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GenAI Tools in Education Disrupt Learners Thinking Process: A Study for Education Sector in Sindh Pakistan

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Abstract

The study aims to investigate the effective use of Generative AI tools in education that may disrupt the learners' thinking and problem-solving skills in the education sector in Sindh Pakistan. The study focused on understanding the factors determining whether the use of GenAI tools in academic learning is productive or risk-promoting dependence on AI-generated solutions. In this context, the proposed model with four suggested hypotheses was developed from past theories based on technology adoption. For quantitative methods, 300 responses were gathered for data analysis using PLS-SEM techniques. In our findings, all constructs such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating condition (FC) have a stronger impact on behaviour intention (BI). This research contributes to the expanding body of literature on integrating technology in education, particularly in leveraging GenAI tools that negatively impact learners, reducing cognitive efforts and limiting opportunities for critical reflection and exploration.

Keywords: GenAI tools, Education sector, Thinking Process, Sindh, Pakistan

Introduction

Education is fundamental for students as it shapes their personal, intellectual, and social development equipping them with the knowledge and skills necessary to lead successful and fulfilling lives (Zimmerman, 2023). Additionally, education provides foundational knowledge in subjects like science, math, history, and literature helping them to understand the world. Through education, learners learn how to analyze situations, critically evaluate information, and make informed decisions (Laupichler et al., 2022). According to the researchers (Chiu, 2023), since technology emerged as a transformative force in education, it has revolutionized teaching and learning processes by creating new opportunities in the modern era. The development of Generative AI (GenAI) technologies involves a branch of artificial intelligence that is becoming more prevalent in educational settings in developed countries

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(Alasadi & Baiz, 2023). Learners are using these technologies to create academic content and customizable resources across various subjects, including science, math, history, and literature. Moreover, Chan et al., (2023), the advanced GenAI tools support learners with numerous advantages across various aspects of their education. It enhances learning with technology, streamlines academic tasks, and increases overall guidance of academic class activities. A study by researchers (Schiff, 2021; Haseski, 2019), believed that while GenAI technologies offer numerous benefits in education, they can also disrupt and potentially hinder learners from critical thinking and cognitive development when misused or over-relied upon. Additionally, learners may become dependent on GenAI tools like ChatGPT, Grammarly, and Wolfram Alpha from completing assignments to problem-solving, bypassing the need to think critically or independently. Another study by researchers (Hamilton et al., 2023), asserted that learners instead of analysing math problems step-by-step may rely on GenAI to provide solutions instantly, skipping the opportunity to develop problem-solving skills. This technological dependency can weaken critical thinking, reasoning, and analytical skills, as learners are no longer actively engaging with the subject material. Furthermore, (Alier, 2024; Aberšek et al., 2023; Shah et al., 2024), asserted when learner relies on historical or scientific explanations, they might fail to verify information against credible sources, especially since GenAI can generate incorrect or biased content. This reduces the learners' ability to evaluate information critically, fostering the passive acceptance of potentially flawed or incomplete knowledge (Majeed et al., 2024). As a result, GenAI technologies can significantly influence education but in some cases, excessive reliance on GenAI tools can disrupt learners thinking approaches and deep learning as emphasized by Naseer & Shaheen (2023). By addressing these potential disruptions thoughtfully, this study aims to investigate learners' intention toward the adoption of GenAI in education and understand their perceptions and opinions regarding the integration of innovative technologies in their academic learning across the educational landscape in Sindh, Pakistan.

The Purpose of Study

The primary purpose of this research is to investigate the adoption of GenAI technologies by learners and their implications on academic practices in education. The study focuses on understanding the factors that contribute to the meaningful and productive use of GenAI tools in the learning environment while addressing the potential challenges. In the shed of past literature, the use of GenAI tools in academic settings to enhance learning rather than replace traditional learning methods. When the learners depend on GenAI tools to answer, they may bypass the process of analysing problems and considering alternatives. The learners who frequently rely on AI may see GenAI as the easiest path to a solution. Moreover, over-relying on GenAI can reduce the need for collaboration with peers or instructors, which is crucial for developing communication, teamwork, and social problem-solving skills. While GenAI has the potential to enhance learners' educational experience, unchecked use can disrupt critical thinking, creativity, and academic integrity. Additionally, the learner uses GenAI tools to generate easy outlines potentially bypassing the intellectual efforts of organizing thoughts independently. Moreover, this study aims to contribute and seeks to explore whether effective integration of GenAI tools in the education sector encourages critical thinking, creativity, and intellectual autonomy, or whether it is risk-promoting dependence on GenAI-generated solutions in the field of education.

