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Digital Technologies Research and Applications
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Assessing the Adoption and Influence of Artificial Intelligence as a Learning Partner among English Learners in Hail

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Received: 13 March 2026; **Revised:** 7 April 2026; **Accepted:** 16 April 2026; **Published:** 30 April 2026

Abstract: Generative artificial intelligence tools offer transformative potential for English language learners, yet the factors driving their adoption remain insufficiently understood, particularly in Arab higher education contexts. This study examined AI tool adoption among undergraduate English learners at the University of Hail, Saudi Arabia, using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as the theoretical framework. A quantitative survey of 318 students tested nine hypothesized relationships between seven UTAUT2 constructs and two outcomes: behavioral intention and use behavior. Partial least squares structural equation modeling (PLS-SEM) revealed exceptional explanatory power, accounting for 80.1% of the variance in behavioral intention and 80.9% in use behavior. Seven of nine hypotheses were supported. Habit emerged as the dominant predictor, exerting the strongest total effect on use behavior ($\beta = 0.518$), operating through both conscious intention and automatic behavioral pathways. Price value, reconceptualized to capture time and effort costs rather than monetary ones, was the second-strongest predictor of intention, followed by hedonic motivation and performance expectancy. Contrary to expectations, effort expectancy and social influence were non-significant. These findings extend UTAUT2 to generative AI in language learning, challenge assumptions about universal predictor applicability, and offer practical guidance for educators and policymakers seeking to promote sustained, effective AI integration in English language education.

Keywords: AI Adoption; UTAUT2; English as a Foreign Language Learners; Saudi Arabia; Habit; PLS-SEM

1. Introduction

The emergence of generative artificial intelligence (AI) tools, particularly large language models such as ChatGPT, Google Gemini, and other AI-powered applications, has created unprecedented opportunities for language learners worldwide. These technologies offer 24/7 accessibility, personalized feedback, and conversational practice without the social anxiety often associated with human interaction [1,2]. Since ChatGPT's public release in November 2022, adoption has been rapid but uneven, with some learners embracing these tools enthusiastically while others remain hesitant or unaware of their potential [3,4].

In the context of English as a Foreign Language (EFL) education, AI tools have demonstrated significant potential to enhance various language skills, including writing [5, 6], speaking [7], vocabulary acquisition [8], and grammar proficiency [9]. Studies across diverse geographical contexts, from China [10,11] to Saudi Arabia [1,12], and from Indonesia [13] to Turkey [14], have documented generally positive perceptions of AI tools among EFL learners. However, the specific factors that drive or inhibit adoption remain insufficiently understood, particularly in the Saudi higher education context.

Despite the proliferation of AI tools and growing interest in their educational applications, the theoretical understanding of adoption factors remains limited. While anecdotal evidence suggests widespread interest, systematic investigation of what motivates English learners to adopt AI tools, and what barriers they encounter, is essential for educators, policymakers, and technology developers seeking to optimize these resources for language learning [15,16].

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) [17] provides a robust framework for examining technology adoption in voluntary, consumer-oriented contexts. However, its application to generative AI tools in language learning settings, particularly in the Arab world, remains relatively unexplored. Recent studies have begun applying UTAUT2 to examine ChatGPT adoption among EFL learners in China [4,16] and other contexts, but research in Saudi Arabia has predominantly employed the simpler Technology Acceptance Model (TAM) [1,8,12], which may not capture the full complexity of factors influencing adoption decisions.

Furthermore, existing Saudi-based studies have examined specific tools [1], specific skills [8, 18], or specific populations [19, 20], but no comprehensive study has applied the full UTAUT2 framework to understand AI tool adoption among English learners in the region. This study addresses this gap by examining the factors influencing English learners' adoption of AI tools at the University of Hail, Saudi Arabia.

This study examines AI tool adoption among undergraduate English learners at a Saudi Arabian university. Several contextual factors make this setting theoretically and practically important. English proficiency is critical in Saudi higher education, with many university programs, particularly in science, technology, engineering, and medicine, using English as the medium of instruction [1]. Students must achieve minimum English proficiency levels for university admission, typically demonstrated through IELTS or TOEFL scores. However, substantial gaps often exist between students' English proficiency and program requirements, creating strong demand for supplementary learning resources.

Saudi Arabia's cultural characteristics may influence technology adoption patterns. Some cultural dimensions classify Saudi Arabia as collectivist and high in power distance, potentially strengthening social influence effects and amplifying instructor influence on student behavior [1,20]. Additionally, Saudi Arabia has invested substantially in educational technology as part of Vision 2030 national transformation strategy, with universities providing robust digital infrastructure and smartphone penetration exceeding 90% among students [19]. This technology-ready environment creates favorable conditions for AI tool adoption.

Crucially, AI tool adoption in this context is entirely voluntary and student-driven. Unlike some educational technologies mandated by institutions, students choose whether to use AI tools based on personal motivations. This voluntary nature makes UTAUT2, designed for consumer contexts, particularly appropriate for understanding adoption processes [17].

Research Questions and Objectives

This study addresses the following research questions:

1. What factors influence English learners' behavioral intention to use AI tools for language learning at the University of Hail?
2. What factors influence English learners' actual use behavior of AI tools for language learning?
3. To what extent does the UTAUT2 framework explain AI tool adoption among English learners in the Saudi higher education context?

The primary objectives are to: (a) identify the key determinants of AI tool adoption among English learners, (b) test the applicability of UTAUT2 in this novel context, and (c) provide evidence-based recommendations for educators and policymakers seeking to optimize AI integration in English language education.

This study contributes to the growing body of literature on AI adoption in language learning in several ways.

First, it extends the application of UTAUT2 to generative AI tools in the Saudi higher education context, providing empirical evidence on the framework's validity in a novel technological and cultural setting. Second, it reconceptualizes the Price Value construct for free technologies, addressing a theoretical gap in understanding how learners evaluate "cost" when tools are monetarily free but require time and effort investments. Third, the findings offer practical implications for educators, curriculum designers, and policymakers seeking to promote effective and ethical AI integration in English language education.

