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A Comparative Analysis of the Factors Influencing EFL Students' and Instructors' Acceptance and Adoption of AI-Assisted Language Learning: A UTAUT-Based Study on ChatGPT

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ABSTRACT

Background. The emergence of artificial intelligence (AI) tools such as ChatGPT has transformed English as a Foreign Language (EFL) education by offering new approaches to language learning and teaching. However, the evidence base remains limited in three important respects: prior studies often homogenize students and instructors, report inconsistent findings on key acceptance determinants, and rarely examine AI adoption through the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) within culturally and pedagogically specific EFL contexts.

Purpose. To address inconsistent and fragmented evidence on AI adoption in language education, this study examines the determinants of ChatGPT adoption among Saudi EFL students and instructors using UTAUT2, and evaluates how demographic factors condition these relationships in a generative AI context.

Method. The study employed a quantitative cross-sectional survey with 345 participants (students and instructors) from four Saudi universities. Separate UTAUT2-based questionnaires were validated through pilot testing and confirmatory factor analysis. Multiple regression analyses were conducted separately for each group to examine determinant effects, with interaction terms used to test the moderating roles of gender, age, and experience.

Results. Across both groups, performance expectancy was the strongest common predictor of behavioral intention (students: $\beta = 0.42$; instructors: $\beta = 0.40$). Beyond this shared effect, the patterns diverged. For students, social influence ($\beta = 0.30$) and hedonic motivation ($\beta = 0.22$) also played a significant role, whereas effort expectancy and habit did not reach significance. For instructors, by contrast, effort expectancy ($\beta = 0.11$) and habit ($\beta = 0.10$) were significant alongside performance expectancy, while social influence and hedonic motivation were not. Facilitating conditions and price value were non-significant in both groups. The moderation analysis further indicated that gender, age, and experience affected selected relationships between predictors and behavioral intention, with these effects varying across students and instructors rather than following a uniform pattern.

Conclusion. Adoption of ChatGPT in Saudi EFL education depends on both shared and group-specific factors, with performance expectancy as the strongest common predictor. The results emphasize the need for culturally informed and targeted strategies that address demographic and experiential differences and provide theoretical and practical guidance for AI integration in language education.

KEYWORDS

ChatGPT; EFL; technology acceptance; behavioral intention; UTAUT2; Saudi higher education; artificial intelligence; education

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INTRODUCTION

The emergence of generative artificial intelligence has altered the landscape of educational technology with unusual speed. Among the most influential developments is ChatGPT, a large language model capable of producing fluent, context-responsive text through conversational interaction. Its rapid diffusion has brought generative AI into everyday academic practice, including language learning, writing support, lesson preparation, and feedback generation. In higher education, this shift has been especially consequential for English as a Foreign Language education, where learners and instructors increasingly encounter AI not as a peripheral digital aid but as an interactive tool that can mediate practice, feedback, explanation, and content production. As a result, questions of whether and why users adopt such systems have become central to current debates on technology integration in language education (Biloš & Budimir, 2024; Dwivedi et al., 2023).

Research on technology adoption offers several established frameworks for explaining users' acceptance of new tools, including the Theory of Planned Behavior, the Technology Acceptance Model, Diffusion of Innovation, Task-Technology Fit, and the Unified Theory of Acceptance and Use of Technology (Ajzen, 1985; Davis, 1989; Goodhue & Thompson, 1995; Rogers, 1995; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003, 2012). Among these, UTAUT2 has been widely used because it provides a parsimonious yet comprehensive account of how *performance expectancy*, *effort expectancy*, *social influence*, *facilitating conditions*, *hedonic motivation*, *price value*, and *habit* shape behavioral intention. However, applying such models to ChatGPT is not a straightforward transfer. Generative conversational AI differs from conventional educational technologies because it is not merely a stable-purpose tool with predictable outputs. Instead, it functions as an interactive content generator whose responses may be useful, persuasive, incomplete, or inaccurate, which requires users to make ongoing judgments about reliability, appropriate reliance, and acceptable use (Ji et al., 2023; Lee & See, 2004; Yan et al., 2024).

This distinction is theoretically important. In the case of ChatGPT, adoption may depend not only on the expected utility and ease of use emphasized in traditional acceptance models, but also on concerns that are particularly salient in knowledge-intensive educational settings, such as trust calibration, verification effort, academic integrity, and pedagogical legitimacy. In other words, users may recognize the performance benefits of ChatGPT while still hesitating to adopt it fully because they remain uncertain about the credibility of its outputs or the institutional acceptability of its use. Prior research on AI in education increasingly suggests that these tensions shape willingness to use generative systems, especially when they are employed in assessment-sensitive or professionally accountable environments (Bin-Nashwan et al., 2023; Cotton et al., 2024; Dawson et al., 2024; Nazaretsky et al., 2022; Nazaretsky et al., 2025). For this reason, ChatGPT can be viewed as a boundary case for UTAUT2, a technology that is still well suited to adoption modeling, yet one that may alter the relative salience and interpretation of established predictors.

This issue becomes even more significant in AI-assisted language learning (AIALL). Research on this area has shown that AI chatbots can support personalized practice, immediate feedback, and opportunities for low-stakes interaction, all of which are relevant to second and foreign language development (Kohnke et al., 2023; Lubis et al., 2024; Wang, 2019). Recent evidence also suggests that AI-supported interventions can enhance affective and motivational dimensions of learning as well as academic performance, which reinforces the relevance of constructs such as *performance expectancy* and *hedonic motivation* in language education (Deng et al., 2025). However, AIALL is accompanied by persistent concerns regarding hallucinated output, overreliance, fabricated content, erosion of critical engagement, and the production of culturally homogenized language that may not reflect local communicative norms (Bhullar et al., 2024; Creely, 2024; Grassini, 2023; Michel-Villarreal et al., 2023). These contradictory tendencies suggest that adoption in language learning contexts cannot be understood solely as a matter of functional convenience. It is also shaped by affective safety, perceived legitimacy, and judgments about the pedagogical consequences of AI use.

The complexity of adoption becomes clearer when students and instructors are considered together rather than in isolation. Much of the existing literature examines one group at a time, which limits understanding of how adoption differs across stakeholder roles. Yet students and instructors do not encounter ChatGPT under the same conditions. For students, the technology may function primarily as a personal learning aid, a source of immediate support, or an engaging conversational partner for practice. For instructors, by contrast, adoption is mediated by professional responsibility, assessment design, policy compliance, and institutional expectations regarding acceptable pedagogical use (Chuang & Yan, 2025; Dawson et al., 2024; Scherer et al., 2019). What appears to be useful and motivating from a learner's perspective may therefore be evaluated more cautiously by instructors, whose decisions are embedded in broader concerns about validity, accountability, and classroom governance. A comparative design is thus not merely descriptive; it is theoretically necessary for determining whether adoption drivers remain stable across roles or are reweighted when generative AI enters contexts of pedagogical authority.

A further complication concerns demographic and experiential variation. Although UTAUT2 identifies gender, age, and experience as important moderators, prior research has produced mixed findings regarding their effects in educational technology adoption. Some studies report stronger performance-oriented effects for male users and stronger social or effort-related effects for female users, whereas others find no meaningful gender differences. Similar inconsistencies appear in the literature on age and experience, with some studies suggesting that younger or less experienced users rely more on social endorsement, while others report no such pattern (Bazelais et al., 2024; Du & Lv, 2024; Elshaer et al., 2024; Foroughi et al., 2023; Grassini et al., 2024; Romero-Rodríguez et al., 2023; Wang et al., 2024). These inconsistencies indicate that moderator effects may be highly context-sensitive rather than universally stable. They also suggest that adoption research on generative AI remains incomplete unless it explains when and for whom particular determinants matter most.

The Saudi EFL context provides a particularly revealing site for examining these issues. Saudi higher education has undergone rapid digital transformation and places increasing emphasis on technology-enhanced learning, yet empirical evidence on AI adoption in this setting remains limited. At the same time, Saudi classrooms are shaped by conditions that may influence acceptance patterns in distinctive ways, including hierarchical educational relationships, gender-segregated learning environments, institutional policy sensitivity, and varying forms of digital access and guidance. In such a setting, adoption is likely to be influenced not only by generic perceptions of usefulness and ease, but also by how social endorsement, pedagogical authority, and contextual legitimacy are negotiated in practice. The Saudi context therefore matters not simply because it is underrepresented, but because it enables a more demanding test of whether established adoption models travel well into culturally and pedagogically specific AIALL environments.