Literature Review

The literature for this study is structured around three pillars that form the framework for the research. These pillars are the "Related Studies", "UTAUT Model", and "Significant Predictors". This section of the study employed the UTAUT model with its significant predictors to understand individuals' intentions regarding adopting and using innovative technologies in the education sector in Sindh, Pakistan. The explanations below provide a detailed discussion of these three pillars.

Related Studies

In a study by the researcher (García et al., 2022), research in the USA emphasized GenAI tools' ability to disrupt traditional thinking by fostering critical and analytical skills in education. As a result, GenAI tools have been studied to encourage brainstorming and enhance engagement in writing tasks, enabling learners to develop non-linear, innovative approaches to problem-solving. Another researcher (Hassan et al., 2023), In India, focuses on GenAI's role in democratizing access to educational resources and encouraging self-directed learning among learners from diverse backgrounds. This study highlights GenAI's role in disrupting rote learning by enabling personalized feedback and adaptive questioning, fostering deeper conceptual understanding. Furthermore, another study (Al-kfairy, 2024) in UAE focuses on universities' adoption of GenAI tools, particularly to drive innovation and collaborative thinking in group projects. As a result, GenAI tools have been shown to challenge conventional pedagogical methods. The researchers (Romero-Rodríguez et al., 2023), In Spain, studies on GenAI tools emphasize their role in improving cognitive flexibility and complex problem-solving among university learners. As a result, GenAI is positioned as a tool for enhancing meta-cognitive skills and breaking rigid thought processes. Moreover, in another study (Sohn & Kwon, 2020), In China, the emphasis is on GenAI tools' ability to support bilingual education and foster globalized learning perspectives. As a result, the study highlights its potential to disrupt traditional language-learning paradigms by enabling conversational practice and real-time feedback. Most researchers suggested (Budhathoki et al., 20204; Kim, 2023; Strzelecki, 2024), that the UTAUT model provides a comprehensive understanding of the factors shaping learners' acceptance and usage of GenAI tools in the education sector. Therefore, the UTAUT model is well-suited for this study to understand how learners effectively integrate and utilize the GenAI tools in their academic learning activities.

Unified Theory of Acceptance and Use of Technology

The UTAUT model developed by (Venkatesh et al. in 2003), provides a framework for technology acceptance based on key determinants and moderating factors. In a study by researchers (Masoomi et al., 2024), the UTAUT model has been widely adapted to fit various technologies and industries, including e-learning, ERPs, e-commerce, and e-banking. Another researcher (Menon & Shilpa, 2023), the UTAUT model has been shown to outperform earlier models such as (TAM and TPB) in explaining variance in behaviour intention and usage behaviour, with predictive power often exceeding 70%. Furthermore, according to other researchers (Budhathoki et al., 2024), UTAUT is particularly relevant for emerging technologies like artificial intelligence, blockchain, and IoT. Therefore, the UTAUT model is crucial for technology acceptance research because it provides a comprehensive framework to understand the factors influencing individuals' decisions to adopt and use technology (Emon et al., 2023). In this context, this research study employed the UTAUT model as a proposed research model by considering its significant factors as dependent and independent variables to understand the learners' intention toward accepting and using GenAI in their academic learning in education sectors in Sindh, Pakistan. The proposed model incorporates four core key determinants for technology adoption and use. By GenAI in the context of education, the researchers can explore how its determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions can disrupt learners from traditional thinking approaches. The following are the explanations of key determinants of the UTAUT model that are significantly integrated with Gen AI tools. Figure 1, shows the proposed research model and suggested hypotheses relationships.