2. Literature Review and Hypothesis Development

The emergence of generative artificial intelligence tools has transformed possibilities for language learning, offering learners personalized, accessible, and interactive support for developing English proficiency [2, 4]. Understanding what drives learners to adopt these tools is essential for educators, policymakers, and technology developers seeking to harness their potential. While anecdotal evidence suggests widespread interest, theoretical understanding of adoption factors remains limited, particularly in the Saudi Arabian context.

This literature review proceeds in three parts. First, we establish UTAUT2 as the theoretical framework, justifying its appropriateness for voluntary technology adoption in educational contexts. Second, we develop nine hypotheses examining relationships between UTAUT2 constructs and adoption outcomes (behavioral intention and use behavior). Third, we synthesize recent empirical studies on AI tool adoption in language learning, identifying patterns, gaps, and opportunities for theoretical contribution.

2.1. Theoretical Framework: UTAUT2

2.1.1. Evolution to UTAUT2

Technology acceptance research has evolved through several generations of models. The Technology Acceptance Model (TAM) [21] established perceived usefulness and perceived ease of use as primary predictors of technology adoption, and continues to be widely applied in contemporary AI adoption research [1,6,8,12]. TAM's parsimony and explanatory power have made it an enduring framework, with recent studies confirming its applicability to ChatGPT adoption among Saudi EFL learners [1], vocabulary acquisition tools [8], and writing assistants [6].

The Unified Theory of Acceptance and Use of Technology (UTAUT) [22] synthesized eight competing models into a unified framework, explaining approximately 70% of variance in behavioral intention in organizational contexts. However, UTAUT was explicitly designed for organizational technology adoption, where use is often mandated or strongly encouraged by employers. Recognizing UTAUT's limitations in consumer contexts, Venkatesh et al. [17] extended the model to UTAUT2 by incorporating three additional constructs, hedonic motivation, price value, and habit, and reconfiguring relationships to reflect voluntary, consumer-driven adoption.

Recent studies have successfully applied UTAUT2 to examine AI tool adoption in language learning contexts. Zheng et al. [4] investigated Chinese EFL learners' acceptance of generative AI tools, finding that performance expectancy, effort expectancy, social influence, hedonic motivation, and habit significantly predicted behavioral intention. Moradi [16] examined ChatGPT acceptance among Chinese university students, revealing that habit considerably influenced both behavioral intention and actual use behavior, while performance expectancy and social influence also positively impacted intention. Alkolaly et al. [23] compared lecturers' and students' attitudes toward generative AI in foreign language teaching, finding significant differences across all UTAUT dimensions, with students demonstrating more positive perceptions and higher acceptance levels.

2.1.2. UTAUT2 Framework and Key Constructs

UTAUT2 extends the original UTAUT by adding three constructs critical for understanding voluntary technology adoption. The framework comprises seven core predictors organized around two dependent variables: behavioral intention (predicted by performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit) and use behavior (predicted by facilitating conditions, habit, and behavioral intention).

Performance Expectancy captures "the degree to which using a technology will provide benefits to consumers in performing certain activities" [17] (p. 159). Derived from TAM's perceived usefulness, this construct reflects instrumental beliefs about whether technology enhances task performance, productivity, or goal achievement. Across AI adoption studies, performance expectancy consistently emerges as a significant predictor of behavioral intention [4,15,16].

Effort Expectancy represents “the degree of ease associated with consumers’ use of technology” [17] (p. 159). Technologies perceived as easy to use are more readily adopted than complex alternatives. However, findings regarding effort expectancy in AI adoption are mixed. While Zheng et al. [4] found significant effects, Moradi [16] reported non-significant results, suggesting that modern AI interfaces may have crossed an ease-of-use threshold for digitally competent users.

Social Influence captures “the extent to which consumers perceive that important others believe they should use a particular technology” [17] (p. 159). In collectivist cultures like Saudi Arabia, social influence effects may be particularly pronounced [1]. Recent studies confirm social influence’s significance in AI adoption across various contexts [4,24].

Facilitating Conditions represent “consumers’ perceptions of the resources and support available to perform a behavior” [17] (p. 159), encompassing internet connectivity, device availability, institutional support, and technical assistance. Moradi [16] found that facilitating conditions exerted a significant influence on actual use behavior despite a weak influence on behavioral intention.

Hedonic Motivation captures “the fun or pleasure derived from using a technology” [17] (p. 161), reflecting intrinsic motivation and engagement for inherent enjoyment rather than instrumental benefits. Studies consistently demonstrate hedonic motivation’s importance in educational technology adoption [2,4,11].

Price Value reflects “consumers’ cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them” [17] (p. 161). For free AI tools, we reconceptualize price value to encompass non-monetary costs including time investment, cognitive effort, and attention [25].

Habit represents “the extent to which people tend to perform behaviors automatically because of learning” [17] (p. 161). Habit theory distinguishes between conscious deliberation and automatic behavioral responses [26,27]. UTAUT2 specifies habit’s dual influence: reinforcing future intentions while also directly triggering behavior automatically. Recent research demonstrates habit’s strong predictive power in AI tool adoption, often exceeding other UTAUT2 constructs [16].

2.1.3. Justification for UTAUT2 in This Study

UTAUT2 is appropriate for this study for several reasons. First, AI tool adoption for language learning represents voluntary, consumer-like behavior rather than organizationally-mandated use. Students choose whether to adopt AI tools based on personal motivations, not employer requirements, a condition that aligns with UTAUT2’s consumer focus.

Second, language learning technologies serve both utilitarian purposes (skill development, academic performance) and hedonic purposes (enjoyment, curiosity, experimentation). UTAUT2’s inclusion of hedonic motivation captures this dual nature, while TAM and original UTAUT focus more narrowly on instrumental benefits [4,11].

Third, habit formation is theoretically important for sustained technology use. UTAUT2’s specification of habit’s dual pathways aligns with the understanding of how repeated AI use may become routinized and automatic [16,27].

Fourth, UTAUT2 has demonstrated strong empirical support across cultures and technologies, including recent applications to AI tool adoption in language learning [4,16,23]. Its comprehensive nature reduces the need for ad hoc construct addition while remaining theoretically grounded.

2.2. Hypothesis Development

We organize hypothesis development around the two dependent variables: behavioral intention (six predictors) and use behavior (three predictors).