To strengthen the explanatory reach of UTAUT2 in this setting, the present study also draws selectively on two influential perspectives from second language acquisition: Krashen's Affective Filter Hypothesis and Vygotsky's Sociocultural Theory. Krashen's framework is relevant because enjoyable, low-pressure interaction with ChatGPT may reduce anxiety and support willingness to engage in language practice, which makes *hedonic motivation* more pedagogically meaningful than simple entertainment (Krashen, 1982). Vygotsky's perspective is equally pertinent because AI use in educational settings is not only an individual choice but also a socially mediated practice shaped by peer modeling, instructor approval, and institutional framing (Vygotsky, 1978). In this sense, *social influence* and *facilitating conditions* may be understood not merely as external adoption variables, but as mechanisms of pedagogical legitimation and mediated participation. The purpose of this theoretical integration is not to replace UTAUT2, but to situate it more convincingly within the realities of language learning and teaching.

Against this background, the current evidence base reveals three interrelated limitations. First, research on ChatGPT adoption in language education remains conceptually fragmented because it often applies technology-acceptance models to generative AI without fully addressing the distinctive issues of trust, verification, and acceptable educational use that conversational AI introduces. Second, prior studies frequently treat users as a homogeneous category, even though students and instructors occupy different positions of agency, accountability, and pedagogical responsibility. Third, evidence on demographic moderators remains inconsistent across contexts, which limits understanding of how role, gender, age, and experience condition adoption patterns in EFL settings. These limitations suggest that the current literature has not yet adequately explained how generative AI is adopted in context-sensitive language-learning environments or whether established UTAUT2 relationships remain stable across stakeholder groups.

The present study addresses these limitations by examining ChatGPT adoption among Saudi EFL students and instructors through the UTAUT2 framework, with particular attention to the moderating roles of gender, age, and experience. The study contributes in three ways. First, it provides a comparative account of adoption across two stakeholder groups that are often studied separately. Second, it evaluates the explanatory adequacy of UTAUT2 in a generative-AI environment where reliability, trust, and integrity concerns may reshape conventional acceptance pathways. Third, it situates adoption within a Saudi EFL context in order to clarify how sociocultural and institutional conditions may influence both the strength and the meaning of adoption predictors. In doing so, the study aims to contribute not only context-specific evidence, but also a more conceptually grounded understanding of AI adoption in language education.

Accordingly, the study is guided by the following research questions:

RQ1: To what extent do Saudi EFL students and instructors differ in the factors that influence their behavioral intention to use ChatGPT in English learning and teaching?

RQ2: To what extent do gender, age, and experience moderate the relationships between UTAUT2 constructs and behavioral intention among Saudi EFL students and instructors?

On the basis of UTAUT2 and the literature reviewed above, the study tests the following hypotheses:

H1: Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit significantly influence Saudi EFL students' and instructors' behavioral intention to use ChatGPT in English learning and teaching.

H2: Gender moderates the relationships between the UTAUT2 constructs and behavioral intention among Saudi EFL students and instructors.

H3: Age moderates the relationships between the UTAUT2 constructs and behavioral intention among Saudi EFL students and instructors.

H4: Experience moderates the relationships between the UTAUT2 constructs and behavioral intention among Saudi EFL students and instructors.

LITERATURE REVIEW

AI–Assisted Language Learning

AI-Assisted Language Learning has emerged as a major development in second and foreign language education, driven by tools such as AI chatbots (e.g., ChatGPT, Gemini, Copilot, & Claude,). Globally, research emphasizes AIALL's ability to personalize learning, provide instant feedback, and adapt content difficulty to learners' proficiency (Lubis et al., 2024; Kohnke, 2023). Such capabilities promote self-directed learning and extend language practice beyond the classroom, while also offering teachers insights for tailoring instruction (Wang, 2019). In Saudi Arabia, these features align with the country's broader educational digitalization goals and its emphasis on technology integration in EFL programs. For the present study, the importance of this literature lies not only in documenting the spread of AIALL, but also in clarifying why users may view ChatGPT as a meaningful academic resource. If students and instructors perceive that the tool can improve language-related work, that judgment is likely to form a central basis for their willingness to use it.

However, concerns remain about the use of AI tools in language learning. These concerns include risks of overreliance and reliability issues stemming from biased or outdated training data, the absence of transparent sourcing, and the potential to generate fabricated content (Bhullar et al., 2024; Gill et al., 2023; Creely, 2024). In educational contexts, such shortcomings can undermine academic integrity, especially when students use AI-generated responses without attribution (Michel-Villarreal et al., 2023; Sullivan et al., 2023). There is also the risk of eroding critical thinking and problem-solving abilities due to passive consumption of AI output (Grassini, 2023; Javaid et al., 2023). These concerns are amplified by the documented phenomenon of "hallucination" in natural language generation, where outputs appear fluent yet remain ungrounded or incorrect. This phenomenon increases the need for verification effort and strengthens the importance of trust calibration, both of which can shape adoption decisions even when perceived usefulness remains high (Ji et al., 2023; Lee & See, 2004). For the present study, this means that willingness to adopt ChatGPT may remain conditional. Users may recognize academic value and still hesitate when reliability, integrity, and verification demands become salient. As a result, the present study does not treat positive evaluations of AI as sufficient on their own, but reads them in relation to the concerns that may qualify or restrain sustained use.

A further criticism, which is particularly relevant in cross-cultural EFL contexts, is the potential cultural homogenization of language. AI chatbots tend to produce grammatically correct but culturally standardized English, shaped by Western linguistic norms, which may fail to reflect regional varieties or local communicative practices (Bhullar et al., 2024; Creely, 2024). This cultural dimension is particularly pertinent for Saudi EFL learners, where integrating localized expressions alongside standard English supports both communicative competence and cultural identity. This cultural dimension also matters analytically because it suggests that acceptance of AI in language learning may depend not only on efficiency or convenience, but also on whether users perceive the tool as pedagogically and culturally appropriate. In this sense, the literature points to adoption as a context-sensitive judgment, not a purely technical one.

Outcomes of AIALL: Pedagogical Gains and Risks

The literature presents contrasting findings on the learning outcomes of AIALL. On one hand, empirical studies show measurable gains in vocabulary acquisition, speaking fluency, and writing accuracy when learners engage regularly with AI chatbots (Kohnke et al., 2023; Wang, 2019). Moreover, AIALL environments provide a psychologically safe space for practice, which mitigates anxiety and encourages experimentation with language forms. Recent meta-analytic evidence indicates that AI-supported interventions can improve academic performance and affective-motivational outcomes on average, which reinforces the relevance of affective and engagement mechanisms for learners' use intentions (Deng et al., 2025). These findings are important for the present study because they indicate why perceived academic value and enjoyable engagement may become important drivers of willingness to use ChatGPT, particularly among students who encounter it directly as a tool for practice, support, and feedback.

On the other hand, negative outcomes have also been reported. Excessive exposure to AI-generated, contextually limited input may restrict learners' adaptability in real-life language use. Furthermore, without critical pedagogical oversight, students may prioritize speed and convenience over reflective learning, which leads to superficial engagement (Michel-Villarreal et al., 2023). These contradictions highlight a tension between efficiency-driven benefits and depth-oriented learning, which reinforces the need for context-sensitive AI integration in EFL curricula. This tension is also central to adoption as stakeholders may simultaneously perceive high performance benefits while withholding sustained use due to integrity risks, assessment validity concerns, or low trust in correctness (Bin-Nashwan et al., 2023; Cotton et al., 2024). This tension provides an important interpretive basis for the present study. If some predictors emerge as strong while others remain weak or inconsistent, those patterns should be understood in relation to the dual character of AIALL as both an enabling resource and a potential pedagogical risk. The literature therefore prepares the expectation that adoption will not follow a uniformly positive logic, even when ChatGPT is perceived as useful.

