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ACCEPTANCE FACTORS OF GENERATIVE AI IN EFL TEACHING: A PEDAGOGICAL PERSPECTIVE

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Abstract. The emergence of generative artificial intelligence (GenAI) has brought abundant potentials and challenges to the educational sector. This study explores the acceptance and adoption of GenAI in English language and its pedagogical affordability for EFL instructors in tertiary level institutions in the Kingdom of Saudi Arabia. An exploratory sequential mixed method was utilized in this study to gain in-depth insights into the quantitative findings. The first quantitative phase recruited 256 EFL instructors in Saudi Arabia while the follow-up qualitative phase incorporated 17 interviewees. The findings of this study indicate that anthropomorphism, trust, ethics and regulations, and pedagogical affordability are significant determinants of instructors' acceptance of GenAI. Conversely, instructors' acceptance was not significantly influenced by communication capability of GenAI. Yet, there was no evidence of significant differences in GenAI acceptance or adoption due to demographic variables such as gender, age, and degree. The pedagogical affordances of GenAI appears to be the most acceptance factor specifically the productivity and efficiency that GenAI afford for instructors. The study recommends establishing ethical guidelines and embracing transparency and accountability to maintain academic integrity.

Keywords**:** Generative AI, acceptance, adoption, language teaching, EFL, Saudi Arabia

I. INTRODUCTION

The integration of generative artificial intelligence (GenAI) into education specifically in language teaching, and assessment has significantly and continuously reshaped the methods of instruction and learning. Recently, there has been a growing interest in how GenAI can improve the language learning process among English language instructors and students who embrace this transformative change.

The potential of GenAI systems to produce and process human language has created new opportunities for individualized, effective, and interactive educational experiences, making learning more engaging. With the help of its diverse range of language learning prompts, students may participate in conversations to enhance their vocabulary, grammar, speaking, and listening abilities while getting immediate feedback. Such applications can overcome the drawbacks of conventional classroom-based language instruction by offering constant, specific, and easily available assistance (Baidoo-Anu & Ansah, 2023). Furthermore, GenAI is being incorporated into language instruction for purposes other than language learning. It improves the development of instructional content, and is capable of creating language-based tests, activities, books, and other educational resources. The process of creating material is streamlined by this automation, which increases its effectiveness and efficiency (Bahroun et al., 2023).

GenAI has improved the language assessment using automated essay grading systems. These tools may grade written assignments, offer thorough criticism, and test critical thinking and linguistic abilities. As a result, instructors may grade assignments more quickly, and students can receive prompt, and consistent comments for improvements (Sharples, 2022). On the other hand, the sustainability of conventional assessment methods is called into question by the unexpected rise in popularity and accessibility of GenAI tools, which can produce engaging essays on any subject, code in a variety of programming languages, and score standardized tests in a variety of subject areas (Smolansky, 2023).

However, incorporating GenAI into teaching poses several challenges. Blake and Guillén (2020) emphasize the necessity of redesigning curricula and teaching techniques to accommodate GenAI tools, a process that can be daunting for instructors due the steep learning curve and required adjustment. Additionally, concerns about reliability and accuracy of AI-generated content impede the acceptance of GenAI. Dai et al. (2023) highlight on the ongoing debate regarding the quality of AI-generated educational materials and assessments, emphasizing worries about potential for errors, misinformation, and the absence of human intuition and contextual understanding. Furthermore, the lack of human interaction in AI-driven instruction is seen as a main barrier to meaningful instructor-student relationships, essential for motivation and engagement, leading to reluctance of adopting GenAI (Pedro et al., 2019). Despite GenAI's potential benefits in enhancing language teaching, instructors should respond to these challenges to foster a more knowledgeable and responsive teaching community.

Although GenAI has been the subject of several studies (Baidoo-Anu & Ansah, 2023; Bahroun et al., 2023; Sharples, 2022; Dai et al., 2023; Pedro et al., 2019), there is limited research on the factors that influence or hinder English language instructors from incorporating GenAI tools into language teaching and assessment. Accordingly, this study seeks to develop an acceptance model of GenAI in the context of English language education through exploring emerging behavioral patterns and predictors. This study may yield useful findings that can help in the integration of GenAI into English language instruction for the improvement of pedagogical experiences among instructors and students. It may also guide higher education institutions in developing proper training and guidelines for EFL instructors to adopt GenAI in teaching and assessment.

II. Literature Review

GenAI has positively impacted various fields including education, significantly influencing language teaching and assessment (Kohnke et al., 2023). It enhances language learning experiences through tailored and flexible approaches to improve language acquisition and assessment of language competency (Prather et al., 2023; Ghafar, 2023). natural language processing (NLP) enables GenAI to personalize language learning experiences using algorithms that can produce human-like written or spoken languages. Chatbots, language tutors, translators are personalized experiences based on GenAI that facilitate interactive discussion and fully immersive language learning experience (Hadi et al., 2023; Divekar, 2022). Moreover, GenAI empowers instructors with adaptive learning materials which assess learners' progress and provide exercises and content that are tailored to meet their individual needs. It allows learners to practice conversation, develop vocabulary, and correct grammar, which ultimately improve language learning. It facilitates cross-cultural communication and aids in comprehending the complicated vocabulary and structure of many languages. (Baidoo-Anu & Ansah, 2023; Sayers et al., 2021).

Another breakthrough of GenAI is grading written assignments, giving prompt feedback, and monitoring students' progress which changes the assessment landscape. Automated essay scoring systems, like the e-rater from ETS, use NLP models to assess written responses fairly and similarly to human grading (Ifenthaler, 2022). GenAI's adaptive testing adjusts questions complexity based on the student's performance. This helps instructors better assess students' writing skills and provide them with immediate feedback, allowing them to focus on engaging and dynamic parts of instruction that promotes dialogue and cross-cultural learning in language classrooms (Dwivedi et al., 2023; Wang et al., 2023).

Nevertheless, instructors articulated long-term consequences of GenAI in language teaching and learning such as over-reliance on GenAI and undermining interpersonal relationships and communication. Since language acquisition is fundamentally social, the excessive usage of GenAI could impede the growth of complex speech and cultural awareness resulted from daily interactions. (Kohnke et al., 2023). Thorough an extensive analysis library of students' academic papers, GenAI can identify potential plagiarism, helping in maintain academic integrity by ensuring fair evaluation (Canzonetta & Kannan, 2016). Farrelly and Baker (2023) and Dwivedi et al. (2023) highlighted ethical concerns regarding GenAI in language assessment, such as plagiarism detection and the potential for students to manipulate GenAI to produce superficially excellent but linguistically flawed work. EFL instructors are also concerned about the impartiality and precision of AI-powered tests, particularly in assessing highly individualized components of language competency like critical thinking and creativity.

Despite these concerns, proponents of GenAI contend that, when utilized wisely, these tools can enhance conventional methods of instruction. GenAI serves as an additional resource, boosting productivity while emphasizing real language skills. Achieving the benefits of GenAI in language teaching requires balancing technology and human interaction (Drew & Wallis, 2014; Pedro, 2019). A balance must also be established between the advantages of GenAI and the need for human supervision. While GenAI-enabled assessment enabled by GenAI can be efficient and objective, human judgment is necessary to ensure the reliability and ethical practice. Researchers and educators will continue addressing ethical and bias-related issues as GenAI develops to fully realize its potentials for language instruction and assessment, which accordingly raise the educational standards (Akhtar, 2023).

What is unique about AI Technology?

There is considerable debate in the literature on how AI technology differs from conventional technology due to its ability to simulate human intelligence, make decisions, and solve problems. According to Kelly et al., 2022 and Salovaara and Tamminen (2009), the conventional acceptance models fail into oversimplifying, leaving out important ethical issues, and possibly mismatching theoretical predictions with the complex problems that AI integration in education presents. This raises the attention towards new perspectives in AI adoption and acceptance across sectors. Alsharhan et al., (2023) reviewed 219 studies on AI acceptance and asserted that most studies proposed or integrate new factors to AI adoption. The most emerging factors in AI literature are anthropomorphism, trust, communication, ethics and policies (Alsharhan et al., 2023; Qin et al., 2020; Ofosu-Ampong et al., 2023; Vaccino-Salvadore, 2023; Huang et al., 2022). The following is a discussion of these factors and its emergence with AI technology.