2.2.1. Predictors of Behavioral Intention

H1. *Performance Expectancy positively influences Behavioral Intention to use AI tools for English learning.*

Performance expectancy (PE) captures instrumental beliefs about whether technology enhances task performance, productivity, or goal achievement [17]. Meta-analyses consistently identify PE as the strongest predictor of behavioral intention across diverse technologies and contexts [28]. Recent AI adoption studies confirm PE’s significance in language learning contexts [4,15,16,24].

For English learners in Saudi Arabia, performance expectancy should be particularly salient. English proficiency is critical for university admission, academic success, and employment opportunities [1]. Students face high-stakes English requirements, including standardized tests (IELTS, TOEFL) and English-medium instruction. AI tools promise multiple performance benefits: improved writing through grammar correction [5,18], expanded vocabulary [8], enhanced pronunciation [7], and accelerated skill development through personalized practice [13]. Students who believe AI tools will improve their English proficiency should demonstrate stronger intentions to adopt these tools.

H2. *Effort Expectancy positively influences Behavioral Intention to use AI tools for English learning.*

Effort expectancy (EE) represents the degree of ease associated with technology use [17]. Technologies perceived as easy to use, intuitive, and requiring minimal effort are more readily adopted than complex alternatives. EE consistently predicts behavioral intention, particularly for novice users [22].

Contemporary AI tools employ conversational interfaces requiring minimal technical skill. For digitally native university students accustomed to chat-based interactions, AI tools present minimal complexity. However, recent ChatGPT adoption studies report mixed findings for EE. Zheng et al. [4] found significant effects among Chinese EFL learners, while Moradi [16] reported non-significant relationships, possibly reflecting that modern AI interfaces have crossed an ease-of-use threshold. Nevertheless, students who perceive AI tools as effortless to use should develop stronger adoption intentions than those perceiving them as requiring substantial effort.

H3. *Social Influence positively influences Behavioral Intention to use AI tools for English learning.*

Social influence (SI) captures social pressures, normative expectations, and perceived opinions of referent others, including peers, family members, instructors, and authority figures [17]. In voluntary contexts, SI effects are typically weaker than in mandatory settings but remain significant [22]. Cultural dimensions moderate SI substantially: collectivist cultures show stronger SI effects than individualist cultures [29].

Saudi Arabia exhibits cultural characteristics that should strengthen SI effects. Some cultural dimensions classify Saudi Arabia as highly collectivist and high in power distance, suggesting Saudi students should be more responsive to peer norms and instructor recommendations compared to Western populations. Recent studies confirm SI's significance in AI adoption across various contexts [4,23,24]. Alotaibi et al. [1] found that social factors influenced Saudi EFL learners' ChatGPT adoption, though the relationship operated partially through attitudes.

H4. *Hedonic Motivation positively influences Behavioral Intention to use AI tools for English learning.*

Hedonic motivation (HM) captures intrinsic motivation, engagement with technology for inherent enjoyment rather than instrumental benefits [17,30]. HM was added to UTAUT2 specifically for consumer contexts, recognizing that voluntary technology adoption is influenced by both utilitarian and hedonic considerations.

AI conversational interactions may generate hedonic experiences through several mechanisms: the novelty of AI-generated responses creates curiosity and interest; the conversational, interactive nature of AI dialogue may be inherently engaging; satisfaction from receiving personalized feedback and seeing language improvement can create positive emotional experiences; experimentation with AI capabilities may be intrinsically rewarding [2].

Recent studies demonstrate HM's importance in ChatGPT acceptance across contexts. Zheng et al. [4] found HM significantly predicted behavioral intention among Chinese EFL learners. Xu and Thien [11] found that perceived enjoyment mediated the effects of other UTAUT constructs on intention to use ChatGPT. Zou et al. [2] reported that perceived enjoyment was a significant predictor of behavioral intention to use AI speech evaluation programs.

H5. *Price Value positively influences Behavioral Intention to use AI tools for English learning.*

Price value (PV) reflects consumers' cognitive tradeoff between perceived benefits and monetary costs [17]. Most leading AI tools (ChatGPT, Google Gemini) are freely available, apparently eliminating monetary cost considerations. However, economic theory recognizes that "free" does not mean "costless" [25]. Using AI tools requires time investment, learning effective prompting strategies, reviewing and evaluating outputs, and integrating feedback, which could be allocated to alternative activities. Cognitive effort, attention, and learning investments similarly constitute non-monetary costs.

We reconceptualize price value for free technologies: PV reflects whether perceived benefits (learning gains, time savings, performance improvements) exceed non-monetary costs (time investment, cognitive effort, attention). Students perceive high PV when AI tools deliver substantial learning benefits with minimal time/effort investment. Moradi [16] found that price value did not demonstrate a significant impact on behavioral intention among Chinese students, suggesting that in contexts where tools are freely available, monetary cost considerations may be less salient. However, this study tests whether the reconceptualized PV, incorporating time and effort costs, significantly influences intention in the Saudi context.

H6. *Habit positively influences Behavioral Intention to use AI tools for English learning.*

Habit reflects automaticity, repeated behaviors in stable contexts become automatic responses, bypassing conscious deliberation [17,26]. Habitual behaviors are characterized by frequency, automaticity, and minimal cognitive engagement.

UTAUT2 specifies the habit's dual influence pathway. First, habit influences behavioral intention: past behavior reinforces future intentions through behavioral momentum, "I've always used this, so I plan to continue." This represents the conscious, reflective component of habit. Second, habit influences use behavior directly through automatic processes (addressed in H8).

Recent research demonstrates habit's strong predictive power in AI tool adoption. Moradi [16] found that habitual behavior considerably influenced both behavioral intention and actual use behavior among Chinese EFL learners, with habit emerging as the dominant factor. Zheng et al. [4] also confirmed habit's significance in predicting behavioral intention. Students who have consistently used AI tools may develop automatic usage patterns, reinforcing continued intention.