Significant Predictors

Performance Expectancy: refers to the degree to which learners perceive that the use of technology will improve learning outcomes and performance. According to researchers (Smith & Johnson, 2023; Camilleri, 2024; Abdaljaleel et al., 2024; Al-kfairy, 2024), GenAI tools like ChatGPT, DALL-E, and adaptive learning systems promise faster, and more accurate solutions in educational tasks (i.e. summarizing information, solving problems, or generating creative ideas). Therefore, learners might prioritize AI-enhance efficiency over deep learning or critical thinking (Jain et al., 2024). Thus, the study posits hypotheses:

H_1: Performance expectancy significantly impacts behaviour intention.

Effort Expectancy: refers to the degree to which learners perceive the ease of use of technology associated with the learning context. According to researchers (Brown & Carter, 2024; Lee & Hernandez, 2022), GenAI tools are user-friendly and significantly reduce the cognitive load required for many academic tasks. Additionally, learners ask to GenAI tools to solve math problems step-by-step, reducing their need to think through it themselves (Smith & Johnson, 2023). Thus, the study posits hypotheses:

H_2: Effort expectancy significantly impacts behaviour intention.

Social Influence: a degree to which learners perceive that important others believe they should use technology for learning outcomes and performance. In a study by researchers (Al-kfairy, 2024; Romero-Rodríguez et al., 2023; Abdaljaleel et al., 2024), the learners' acceptance of GenAI tools in education is often influenced by friends, peers, instructors, and institution mandates (Bhat et al., 2024). Thus, the study posits hypotheses:

H_3: Social Influence significantly impacts behaviour intention.

Facilitating Conditions: refers to the ability of resources and technological infrastructure support from the institutions. The researchers (Maheshwari, 2023; Bhat et al., 2024), asserted that institutional provision providing structured access to GenAI tools ensures the learners have the technical and infrastructural support to experiment and learn (Abdaljaleel et al., 2024).

H_4: Facilitating conditions significantly impacts behaviour intention.

Behaviour Intention: serves as a dependent and a precursor to actual use behaviour (Lee & Hernandez, 2022; Bhat et al., 2024). All the determinants significantly amplify this construct toward the acceptance and use of GenAI tools in education.

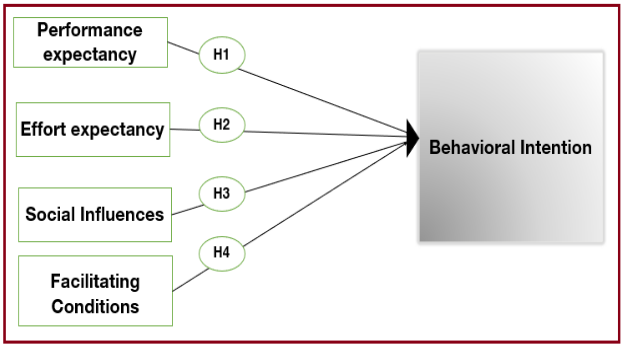

Fig. 1: Proposed Research Model

Research Methodology

Research Design and Data Collection

The data-gathering team consists of learners who have been registered and involved in academic learning, actively participate in the academic journey experience, and understand how technological tools are valuable tools in their academic engagements. This study employed a quantitative approach by collecting and analysing numerical data (Morgan, 2023; Mogavi et al., 2024). A web-based questionnaire (Google Form) was developed to relate to the latest technological features preventing any missing values or outliers (Kassim, 2024). A link was shared with all administrators and heads of departments for data collection from targeted participants with ethical considerations. The participants may include active students from diverse educational levels, enrolled in public and private institutions situated in densely urban areas such as Karachi, Hyderabad, and Sukkur across Sindh, Pakistan. The participants in this study can provide insights into foundational educational practices, technological exposure, and engagements in digital tools. Additionally, this group offers perspectives on higher-order cognitive engagement, GenAI tools usage, and critical thinking skills. Partial Least Square Structural Equation Modelling (PLS-SEM) techniques were utilized to validate the proposed research model and suggested hypotheses to achieve research objectives. In a study by researchers (Hair & Alamer, 2022), a minimum of 150 participants are recommended for the PLS-SEM approach. Other researchers (Foroughi et al., 2024), suggested at least 200 participants are required for an acceptable (PLS-SEM) modeling approach. However, to achieve robust results, a sample size should be calculated using a G*Power calculator more suitable, depending on effect size and power requirements. Therefore, this study gathered 300 participants, supportive and ideal for partial least square structure equation modelling (PLS-SEM) with its two techniques of measurement and structural model assessments using the SmartPLS Ver 4.0. According to the researchers (Cheah et al., 2024; Foroughi et al., 2024), the SmartPLS ver 4.0 statistical tool is widely used for PLS-SEM techniques for modelling to analyse the complex relation between variables. In addition, SmartPLS is a best-fit tool for small sample sizes in exploratory research.