Anthropomorphism

GenAI has made remarkable strides in natural language generation, exhibiting an ability to produce outputs that closely mimic human writing styles and patterns. This anthropomorphization of GenAI responses imbues the technology with a perceived sense of humanness, fostering heightened expectations among users regarding the system's capabilities and performance (Ma & Huo, 2023). The human-like quality of GenAI responses, characterized by considerate and affable language, facilitates seamless and enjoyable user interactions with these systems (Ma & Huo, 2023). As such, understanding the impacts and implications of this anthropomorphization warrants rigorous academic inquiry to elucidate the psychological, social, and ethical dimensions of human-GenAI interaction dynamics. In essence, anthropomorphism refers to how much a user views the AI agent as human-like during their interactions (Du et al., 2022). Therefore, the following hypothesis was formulated as follows:

H1: Perceived Anthropomorphism (ANTH) positively influence EFL instructors' behavioral intentions (BI) to use GenAI.

Trust

GenAI is described as a black-box since machine learning and algorithm cannot be observed by end-user (Rai, 2020). Therefore, users' trust of GneAI plays a significant role towards their acceptance and adoption of such technology. This study measured three dimensions of trust: benevolence, trust ability, and integrity. Benevolence is the state of the GenAI's aim being in line with that of the user, whereas trust ability refers to the proficiency of an AI application in successfully carrying out a task given by the user (Yang & Wibowo, 2022). Conversely, integrity refers to whether the AI's actions continually align with the moral ideals approved by the user groups (Novozhilova et al., 2024). Thus, this study hypothesize that as follows:

H2: Perceived Trust (TRST) positively influences EFL instructors' behavioral intentions (BI) to use GenAI.

Communication

The advancement in NLP has powered the conversational capability of GenAI to understand, interpret, and respond to human language in a natural, contextually relevant manner (Huang et al., 2022). As GenAI can mimic interpersonal conversations, EFL instructors started to apply various GenAI applications to support communication skills in authentic contexts (Huang et al., 2022). Thus, this study derived this construct from social presence component of Community of Inquiry Framework that include interpersonal communication, open communication, and task-oriented (cohesive) communication (Garrison, 2016). The hypothesis was formulated as follows:

H3: Perceived Communication (COMM) positively influences EFL instructors' behavioral intentions (BI) to use GenAI.

Pedagogical affordance

Pedagogical affordances are the features of a GenAI application that indicate if and how a specific learning behavior could be implemented in a certain setting (Kirschner et al., 2004). The pedagogical affordances influence EFL instructors' decisions to adopt GenAI to empower different pedagogical interventions such conversational partners and language coaching (Crompton et al., 2024). GenAI offers various pedagogical affordances that includes motivation, interlocution, simulation, knowledge transmission, helpline, recommendation, personalization and adaptation, immediate feedback, gamification and engagement, inclusivity, tutoring, and teacher's productivity (Nguyen, 2023; Huang et al., 2022).

Therefore, this study hypothesize this construct as follows:

H4: Pedagogical Affordance (PDGY) positively influence EFL instructors' behavioral intentions (BI) to use GenAI.

Ethics and regulations

With the growing interest in GenAI, more challenges are emerging in the daily practice of instructors and students. Among these challenges are data privacy and security, bias and lack of diversity, accessibility and reliability, and academic integrity (Vaccino-Salvadore, 2023). Therefore, the United Nations Educational, Scientific and Cultural Organization (UNESCO) issued AI in education guidelines for policymakers to help them in best to leverage the opportunities while addressing the risks, presented by the growing connection between AI and education (UNESCO, 2021). In the 2023 survey, UNESCO reported only seven countries have developed policies or frameworks for AI in education; thus, UNESCO recommends regulating GenAI in education to address the numerous challenges of educational GenAI (UNESCO, 2023). Consequently, this study hypothesize ethical dimension of educational GenAI as follows:

H5: Perceived Ethics and Regulations (ETHC) positively influence EFL instructors' use behavior (UB) of GenAI.

Acceptance of GenAI in language teaching and assessment

There are technological, pedagogical, and cultural dimensions impact the acceptance of GenAI in language teaching and assessment. The efficacy and dependability of GenAI have attracted instructors' attentions towards GenAI particularly the capacity to comprehend and produce human-like language (Bahroun et al., 2023; Sharadgah & Sa'di, 2022; Alqahtani et al., 2023). Luckin and Cukurova (2019) assert that well-designed AI tools can positively impact learning outcomes and accelerate the acquisition of language skills allowing instructors to witness tangible improvements in student performance. The alignment of GenAI with educational goals is another critical factor for instructors to adopt it. They consider GenAI for improving language skills,

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encouraging students' participation, and meeting individual needs through a mixed-learning environment that maximizes the benefits of both human and AI interactions (Ruiz-Rojas et al., 2023; Wang et al., 2023; Alshahrani, 2023). Instructors training on GenAI is another determinant of their acceptance of this technology (Baidoo-Anu & Ansah, 2023). Educators may be hesitant to embrace GenAI if they perceive it is a hard and destructive innovation that requires significant modifications to their current instructional setting (Cardon et al., 2023; Prasad Agrawal, 2023; Lim et al., 2023). Thus, the know-how training and collaborative networks were significant acceptance factors among EFL instructors (Dwivedi et al., 2023; Chounta et al., 2022).

In contrast, ethical and societal concerns, including data privacy and academic dishonesty are negative factors affecting GenAI acceptability. Addressing these issues through clear guidelines and ethical frameworks promotes trust and wider adoption of GenAI (Bahroun et al., 2023; Pedro et al., 2019; Dwivedi et al., 2023). Therefore, an interplay of technological, pedagogical, ethical, and support factors is the key of ideal adoption of GenAI (Chan, 2023; Yilmaz & Yilmaz, 2023).

Research aim & scope

This research investigate the acceptance level of GenAI (e.g. ChatGPT) among EFL instructors and professors in Saudi universities. This research propose a GenAI acceptance model in the context of English language education. The model proposes five determinants (latent variables) of GenAI acceptance by EFL instructors that include (1) Perceived Anthropomorphism (ANTH), (2) Perceived Trust (TRST), (3) Perceived Communication (COMM), (4) Pedagogical Affordance (PDGY), and (5) Perceived Ethics and Regulations (ETHC). (See research model)

Research Questions

1. To what extent the constructs of Perceived Anthropomorphism (ANTH), Perceived Trust (TRST), Perceived Communication (COMM), and Pedagogical Affordance (PDGY) positively influence EFL instructors' behavioral intentions (BI) to use GenAI?
2. To what extent the constructs of Perceived Ethics and Regulations (ETHC) positively influence EFL instructors' use behavior (UB) of GenAI?
3. To what extent the constructs of Behavioral Intention (BI) predicts the Use Behavior (UB) of EFL instructors?
4. To what extent gender, age, and degree moderate the influence of perceived anthropomorphism (ANTH), perceived trust (TRST), Perceived Communication (COMM), Pedagogical Affordance (PDGY), and Perceived Ethics and Regulations (ETHC) on behavioral intention (BI) and use behavior (UB)?

Research hypotheses

H1: Perceived Anthropomorphism (ANTH) positively influence EFL instructors' behavioral intentions (BI) to use GenAI.

H2: Perceived Trust (TRST) positively influence EFL instructors' behavioral intentions (BI) to use GenAI.

H3: Perceived Communication (COMM) positively influence EFL instructors' behavioral intentions (BI) to use GenAI.

H4: Pedagogical Affordance (PDGY) positively influence EFL instructors' behavioral intentions (BI) to use GenAI.

H5: Perceived Ethics and Regulations (ETHC) positively influence EFL instructors' use behavior (UB) of GenAI.

H6: Behavioral intention (BI) have a significant positive influence on EFL instructors' use behavior (UB) of GenAI.

H7.1,2,3,4,5: Gender moderates the influence of Perceived Anthropomorphism (ANTH), Perceived Trust (TRST), Perceived Communication (COMM), and Pedagogical Affordance (PDGY) on behavioral intentions (BI) and moderate the influence of Perceived Ethics and Regulations (ETHC) on use behavior (UB) of GenAI.

H8.1,2,3,4,5: Age moderates the influence of Perceived Anthropomorphism (ANTH), Perceived Trust (TRST), Perceived Communication (COMM), and Pedagogical Affordance (PDGY) on behavioral intentions (BI) and moderate the influence of Perceived Ethics and Regulations (ETHC) on use behavior (UB) of GenAI.

H9.1,2,3,4,5: Degree moderates the influence of Perceived Anthropomorphism (ANTH), Perceived Trust (TRST), Perceived Communication (COMM), and Pedagogical Affordance (PDGY) on behavioral intentions (BI) and moderate the influence of Perceived Ethics and Regulations (ETHC) on use behavior (UB) of GenAI.

III. METHODS

The population of this research is all EFL instructors in Saudi Arabian universities including public, private, and technical universities and colleges. The sample of this research is 256 EFL instructors and professors in Saudi universities invited over emails.