2.2.2. Predictors of Use Behavior

H7. *Facilitating Conditions positively influence the Use Behavior of AI tools for English learning.*

Facilitating conditions (FC) capture beliefs about whether necessary infrastructure, resources, and assistance exist to enable technology use [17]. UTAUT2 specifies FC's direct effect on use behavior rather than behavioral intention, as resource availability enables behavioral enactment but does not necessarily shape conscious intentions.

For AI tools, FC encompasses internet connectivity and bandwidth, device availability (computers, smartphones), institutional support and technical assistance, and English language proficiency for effective interaction. Saudi universities generally provide robust technological infrastructure, including WiFi networks and computer laboratories. High smartphone penetration means most students possess devices capable of accessing AI tools [19].

Moradi [16] found that facilitating conditions exerted a significant influence on actual use behavior, despite a weak influence on behavioral intention. Students with better access to resources and support should demonstrate higher actual AI usage.

H8. *Habit positively influences Use Behavior of AI tools for English learning.*

As discussed in H6, habit influences behavior through dual pathways. While H6 addresses habit's influence on behavioral intention (the conscious, reflective pathway), H8 addresses habit's direct influence on use behavior (the automatic, impulsive pathway).

The direct habit → behavior path reflects automaticity: situational cues automatically trigger technology use without conscious decision-making [17, 27]. Students who have developed strong AI usage habits automatically consult these tools when encountering language problems, beginning assignments, or engaging in language practice.

Empirical research demonstrates that habit directly predicts technology use behavior with large effect sizes. Moradi [16] confirmed habit's strong direct effect on use behavior among Chinese EFL learners, with the total effect of habit on behavior (combining direct and indirect effects through intention) making it the strongest overall influence on AI tool usage.

H9. *Behavioral Intention positively influences Use Behavior of AI tools for English learning.*

Behavioral intention (BI) represents planned future engagement with technology, serving as the immediate antecedent of actual behavior [31]. The intention-behavior relationship forms the core theoretical mechanism of reasoned action theories: conscious adoption decisions translate into observable actions.

Meta-analyses report moderate-to-strong intention-behavior correlations across behavioral domains [32]. In UTAUT2, behavioral intention mediates most constructs' effects on use behavior. Recent AI adoption studies confirm the strong intention-behavior link. Moradi [16] found that behavioral intention was the strongest direct predictor of use behavior among Chinese EFL learners. Alrishan [15] confirmed that behavioral intention significantly predicted actual AI tool use among Omani students. Students who intend to use AI tools, who plan to incorporate them into language learning, should demonstrate higher actual usage.

2.3. Recent Empirical Evidence on AI Adoption in Language Learning

A growing body of empirical research has examined factors influencing AI tool adoption in language learning across diverse contexts. **Table 1** summarizes key studies applying technology acceptance frameworks to AI adoption in EFL settings.

Table 1. Summary of Recent AI Adoption Studies in EFL Contexts.

Study	Context	Framework	Key Findings
Zheng et al. [4]	China (N = 620)	UTAUT2 + SDT	PE, EE, SI, HM, habit, and SDT motivation predicted BI; PV was non-significant
Moradi [16]	China (N = 340)	UTAUT2	Habit strongest predictor; PE and SI were significant; HM, EE, and PV were non-significant
Alotaibi et al. [1]	Saudi Arabia (N = 184)	TAM	PU and PEoU significantly affected adoption; no significant PEoU-attitude relationship
Aksakalli and Daşer [14]	Turkey (N = 874)	TAM	Positive perceptions; gender variations in usage frequency; positive correlation between usage and perceptions
Boudouaia et al. [5]	Algeria (N = 76)	TAM	ChatGPT-4 improved writing skills and acceptance; the experimental group outperformed the control group
Almusharraf et al. [18]	Saudi Arabia (N = 399)	Extended TAM	AI writing strategies associated with satisfaction, self-efficacy, and behavioral intention
Alsaedi [12]	Saudi Arabia	TAM	Students perceived ChatGPT as useful and easy to use; strong behavioral intentions; concerns about overreliance
Alrishan [15]	Oman (N = 255)	UTAUT	BI and FC predicted actual use; PE, EE, and SI shaped BI; prior AI experience moderated the intention-usage relationship
Parviz and Arthur [24]	Iran (N = 444)	UTAUT + TPACK	PE and SI are critical for adoption intentions; a negative relationship between AI-TPACK and BI
Xu and Thien [11]	China (N = 432)	UTAUT + Enjoyment	EE, PE, SI, and perceived enjoyment predicted BI; enjoyment mediated other relationships
Zou et al. [2]	China (N = 218)	IMTA	PU and perceived enjoyment significant predictors of BI; interface design and feedback accuracy concerns
Hu and Gong [6]	China (N = 304)	TAM + TTF	PU and PEoU explained attitude, which influenced BI; task technology fit significantly affected BI
Al-Bukhrani et al. [33]	Yemen (N = 150)	TRA	Attitudes (β = 0.472) and subjective norms (β = 0.588) strongly predicted BI (R^2 = 61.7%); perceived barriers were non-significant

Several patterns emerge from this synthesis. First, UTAUT2 demonstrates strong explanatory power across contexts, typically explaining substantial variance in behavioral intention and use behavior [4,16]. Second, performance expectancy consistently emerges as a significant predictor, though its relative importance varies across studies. Third, habit appears to be particularly important in AI adoption, with Moradi [16] identifying it as the dominant factor. Fourth, findings for effort expectancy and price value are mixed, suggesting contextual and technological factors may moderate their effects. Fifth, studies in Saudi Arabia have predominantly employed TAM rather than UTAUT2, creating an opportunity for theoretical extension.

This opportunity is further highlighted by local research employing alternative theoretical lenses. For instance, Al-Bukhrani et al. [33] applied the Theory of Reasoned Action (TRA) to investigate the adoption of AI writing tools among a diverse sample of 150 academic researchers. Complementing this work, Alshaie et al. [34] examined faculty perceptions of AI personalized learning systems at the same institution, revealing that teacher effectiveness and lifelong learning opportunities—rather than equity or quality outcomes alone—drive faculty adoption intentions, underscoring that institutional implementation strategies must address professional development alongside pedagogical values. Their findings reinforce the critical roles of individual attitudes (β = 0.472, $p < 0.001$) and subjective norms (β = 0.588, $p < 0.001$) as strong, direct predictors of behavioral intention, together explaining a substantial 61.7% of its variance. Notably, their research revealed that perceived barriers (e.g., ethical concerns, technical difficulties) did not significantly influence either attitudes or adoption intentions, suggesting that in academic contexts, the perceived functional benefits and social motivators may override potential obstacles.

