	TK3	0.910				
Behavioral Intentions	BI1	0.839	0.838	0.838	0.722	0.838
	BI2	0.860				
ChatGPT Usage	Usage	1	1	1	1	1

The table above shows the indicator reliability is shown by the outer loadings of individual questions the recommended threshold for reflective indicators is in the range of 0.70-0.90 (Hair et al., 2019), as show int the above table all indicators have values > 0.708.

Hypotheses

The hypotheses are evaluated using bootstrapping in SMARTPLS using 5000 subsamples , the effect of performance expectancy on behavioral intentions shows that it moderate and positive effect (β= 0.408, T= 0.058) the relationship is not statistically significant, the effort expectancy on behavioral intentions (β= 0.102, T= 0.023) shows weak and positive effect and the relationship is now statistically not significant. The facilitating conditions also have weak positive effect on behavioral intentions (β= 0.126, T= 0.032) the relationship is also not statistically significant. The social influence have positive and weak effect on behavioral intention ((β= 0.256, T= 0.051),the perceived interactivity have weak effect on behavioral intentions (β= 0.016, T= 0.001) and the effect as not statistically significant. The information quality has negative weak effect on behavioral intentions (β= 0.247, T= 0.006) and the relationship is not statistically significant. The Source trustworthiness has moderate positive effect on behavioral intentions (β= 0.368, T= 0.017) and the relationship is not statistically significant.

Table 2
Hypotheses

Hypothesis	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.
PE -> BI	0.408	0.737	7.041	0.058
EE -> BI	0.102	0.179	4.406	0.023
FC -> BI	0.126	0.303	3.892	0.032
SI -> BI	0.256	0.002	5.011	0.051
PI -> BI	0.016	1.252	30.768	0.001
IQ -> BI	-0.247	1.569	43.016	-0.006
ST -> BI	0.368	0.535	22.140	0.017
TK -> BI	0.014	0.249	4.761	-0.003
BI -> usage	0.385	0.384	0.083	4.659

The behavioral intentions have positive moderate effect on ChatGPT (β= 0.3385, T= 4.659), and the relationship is statistically significant. The above results show that almost all hypotheses are not statistically significant except the last one.

The assessment of Structural Model

The structural model is evaluated based on coefficient of determinant the variance shows the exogenous variables explain 78% variance on behavioral intentions quite strong (Hair et al., 2019). While the variance shown by behavioral intentions on ChatGPT usage is only 14.2%. which is weak.

Table 3
Coefficient of determinant

Construct	R^2
Behavioral Intentions	0.780
ChatGPT Usage	0.142

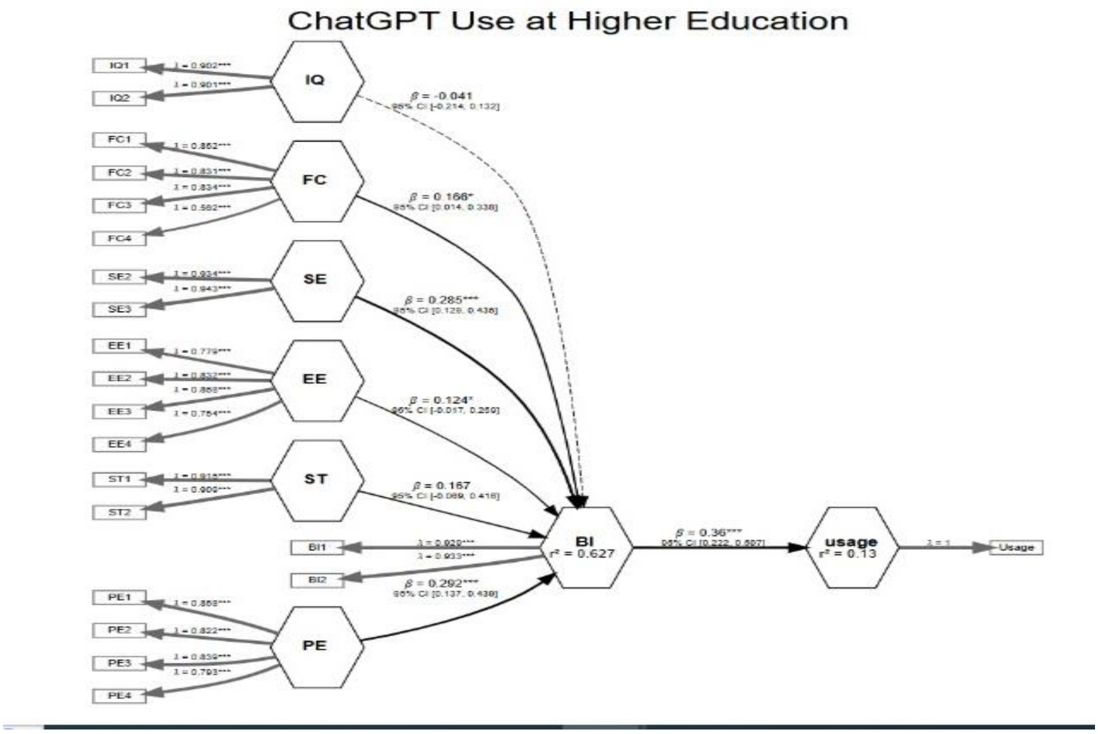

Figure 1 Path diagram of latent constructs

IQ = Information Quality, FC = facilitating conditions, SE = Social Influence, EE = Effort Expectancy, ST= Source Trustworthiness, PE= Performance Expectancy , BI= Behaviorial Intentions, Usage= ChatGPT Usage.