UTAUT2 Construct Definitions

UTAUT2 provides the main analytical framework for the present study because it captures the principal determinants that have repeatedly been used to explain technology acceptance across educational and consumer settings, namely *performance expectancy*, *effort expectancy, social influence, facilitating conditions, hedonic motivation, price value,* and *habit* (Venkatesh et al., 2003, 2012). In the context of ChatGPT adoption in Saudi EFL higher education, these constructs require contextual interpretation rather than mechanical transfer. *Performance expectancy* concerns the perceived contribution of ChatGPT to language learning and teaching outcomes; *effort expectancy* refers to the perceived ease with which the tool can be incorporated into academic tasks; *social influence* captures the normative force of peers, colleagues, and institutional actors; *facilitating conditions* refer to the availability of access, support, and enabling resources; *hedonic motivation* reflects the extent to which interaction with the tool is experienced as engaging; *price value* concerns the perceived balance between benefit and cost; and *habit* refers to the degree to which repeated use becomes routinized. Yet generative AI also introduces complications that are less visible in conventional adoption research. Because ChatGPT may produce fluent but inaccurate or ungrounded output, judgments of usefulness, ease, and even enjoyment may be shaped by verification effort, trust calibration, and acceptable-use concerns (Ji et al., 2023; Lee & See, 2004; Hoff & Bashir, 2015). For this reason, applying UTAUT2 to ChatGPT is theoretically informative not only because it tests the explanatory power of the model, but also because it helps identify which of its established pathways remain stable and which become less self-sufficient in a generative AI environment (Nazaretsky et al., 2022; Nazaretsky et al., 2025; Susarla et al., 2023; Yan et al., 2024).

The present study does not treat UTAUT2 as a list of variables, but as the main framework through which the relative weight of different adoption pathways can be interpreted. The present study uses the model to examine which determinants retain explanatory stability in a generative AI setting and which become more contingent because users must also evaluate trust, verification, and acceptable academic use. This point is especially important for the interpretation of the results. The study does not ask only whether the UTAUT2 constructs predict behavioral intention, but also how their predictive strength should be understood in an environment where usefulness may coexist with uncertainty. On this basis, performance expectancy may remain relatively stable because both students and instructors are likely to value academic utility, whereas effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit may vary more by role and context.

Cultural Moderators of Technology Adoption in Language Learning

Research on technology acceptance has repeatedly shown that the core UTAUT2 determinants do not operate with equal strength across contexts, and moderator effects remain especially unstable. Gender-related findings are mixed. Some studies report stronger performance-oriented pathways among male users and stronger effort- or socially mediated pathways among female users, whereas others find no significant gender differences at all (Elshaer et al., 2024; Foroughi et al., 2023; Grassini et al., 2024; Romero-Rodríguez et al., 2023). Similar inconsistency appears in relation to age and experience. Some studies suggest that younger or less experienced users rely more heavily on social cues, while others report weak or non-significant moderation effects (Bazelais et al., 2024; Du & Lv, 2024; Wang et al., 2024). These inconsistencies suggest that moderation effects are not fixed properties of the model, but conditional patterns shaped by institutional culture, technological familiarity, and the social organization of use. This issue is particularly relevant in Saudi higher education, where hierarchical teacher–student relations, gender-segregated educational environments, and uneven digital experience may alter the way adoption determinants translate into behavioral intention. In this respect, demographic moderation is not a secondary technical issue, but part of the broader question of whether generative AI adoption follows the same logic across users, roles, and contexts. For the present study, this means that gender, age, and experience should not be treated as routine background variables only. They matter because they may clarify when adoption relationships remain stable and when they change according to social position, technological familiarity, or the structure of educational participation in the Saudi context.

Comparative Perspectives: Students vs. Instructors in AIALL Adoption

Much of the literature on AI-assisted language learning examines either students or instructors in isolation, which limits the field's ability to explain whether adoption follows the same logic across educational roles. This is a significant limitation. Students typically encounter AI tools as resources for personal learning support, practice, drafting, and feedback, whereas instructors evaluate them within a wider framework of pedagogical design, assessment validity, institutional policy, and professional accountability (Chuang & Yan, 2025; Dawson et al., 2024). The difference is not merely practical; it is analytical. A factor that encourages experimentation and sustained use among students may carry less weight for instructors, whose decisions are shaped by classroom governance, acceptable-use concerns, and the need to integrate technology into established teaching routines. Prior research in educational technology points in this direction. Student acceptance is often tied to perceived usefulness and engagement, while teacher adoption is more closely linked to feasibility, professional beliefs, and the conditions under which technology can be incorporated into instructional work (Ertmer & Ottenbreit-Leftwich, 2010; Santini et al., 2025; Scherer et al., 2019). In the Saudi context, this distinction may be even sharper because students often access AI tools informally and beyond institutional oversight, whereas instructors must navigate policy sensitivity, assessment integrity, and culturally mediated expectations about appropriate classroom practice. A student–instructor comparison is therefore not simply descriptive. It provides a direct test of whether the explanatory balance of UTAUT2 remains stable across roles or is reweighted when adoption takes place under different conditions of agency and accountability. This comparison is therefore central to the argument of the present study. Its purpose is not only to identify whether students and instructors differ, but also to explain why particular predictors may matter more for one group than for the other. The literature thus frames group comparison as theoretically necessary for understanding role-specific adoption, not as a secondary descriptive exercise.

Blended Theoretical Model: Integrating UTAUT2 with Second Language Acquisition Theories

While UTAUT2 provides a robust framework for explaining technology adoption, its application to AI-assisted language learning can be sharpened by drawing on established perspectives from Second Language Acquisition (SLA). In the present study, Krashen's Affective Filter Hypothesis and Vygotsky's Sociocultural Theory are used to extend the interpretive reach of UTAUT2 rather than to replace it. These perspectives help situate technology acceptance within the pedagogical, affective, and socially mediated realities of language learning in Saudi EFL higher education. This theoretical combination is important because the present study requires more than a prediction model. UTAUT2 identifies the principal adoption pathways, whereas SLA theories help explain why those pathways may carry particular meanings in a language-learning environment.

Krashen's Affective Filter Hypothesis and UTAUT2

Krashen's Affective Filter Hypothesis holds that affective variables such as motivation, anxiety, and self-confidence shape the extent to which language input is successfully processed and internalized (Krashen, 1982). When the affective filter is low, learners are more likely to engage with input and take risks in language use; when it is high, participation becomes more inhibited. This perspective is relevant to the present study because some UTAUT2 constructs can be read not only as adoption variables, but also as conditions that may facilitate or constrain engagement in language practice.

In this regard, *hedonic motivation* is particularly important. Enjoyable interaction with ChatGPT may reduce tension, make practice feel less evaluative, and encourage learners to experiment more freely with language. Performance expectancy may also carry an affective dimension because learners who perceive the tool as genuinely helpful may feel more confident in using it for drafting, feedback, or rehearsal. In language-learning settings, then, perceived usefulness and enjoyment are not merely technical drivers of adoption; they may also shape the psychological conditions under which learners are willing to participate. This interpretation is consistent with research showing that AI-supported learning environments can strengthen both performance outcomes and affective-motivational engagement (Deng et al., 2025; Papi & Khajavy, 2023).

At the same time, the use of ChatGPT may also generate conditions that work in the opposite direction. Concerns about inaccurate output, inappropriate reliance, or uncertainty over acceptable academic use may introduce hesitation rather than confidence. In such cases, the learner may perceive the tool as useful and still remain cautious about sustained engagement. This is particularly relevant in generative AI environments, where fluency of output does not guarantee correctness and where verification becomes part of the user experience (Cotton et al., 2024; Ji et al., 2023; Lee & See, 2004). From a Krashenian perspective, these concerns can be understood as factors that may raise the affective barrier to use, even when the tool is perceived positively in other respects.

Vygotsky's Sociocultural Theory and UTAUT2

Vygotsky's Sociocultural Theory offers a complementary perspective by treating learning as a socially mediated process rather than a purely individual one (Vygotsky, 1978). Development takes place through interaction, guidance, and participation in socially organized activity. This perspective is especially useful for interpreting technology use in educational settings, where uptake is shaped not only by personal preference, but also by the norms, expectations, and forms of support that structure participation.

Within UTAUT2, *social influence* and *facilitating conditions* are particularly amenable to sociocultural interpretation. Social influence can be understood as the normative and interpersonal dimension of mediation, as peers, instructors, and institutional actors may legitimize or discourage AI use through approval, modeling, or explicit guidance. Facilitating conditions, in turn, represent the material and organizational side of mediation, including access, training, and sanctioned support for use. In the context of AI-assisted language learning, these constructs do not simply describe external conditions; they also reflect the degree to which AI use is embedded in recognizable pedagogical practice. This point becomes especially important when the tool can generate assessment-ready text and therefore requires explicit framing of acceptable and unacceptable use (Dawson et al., 2024; Nassaji & Cumming, 2000; Nazaretsky et al., 2022).