Extending the application of foundational technology acceptance models, the application of a modified UTAUT model to virtual classrooms demonstrated the framework's potential in the Saudi context, even before the widespread adoption of generative AI. More recently, Aljabr et al. [35] provided qualitative insights into the specific challenges (e.g., academic integrity) and opportunities (e.g., personalized support) that shape the integration of AI in English teaching, factors that likely influence students' underlying perceptions. Additionally, Almutairi et al. [36] underscored the institutional imperative to respond to the fourth industrial revolution, creating a macro-level environment where understanding the micro-level factors of student AI adoption is increasingly critical.

3. Methodology

3.1. Research Design

This study employed a quantitative, cross-sectional survey design to examine factors influencing English learners' adoption of generative AI tools at the University of Hail, Saudi Arabia. The quantitative approach was appropriate for testing theoretically derived hypotheses grounded in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) [17] and identifying the relative explanatory power of multiple predictors on behavioral intention and use behavior. The cross-sectional design captured current adoption patterns at a specific point in time, aligning with established practice in technology acceptance research.

3.2. Participants and Sampling

The target population comprised undergraduate students enrolled in the English Language Program at the University of Hail, Saudi Arabia, during Fall 2025. A convenience sampling strategy yielded 318 respondents, exceeding the minimum sample requirement of 290 determined through the inverse square root method [37] for detecting small effect sizes ($\beta \geq 0.15$) with 80% power at $\alpha = 0.05$. The sample comprised 226 males (71.1%) and 92 females (28.9%), reflecting institutional demographics. Academic levels included first-year (73.3%), second-year (13.8%), third-year (7.9%), fourth-year (3.5%), and postgraduate students (1.6%). Regarding AI experience, 31.8% reported less than three months of usage, 23.0% 3–6 months, 15.1% 6–12 months, 18.9% more than one year, and 11.3% no prior experience.

3.3. Instrument Development

A structured self-administered questionnaire measured nine UTAUT2 constructs using multi-item scales adapted from validated instruments [4,17]. All items employed five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree), with five items per construct. Performance Expectancy assessed beliefs about AI tools' usefulness for English learning (e.g., "Using AI tools improves my English learning performance"). Effort Expectancy measured perceived ease of use (e.g., "Learning to use AI tools is easy for me"). Social Influence captured perceptions of important others' opinions (e.g., "My instructors recommend using AI tools"). Facilitating Conditions assessed resource availability (e.g., "I have the resources necessary to use AI tools"). Hedonic Motivation measured enjoyment (e.g., "Using AI tools is enjoyable"). Price Value evaluated value relative to time and effort costs (e.g., "AI tools are good value for the time I invest"). Habit assessed automaticity (e.g., "Using AI tools has become automatic to me"). Behavioral Intention measured future use plans (e.g., "I intend to continue using AI tools"). Use Behavior assessed current usage (e.g., "I use AI tools regularly for English learning"). Content validity was established through review by three faculty specialists in applied linguistics and educational technology. A pilot test with 30 students confirmed satisfactory reliability ($\alpha > 0.80$) and clarity.

3.4. Data Collection

Data were collected in December 2025 through an online Google Form distributed via WhatsApp to undergraduate English learners. The Google Form was configured with required response settings to prevent missing data. Research assistants explained the study purpose, emphasized voluntary participation, and assured confidentiality. Written informed consent was obtained through the first page of the form. No incentives were offered. Data collection continued for three weeks, yielding 318 complete and usable responses.

3.5. Data Analysis

Data analysis employed SPSS version 28 for descriptive statistics and SmartPLS 4.0 for structural equation modeling. PLS-SEM was selected because it is appropriate for predictive-explanatory research maximizing variance explained in dependent variables, handles complex models without normality assumptions, and performs well with sample sizes that may not support covariance-based SEM [38]. Preliminary screening revealed no missing values or problematic outliers. Harman's single-factor test indicated common method bias was not a major concern (first factor explained 38.4% of variance).

The measurement model was assessed following Hair et al. [38] criteria: indicator reliability (outer loadings ≥ 0.70), internal consistency (Cronbach's α, composite reliability ≥ 0.70), convergent validity (average variance extracted ≥ 0.50), discriminant validity (Fornell-Larcker criterion, heterotrait-monotrait ratio < 0.90), and multicollinearity (variance inflation factor < 5.0). All criteria were satisfied.

The structural model was evaluated using: model fit (standardized root mean square residual < 0.08), explanatory power (R^2), predictive relevance (Q^2 via blindfolding), path coefficients with significance testing using 5,000 bootstrap samples generating *t*-values, *p*-values, and 95% confidence intervals, and effect sizes (f^2) following Cohen's guidelines (0.02 = small, 0.15 = medium, 0.35 = large). Hypotheses were supported at $p < 0.05$ with confidence intervals excluding zero.

3.6. Ethical Considerations

Ethical approval for this study was granted by the Research Ethics Committee (REC) at the University of Hail (Approval No. H-2025-1005; December 8, 2025). The REC is registered with the Saudi National Committee of Bioethics (HAP-08-L-158).

Written informed consent was obtained from all participants prior to data collection. Participation was voluntary, and anonymity and confidentiality were ensured. No personally identifiable information was collected, and all data were stored securely. Findings are reported in aggregate form, and no incentives were offered.

4. Results

4.1. Descriptive Statistics

4.1.1. Sample Characteristics

The final sample comprised 318 undergraduate English language learners at the University of Hail, Saudi Arabia. Data collection was conducted in December 2025. Preliminary data screening revealed no missing values or problematic response patterns, resulting in a 100% usable response rate. **Table 2** presents the demographic characteristics of the participants.

Table 2. Demographic Characteristics of Respondents (N = 318).