Development of Survey Questionnaire

A survey questionnaire was designed, to address the construct items related to past research studies. Additionally, a survey questionnaire comprises 27 items addressing the validation of the proposed model and suggested hypotheses. The first part consists of demographic information related to participants' personal profile information, while the second part is associated with survey questions aiming to assess how effective use of the GenAI tools in education disrupts learners' thinking process. Table 1.1 represents the formation of survey questionnaires to address constructs and their items including the sources related to past studies. Each construct was composed of four measurement items. The survey instrument employed cross-sectional studies with a five-item Likert scaling ranging from 1 with strongly disagree, and 5 with strongly agree, to capture the valuable insights and opinions regarding the academic journey experience of learners (Naqid et al., 2023).

Table 1: Summary of Survey Questionnaire

Construct	*Items (code)*	*Sources*
Performance Expectancy (PE)	PE1 PE2 PE3 PE4	(Venkatesh et al., 2003; Sharkaet al., 2023)
Effort Expectancy (EE)	EE1 EE2 EE3 EE4	
Social Influence (SI)	SI1 SI2 SI3 SI4	
Facilitating Conditions (FC)	FC1 FC2 FC3 FC4	
Behaviour Intention (BI)	BI1 BI2 BI3 BI4	

Results and Discussion

Descriptive Statistics

A total of 300 responses were received from learners who are actively engaged in their academic journey in the education sector in Sindh, Pakistan. According to the demographic analysis, most of the learners as targeted participants were male 225 (75%) and female 75 (25%). The age distribution indicated that 150 participants (50%) were between 14 and 18 years old, an number 33 (12.8%) fell within the 19–22 age bracket, 75 participants (25.4%) were aged between 23 - 26 years, and the age above 27+ 32 (12.2%). Geographically, most of the learners recorded their initial responses in Karachi 190 (65.6%), followed by Hyderabad 55 (17.2%) and Sukkur 55 (17.2%). Regarding academic levels, most learners were from O/A levels 150 (50%). In contrast, a smaller proportion 75 (25%) were from Higher Secondary Schools (HSC), 75 (25%) from bachelor's, and the master of the academic levels did not participate. The detailed demographic distribution is summarized in Table 1, where (N) denotes the number of participants.

Assessment of Measurement Model

To test the hypotheses, the researchers evaluated the measurement model assessment to ensure the reliability and

Table 2: Descriptive Analysis (N=300)

Demographic Information	*Frequency*	*Percentage (%)*
Gender		
Male	225	75
Female	75	25
Age		
14-18	150	50
19-22	33	12.8
23-26	75	25
27+	32	12.2
Public/Private institutions in Sindh, Pakistan		
Karachi	190	65.6
Hyderabad	55	17.2
Sukkur	55	17.2
Academic Levels		
O/A Levels	150	50
HSC (Higher Secondary School)	75	25
Bachelor	75	25
Master	--	--

Table 3. Convergent validity acceptable results

Constructs	*Items*	*Loading*	*Cronbach's*	*CR*	*AVG*
Behaviour Intention	BI1	0.845	0.874	0.894	0.679
	BI2	0.874			
	BI3	0.759			
	BI4	0.814			
Performance Expectancy	PE1	0.867	0.894	0.912	0.673
	PE2	0.711			
	PE3	0.745			
	PE4	0.873			
Effort Expectancy	EE1	0.789	0.863	0.793	0.659
	EE2	0.654			
	EE3	0.582			
	EE4	0.767			
Social Influence	SI1	0.867	0.847	0.801	0.681
	SI2	0.783			
	SI3	0.642			
	SI4	0.518			
Facilitating Condition	FC1	0.847	0.829	0.836	0.752
	FC2	0.784			
	FC3	0.613			
	FC4	0.742			