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Research Model:

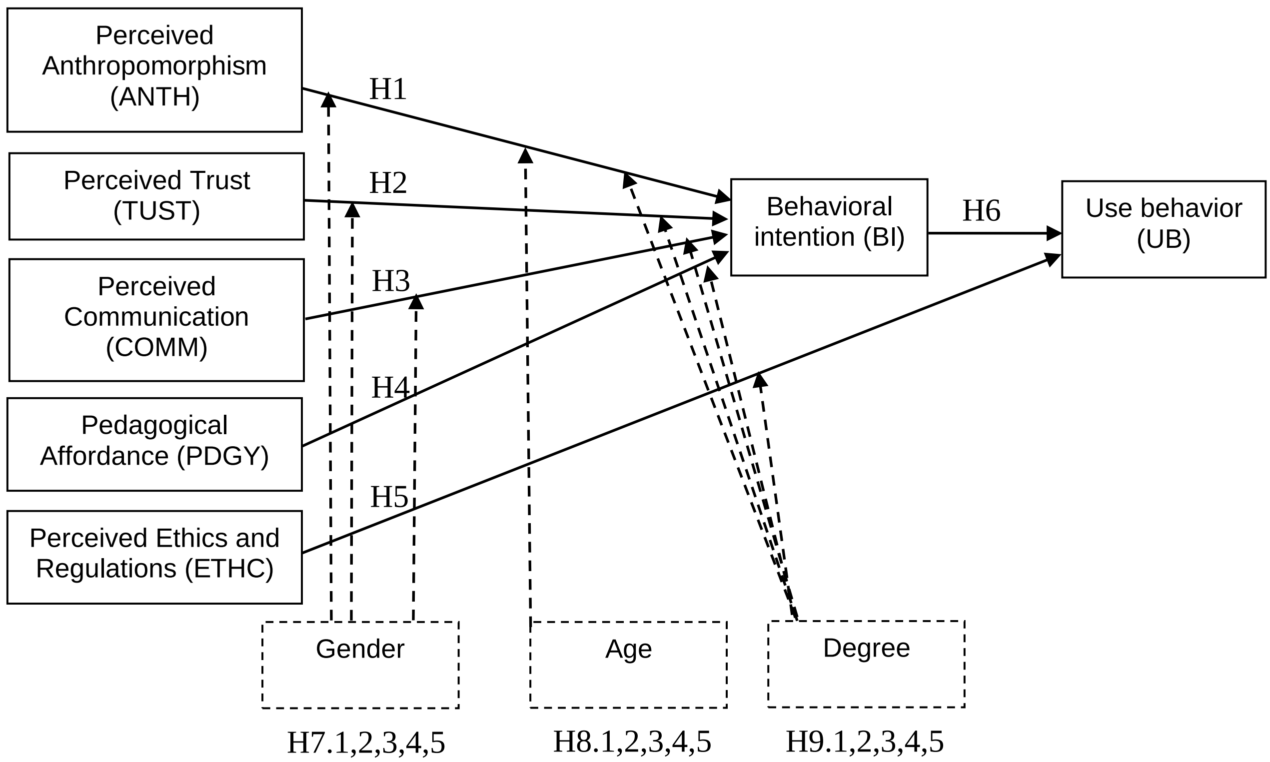

Figure 1: Research model

The current study utilizes an exploratory sequential mixed method approach to investigate the research hypotheses. A mixed-method research design is better suited to this study as it is a process of gathering, interpreting, and combining quantitative and qualitative research into a single study since the goal of this study is to better comprehend a research problem or issue that either research approach could do on its own (Creswell & Plano Clark, 2007). It consists of two main phases. First, quantifiable data is gathered using a structured questionnaire that included Likert-scale questions ranking the perceived impact of key factors. To summarize the quantitative data, descriptive statistics such as means and standard deviations were employed, presenting a numerical summary of the aspects influencing GenAI acceptability. The questionnaire was design based on an extensive review od acceptance models and theories including TAM, UTAUT, and Diffusion of Innovation theory influence. The questionnaire design incorporated a matrix development of all emerging AI acceptance factors in the literature such as pedagogical affordance, anthropomorphism, and ethics and regulations. As shown in Figure 1, the final model is based on the frequency and relevance of the proposed constructs. Participants were asked to score their level of agreement on a Likert scale, and structural equation modeling was performed to measure influence of each construct on GenAI acceptance.

Second, an in-depth open-ended interview with English language instructors was conducted to collect data on the factors that influence their acceptance of GenAI in teaching and assessment. Qualitative method provided an in-depth analysis of prevailing factors that enable English language instructors to accept GenAI in their teaching. The qualitative responses will be subjected to content analysis for the identification of recurring themes and patterns. The qualitative analysis is conducted to better understand the concerns that are inhibiting the acceptance of GenAI in English language education. To allow instructors to discuss their issues in depth, an interview protocol was developed informed by the qualitative analysis findings. The interview invitation was sent to 17 EFL professors and instructors who agreed in the first phase in the study to participate in the follow-up interview. The issues were then classified and analyzed using theme analysis. Descriptive statistics were used to quantify the prevalence and degree of each mentioned concerns to supplement the results of the qualitative analysis. This sequential mixed-methods approach provided a more nuanced understanding of the acceptance issues.

The mixed-methods methodology used in this study ensures a thorough examination of the factors and theories associated with the acceptance of GenAI by English language instructors.

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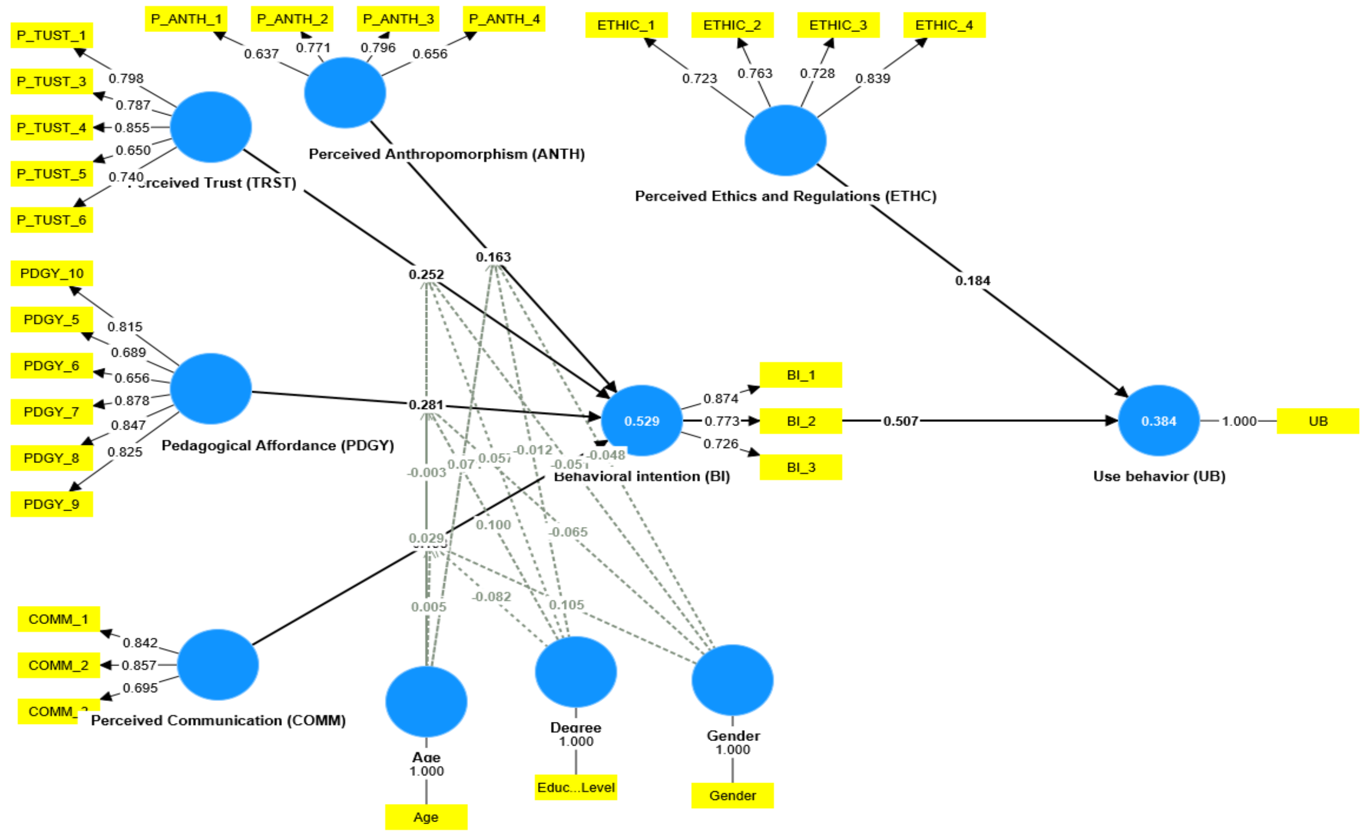
IV. RESULTS

Frequency Analysis:

Table 1: Frequency analysis of participants' demographics

Variable	Categories	Frequency (%)
Age	18 to 28 years	(2) 0.8%
	29 to 39 years	(82) 31.9%
	40 or more older	(173) 67.3%
Degree	Bachelor	(7) 2.7%
	Masters	(67)26.1%
	Doctoral Degree	(183) 71.2%
	Male	(115) 44.7%
Gender	Female	(142) 55.3%

Table 1 presents a frequency analysis of age, degree, and gender. The majority (67.3%) of participants were 40 years of age or older, with 31.9% aged between 29 and 39. The age range of 18 to 28 years had a reduced representation. Doctoral degrees were the most common educational attainment, followed by master's degrees at 26.1%. Only 2.7% had a bachelor's degree. The gender distribution was 55.3% female and 44.7% male. This summary provides a concise summary of the data.