Characteristic	Category	Frequency	Percentage
Gender	Male	226	71.1%
	Female	92	28.9%
Academic Level	Year 1	233	73.3%
	Year 2	44	13.8%
	Year 3	25	7.9%
	Year 4	11	3.5%
	Postgraduate	5	1.6%
AI Tool Usage Experience	Less than 3 months	101	31.8%
	3–6 months	73	23.0%
	6–12 months	48	15.1%
	More than 1 year	60	18.9%
	I have not used AI tools	36	11.3%

The sample comprised 226 males (71.1%) and 92 females (28.9%), reflecting the gender composition of the English language program at the University of Hail. The majority of participants were first-year students (73.3%), followed by second-year students (13.8%). Regarding AI tool experience, approximately half (54.8%) had been using AI tools for less than 6 months, while 18.9% reported more than one year of experience.

4.1.2. AI Tool Usage Patterns

Participants were asked about their usage patterns of AI tools for English language learning. **Table 3** presents the frequency of AI tool usage and the hours spent per week using AI tools.

Table 3. AI Tool Usage Patterns (N = 318).

Usage Pattern	Category	Frequency	Percentage
Frequency of AI Tool Use	Never	55	17.3%
	Rarely	72	22.6%
	Occasionally	95	29.9%
	Frequently	48	15.1%
	Very Frequently	18	5.7%
	Daily	30	9.4%
Hours per Week Using AI	Less than 1 h	151	47.5%
	1–3 h	90	28.3%
	4–6 h	51	16.0%
	7–10 h	17	5.3%
	More than 10 h	9	2.8%
Most Commonly Used AI Tools	ChatGPT	186	58.5%
	Google Gemini	18	5.7%
	Other AI Tools	114	35.8%

The majority of participants (60.1%) had used AI tools at least occasionally, with 29.9% reporting occasional use as the most common frequency. However, usage intensity was generally low, with approximately half (47.5%) using AI tools for less than 1 h/week. Only 2.8% reported using AI tools for more than 10 h weekly, suggesting that intensive engagement with AI for language learning remains uncommon.

ChatGPT was by far the most commonly mentioned AI tool (58.5%), followed by Google Gemini (5.7%) and other tools (35.8%). The dominance of ChatGPT aligns with its widespread availability and user-friendly interface. The relatively low usage intensity suggests that while AI tools are recognized and accessible, they have not yet become deeply integrated into students' regular language learning routines.

4.1.3. Descriptive Statistics of Study Variables

Table 4 presents the descriptive statistics (mean, standard deviation, minimum, and maximum values) for all study constructs. All constructs were measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Table 4. Descriptive Statistics of Study Constructs (N = 318).

Construct	Mean	SD	Min	Max
Performance Expectancy (PE)	3.40	1.09	1.00	5.00
Effort Expectancy (EE)	3.39	1.06	1.00	5.00
Social Influence (SI)	3.25	1.01	1.00	5.00
Facilitating Conditions (FC)	3.37	1.06	1.00	5.00
Hedonic Motivation (HM)	3.34	1.10	1.00	5.00
Habit (HT)	3.22	1.09	1.00	5.00
Price Value (PV)	3.21	1.08	1.00	5.00
Behavioral Intention (BI)	3.27	1.09	1.00	5.00
Use Behavior (UB)	3.19	1.10	1.00	5.00

Note: All constructs measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). SD = Standard Deviation.

The descriptive statistics reveal moderate levels across all constructs, with mean scores ranging from 3.19 (Use Behavior) to 3.40 (Performance Expectancy), indicating that participants generally held neutral-to-slightly-positive perceptions of AI tools for English learning. Performance Expectancy showed the highest mean (M = 3.40, SD = 1.09), suggesting that students believed AI tools would enhance their learning performance. Conversely, Use Behavior demonstrated the lowest mean (M = 3.19, SD = 1.10), indicating that actual usage levels remained moderate despite positive beliefs and intentions.

The relatively large standard deviations (ranging from 1.01 to 1.10) across all constructs suggest considerable individual variation in perceptions and usage patterns. The full range of responses (1–5) was observed for each construct, indicating that the sample included individuals with diverse experiences and attitudes toward AI tools for English learning, from strongly negative to strongly positive. This variability is appropriate for investigating factors that differentiate adopters from non-adopters and for understanding the range of motivations and barriers to AI tool usage.

4.2. Measurement Model Assessment

The measurement model assessment evaluated the reliability and validity of the constructs through multiple criteria: indicator reliability (outer loadings), internal consistency reliability (Cronbach's alpha, rho_A, composite reliability), convergent validity (average variance extracted), discriminant validity (Fornell-Larcker criterion, HTMT, cross-loadings), and multicollinearity (variance inflation factor). **Figure 1** presents the measurement model with outer loadings for all indicators.

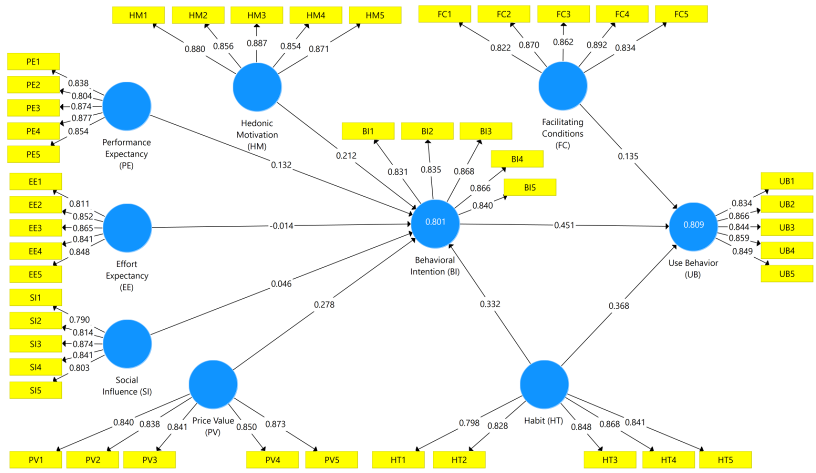

Figure 1. Measurement Model with Outer Loadings.