Conclusion

The aim of this research is to study the effects of performance expectancy, effort expectancy, social influence, source trustworthiness, facilitating conditions, information quality, technical knowledge, perceived interactivity on behavioral intentions and usage. The findings show that none the above variables have any significant effect on behavioral intention to use ChatGPT, except behavioral intentions, which has positive and significant effect on ChatGPT usage. This highlights that undergraduate students in Jamshoro have strongest variation on ChatGPT usage (78%), while behavioral intentions explain only 14%

variance. The implication of this study shows that behavioral intentions is influenced by the performance expectancy, effort expectancy, social influence, source trustworthiness, facilitating conditions, information quality, technical knowledge, perceived interactivity. This shows that these variables are important and strong predictors of behavioral intentions. While actual ChatGPT usage is not strongly influenced by behavioral intentions. Therefore, future studies should consider more variables that might affect actual ChatGPT usage of undergraduate students. This research indicates the lack of sufficient sample size, future studies should consider higher sample size on order of 500-1000.

Recommendations

Recommendations for future research and applications can be drawn from the current research study. The sample size should be increased; between 500 to 1000 participants should be included in future studies to have more reliable data output. For example, behavior intention had a very low influence on actual usage of ChatGPT; thus, personal innovativeness, perceived risk, self-efficacy, and intrinsic motivation might be studied through future studies. More insights and the discovery of attitudinal underpinnings that could be slipped off quantitatively would help in finding a great way to do this through a longitudinal and qualitative study. Research that will focus on the contextual factors involved such as the extent to which it is used in the curriculum and institutional support with intervention designs targeted at increasing predictors for behavioral intentions can guide decisions on how best to effectively enhance the use of ChatGPT. Comparative studies with several universities or regions could also provide insights for regional or, most important, institutional differences in influencing use.

Another interesting recommendation is the enhancement of the interactivity of ChatGPT, because it was proved to be an important predictor of the perceived interactivity dimension. Universities may, for example, devise policies and practices that allow effective use of AI tools to bring about better learning outcomes by training workshops, sessions, and curriculum integration. Behavioral intentions still hold great importance, despite their ability to explain low variance in actual usage, and learning about enhancing factors of these intentions is essential. Future research will have to get much more insight into how these intentions are translated into actual usage by examining the role of habit formation and the incentive for continued use. Heedful of such recommendations, future research could perform better on these counts and thus develop a much rounder understanding of what underlies ChatGPT use among undergraduate students.

References

Acosta-Enriquez, B. G. (2024). Knowledge, attitudes, and perceived Ethics regarding the use of ChatGPT among generation Z university students. *International Journal for Educational Integrity*, *20*(1). https://doi.org/10.1007/s40979-024-00157-4

Bharatha, A., Ojeh, N., Fazle Rabbi, A. M., Campbell, M. H., Krishnamurthy, K., Layne-Yarde, R. N., ... & Majumder, M. A. A. (2024). Comparing the Performance of ChatGPT-4 and Medical Students on MCQs at Varied Levels of Bloom's Taxonomy. Advances in Medical Education and Practice, 393-400.

Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). *Computers and Education: Artificial Intelligence*, *6*, 100198.

Gong, F. (2023). The Impact of Generative AI like ChatGPT on Digital Literacy Education in University Libraries. *Documentation, Information and Knowledge*, *40*(5). https://doi.org/10.13366/j.dik.2023.05.097

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., & Hüllermeier, E. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274.

Naseem, U., Razzak, I., Khan, S. K., & Prasad, M. (2021). A comprehensive survey on word representation models: From classical to state-of-the-art word representation language models. *Transactions on Asian and Low-Resource Language Information Processing*, *20*(5), 1–35.

Nitzl, C., & Chin, W. W. (2017). The case of partial least squares (PLS) path modeling in managerial accounting research. *Journal of Management Control*, *28*, 137–156.

Rospigliosi, P. 'asher.' (2023). Artificial intelligence in teaching and learning: What questions should we ask of ChatGPT? *Interactive Learning Environments*, *31*(1), 1–3.

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, *10*(1), 15.

Yilmaz, R. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence*, *4* https://doi.org/10.1016/j.caeai.2023.100147