A sociocultural lens is also helpful in clarifying why adoption may differ across stakeholder groups. Students often encounter AI tools as part of their own learning routines, shaped by peer behavior and informal experimentation. Instructors, by contrast, engage with them under more formal conditions of pedagogical responsibility, institutional policy, and classroom governance. For that reason, the meaning of *social influence* and *facilitating conditions* may not be identical across groups. The same technology may be experienced by students as a socially normalized learning aid, while for instructors its legitimacy may depend more heavily on whether it can be incorporated into teaching practice without undermining assessment validity or instructional control (Chuang & Yan, 2025; Ertmer & Ottenbreit-Leftwich, 2010).

Interpretive Value of the Blended Model

Krashen's framework draws attention to the affective conditions of engagement, especially where enjoyment, confidence, and anxiety may shape willingness to use ChatGPT. Vygotsky's framework highlights the social and institutional mediation of use, particularly where legitimacy, modeling, and guided participation shape adoption. These perspectives make it possible to read technology acceptance not as a purely technical decision, but as a process embedded in pedagogical purpose, social organization, and role-specific responsibility. This is especially important in Saudi EFL classrooms, where AI use is likely to be filtered through both educational norms and broader questions of acceptable academic practice.

The reviewed literature suggests that some relationships may remain relatively stable, especially where users recognize clear academic value in ChatGPT. Other relationships may prove more context-sensitive, especially where adoption depends on social endorsement, institutional support, enjoyment, routinized use, or demographic variation. In this way, the literature review establishes how those findings will be used to interpret the results of the present study, which relationships may remain robust, which may vary by context, and why the student-instructor comparison matters theoretically.

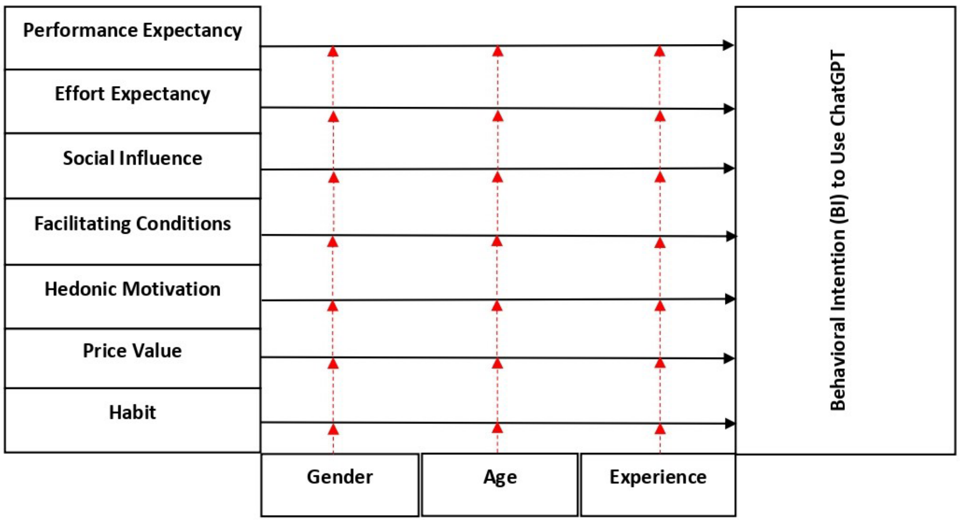
METHOD

Research Design

The present study employed a quantitative method to investigate the factors influencing Saudi EFL students' and instructors' acceptance and adoption of ChatGPT. The study incorporated three moderating variables (*gender*, *age*, and *experience*) to assess their effect on seven predictor variables (*performance expectancy*, *effort expectancy*, *social influence*, *facilitating conditions*, *hedonic motivation*, *price value*, and *habit*) and one outcome variable (*behavioral intention* to use ChatGPT). The study model is presented in Figure 1.

Figure 1

The Modified Study Model Adapted from UTAUT2 Model



Note. Adopted from Venkatesh et al. (2012).

Table 1

Frequency Distributions of EFL Students and Instructors Demographics

Variable	EFL Students (N= 181)			EFL Instructors (N= 164)			Total (N= 345)	
	Category	*f*	%	Category	*f*	%	*f*	%
Gender	Male	92	51%	Male	87	53%	179	51.9%
	Female	89	49%	Female	77	47%	166	48.1%
	Total	181	100%	Total	164	100%	345	100%
Age	Young (18–23 yrs)	123	68%	Young (25–45 yrs)	108	66%	231	67%
	Old (23yrs +)	58	32%	Old (45yrs +)	56	34%	114	33%
	Total	181	100%	Total	164	100%	345	100%
Experience	No/or < 1yr	60	33%	No/or < 1yr	80	49%	140	40.6%
	1yr+	121	67%	1yr+	84	51%	205	59.4%
	Total	181	100%	Total	164	100%	345	100%

Participants

The study involved 181 EFL students and 164 instructors from four Saudi public and private universities, with a total of 345 participants. The student sample distributed across various college levels: 33 first-year students (18%), 39 second-year students (22%), 47 third-year students (26%), and 62 fourth-year students (34%). The instructor sample included diverse academic ranks: 51 BA holders (31%), 57 MA holders (35%), and 56 Ph.D. holders (34%).

To enable meaningful subgroup analysis, participants were divided into categories based on gender, age, and experience with ChatGPT. The "young" versus "old" distinction followed a median split within each stakeholder group, a practice supported in prior UTAUT2 studies that use relative age groupings to explore moderation effects (e.g., Venkatesh et al., 2012; Elshaer et al., 2024). The rationale for a relative rather than fixed-age cutoff is that adoption patterns can differ significantly within the same cultural and institutional context depending on where participants fall relative to the group's age distribution. For experience, the one-year threshold aligns with prior technology adoption research that treats one year of sustained use as sufficient for habit formation (Lankton et al., 2015) and corresponds with the period during which ChatGPT became widely available in Saudi educational institutions.

Among total sample (N = 345), as shown in (Table 1), 51.9% were male and 48.1% were female. Age distribution showed that 67% were classified as young, while 33% were classified as old. Regarding ChatGPT experience, 40.6% had no experience or less than one year of use, while 59.4% had more than one year. In the student sample (N = 181), 51% were male and 49% female. Age-wise, 68% were between 18 and 23 years old, while 32% were over 23. Regarding experience, 33% had no or less than one year of use, while 67% had more than one year. In the instructor sample (N = 164), 53% were male and 47% female. Age-wise, 66% were between 25 and 45 years old, while 34% were over 45. Regarding experience, 49% had no or less than one year of use, while 51% had more than one year.

Instrument

A questionnaire survey was employed to gather data, and SPSS was used to analyze the results. This method offers a structured, scalable, and efficient approach to collecting and analyzing perceptions (Bryman, 2016). Two parallel instruments were developed: one for EFL students and one for EFL instructors, based on the UTAUT2 model (Venkatesh et al., 2012). Each instrument measured: *performance expectancy* (4 items), *effort expectancy* (4), *social influence* (3), *facilitating conditions* (4), *hedonic motivation* (3), *price value* (3), *habit* (4), and *behavioral intention* (3). Items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). To minimize bias, participants were informed that participation was voluntary, responses anonymous, and confidentiality maintained.

Validity & Reliability

Item development began with a review by three EFL instructors to ensure content validity. An exploratory factor analysis (EFA) was conducted during pilot testing using SPSS to assess dimensionality and identify poorly performing items. Items with low loadings (< 0.50) or substantial cross-loadings were removed. The refined instrument was then subjected to confirmatory factor analysis (CFA) on the main dataset using AMOS with Maximum Likelihood estimation to verify the measurement model. The CFA demonstrated good model fit (CFI > 0.95, TLI > 0.95, RMSEA < 0.05), and all retained items loaded significantly (> 0.60) on their intended constructs. This two-stage validation procedure ensured that construct validity was supported both statistically and theoretically in alignment with UTAUT2 dimensions.

The student questionnaire's reliability coefficients (Cronbach's α) were: PE (0.85), EE (0.82), SI (0.78), FC (0.80), HM (0.81), PV (0.79), HT (0.84), and BI (0.83), with an overall α = 0.82. The instructor questionnaire's coefficients were: PE (0.87), EE (0.84), SI (0.80), FC (0.82), HM (0.83), PV (0.81), HT (0.86), and BI (0.85), with an overall α = 0.84, which indicate high internal consistency for both instruments.