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Construct reliability and validity:

Confirmatory factor analysis (CFA) is a crucial analytical framework used to evaluate the dependability and accuracy of components in research findings. It employs measures such as construct reliability (CR), composite reliability (CR), factor loadings, and different criteria analyses to assess the efficacy of the measurement model. Construct reliability quantifies the degree of internal consistency and reliability of a construct in a research investigation. Composite reliability assesses the internal consistency of latent variables or constructs by considering the factor loadings of indicators and their associated measurement errors. A coefficient of reliability (CR) that surpasses 0.70 is considered satisfactory, indicating a substantial level of reliability. According to Mohd Dzin and Lay (2021), Average Variance Extracted (AVE) quantifies the degree to which a construct captures variance relative to the variance attributable to measurement error. An AVE value exceeding 0.50 is typically used as a criterion for adequacy, indicating that the construct explains a larger proportion of variance than measurement error. Factor loadings are quantitative numbers that represent the strength and direction of the relationship between observed variables and underlying constructs. To ensure that indicators effectively measure desired concepts, it is important for the factor loadings to be statistically significant and relatively large, typically surpassing a threshold of 0.70. The Fornell-Larcker Criterion Analysis is a statistical method used in academic research to evaluate the discriminant validity of components in a measurement model. The process involves comparing the square root of Average Variance Extracted (AVE) for each construct with the correlations between that construct and other constructs. High loadings indicate a greater level of shared variance among the constructs, while low loadings indicate limited explanatory power and fewer estimated parameters connecting the construct (Hair et al., 2021a).

Table 2: Summary for factor loading & validity of Constructs

	factor loading	Cronbach's Alpha	Composite reliability	AVE	Delete items
BI_1	0.874	0.71	0.835	0.629	
BI_2	0.773				
BI_3	0.726				
COMM_1	0.842	0.719	0.842	0.642	
COMM_2	0.857				
COMM_3	0.695				
ETHIC_1	0.723	0.832	0.849	0.584	
ETHIC_2	0.763				
ETHIC_3	0.728				
ETHIC_4	0.839				
PDGY_10	0.815	0.876	0.907	0.623	PDGY 1 to 4 items delete
PDGY_5	0.689				
PDGY_6	0.656				
PDGY_7	0.878				
PDGY_8	0.847				
PDGY_9	0.825				
P_ANTH_1	0.637	0.876	0.907	0.623	
P_ANTH_2	0.771				
P_ANTH_3	0.796				
P_ANTH_4	0.656				
P_TUST_1	0.798	0.828	0.878	0.591	P Trust 2 item delete
P_TUST_3	0.787				
P_TUST_4	0.855				
P_TUST_5	0.650				
P_TUST_6	0.740				
UB	1.000				

Behavioral intention (BI), Pedagogical Affordance (PDGY, Perceived Anthropomorphism (ANTH), Use behavior (UB), Perceived Communication (COMM), Perceived Ethics and Regulations (ETHC), Perceived Trust (TRST),

Result Summary for factor loading & Validity of Constructs:

The factor loadings indicate the associations between the observable variables (items) and the underlying latent constructs in a measurement model. This study typically deems factor loadings above 0.5 appropriate. As Table 2 depicts, the Behavioral Intention (BI) construct shows significant factor loadings for all three items (BI_1, BI_2, and BI_3), with BI_1 having the highest loading of 0.874, followed by BI_2 at 0.773, and BI_3 at 0.726. This indicates that these items consistently assess the target behavioral dimension. Similarly, the factor loadings for Perceived Communication (COMM) are 0.842 for COMM_1 and 0.857 for COMM_2, demonstrating a significant link with the underlying concept. Nevertheless, COMM_3 exhibits a slightly lower loading of 0.695, although it still makes a

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significant contribution to the construct. The Perceived Ethics and Regulations (ETHIC) construct includes items (ETHIC_1, ETHIC_2, ETHIC_3, and ETHIC_4) with factor loadings ranging from 0.723 to 0.839, indicating that they accurately assess views of ethics and regulations. The elements PDGY_7 and PDGY_8 have high factor loadings of 0.878 and 0.847, respectively, indicating their strong association with pedagogical affordances (PDGY). Additionally, PDGY_10 also demonstrates a strong loading of 0.815. Nevertheless, PDGY_5, PDGY_6, and PDGY_9 have lower loadings, suggesting a weaker association with the underlying construct. The construct of perceived anthropomorphism (ANTH) exhibits factor loadings ranging from moderate to high. Specifically, P_ANTH_1, P_ANTH_3, and P_ANTH_4 demonstrate acceptable loadings, whereas P_ANTH_2 has a lower loading of 0.771. Perceived Trust (TRST) exhibits substantial factor loadings on its items (P_TUST_1, P_TUST_3, P_TUST_4, P_TUST_5, and P_TUST_6), suggesting that these items effectively capture the trust concept.

In summary, most of the questions demonstrate satisfactory factor loadings, thereby confirming the validity of the constructs they aim to evaluate. Nevertheless, certain components may require additional scrutiny or refining in order to enhance their impact on their respective structures. In addition, conducting a more in-depth analysis utilizing measures like Cronbach's alpha, composite reliability, and average variance extracted (AVE) allows for the evaluation of the reliability and convergent validity of the components, thereby offering a thorough comprehension of the measurement model.

Table 3: Discriminant validity using Heterotrait-monotrait ratio (HTMT) - Matrix

	(BI)	(PDGY)	(ANTH)	(COMM)	(ETHC)	(TRST)	(UB)
Behavioral intention (BI)							
Pedagogical Affordance (PDGY)	0.757						
Perceived Anthropomorphism (ANTH)	0.568	0.46					
Perceived Communication (COMM)	0.756	0.794	0.521				
Perceived Ethics and Regulations (ETHC)	0.466	0.593	0.202	0.498			
Perceived Trust (TRST)	0.756	0.823	0.438	0.881	0.541		
Use behavior (UB)	0.691	0.751	0.504	0.63	0.339	0.666	

The study evaluated discriminant validity using the heterotrait-monotrait ratio (HTMT) for various constructs such as Behavioral Intention (BI), Pedagogical Affordance (PDGY), Perceived Anthropomorphism (ANTH), Perceived Communication (COMM), Perceived Ethics and Regulations (ETHC), Perceived Trust (TRST), and Use Behavior (UB). Table 3 indicates the strength of the constructs' association with their own measurements. The results consistently fall below the threshold of 0.85, indicating sufficient discriminant validity. The BI concept demonstrates discriminant validity with other components, with HTMT values ranging from 0.466 to 0.757. PDGY also demonstrates discriminant validity, with HTMT values ranging from 0.46 to 0.794. ANTH, COMM, ETHC, TRST, and UB all demonstrate discriminant validity. These results confirm the measurement model's ability to differentiate between components and ensure accurate capture of distinct elements. This allows for meaningful interpretation of their interactions in future analyses.