4.2.1. Indicator Reliability and Internal Consistency

Indicator reliability was assessed through outer loadings, which represent the correlation between each indicator and its respective construct. Internal consistency was evaluated using Cronbach's alpha (α), rho_A (ρ_A), composite reliability (CR), and average variance extracted (AVE). Multicollinearity at the indicator level was assessed using the variance inflation factor (VIF). **Table 5** presents the complete measurement model assessment results.

Table 5. Measurement Model Assessment: Loadings, Reliability, and Validity.

Construct/Item	Loading	VIF	α	rho_A	CR	AVE
Performance Expectancy (PE)			0.904	0.907	0.928	0.722
PE1	0.838	2.301				
PE2	0.804	2.008				
PE3	0.874	2.677				
PE4	0.877	2.689				
PE5	0.854	2.502				
Effort Expectancy (EE)			0.899	0.899	0.925	0.712
EE1	0.811	1.996				
EE2	0.852	2.403				
EE3	0.865	2.578				
EE4	0.841	2.214				
EE5	0.848	2.410				
Social Influence (SI)			0.882	0.884	0.914	0.681
SI1	0.790	1.901				
SI2	0.814	2.056				
SI3	0.874	2.817				
SI4	0.841	2.309				
SI5	0.803	2.054				
Facilitating Conditions (FC)			0.909	0.909	0.932	0.733
FC1	0.822	2.123				
FC2	0.870	2.978				
FC3	0.862	2.572				
FC4	0.892	3.402				
FC5	0.834	2.222				
Hedonic Motivation (HM)			0.919	0.920	0.939	0.756
HM1	0.880	2.943				
HM2	0.856	2.716				
HM3	0.887	3.084				
HM4	0.854	2.581				
HM5	0.871	3.044				
Price Value (PV)			0.903	0.904	0.928	0.720
PV1	0.840	2.269				
PV2	0.838	2.409				
PV3	0.841	2.314				
PV4	0.850	2.589				
PV5	0.873	2.725				

Table 5. *Cont.*

Construct/Item	Loading	VIF	α	rho_A	CR	AVE
Habit (HT)			0.893	0.893	0.921	0.701
HT1	0.798	1.945				
HT2	0.828	2.158				
HT3	0.848	2.389				
HT4	0.868	2.651				
HT5	0.841	2.450				
Behavioral Intention (BI)			0.902	0.902	0.928	0.719
BI1	0.831	2.228				
BI2	0.835	2.284				
BI3	0.868	2.859				
BI4	0.866	2.636				
BI5	0.840	2.442				
Use Behavior (UB)			0.904	0.904	0.929	0.723
UB1	0.834	2.244				
UB2	0.866	2.771				
UB3	0.844	2.410				
UB4	0.859	2.672				
UB5	0.849	2.538				

Note: All loadings > 0.70; α, CR > 0.70; AVE > 0.50; VIF < 5.0 indicate acceptable measurement quality [38].

As shown in **Table 5**, all 45 indicators demonstrated loadings exceeding the recommended threshold of 0.70 [38], ranging from 0.790 to 0.892. These high loadings indicate strong indicator reliability. All constructs demonstrated excellent internal consistency, with Cronbach's alpha values ranging from 0.882 to 0.919, substantially exceeding the 0.70 threshold [39]. Composite reliability values ranged from 0.914 to 0.939, all surpassing the recommended 0.70 threshold. All VIF values remained below 5.0, indicating no critical multicollinearity issues at the indicator level.

4.2.2. Convergent Validity

Convergent validity assesses the extent to which indicators of the same construct converge or share a high proportion of variance. This was evaluated through AVE, which should exceed 0.50, indicating that the construct explains more than half of the variance in its indicators [40]. As shown in **Table 5**, all AVE values exceeded 0.68, well above the required threshold. The highest convergent validity was observed for Hedonic Motivation (AVE = 0.756), while the lowest was for Social Influence (AVE = 0.681), though still indicating strong convergent validity. These results confirm that each construct's indicators converge to measure a unified underlying concept.

4.2.3. Discriminant Validity

Discriminant validity ensures that each construct is empirically distinct from other constructs in the model. This was assessed using three complementary criteria: the Fornell-Larcker criterion (**Table 6**), the Heterotrait-Monotrait ratio (**Table 7**), and cross-loadings.

The Fornell-Larcker criterion requires that the square root of each construct's AVE (shown on the diagonal in **Table 6**) exceeds its correlations with all other constructs [40].

Table 6. Discriminant Validity: Fornell-Larcker Criterion.

	BI	EE	FC	HT	HM	PE	PV	SI	UB
BI	0.848								
EE	0.756	0.844							
FC	0.808	0.846	0.856						
HT	0.832	0.743	0.775	0.837					
HM	0.823	0.817	0.866	0.802	0.870				
PE	0.748	0.818	0.763	0.679	0.773	0.850			
PV	0.821	0.738	0.782	0.775	0.783	0.735	0.849		
SI	0.756	0.816	0.837	0.770	0.797	0.736	0.719	0.825	
UB	0.867	0.740	0.785	0.848	0.795	0.695	0.773	0.723	0.851

Note: Diagonal elements represent the square root of AVE; off-diagonal elements represent inter-construct correlations.

The Fornell-Larcker criterion was satisfied, as all diagonal values (square roots of AVE) exceeded the corresponding off-diagonal correlation values in their respective rows and columns, confirming discriminant validity.

As a more stringent assessment, the Heterotrait-Monotrait (HTMT) ratio was examined. HTMT values should be below 0.85 (conservative threshold) or 0.90 (liberal threshold) to establish discriminant validity [41]. **Table 7** presents the HTMT results.

Table 7. Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT).

	BI	EE	FC	HT	HM	PE	PV	SI
EE	0.840							
FC	0.893	0.935						
HT	0.927	0.830	0.860					
HM	0.903	0.899	0.948	0.886				
PE	0.826	0.908	0.840	0.756	0.847			
PV	0.908	0.819	0.864	0.862	0.859	0.812		
SI	0.847	0.917	0.934	0.868	0.886	0.824	0.807	
UB	0.959	0.821	0.866	0.944	0.872	0.769	0.853	0.810

Several HTMT values exceeded the conservative 0.85 threshold, most notably for the relationships between Behavioral Intention and Use Behavior (HTMT = 0.959), Habit and Use Behavior (HTMT = 0.944), and Hedonic Motivation and Facilitating Conditions (HTMT = 0.948). However, these elevated values are theoretically justified within the UTAUT2 framework. The high correlation between Behavioral Intention and Use Behavior is expected and central to the theory, as intention is theorized to be the primary antecedent of actual behavior [17]. Similarly, the strong relationship between Habit and Use Behavior reflects the dual-pathway nature of habit, which influences behavior both directly and indirectly through intention [27]. Such high inter-construct correlations are commonly observed and accepted in UTAUT2 models [42].