validity (Convergent and discriminant) of the latent variables. The instrument demonstrated high reliability with Cronbach α values ranging from 0.829 to 0.894 (Hair et al., 2013). Therefore, all constructs in this study exceed the reliability coefficient alpha (α) of 0.7, and the researchers can confidently assert that their measurement instruments are dependable and acceptable for the next step. As outlined by researchers (Cheung et al., 2023; Goretzko et al., 2024), construct validity refers to the extent to which a set of observed variables accurately represent the theoretical latent variables. The convergent validity was assessed through (CR) Composite reliability and (AVE) Average variance extracted. CR measures the internal consistency of the set of indicators for the latent construct but is more precise. CR values of 0.7 or higher are generally considered acceptable ranging from 0.793 to 0.912. While AVE evaluates the extent to which a construct explains the variance of its indicators. AVE values of 0.50 or above indicate satisfactory convergent validity ranging from 0.659 to 0.752, which means the concept accounts for at least 50% of the variance in its indicators. Table 3 represents the criterion of validity (AVE > 0.50 and CR > 0.7), all the results achieved acceptable convergent validity including adequate reliability results. According to researchers (Fornell & Larcker, 1981), stated that to assess the discriminant validity by comparing the square root of AVE of each construct within the correlation between the construct and all other constructs in the model. For the discriminant validity, in Table 4, diagonal values representing the square root of the AVE for the construct should be greater than its correlation with any other construct in the model.

Table 4. Fornell and Larcker Scale

	BI	*PE*	*EE*	*SI*	*FC*
BI	0.824				
PE	0.745	0.820			
EE	0.582	0.658	0.811		
SI	0.641	0.461	0.575	0.825	
FC	0.447	0.312	0.402	0.421	0.867

Assessment of Structural Model

Four hypotheses were tested (Wong, 2013; Ramayah et al., 2018), Table 5 shows the hypotheses' testing results. Based on our findings, all hypotheses H1, H2, H3, and H4 are significantly supported and have a greater impact on behaviour intention (BI). The result suggested performance expectancy increases satisfaction in using GenAI tools in education, where (β = 0.397, p = 0.000). Hence, H1 is statistically supported. Effort expectancy can increase satisfaction in using GenAI tools in education encouraging learners with its user-friendly features, where (β = 0.908, p = 0.001). Therefore, H2 is accepted. Social influence could increase satisfaction, where (β = 0.453, p = 0.001). Thus, H3 is supported. Facilitating conditions would increase satisfaction, where (β = 0.333, p = 0.001). Hence, H4 is accepted.

Table 5: Structural Model Results: Research Hypotheses Significant

	Hypothesis	*Path*	*t - value*	*P values*	*Decision*
PE→ BI	H1	0.379	5.261	0.000	Supported
EE→ BI	H2	0.908	4.708	0.001	Supported
SI→ BI	H3	0.453	7.404	0.001	Supported
FC→ BI	H4	0.333	2.568	0.001	Supported

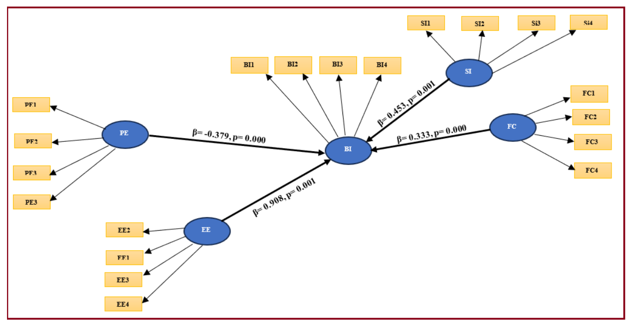

Fig. 2: Summary of Path Coefficients

Figure 2, summarizes the path coefficient results based on the suggested hypotheses defined in Figure 1. Therefore, the detailed discussions of the findings are as follows:

The Impact of PE on BI

The coefficient of performance expectancy Cronbach's α estimate (0.912) revealed that PE has strong internal consistency. Performance expectancy (H1: PE → BI), as a result (β = 0.397, p-value = 0.000), was found acceptable. The data support the notion that learners perceive the use of GenAI tools as beneficial for their academic tasks and performance. The findings are consistent with previous research investigations (Camilleri, 2024; Strzelecki, 2023). These researchers concluded that PE directly leads to behavior intentions because learners may believe that using GenAI tools is faster information retrieval, better explaining complex topics, and improves assignment quality.