Table 4: Discriminant validity, Fornell-Larcker criterion

	(BI)	(PDGY)	(ANTH)	(COMM)	(ETHC)	(TRST)	(UB)
Behavioral intention (BI)							
Pedagogical Affordance (PDGY)	0.625	0.789					
Perceived Anthropomorphism (ANTH)	0.445	0.389	0.718				
Perceived Communication (COMM)	0.559	0.633	0.41	0.801			
Perceived Ethics and Regulations (ETHC)	0.497	0.603	0.223	0.501	0.765		
Perceived Trust (TRST)	0.619	0.717	0.388	0.707	0.585	0.769	
Use behavior (UB)	0.599	0.709	0.452	0.54	0.436	0.621	

The correlation matrix is utilized to evaluate discriminant validity by analyzing the correlations among constructs. It is crucial to verify that these correlations are below the square root of the average variance extracted (AVE) for each construct. The diagonal in the matrix serves as a reference point, representing the square root of the Average Variance Extracted (AVE) for each construct. By comparing the off-diagonal correlations with these values, one can gain insights into the discriminant validity (Ab Hamid et al., 2017). Regarding Behavioral Intention (BI), all correlations with other constructs are below the square root of BI's AVE (0.793) as presented in Table 4, which suggests that there is discriminant validity. Similarly, the Pedagogical Affordance (PDGY) demonstrates discriminant validity, as all

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correlations with other constructs are lower than the square root of PDGY's Average Variance Extracted (AVE) value of 0.789. Perceived Anthropomorphism (ANTH) demonstrates discriminant validity, since all correlations with other constructs are below the square root of ANTH's Average Variance Extracted (AVE) value of 0.718. Perceived Communication (COMM) exhibits discriminant validity, as all correlations with other variables are below the square root of COMM's Average Variance Extracted (AVE) value of 0.801. To summarize, the correlation matrix indicates that all constructs possess discriminant validity. This is evident from the fact that the correlations across constructs are generally smaller than their respective Average Variance Extracted (AVE) values, which demonstrates that the constructs assess separate characteristics.

Collinearity assessment (VIF)

Multicollinearity is a regression modelling phenomenon where there is a significant connection between two or more exogenous variables, leading to bias. This can result in exaggerated regression estimations, such as R2 and Beta coefficients (Hair, Jr Black, Babin, & Anderson, 2019), which can impact the study's conclusion and outcome. To detect this issue, (Hair Jr, Sarstedt, Hopkins, & Volker, 2014) the collinearity evaluation can be used when the variance inflation factor (VIF) value for each variable exceeds 5. To avoid common method bias, the VIF must be lower than 3.3. Table 5 shows that no instances of multicollinearity or common method bias were detected in the research model. The absence of these issues is explained by the Variance Inflation Factors (VIFs) of all constructs being below the established standards of 3.3 for common method bias and 5 for multicollinearity (Hair et al., 2021b).

Table 5: Collinearity assessment (VIF)

	VIF	Collinearity Problem (VIF>5)?	Common Method Bias Problem (VIF>3.3?)
Behavioral intention (BI) -> Use behavior (UB)	1.328	No	No
Pedagogical Affordance (PDGY) -> Behavioral intention (BI)	2.237	No	No
Perceived Anthropomorphism (ANTH) -> Behavioral intention (BI)	1.25	No	No
Perceived Communication (COMM) -> Behavioral intention (BI)	2.205	No	No
Perceived Ethics and Regulations (ETHC) -> Use behavior (UB)	1.328	No	No
Perceived Trust (TRST) -> Behavioral intention (BI)	2.651	No	No

Hypothesis testing:

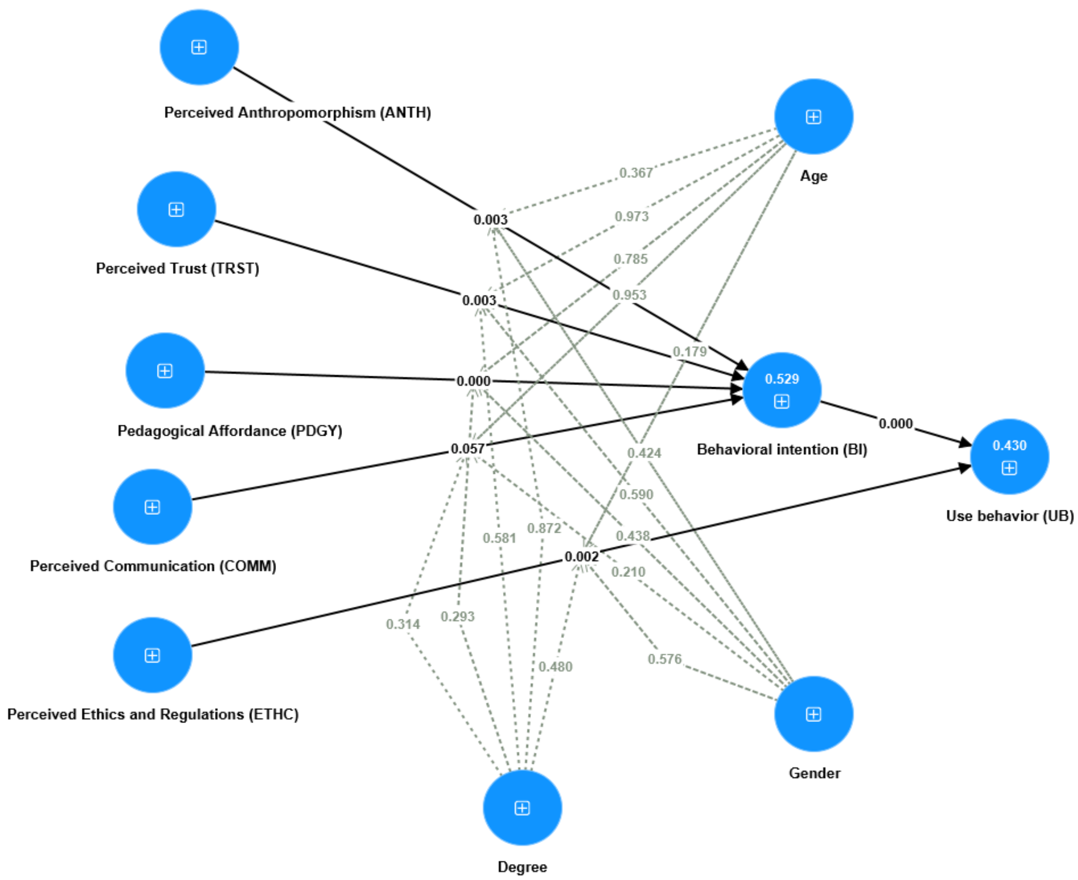

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Figure 3: Hypotheses testing results

Hypothesis testing: Direct Effect:

The study focused on analyzing the relationships in hypothesis testing for direct impacts. Table 6 displays that the relationship between Behavioral Intention (BI) and Use Behavior (UB) was shown to be statistically significant and positive (β = 0.481, *p* < 0.001). This means that higher levels of behavioral intention are linked to greater use behavior. The relationship between Pedagogical Affordance (PDGY) and Behavioral Intention (BI) was found to have a substantial positive effect (β = 0.283, *p* < 0.001). This indicates that perceptions of pedagogical affordance have a beneficial influence on behavioral intention. Perceived The study found that anthropomorphism (ANTH) had a notable and positive impact on Behavioral Intention (BI) (β = 0.174, *p* = 0.003). This suggests that individuals who perceive higher levels of anthropomorphism are more likely to have a stronger intention to engage in certain behaviors. The association between Perceived Communication (COMM) and Behavioral Intention (BI) was slightly significant (β = 0.124, *p* = 0.057), indicating a weak beneficial impact of perceived communication on behavioral intention. Perceived Ethics and rules (ETHC) had a notable and positive impact on Use Behavior (UB) (β = 0.171, *p* = 0.002), suggesting that individuals' perceptions of ethics and rules have a favorable influence on their use behavior. Perceived Trust (TRST) had a notable and positive impact on Behavioral Intention (BI) (β = 0.258, *p* = 0.003), suggesting that greater levels of perceived trust are linked to higher behavioral intention. The results indicate that beliefs regarding the potential for teaching, attributing human characteristics to non-human entities, moral principles and rules, and confidence have a substantial impact on the intention to act and actual behavior. Nevertheless, the impact of perceived communication on behavioral intention was only somewhat significant. These findings offer valuable information about the elements that influence behavioral intention and use behavior. This knowledge can be used to develop interventions or tactics to encourage desired behaviors.