Data Collection & Analysis

A convenience sampling strategy was used, with the questionnaires distributed online via email. This approach enabled efficient recruitment of participants from multiple institutions and supported coverage of geographically dispersed respondents within the Saudi higher education context. The online format also ensured standardized administration of the survey instrument and facilitated consistent data capture across participants.

After establishing construct validity and reliability through confirmatory factor analysis, composite scores were computed for each construct and analyzed using multiple regression. Given the study's focus on examining predictive relationships and comparing effect patterns across stakeholder groups, multiple regression provided a suitable analytical approach. Multiple regression was conducted separately for students and instructors to assess the effects of the seven UTAUT2 predictors on behavioral intention, with interaction terms included to test the moderating roles of gender, age, and experience. Estimating the models separately allowed for clearer identification of group-specific effects and supported direct comparison of coefficient patterns across students and instructors. This analytical design ensured that the contribution of each predictor and moderator could be interpreted with respect to both within-group dynamics and cross-group variation.

RESULTS

Preliminary Assumption Testing: Normality Assessment

Prior to conducting regression analyses, the assumptions of normality and independence were examined. Shapiro–Wilk tests indicated no significant deviations from normality for students ($W = 0.980$, $p = 0.120$) or instructors ($W = 0.985$, $p = 0.093$). Similarly, Kolmogorov–Smirnov tests were non-significant for both students ($D = 0.067$, $p = 0.200$) and instructors ($D = 0.062$, $p = 0.200$). These results indicate that the normality assumption for regression analysis was adequately satisfied. In addition, inspection of standardized residuals, skewness, and kurtosis values further supported this conclusion.

Direct Effects of UTAUT2 Constructs on Students' Behavioral Intention (H1)

The multiple regression analysis for students (Table 2) shows that *performance expectancy*, *social influence*, and *hedonic motivation* have significant positive effects on students' *behavioral intention* to adopt ChatGPT. In terms of effect size, the standardized beta coefficients (β) indicate that *performance expectancy* ($\beta = 0.42$) represents the strongest predictor, followed by *social influence* ($\beta = 0.30$) and *hedonic motivation* ($\beta = 0.22$). These effects indicate that students' perceptions of ChatGPT's usefulness, the influence of their peers, and the enjoyment they encounter when using the tool play a major role in their intention to use it. However, *Effort expectancy*, *facilitating conditions*, *price value*, and *habit* were found to be non-significant, with very small standardized beta values ($\beta = 0.02$ and $\beta = 0.11$ respectively). This indicates negligible effect sizes and suggests that students do not rely heavily on the ease of use, available support, perceived value of ChatGPT, or their *habit*ual use in forming their intentions to employ the tool in their learning.

Table 2

Regression Results for the Direct Effects of UTAUT2 Constructs on Students' Behavioral Intention (H1)

Variable	B	Std. Error	Beta	*t*-value	*p*-value
Constant	0.25	0.12	-	2.08	0.039
PE	0.40	0.12	0.42	3.33	< .001
EE	0.02	0.10	0.02	0.20	0.840
SI	0.28	0.09	0.30	3.11	0.002
FC	0.10	0.09	0.11	1.11	0.270
HM	0.20	0.11	0.22	3.00	0.003
PV	0.18	0.10	0.20	1.80	0.072
HT	0.30	0.09	0.35	1.85	0.065

Note. Dependent variable: Behavioral intention to use ChatGPT.

Moderating Effects of Gender, Age, and Experience on Students' Behavioral Intention (H2–H4)

Interactions between the UTAUT constructs and students' gender, age, and experience reveal additional insights (Table 3). *Gender* significantly moderated the relationships between students' *performance expectancy*, *social influence*, and *hedonic motivation*, and their *behavioral intention*, which shows that female students, in particular, are more influenced by these constructs than their male counterparts. The standardized beta values for these interaction terms (β = 0.18, β = 0.15, and β = 0.23 respectively) indicate moderate effect sizes. *Age* significantly moderated the impact of *effort expectancy* and *price value*, with older students finding ChatGPT easier to use and perceiving its value more positively than younger students. *Experience* also significantly moderated the effects of *performance expectancy*, *social influence*, *hedonic motivation*, and *habit* which represent meaningful interaction effects. This result suggests that more experienced students find ChatGPT more useful, are more influenced by their peers, feel more excited toward using ChatGPT, and have stronger *habit*s in its use.

Direct Effects of UTAUT2 Constructs on Instructors' Behavioral Intention (H1)

The multiple regression analysis for instructors (Table 4) shows that their *performance expectancy*, *effort expectancy,* and *habit* were both significant predictors of *behavioral intention*. Based on standardized beta coefficients, *performance expectancy* shows the largest effect size (β = 0.40), followed by *effort expectancy* (β = 0.11) and *habit* (β = 0.10). This suggests that instructors believe that ChatGPT will improve their performance and that the ease of use as well as their *habit*ual use of ChatGPT play a role in their decision to adopt the tool. On the other hand, *social influence*, *facilitating conditions*, *hedonic motivation*, and *price value* were not found to have significant effects on *behavioral intention* for instructors, with small standardized beta coefficients indicating limited effect sizes, which implies that these factors do not heavily influence their decision to adopt ChatGPT.

Moderating Effects of Gender, Age, and Experience on Instructors' Behavioral Intention (H2–H4)

When looking at the moderating effects (Table 5), instructors' *gender* was found to significantly moderate the relationship between the independent variables (*performance expectancy*, *social influence*, *hedonic motivation*, and *habit***)** and the dependent variable (*behavioral intention*), with female instructors showing stronger relationships for these factors. In terms of effect size, the standardized beta coefficients show moderate interaction effects for these relationships (β = 0.20 for *performance expectancy*, β = 0.15 for *social influence*, β = 0.24 for *hedonic motivation*, and β = 0.21 for *habit*). *Age* significantly moderated the effects of *effort expectancy* and *facilitating conditions* on *behavioral intention*, with older instructors responding more strongly than younger instructors. The standardized beta coefficients for these interactions (β = −0.16 and β = 0.17 respectively) indicate moderate interaction effects. *Experience* moderated the relationships between *performance expectancy* and *habit* and *behavioral intention*, with more experienced instructors showing a stronger influence of these factors than their less experienced counterparts. The standardized beta coefficients for these interactions (β = 0.23 and β = 0.22 respectively) also demonstrate meaningful effect sizes.

Cross-Stakeholder Comparison

A comparison of the regression results indicates both similarities and differences between students and instructors. *Performance expectancy* significantly predicted *behavioral intention* in both groups and demonstrated the largest standardized effect size among all predictors (students β = 0.42; instructors β = 0.40). *Social influence* and *hedonic motivation* were significant predictors for students but not for instructors, with moderate standardized beta coefficients observed only among students. In contrast, *effort expectancy* and habit were significant predictors for instructors but not for students. *Facilitating conditions* and *price value* were non-significant for both groups and exhibited relatively small standardized beta values. Regarding moderation effects, *gender* moderated more relationships among instructors than students. *Age* moderated *effort expectancy* in both groups, but *facilitating conditions* were significant only for instructors and *price value* only for students. *Experience* moderated *performance expectancy* and *habit* for both groups, while additional moderation effects for *social influence* and *hedonic motivation* were observed only among students. These results demonstrate variation in the pattern of significant predictors and interaction effects across stakeholder groups.

Hypothesis Testing

To provide a consolidated overview of hypothesis testing outcomes across stakeholder groups, summary tables (Tables 6-9) are presented below. These tables synthesize the regression and moderation findings reported in Tables 4–7 and indicate which hypotheses were supported.

As shown in Table 6, the results showed that *performance expectancy* significantly predicted *behavioral intention* in both groups. For students, *social influence* and *hedonic motivation* were also significant predictors, whereas for instructors, *effort expectancy* and *habit* were significant. *Facilitating conditions* and *price value* were not significant in either group. These findings indicate partial support for H1.