The Impact of EE on BI

The coefficient of performance expectancy Cronbach's α estimate (0.793) revealed that EE has strong internal consistency. Effort expectancy (H2: EE → BI), as a result (β = 0.908, p-value = 0.001), was found statistically supported.

The result indicates a positive and strong relationship between EE and BI, implying that learners are more likely to adopt GenAI because they perceive them as user-friendly and requiring minimal effort to operate. This simplicity and intuitiveness in the interface and functionalities of GenAI tools play a crucial role in their acceptance among learners (Bhat et al., 2024; Sobaih et al., 2024).

The Impact of SI on BI

The coefficient of social influence Cronbach's α estimate (0.801) revealed that SI has strong internal consistency. Social influence (H3: EE → BI), as a result (β = 0.453, p-value = 0.001), was significantly supported. SI positive effect BI, suggests that when learners see others successfully using GenAI tools or hear about their academic benefits (Tiwari et al., 2024; Strzelecki, 2024). Learners may develop favourable behaviour intentions based on how GenAI tools are portrayed in their academic environment as enhancing problem-solving abilities.

The Impact of FC on BI

The coefficient of facilitating conditions Cronbach's α estimate (0.836) revealed that FC has strong internal consistency. Facilitating conditions (H4: EE → BI), as a result (β = 0.333, p-value = 0.001), was significantly supported. FC positive effect BI, suggests in the education sector with fully equipped such as availability of devices and reliable internet facilities impacting learners using GenAI tools (Tiwari et al., 2024; Strzelecki, 2023; Bhat et al., 2024). These researchers demonstrated that learners in an environment with robust facilitating conditions are more likely to perceive GenAI tools as useful and easy to use in their academic activities.

The coefficient of (R^2) and (Q^2)

The (R^2) measures the portion of the variance in the dependent variable BI, that can be explained by independent variables in the model to indicate the explanatory power of the model. Therefore, (R^2 = 0.61) higher value suggests the model explains the large portion of the variability in the outcome variable. While a positive (Q^2) value indicates that the model has a predictive relevance. Thus, (Q^2 = 0.48) confirms the model's predictive quality.

Conclusion

GenAI in education enhances learning with technology, streamlines academic tasks, and increases overall guidance of learning activities. These technological features reduce the learners' ability to evaluate information critically, fostering the passive acceptance of potentially flawed or incomplete knowledge. In this context, this research study employed the UTAUT as a research model by considering its significant factors to understand the learners' intention toward accepting and using GenAI in their academic learning in education sectors in Sindh, Pakistan. For the quantitative research method, A total of 300 responses were received from active learners from the education sectors in Sindh, Pakistan. In our findings, all suggested hypotheses such as PE, EE, SI, and FC have a greater impact on behaviour intention. This study empirically contributed by focusing on how emerging technologies in education influence higher-order thinking skills such as critical analysis and synthesis of ideas at the early stage of learners in the education sector in Sindh, Pakistan.

Research Implications

The study of GenAI tools in the education sector disrupts learners' thinking process in Sindh Pakistan offering valuable insights and several implications for government officials, and educational stakeholders, including policymakers, educators, and technologists. The study reveals how GenAI tools may disrupt traditional learning methods by altering cognitive engagements. These tools may enhance the efficacy but at the risk of diminishing critical thinking, problem-solving, and deep learning approaches. In addition, this study highlights that while GenAI tools can facilitate learning, they also risk reducing learners' higher-order thinking skills. Therefore, this research aimed to contribute to the growing body of knowledge on the intersection of technology in education, particularly in leveraging GenAI technologies that negatively impact learners, enhancing learning experiences and outcomes.

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