Table 6: Hypothesis testing for direct impacts

	Beta	SD	t value	p values
Behavioral intention (BI) -> Use behavior (UB)	0.481	0.061	7.811	0.000
Pedagogical Affordance (PDGY) -> Behavioral intention (BI)	0.283	0.08	3.513	0.000
Perceived Anthropomorphism (ANTH) -> Behavioral intention (BI)	0.174	0.055	2.984	0.003
Perceived Communication (COMM) -> Behavioral intention (BI)	0.124	0.072	1.903	0.057
Perceived Ethics and Regulations (ETHC) -> Use behavior (UB)	0.171	0.055	3.049	0.002
Perceived Trust (TRST) -> Behavioral intention (BI)	0.258	0.086	2.95	0.003

Mediation Effect:

According to Table 7, mediation analysis in this table check the relationship between independent, mediator and dependent variables. The way communication is perceived indirectly affects how people behave by influencing their intention to act. The indirect impact was slightly significant (*β* = 0.059, *p* = 0.064), indicating that the connection between perceived communication and use behavior is partly influenced by behavioral intention. Perceived Trust (TRST) has an indirect impact on Use Behavior (UB) via influencing Behavioral Intention (BI). The indirect impact was statistically significant (β = 0.124, *p* = 0.007), suggesting that the relationship between perceived trust and use behavior is somewhat influenced by behavioral intention. Pedagogical Affordance (PDGY) has an indirect impact on Use Behavior (UB) via influencing Behavioral Intention (BI). The indirect impact was statistically significant (β = 0.137, *p* = 0.002), indicating that the link between pedagogical affordance and use behavior is partially influenced by behavioral intention. Perceived Anthropomorphism (ANTH) has an indirect influence on Use Behavior (UB) by affecting Behavioral Intention (BI) as a mediator. The indirect effect was statistically significant (β = 0.083, *p* = 0.004), suggesting that the connection between perceived anthropomorphism and use behavior is partially influenced by behavioral intention. The results emphasize how behavioral intention acts as a mediator in the connections between perceived communication, trust, pedagogical affordance, anthropomorphism, and use behavior. They propose that these characteristics have a direct impact on use behavior and also indirectly affect it by influencing behavioral intention. Gaining an understanding of these mediation effects can provide valuable insights into the fundamental mechanisms that influence behavior. This knowledge can then be used to develop interventions or strategies that try to encourage desired behaviors in different situations.

Table 7: Mediation analysis of independent, mediator and dependent variables

	Beta	SD	t value	p values
Perceived Communication (COMM) -> Behavioral intention (BI) -> Use behavior (UB)	0.059	0.036	1.85	0.064
Perceived Trust (TRST) -> Behavioral intention (BI) -> Use behavior (UB)	0.124	0.045	2.689	0.007
Pedagogical Affordance (PDGY) -> Behavioral intention (BI) -> Use behavior (UB)	0.137	0.044	3.091	0.002
Perceived Anthropomorphism (ANTH) -> Behavioral intention (BI) -> Use behavior (UB)	0.083	0.027	2.863	0.004

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Moderator effect

The analysis examines the moderating effects of age, education level (degree), and gender on the relationships between various perceived constructs and behavioral intention (BI) or use behavior (UB). The study found that most interactions between demographic factors (age, education level, and gender) and perceived constructs on behavioral intention or use behavior were not statistically significant. However, age and gender yielded potential moderating effects of certain constructs.

Table 8 depicts that the combined influence of age and perceived ethics and regulations on use behavior showed a tendency towards significance (p = 0.179, t = 1.343). This indicates that age might have a moderating influence on the connection between perceived ethics and laws and usage behavior. Elderly adults may exhibit distinct responses to perceived ethical considerations in contrast to younger individuals, hence changing their behavior accordingly.

In addition, the combined influence of gender and perceived communication on behavioral intention was nearly statistically significant (p = 0.21, t = 1.254). This indicates that gender may have a moderating influence on the connection between perceived communication and behavioral intention. Gender differences may influence how individuals respond to perceived communication cues, which in turn affects their behavioral intentions.

Table 8: Moderator effects of age and gender

Moderators' effects	Beta	SD	T value	P values
Age x Perceived Ethics and Regulations (ETHC) -> Use behavior (UB)	-0.074	0.055	1.343	0.179
Gender x Perceived Communication (COMM) -> Behavioral intention (BI)	0.105	0.084	1.254	0.21

Discussion

The model developed in this study is to capture the acceptance factors of EFL/ESL instructors of GenAI through five determinants: anthropomorphism, trust, communication, pedagogical affordance, and ethics and regulations. The quantitative and qualitative data used to examine the influence of these constructs on instructors' behavioral intentions (BI) and use behavior (UB) of GenAI.

Supporting hypotheses H1, H2, and H4, the results addressed Research Question 1 and showed that perceived anthropomorphism (ANTH), perceived trust (TRST), and pedagogical affordance (PDGY) had substantial positive effects on the behavioral intentions (BI) of EFL teachers to utilize GenAI. These findings indicate that teachers are more likely to want to include GenAI in their teaching methods if they believe it to have human-like qualities, trust the technology, and understand its pedagogical worth. H3 is somewhat supported, nevertheless, by the smaller, marginally significant effect of perceived communication (COMM) on behavioral intention. This suggests that although teachers' views on GenAI communication may affect their intents, other variables could be more important.

The qualitative analysis confirmed this finding where many EFL instructors utilized the human-like capability of GenAI to create interactive learning environments. For example, interviewee #7 stated that:

"I provide my students with a prompt to ask AI to act like a character. My students then have conversations with the AI agent".

However, other participants were skeptical about GenAI ability to mimic human language capabilities where interviewee #13, for instance, highlighted that:

" I am concerned about the loss of authenticity... learning a language is also about cultural nuances and human interaction which AI might not fully replicate".

In addition, qualitative data reveals that instructors trust of GenAI is task-oriented towards lesson planning and grading while they reported significant concerns regarding GenAI's outputs reliability and accuracy in other tasks.

In line with Farrelly and Baker (2023) and Dwivedi et al. (2023), many interviewees expressed concerns about GenAI misleading information and dysfunction in assessing high-order thinking tasks. This suggests that while trust is a positive factor, it is tempered by reliability and accuracy, influencing the extent to which EFL instructors are willing to adopt GenAI. Interestingly, the qualitative analysis support the insignificance of perceived communication in influencing GenAI acceptance where mixed reactions were reported. Although some interviewees believed GenAI has strong capabilities that can leveraged for teaching communication skills, other interviewees indicated the limited capabilities of GenAI to prompted language make it a secondary source to other pedagogical needs such as writing skills. This could be attributed to the contextual factors that instructors may prioritize different aspects of GenAI's functions based on their specific teaching needs.

Unlike other constructs in the model, the results of question 2 found perceived ethics and regulations (ETHC) as a positive influencer on EFL instructors actual use (UB) of GenAI supporting H5. This suggests that the more educational institutions have GenAI ethical guidelines and policies, the more their EFL instructors are willing to adopt GenAI in their teaching and assessment. This is supported by qualitative data where some interviewees, due to the lack of institutional guidelines, took the initiative to guide their students and educate them on the ethical and proper use of GenAI in their courses. For example, interviewee #2 stated that:

"one student made a claim about the play Macbeth by Shakespeare…I showed him the actual text of the play and proved to him that AI has made a mistake in interpreting factual data".

This incident highlights the importance of institutional GenAI guidelines and instructors monitoring to encourage GenAI ethical adoption.

Regarding the third question, instructors' behavioral intention (BI) towards GenAI has a positive influence on their use behavior (UB), supporting H6. This finding aligns with well-established theory of reasoned behavior, which posits behavioral intentions as robust predictors of actual behaviors. The qualitative data reveals the link between behavioral intention and use behavior is driven by the practical benefits acknowledged by instructors who found GenAI supportive and innovative in their teaching. On the hand, some interviewees reported challenges that might weaken their actual use of GenAI overtime such as privacy concerns, lack of manual oversight, and potential over-reliance of GenAI.

regarding the fourth question, the study found limited evidence of moderation effects by gender, age, and degree on the relationship between the proposed five constructs and behavioral intention (BI) or use behavior (UB). This is supported by the qualitative analysis where only interviewee #4 expressed ethical concerns among older instructors who value academic integrity. She stated that:

"Older adults may exhibit distinct responses to perceived ethical considerations".

Further qualitative insights

The qualitative analysis provides this study with deep findings that reflect both individual and collective perspectives on the adoption of GenAI.

Cautious experimentation Vs. enthusiastic adoption:

Two clear categorical attitudes have emerged reflecting both conservative and progressive adoption and acceptance of GenAI. Instructors who exhibit cautious experimentation recognize the potentials of GenAI such as efficiency and idea generation, but remain vigilant about its pitfalls such as over-reliance, ethical concerns, and privacy threats. They tend to balance GenAI's use with conventional methods and materials with strong emphasis on ethical guidelines and practice. In contrast, progressive instructors lean towards full embracement of GenAI capabilities to increase their productivity, create more engaging materials, and personalize learning experiences. This spectrum of GenAI adoption reflects the broader dialogue within the academic community about GenAI applications in educational practices.

Ethics and guidelines as foundation for trust in GenAI:

Instructors consistently emphasize the importance of ethical guidance which in turn foster trust on GenAI and responsible use behavior. They belief such guidelines and policies will maintain the academic integrity and protect the core academic values for a successful and sustainable adoption of GenAI in academia. This is explained in many incidents where instructors set course guidelines for their students to use GenAI in their deliverables. Interviewee #1 asserted that:

"I guide [my students] through the ethical way of using the AI". Similarly, interviewee #11 contended that "students should be educated on how to use AI ethically and properly".