As presented in Table 7, the results showed that *gender* significantly moderated the effects of *performance expectancy*,

Table 3

Regression Results for the Moderating Effects of Gender, Age, and Experience on Students' Behavioral Intention (H2–H4)

Interaction	B	Std. Error	Beta	*t*-value	*p*-value
Gender * PE	0.15	0.07	0.18	2.14	0.034
Gender * EE	-0.05	0.06	-0.06	-0.83	0.407
Gender * SI	0.12	0.05	0.15	2.40	0.018
Gender * FC	0.08	0.06	0.09	1.33	0.184
Gender * HM	0.22	0.08	0.23	2.75	0.006
Gender * PV	0.10	0.06	0.11	1.67	0.097
Gender * HT	0.09	0.07	0.20	2.57	0.101
Age * PE	0.08	0.07	0.10	1.14	0.255
Age * EE	0.12	0.06	0.14	2.00	0.047
Age * SI	0.05	0.05	0.06	1.00	0.318
Age * FC	-0.07	0.06	-0.09	-1.17	0.245
Age * HM	0.10	0.08	0.12	1.25	0.213
Age * PV	0.13	0.06	0.15	2.17	0.031
Age * HT	0.12	0.07	0.13	1.71	0.089
Experience * PE	0.18	0.07	0.20	2.57	0.011
Experience * EE	0.05	0.06	0.06	0.83	0.407
Experience * SI	0.22	0.08	0.25	2.75	< .001
Experience * FC	0.08	0.06	0.09	1.33	0.179
Experience * HM	0.20	0.08	0.23	2.75	< .001
Experience * PV	0.10	0.06	0.11	1.67	0.097
Experience * HT	0.18	0.07	0.20	2.57	< .001

Table 4

Regression Results for the Direct Effects of UTAUT2 Constructs on Instructors' Behavioral Intention (H1)

Variable	B	Std. Error	Beta	*t*-value	*p*-value
Constant	0.30	0.14	-	2.14	0.038
PE	0.42	0.12	0.40	3.50	< .001
EE	0.10	0.09	0.11	3.10	0.002
SI	0.33	0.11	0.32	1.10	0.273
FC	0.11	0.10	0.12	1.12	0.270
HM	0.09	0.08	0.09	1.10	0.302
PV	0.20	0.11	0.19	1.82	0.071
HT	0.10	0.09	0.10	3.00	0.003

Note. Dependent variable: Behavioral intention to Use ChatGPT.

social influence, and *hedonic motivation* among students. For instructors, *gender* significantly moderated *performance expectancy*, *social influence*, *hedonic motivation*, and *habit*. The remaining interaction effects were not significant, which signifies partial support for H2.

As reported in Table 8, the results showed that *age* significantly moderated *effort expectancy* and *price value* for students. Among instructors, *age* significantly moderated *effort expectancy* and *facilitating conditions*. Other age-based inter-

Table 5

Regression Results for the Moderating Effects of Gender, Age, and Experience on Instructors' Behavioral Intention (H2–H4)

Interaction	B	Std. Error	Beta	t-value	p-value
Gender * PE	0.17	0.07	0.20	2.43	0.016
Gender * EE	-0.06	0.06	-0.07	-0.91	0.361
Gender * SI	0.13	0.06	0.15	2.10	0.037
Gender * FC	0.09	0.07	0.10	1.29	0.196
Gender * HM	0.23	0.08	0.24	2.78	0.006
Gender * PV	0.11	0.07	0.12	1.70	0.091
Gender * HT	0.19	0.07	0.21	2.64	< .001
Age * PE	0.10	0.07	0.12	1.30	0.194
Age * EE	-0.14	0.07	-0.16	-2.00	0.047
Age * SI	0.07	0.06	0.08	1.15	0.251
Age * FC	0.15	0.07	0.17	2.20	0.029
Age * HM	0.12	0.08	0.13	1.50	0.213
Age * PV	-0.09	0.07	-0.11	-1.30	0.192
Age * HT	0.13	0.07	0.15	1.71	0.091
Experience * PE	0.21	0.07	0.23	2.57	0.011
Experience * EE	0.06	0.06	0.07	0.89	0.404
Experience * SI	0.12	0.08	0.09	2.75	0.101
Experience * FC	0.10	0.07	0.12	1.33	0.184
Experience * HM	0.13	0.08	0.12	2.75	0.171
Experience * PV	0.11	0.07	0.13	1.67	0.093
Experience * HT	0.20	0.07	0.22	2.57	< .001

Table 6

Regression Results for the Direct Effects of UTAUT2 Constructs on Behavioral Intention Among Students and Instructors (H1 Comparison)

Relationship	(Students)			(Instructors)		
	β **value**	***p*-value**	**Outcome**	***β*** **value**	***p*-value**	**Outcome**
PE → BI	0.42	< .001	Supported	0.40	< .001	Supported
EE → BI	0.02	0.840	Not supported	0.11	0.002	Supported
SI → BI	0.30	0.002	Supported	0.32	0.273	Not supported
FC → BI	0.11	0.270	Not supported	0.12	0.270	Not supported
HM → BI	0.22	0.003	Supported	0.09	0.302	Not supported
PV → BI	0.20	0.072	Not supported	0.19	0.071	Not supported
HT → BI	0.10	0.065	Not supported	0.10	0.003	Supported

action effects were not statistically significant, which indicates partial support for H3.

As shown in Table 9, the results showed that *experience* significantly moderated *performance expectancy*, *social influence*, *hedonic motivation*, and *habit* for students. For instructors, *experience* significantly moderated *performance expectancy* and *habit*. The remaining moderation effects were not significant, which leads to partial support for H4.

Table 7

Regression Results for the Moderating Effects of Gender on the Relationships Between UTAUT2 Constructs and Behavioral Intention Among Students and Instructors (H2)

Relationship	(Students)			(Instructors)		
	β value	***p*-value**	**Outcome**	**β value**	***p*-value**	**Outcome**
PE*Gender → BI	0.18	0.034	Supported	0.20	0.016	Supported
EE*Gender → BI	-0.06	0.407	Not supported	-0.07	0.361	Not supported
SI*Gender → BI	0.15	0.018	Supported	0.15	0.037	Supported
FC*Gender → BI	0.09	0.184	Not supported	0.10	0.196	Not supported
HM*Gender → BI	0.23	0.006	Supported	0.24	0.006	Supported
PV*Gender → BI	0.11	0.097	Not supported	0.12	0.091	Not supported
HT*Gender → BI	0.20	0.101	Not supported	0.21	< .001	Supported

Table 8

Regression Results for the Moderating Effects of Age on the Relationships Between UTAUT2 Constructs and Behavioral Intention Among Students and Instructors (H3)

Relationship	(Students)			(Instructors)		
	β value	***p*-value**	**Outcome**	**β value**	***p*-value**	**Outcome**
PE*Age → BI	0.10	0.255	Not supported	0.12	0.194	Not supported
EE*Age → BI	0.14	0.047	Supported	-0.16	0.047	Supported
SI*Age → BI	0.06	0.318	Not supported	0.08	0.251	Not supported
FC*Age → BI	-0.09	0.245	Not supported	0.17	0.029	Supported
HM*Age → BI	0.12	0.213	Not supported	0.13	0.213	Not supported
PV*Age → BI	0.15	0.031	Supported	-0.11	0.192	Not supported
HT*Age → BI	0.13	0.089	Not supported	0.15	0.091	Not supported

Table 9

Regression Results for the Moderating Effects of Experience on the Relationships Between UTAUT2 Constructs and Behavioral Intention Among Students and Instructors (H4)

Relationship	(Students)			(Instructors)		
	β value	***p*-value**	**Outcome**	**β value**	***p*-value**	**Outcome**
PE*Exp → BI	0.20	0.011	Supported	0.23	0.011	Supported
EE*Exp → BI	0.06	0.407	Not supported	0.07	0.404	Not supported
SI*Exp → BI	0.25	< .001	Supported	0.09	0.101	Not supported
FC*Exp → BI	0.09	0.179	Not supported	0.12	0.184	Not supported
HM*Exp → BI	0.23	< .001	Supported	0.12	0.171	Not supported
PV*Exp → BI	0.11	0.097	Not supported	0.13	0.093	Not supported
HT*Exp → BI	0.20	< .001	Supported	0.22	< .001	Supported

Overall, the findings indicate partial support for the proposed UTAUT2 relationships, with variations observed across stakeholder groups and moderating variables.

DISCUSSION

The findings refine the current picture of ChatGPT adoption in language education in three important ways. First, they show that adoption cannot be treated as a uniform process across educational users. Second, they indicate that UTAUT2 remains useful in a generative AI environment, but not all of its core determinants retain equal explanatory weight. Third, they show that demographic conditions do not exert broad, uniform effects; rather, they selectively reshape specific construct–intention relationships. In this respect, the study speaks directly to a wider gap in the literature, where research has often treated students and instructors as a single user category and has tended to assume that established technology-acceptance patterns transfer to generative AI without substantial reweighting.

The strongest common result is the role of *performance expectancy*. For both students and instructors, perceived usefulness was the most powerful predictor of behavioral intention. This is consistent with the central position of *performance expectancy* in UTAUT and UTAUT2 (Venkatesh et al., 2003, 2012). At the same time, in the case of ChatGPT, usefulness is unlikely to be understood in narrowly instrumental terms. In language education, a tool is not judged only by speed or convenience, but by whether its output can be used productively without compromising learning quality, pedagogical judgment, or academic integrity. The fact that *performance expectancy* remained dominant across both groups suggests that users were willing to engage with ChatGPT when they perceived clear academic benefit, even though generative AI introduces uncertainty regarding correctness, source transparency, and appropriate reliance. In that sense, the result confirms the continued explanatory strength of UTAUT2 while also supporting the view that generative AI complicates, rather than displaces, the logic of perceived usefulness (Dwivedi et al., 2023; Ji et al., 2023; Lee & See, 2004; Susarla et al., 2023). This pattern also aligns with findings that identify *performance expectancy* as a major predictor of intention to use ChatGPT in higher education across both student and faculty samples (Faraon et al., 2025; Kaya & Adıgüzel, 2025).

Beyond this shared foundation, the adoption structure differed clearly by stakeholder role. Among students, *social influence* and *hedonic motivation* were significant, whereas effort expectancy and *habit* were not. This pattern suggests that student adoption was shaped not only by expected benefit, but also by whether ChatGPT use was socially legible and experientially attractive. Such a configuration is plausible in EFL settings, where students often turn to AI tools for drafting support, language practice, and low-stakes interaction outside formal classroom evaluation. In that context, *hedonic motivation* should not be reduced to simple enjoyment. It may capture a lower-friction form of engagement in which learners feel able to experiment, rehearse, and seek feedback with less anxiety than in teacher-monitored settings. This interpretation is consistent with work on AI-assisted language learning that emphasizes interaction, immediacy of feedback, and motivational support (Kohnke, 2023; Lubis et al., 2024; Wang, 2019), and it is also compatible with Krashen's argument that reduced anxiety facilitates engagement with language input and output (Krashen, 1982). A similar interpretation appears in Faraon et al. (2025), where *hedonic motivation* contributed to students' intention to use ChatGPT in some contexts, which supports the view that exploratory and low-pressure engagement can shape student adoption alongside perceived usefulness.

The significance of *social influence* for students is equally important. In much of the technology-adoption literature, student use is treated as increasingly individualized, especially where access is easy and digital tools are familiar. The present findings point to a more social logic. Students' behavioral intention appears to depend in part on whether ChatGPT use is normalized through peer behavior and instructor approval. This matters because it suggests that adoption in AI-assisted language learning is also a question of legitimacy. Where acceptable use remains unsettled, students may rely on social cues to determine whether a tool is an academically appropriate resource or a shortcut of uncertain status. This interpretation fits the sociocultural orientation adopted in the study, where technology use is understood as socially mediated rather than purely individual (Vygotsky, 1978). It also aligns with recent work arguing that AI adoption in education is shaped by institutional framing, guidance, and norms of responsible use (Dawson et al., 2024; Nazaretsky et al., 2022). This analysis is also compatible with Rafidi and El Khatib's (2025) findings, which highlight the importance of institutional guidance, responsible use, and academic legitimacy in shaping students' perceptions of ChatGPT in higher education.

The instructor profile was structured differently. For instructors, effort expectancy and *habit* were significant, whereas *social influence* and *hedonic motivation* were not. This difference is theoretically consequential because it shows why student and teacher adoption should not be collapsed into a single model of "educational user" acceptance. Instructors do not approach ChatGPT only as a potentially helpful tool. They must decide whether it can be incorporated into teaching practice without creating additional burden, undermining assessment validity, or disrupting existing workflows. Under such conditions, ease of integration becomes more important than novelty or peer endorsement. The significance of effort expectancy therefore corresponds with research showing that teacher adoption of educational technologies depends heavily on usability, compatibility, and perceived manageability within professional routines (Ertmer & Ottenbreit-Leftwich, 2010; Scherer et al., 2019). This interpretation is strengthened by Kaya and Adıgüzel (2025), who likewise found effort expectancy and *performance expectancy* to be central predictors of behavioral intention in higher education users.

Given the relative novelty of ChatGPT, *habit* is unlikely to represent long-established automaticity. More plausibly, it reflects emerging routinization, where repeated use has begun to turn the tool into a regular part of instructional work. This interpretation is important because it suggests that in generative AI settings, the meaning of *habit* may shift from mature automatic behavior to early but consequential incorporation into recurring tasks (Cooper & Zmud, 1990; Limayem et al., 2007). This view is also consistent with evidence that *habit*ual use of ChatGPT is still developing in higher education, which supports a cautious reading of *habit* as emerging routine rather than fully stabilized practice (Kaya & Adıgüzel, 2025).

The non-significance of *facilitating conditions* and *price value* in both groups deserves serious attention. These findings are not peripheral. They help specify the limits of conventional UTAUT2 expectations in the case of ChatGPT. One explanation is straightforward. When a tool is widely accessible through personal devices, standard internet infrastructure, and a free or low-cost entry model, formal support and financial considerations lose part of their discriminating power. Yet the more important implication is conceptual. ChatGPT can be adopted informally, individually, and often outside institutional provision. In such circumstances, adoption is less dependent on formal infrastructural readiness than on judgments of usefulness, legitimacy, and manageable incorporation. This is precisely where generative AI begins to differ from more conventional educational technologies. What matters is not only whether the system is available, but whether its use can be justified, trusted, and fitted into pedagogical activity. Research on trust in AI-powered educational technologies points in the same direction by showing that willingness to adopt depends not only on access, but also on confidence in the system and clarity about appropriate use (Nazaretsky et al., 2022; Nazaretsky et al., 2025). A related pattern appears in Tbaishat et al. (2025), who found that perceived benefits and technology self-efficacy were more influential than university support in explaining students' responses to generative AI, which reinforces the present argument that formal support conditions may carry less explanatory weight than perceived usefulness and practical value.

The moderation results reinforce the broader claim that adoption is conditional rather than uniform. Gender, age, and experience did not function as generic background variables. Instead, they altered selected pathways, and they did so differently for students and instructors. This selective pattern is more informative than a blanket moderation effect would have been because it shows that the salience of UTAUT2 determinants is contextually redistributed rather than globally strengthened or weakened. Gender strengthened the effects of *performance expectancy*, *social influence*, and *hedonic motivation* among students, and the same pattern appeared among instructors with the addition of *habit*. These findings should be interpreted cautiously. The broader literature on gender and technology adoption remains mixed, and the present data do not warrant essentialist conclusions (Elshaer et al., 2024; Foroughi et al., 2023; Grassini et al., 2024; Romero-Rodríguez et al., 2023). Even so, the pattern suggests that in this setting gender may shape how value, social legitimation, and engagement are converted into behavioral intention rather than simply determining overall openness to the technology. This cautious interpretation is also in line with cross-context evidence showing that the strength of key predictors may vary by setting rather than operate as fixed and universal effects (Faraon et al., 2025).

Age showed a similarly differentiated role. Among students, age moderated effort expectancy and *price value*, whereas among instructors, it moderated effort expectancy and *facilitating conditions*. These effects do not support a simple generational contrast between "digital natives" and "older resisters." What they suggest instead is that age changes the terms on which adoption is evaluated. For students, age seems to sharpen attention to usability and perceived value. For instructors, it appears to heighten sensitivity to usability and institutional support. This is broadly consistent with research showing that older users often evaluate new technologies through clearer thresholds of manageability, stability, and support, whereas younger users may take some of these conditions for granted (Scherer et al., 2019; Venkatesh et al., 2012). In the present study, age therefore matters less as a fixed demographic category than as a condition that alters the criteria of acceptability.

Experience produced the clearest moderation pattern. For students, it strengthened the effects of *performance expectancy*, *social influence*, *hedonic motivation*, and *habit*; for instructors, it strengthened *performance expectancy* and *habit*. This result suggests that repeated use does more than increase familiarity. It changes what the tool is perceived to be for. Among students, experience appears to amplify both value recognition and the social and affective pathways through which ChatGPT becomes integrated into language practice. Among instructors, experience seems to consolidate pedagogical usefulness and routinization. This is an important result because it moves the discussion beyond one-step models of intention. In generative AI environments, users learn over time not only how to operate the system, but also when it is genuinely helpful, where it is unreliable, and how much verification its outputs require. Experience therefore appears to be part of the formation of adoption judgment itself, not merely a background control variable. This interpretation also fits findings that students' evaluations of ChatGPT become more differentiated through actual use, especially when reliability, task fit, and responsible use become more salient (Rafidi & El Khatib, 2025).