Interconnectedness of trust and pedagogical affordability:

Instructors tend to build trust on GenAI through its pedagogical affordance as they see more tangible improvement in their teaching practice. Contrary to the dimensional trust proposed in the model, instructors view GenAI's trust as a domain specific, reflecting GenAI success (ability) in the carrying out the required tasks. This could be attributed to the clarity of educational tasks where GenAI is required to perform certain tasks with predefined criteria; however, more vague tasks might reveal less trust in GenAI's ability. This finding is aligned with Novozhilova et al. (2024) and Yang and Wibowo's (2022) findings of AI ability is the main driver of AI trust.

Over-reliance on GenAI:

Many instructors express concerns about the excessive dependence on GenAI could lead to laziness and addiction which undermines students' motivation, creativity, and critical thinking. Interviewees shared their divers' strategies in mitigating such a risk ranging from using AI detection systems and redoing the assignments in class to setting oral reflective discussion with students to defend their arguments. This finding reflects the ongoing debate in the literature regarding maintaining the academic integrity in embracing GenAI applications in education (Mohammadkarimi, 2023; Vaccino-Salvadore, 2023).

Productivity as a main driver of pedagogical affordability:

All interviewees reported improvements in their productivity with GenAI including efficiency in teaching workflows, streamlined assessment processes, interactive learning materials. The most recurring tasks that instructors associate with GenAI were lesson planning, providing feedback, and grading. Thus, instructors found the efficiency gains facilitated by GenAI have enabled them to invest more time and effort in improving their teaching and assessment practices. Collectively, they reported that enhancing students engagement, personalizing learning experience, and adopting innovative teaching strategies were the most emerging pedagogical affordances of GenAI. This finding is echoed in the literature wherein GenAI enforce EFL instructors' productivity and thus freeing up their times for more innovative teaching interventions (Nguyen, 2023; An et al., 2023; Huang et al, 2022).

V. Conclusions

This study explored the acceptance of GenAI among EFL instructors in Saudi universities. Embracing the unique challenges, contexts, and linguistic complexities of EFL, this study proposed a novel model that capture the most adoption factors. That includes anthropomorphism, trust, communication, pedagogical affordance, and ethics and regulations. The mixed method approach enables the study to deepen the understanding of instructors' behavioral intentions and use of GenAI. The findings assert that anthropomorphism, trust, pedagogical affordability, and ethics and regulations are significant factors to EFL instructors in GenAI acceptance. Pedagogical affordability appears to be the priority to instructors allowing them to be more productive and create rooms for more innovative teaching practice. Lesson planning, grading, and feedback are the most common pedagogical uses of GenAI by instructors. It is recommended that educational institutions to invest in GenAI technology and provide supportive environment to empower instructors with the knowledge and skills of GenAI educational integration.

From academic integrity perspective, instructors lack the appropriate guidelines and policies that lead them to report serious concerns about over-reliance, motivation undermining, misleading information, and privacy of students' data. This entails universities to develop AI guidelines and policies that ensure ethical usage and maintain academic integrity as well as students' well-being. Such guidelines should embrace transparency, accountability, privacy protection, and consistency among different programs and disciplines. Yet, It is not evident that demographics of instructors influence their adoption of GenAI leaving room for more further research and intervention that address behavioral variations of GenAI adoption. This could inform policy makers and training providers about the proper interventions to integrate GenAI in education among different stakeholders.

This study was limited to a sample size in both quantitative and qualitative phases, limiting the generalizability of the findings. Supporting that, the author received a few emails asking to withdraw from study as they not fully aware of GenAI and its educational uses. Thus, as AI technology is emerging, cross-sectional study might not capture potentials changes in perceptions and behaviors over time. Longitudinal and meta-analysis studies could reveal interesting findings in this essence.

References

Ab Hamid, M. R., Sami, W., & Mohmad Sidek, M. H. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. *Journal of Physics*. Conference Series, 890, 012163. https://doi.org/10.1088/1742-6596/890/1/012163

Akhtar, F. (2023). *Regulating Artificial Intelligence for a Safer and More Ethical Future: A Review of the EU's AI Act*. Available at SSRN 4560224. https://dx.doi.org/10.2139/ssrn.4560224

Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., bin Saleh, K., Alowais, S. A., Alshaya, O. A., Rahman, I., Al Yami, M. S., & Albekairy, A. M. (2023). The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. *Research in Social & Administrative Pharmacy: RSAP*, 19(8), 1236–1242. https://doi.org/10.1016/j.sapharm.2023.05.016

Alshahrani, A. (2023). The impact of ChatGPT on blended learning: Current trends and future research directions. *International Journal of Data and Network Science*, 7(4), 2029-2040. http://dx.doi.org/10.5267/j.ijdns.2023.6.010

Alsharhan, A., Al-Emran, M., & Shaalan, K. (2023). Chatbot adoption: A multiperspective systematic review and future research agenda. *IEEE Transactions on Engineering Management*, 1–13. https://doi.org/10.1109/tem.2023.3298360

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2023). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. Education and Information Technologies, 28(5), 5187–5208. https://doi.org/10.1007/s10639-022-11286-z

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability*, 15(17), 12983. https://doi.org/10.3390/su151712983

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, 7(1), 52-62. https://doi.org/10.61969/jai.1337500

Blake, R. J., & Guillén, G. (2020). *Brave new digital classroom: Technology and foreign language learning*, third edition. Georgetown University Press.

Canzonetta, J., & Kannan, V. (2016). Globalizing plagiarism & writing assessment: a case study of Turnitin. *Journal of Writing Assessment*, 9(2). https://escholarship.org/uc/item/5vq519dr

Cardon, P., Fleischmann, C., Aritz, J., Logemann, M., & Heidewald, J. (2023). The challenges and opportunities of AI-assisted writing: Developing AI literacy for the AI age. *Business and Professional Communication Quarterly*, 86(3), 257–295. https://doi.org/10.1177/23294906231176517

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. International Journal of Educational Technology in Higher Education, 20(1), 38. https://doi.org/10.1186/s41239-023-00408-3

Chounta, I.-A., Bardone, E., Raudsep, A., & Pedaste, M. (2022). Exploring teachers' perceptions of artificial intelligence as a tool to support their practice in Estonian K-12 education. *International Journal of Artificial Intelligence in Education*, 32(3), 725–755. https://doi.org/10.1007/s40593-021-00243-5

Crompton, H., Edmett, A., Ichaporia, N., & Burke, D. (2024). AI and English language teaching: Affordances and challenges. *British Journal of Educational Technology* (BJET). https://doi.org/10.1111/bjet.13460

Dai, Y., Liu, A., & Lim, C. P. (2023). Reconceptualizing ChatGPT and generative AI as a student-driven innovation in higher education. *Procedia CIRP*, 119, 84–90. https://doi.org/10.1016/j.procir.2023.05.002

Divekar, R. R. (2020). *AI enabled foreign language immersion: Technology and method to acquire foreign languages with AI in immersive virtual worlds*. [Doctoral dissertation, Rensselaer Polytechnic Institute - Troy, New York]. ProQuest Dissertations and Theses Global.

Drew, S. A. W., & Wallis, J. L. (2014). The use of Appreciative Inquiry in the Practices of Large-Scale Organisational Change a Review and Critique: A review and critique. Journal of General Management, 39(4), 3–26. https://doi.org/10.1177/030630701403900402

Du, X., Zhao, X., Wu, C.-H., & Feng, K. (2021). Functionality, emotion, and acceptance of artificial intelligence virtual assistants: The moderating effect of social norms. *Journal of global information management*, 30(7), 1–21. https://doi.org/10.4018/jgim.290418

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion Paper: “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71(102642), 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Farrelly, T., & Baker, N. (2023). Generative Artificial Intelligence: Implications and Considerations for Higher Education Practice. *Education Sciences*, 13(11), 1109. https://doi.org/10.3390/educsci13111109

Garrison, D. R. (2016). *E-learning in the 21st century: A community of inquiry framework for research and practice* (3rd ed.). Routledge.

Ghafar, Z. N. (2023). ChatGPT: a New Tool to Improve Teaching and Evaluation of Second and Foreign Languages a Review of ChatGPT: the Future of Education. International *Journal of Applied Research and Sustainable Sciences*, 1(2), 73–86. https://doi.org/10.59890/ijarss.v1i2.392

Hadi, M. U., Tashi, Q. al, Qureshi, R., Shah, A., Muneer, A., Irfan, M., Zafar, A., Shaikh, M. B., Akhtar, N., Wu, J., & Mirjalili, S. (2023). *Large Language Models: A comprehensive survey of its applications, challenges, limitations, and future prospects*. https://doi.org/10.36227/techrxiv.23589741.v4

Hair, J. F., Jr Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed.). Cengage Learning.