These results support a more differentiated account of AI adoption in language education than the one often implied in current work. UTAUT2 remains analytically productive, but its predictors do not operate as a fixed template across stakeholder groups. What remains relatively stable is perceived usefulness. What varies is the pathway through which usefulness is translated into intention. For students, that pathway is more strongly shaped by social legitimation and low-pressure engagement. For instructors, it is shaped by usability and emerging routine. This distinction matters because it addresses the broader problem identified in the introduction. The issue was not simply that Saudi EFL settings had been understudied. The larger issue was that existing research had insufficiently explained whether generative AI reweights the established determinants of adoption and whether this reweighting differs across roles and conditions of use. The present findings suggest that it does. This conclusion is further supported by comparative research that links ChatGPT adoption to contextual variation, user role, and institutional framing rather than to a single stable pattern of technology acceptance (Faraon et al., 2025; Kaya & Adıgüzel, 2025; Tbaishat et al., 2025).

Theoretical Contribution

This study contributes to the literature by showing that ChatGPT adoption in language education is better understood as a differentiated rather than uniform process. Although UTAUT2 remains a useful explanatory framework, the present findings suggest that its predictors do not operate with equal salience across educational roles. Performance expectancy remained central for both students and instructors, but the surrounding pathways differed. Student intention was shaped more strongly by social influence and hedonic motivation, whereas instructor intention depended more on effort expectancy and habit. This pattern indicates that generative AI adoption does not simply reproduce the standard acceptance structure commonly reported for more conventional educational technologies.

The study also contributes by clarifying how generative AI may alter the interpretation of some established UTAUT2 constructs. In this context, performance expectancy appears to be bound up with judgments about reliability and acceptable reliance; hedonic motivation is more plausibly interpreted as low-friction engagement than as simple enjoyment; social influence reflects not only interpersonal pressure but also pedagogical legitimacy; and habit may capture rapid routinization rather than long-settled automaticity. These shifts do not invalidate UTAUT2, but they do suggest that its constructs require closer contextual reading in AI-assisted language learning. In that sense, the study extends current work not merely by applying the model to a new setting, but by showing how stakeholder role and the distinctive features of generative AI reshape the explanatory balance of the framework.

Practical Implications

The practical implications of the study follow directly from the role-specific structure of the results. For students, adoption was shaped by *performance expectancy*, *social influence*, and *hedonic motivation*. This suggests that implementation is unlikely to succeed if ChatGPT is treated only as an individually available tool. Its educational use needs to be framed as both academically valuable and pedagogically legitimate. Structured classroom activities, guided peer interaction, and explicit discussion of appropriate use may therefore be more effective than simple access alone, particularly in EFL settings where students may be unsure how to integrate AI into language practice responsibly.

For instructors, the strongest additional predictors were *effort expectancy* and *habit*. This points to a different implementation priority. Professional development should focus less on abstract promotion of AI and more on manageable pedagogical use. Instructors are more likely to adopt ChatGPT when its functions are clearly tied to real teaching tasks and when the effort required for integration remains low. Practical training built around lesson preparation, feedback support, and controlled classroom applications is likely to be more useful than general orientation sessions. More broadly, the findings suggest that successful AI integration in EFL higher education depends on role-sensitive support rather than one-size-fits-all implementation. Institutions need not only to provide access, but also to clarify educational value, acceptable use, and feasible modes of incorporation into teaching and learning practice.

Limitations

Several limitations should be taken into account when interpreting the findings. First, the study is context-specific. Because it focuses on Saudi EFL students and instructors, the results should not be generalized uncritically to other educational systems, linguistic environments, or cultural settings where patterns of AI adoption may differ. The study offers evidence from a meaningful context, but not a universal model of language-education adoption.

Second, the design is cross-sectional and based on self-reported survey data. The results therefore capture stated behavioral intention at one point in time rather than changes in adoption over time or actual patterns of use. This is particularly important in the case of ChatGPT, where perceptions may shift rapidly as familiarity, institutional guidance, and public debate evolve. In addition, self-report data may be affected by overestimation, underestimation, or socially desirable responding.

Third, the sampling strategy places limits on representativeness. The use of convenience sampling and online questionnaire distribution increases the likelihood of self-selection bias. Participants with stronger interest in digital tools, greater confidence in technology, or prior exposure to ChatGPT may have been more likely to respond, which may in turn have influenced the level of reported intention and the observed strength of some predictor–intention relationships. The results should therefore be read as associations within a reachable and self-selected sample rather than as population estimates for all Saudi EFL students and instructors.

Finally, the study relies on regression analysis using CFA-validated composite scores rather than a full structural equation model (SEM). This approach was appropriate for transparent comparison across stakeholder groups, but it does not model all latent relationships simultaneously or account for measurement error in the same way that SEM would. In addition, the study did not directly measure potentially relevant constructs such as trust, verification effort, institutional policy awareness, or actual frequency of AI use. These omissions are important because the discussion suggests that such factors may be central in generative AI settings.

Future Research

Future research should examine ChatGPT adoption longitudinally in order to capture how intention, routinization, and perceived value change over time. This is especially important in generative AI contexts, where early experimentation may develop into sustained pedagogical use, cautious withdrawal, or selective incorporation depending on user experience and institutional framing. Studies that follow both students and instructors across longer periods would make it possible to distinguish initial curiosity from stable adoption.

There is also a need for broader and methodologically richer designs. Comparative studies across countries, institutional types, and educational levels would help determine which findings are context-specific and which travel more widely. Qualitative work, including interviews, focus groups, and classroom-based inquiry, would be particularly valuable for examining issues that were not directly measured here, such as trust, verification practices, perceptions of legitimacy, and judgments about acceptable use. Future studies should also consider extending the model by incorporating variables such as digital literacy, policy awareness, pedagogical beliefs, and actual use behavior. Finally, it would be useful to investigate how adoption relates to concrete educational outcomes, including language development, teaching practice, assessment design, and the quality of student engagement in AI-assisted language learning.

CONCLUSION

This study set out to address a persistent weakness in the emerging literature on generative AI in language education, which tends to assume that educational users respond to ChatGPT in broadly similar ways and that established technology-acceptance relationships transfer intact into AI-mediated settings. The findings challenge both assumptions. While *performance* expectancy remained the strongest common predictor of behavioral intention for both Saudi EFL students and instructors, the surrounding structure of adoption differed in systematic ways. Student intention was shaped more strongly by *social influence* and *hedonic motivation*, whereas instructor intention depended more on effort expectancy and *habit*. Gender, age, and experience further conditioned selected pathways. They indicate that adoption is not only role-differentiated but also shaped by user position and modes of use.

These results carry implications beyond the immediate study context. They suggest that generative AI does not simply enter language education as another digital tool whose acceptance can be inferred from existing adoption research without qualification. ChatGPT is adopted under conditions shaped by pedagogical responsibility, social legitimacy, evaluative caution, and repeated experience. What remains stable is the importance of perceived academic benefit. What shifts is the pathway through which that benefit is translated into intention. For students, the route to adoption appears more closely tied to socially mediated legitimacy and low-friction engagement. For instructors, it is more closely tied to usability and the gradual incorporation of the tool into professional routine. This distinction is not incidental. It indicates that stakeholder role is an explanatory condition in its own right.

The study therefore contributes to current scholarship in a more substantive sense than context novelty alone would suggest. Its value lies not simply in examining Saudi EFL higher education, but in showing that the acceptance of generative AI in language education is structured by differentiated logics that conventional adoption research has too often blurred. UTAUT2 remains analytically productive in this domain, but its constructs do not operate as a fixed template. Their salience is reweighted by the distinctive features of generative AI and by the educational roles through which that technology is encountered, judged, and used.

Future research now needs to move beyond static accounts of intention and examine how adoption develops over time, how trust and verification shape actual use, and how these processes relate to pedagogical practice and language-learning outcomes. Even within the limits of the present design, the central conclusion is clear, namely that ChatGPT adoption in language education is neither generic nor homogeneous. Students and instructors do not adopt generative AI under the same conditions, for the same reasons, or with the same consequences.

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