Hair, J. F., Jr, Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021b). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (1st ed.). Springer Nature.

Hair, J. F., Jr, Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, 26(2), 106–121. https://doi.org/10.1108/ebr-10-2013-0128

Hair, J., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021a). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

Huang, W., Hew, K. F., & Fryer, L. K. (2022). Chatbots for language learning—Are they really useful? A systematic review of chatbot-supported language learning. *Journal of Computer Assisted Learning*, 38(1), 237–257. https://doi.org/10.1111/jcal.12610

Ifenthaler, D. (2022). Automated Essay Scoring Systems. In *Handbook of Open, Distance and Digital Education* (pp. 1–15). Springer Nature Singapore.

Ifenthaler, D. (2022). Automated essay scoring systems. In *Handbook of open, distance and digital education* (pp. 1-15). Singapore: Springer Nature Singapore.

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, 77(101925), 101925. https://doi.org/10.1016/j.tele.2022.101925

Kirschner, P., Strijbos, J.-W., Kreijns, K., & Beers, P. J. (2004). Designing electronic collaborative learning environments. *Educational Technology Research and Development: ETR & D*, 52(3), 47–66. https://doi.org/10.1007/bf02504675

Kohnke, L., Moorhouse, B. L., & Zou, D. (2023b). Exploring generative artificial intelligence preparedness among university language instructors: A case study. Computers and Education: Artificial Intelligence, 5(100156), 100156. https://doi.org/10.1016/j.caeai.2023.100156

Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. *The International Journal of Management Education*, 21(2), 100790. https://doi.org/10.1016/j.ijme.2023.100790

Ma, X., & Huo, Y. (2023). Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society*, 75(102362), 102362. https://doi.org/10.1016/j.techsoc.2023.102362

Mohammadkarimi, E. (2023). Teachers’ reflections on academic dishonesty in EFL students’ writings in the era of artificial intelligence. *Journal of Applied Learning & Teaching*, 6(2), 105–113. https://doi.org/10.37074/jalt.2023.6.2.10

Mohd Dzin, N. H., & Lay, Y. F. (2021). Validity and reliability of adapted self-efficacy scales in Malaysian context using PLS-SEM approach. *Education Sciences*, 11(11), 676. https://doi.org/10.3390/educsci11110676

Nguyen, T. T. H. (2023). EFL teachers’ perspectives toward the use of ChatGPT in writing classes: A case study at Van Lang University. *International Journal of*

Language Instruction, 2(3), 1–47. https://doi.org/10.54855/ijli.23231

Novozhilova, E., Mays, K., Paik, S., & Katz, J. E. (2024). More capable, less benevolent: Trust perceptions of AI systems across societal contexts. *Machine Learning and Knowledge Extraction*, 6(1), 342–366. https://doi.org/10.3390/make6010017

Ofosu-Ampong, K., Acheampong, B., Kevor, M.-O., & Amankwah-Sarfo, F. (2023). Acceptance of artificial intelligence (ChatGPT) in education: Trust, innovativeness and psychological need of students. *Information and Knowledge Management*. https://doi.org/10.7176/ikm/13-4-03

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). *Artificial intelligence in education: Challenges and opportunities for sustainable development* (Working Paper No. ED-2019/WS/8). The United Nations Educational, Scientific and Cultural Organization (UNESCO). https://unesdoc.unesco.org/ark:/48223/pf0000366994

Prasad Agrawal, K. (2023). Towards adoption of generative AI in organizational settings. *Journal of Computer Information Systems*, 1–16. https://doi.org/10.1080/08874417.2023.2240744

Prather, J., Denny, P., Leinonen, J., Becker, B. A., Albluwi, I., Craig, M., Keuning, H., Kiesler, N., Kohn, T., Luxton-Reilly, A., MacNeil, S., Petersen, A., Pettit, R., Reeves, B. N., & Savelka, J. (2023). The robots are here: Navigating the generative AI revolution in computing education. *Proceedings of the 2023 Working Group Reports on Innovation and Technology in Computer Science Education* (pp. 108–159). Association for Computing Machinery. https://doi.org/10.1145/3623762.3633499

Qin, F., Li, K., & Yan, J. (2020). Understanding user trust in artificial intelligence-based educational systems: Evidence from China. *British Journal of Educational Technology (BJET)*, 51(5), 1693–1710. https://doi.org/10.1111/bjet.12994

Rai, A. (2020). Explainable AI: from black box to glass box. *Journal of the Academy of Marketing Science*, 48(1), 137–141. https://doi.org/10.1007/s11747-019-00710-5

Ruiz-Rojas, L. I., Acosta-Vargas, P., De-Moreta-Llovet, J., & Gonzalez-Rodriguez, M. (2023). Empowering Education with Generative Artificial Intelligence Tools: Approach with an Instructional Design Matrix. *Sustainability*, 15(15), 11524. https://doi.org/10.3390/su151511524

Salovaara, A., & Tamminen, S. (2009). Acceptance or appropriation? A design-oriented critique of technology acceptance models. In *Future Interaction Design II* (pp. 157–173). Springer London.

Sayers, D., Sousa-Silva, R., Höhn, S., Ahmedi, L., Allkivi-Metsoja, K., Anastasiou, D., Beňuš, Š., Bowker, L., Bytyçi, E., Catala, A., Çepani, A., Chacón-Beltrán, R., Dadi, S., Dalipi, F., Despotovic, V., Doczekalska, A., Drude, S., Fort, K., Fuchs, R., … Yildirim Yayilgan, S. (2021). *The Dawn of the Human-Machine Era: A forecast of new and emerging language technologies* (University of Jyväskylä, Ed.). Open Science Centre, University of Jyväskylä.

Sharadgah, T. A., & Sa'di, R. A. (2022). A systematic review of research on the use of artificial intelligence in English language teaching and learning (2015-2021): What are the current effects? *Journal of Information Technology Education Research*, 21, 337–377. https://doi.org/10.28945/4999

Sharples, M. (2022). Automated essay writing: An AIED opinion. *International Journal of Artificial Intelligence in Education*, 32(4), 1119–1126. https://doi.org/10.1007/s40593-022-00300-7

Silva, P. (2015). Davis' Technology Acceptance Model (TAM) (1989). In *Information Seeking Behavior and Technology Adoption* (pp. 205–219). IGI Global.

Smolansky, A., Cram, A., Raduescu, C., Zeivots, S., Huber, E., & Kizilcec, R. F. (2023, July). Educator and Student Perspectives on the Impact of Generative AI on Assessments in Higher Education. *In Proceedings of the Tenth ACM Conference on Learning@ Scale* (pp. 378-382). Association for Computing Machinery. https://doi.org/10.1145/3573051.3596191

UNESCO. (2021). *AI and education: guidance for policy-makers*. UNESCO. https://doi.org/10.54675/pcsp7350

UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO. https://doi.org/10.54675/ewzm9535

Vaccino-Salvadore, S. (2023). Exploring the ethical dimensions of using ChatGPT in language learning and beyond. *Languages*, 8(3), 191. https://doi.org/10.3390/languages8030191

Vaccino-Salvadore, S. (2023). Exploring the ethical dimensions of using ChatGPT in language learning and beyond. *Languages*, 8(3), 191. https://doi.org/10.3390/languages8030191

Valente, T. W. (2005). Network Models and Methods for Studying the Diffusion of Innovations. In P. J. Carrington, J. Scott, & S. Wasserman (Eds.), *Models and Methods in Social Network Analysis* (pp. 98–116). chapter, Cambridge: Cambridge University Press.

Venkatesh, Morris, Davis, & Davis. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, 27(3), 425. https://doi.org/10.2307/30036540

Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the Potential Impact of Artificial Intelligence (AI) on International Students in Higher Education:

Journal of Education, Teaching, and Learning
Volume 9 Number 2 September 2024. Page 196-211
p-ISSN: 2477-5924 e-ISSN: 2477-8478

Generative AI, Chatbots, Analytics, and International Student Success. *Applied Sciences*, 13(11), 6716. https://doi.org/10.3390/app13116716

Yang, R., & Wibowo, S. (2022). User trust in artificial intelligence: A comprehensive conceptual framework. *Electronic Markets*, 32(4), 2053–2077. https://doi.org/10.1007/s12525-022-00592-6

Yilmaz, R., & Karaoglan Yilmaz, F. G. (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(100147), 100147. https://doi.org/10.1016/j.caeai.2023.100147