Additionally, cross-loadings analysis confirmed that all indicators loaded most strongly on their intended constructs, providing further evidence of discriminant validity. Given that (1) the Fornell-Larcker criterion was satisfied, (2) cross-loadings showed appropriate patterns, and (3) the theoretically expected relationships show high correlations in HTMT, discriminant validity was deemed acceptable for this study.

4.2.4. Measurement Model Summary

All measurement model criteria were met or exceeded, establishing the reliability and validity of the constructs. Indicator loadings were strong (0.790–0.892), internal consistency was excellent (α > 0.88, CR > 0.91), convergent validity was established (AVE > 0.68), discriminant validity was acceptable with theoretically justified high correlations, and multicollinearity was within acceptable limits (VIF < 5.0). These results confirm that the measurement model is robust and appropriate for proceeding to structural model assessment.

4.3. Structural Model Assessment

Following the confirmation of measurement model quality, the structural model was evaluated to test the hypothesized relationships. The assessment examined model fit, explanatory power (R^2), predictive relevance (Q^2), path coefficients, and effect sizes (f^2). **Figure 2** presents the structural model with path coefficients and significance levels.

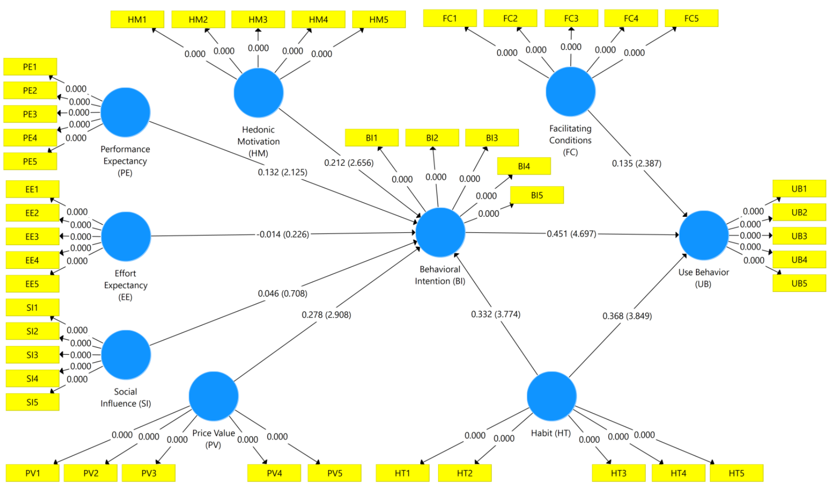

Figure 2. Structural Model with Path Coefficients and *p*-Values.

4.3.1. Model Fit

Model fit was assessed using two indices recommended for PLS-SEM: the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). The SRMR value of 0.046 was well below the threshold of 0.08, indicating excellent model fit [43]. The NFI value of 0.781, while below the ideal threshold of 0.90, is acceptable for PLS-SEM, which prioritizes predictive accuracy over model fit indices designed for covariance-based SEM [44]. Overall, the fit indices suggest that the model adequately represents the observed data.

4.3.2. Explanatory and Predictive Power

The coefficient of determination (R^2) indicates the proportion of variance in the endogenous constructs explained by their predictors. The Stone-Geisser Q^2 value assesses the model's predictive relevance through a blindfolding procedure. **Table 8** presents the R^2 and Q^2 values for both dependent variables.

Table 8. Explanatory and Predictive Power of the Model.

Endogenous Variable	R^2	R^2 Adjusted	Q^2	Assessment
Behavioral Intention (BI)	0.801	0.798	0.567	Substantial
Use Behavior (UB)	0.809	0.807	0.576	Substantial

Note: $R^2 \geq 0.67$ = substantial, ≥ 0.33 = moderate, ≥ 0.19 = weak [45]; $Q^2 > 0.35$ = large, > 0.15 = medium, > 0 = small predictive relevance.

The model explained 80.1% of the variance in Behavioral Intention and 80.9% of the variance in Use Behavior. According to established guidelines [38,45], both values represent substantial explanatory power ($R^2 \geq 0.67$). These results exceed typical R^2 values reported in UTAUT2 studies, which generally range from 0.50 to 0.70 for behavioral intention [17,42]. The exceptionally high R^2 values indicate that the UTAUT2 framework effectively captures the key determinants of AI tool adoption among English learners in this context.

The model demonstrated strong predictive relevance, with Q^2 values of 0.567 for Behavioral Intention and 0.576 for Use Behavior. According to established thresholds, both values represent large predictive relevance ($Q^2 > 0.35$), confirming that the model possesses excellent out-of-sample predictive capability [46,47]. Additionally, PLSpredict analysis yielded Q^2predict values of 0.783 for Behavioral Intention and 0.765 for Use Behavior, with RMSE values of 0.469 and 0.488, respectively, further confirming the model's strong predictive accuracy [48].

4.3.3. Hypothesis Testing Results

Path coefficients (β) were estimated using 5,000 bootstrap samples to test the nine hypotheses. **Table 9** presents the results of hypothesis testing, including path coefficients, *t*-values, *p*-values, 95% confidence intervals, effect sizes (f^2), and hypothesis decisions.

Table 9. Structural Path Analysis and Hypothesis Testing.

H	Path	β	*t*-Value	*p*-Value	95% CI	f^2	Decision
H1	PE → BI	0.132	2.117	0.034*	[0.019, 0.262]	0.024	Supported
H2	EE → BI	−0.014	0.227	0.821	[−0.133, 0.107]	0.000	Not Supported
H3	SI → BI	0.046	0.703	0.482	[−0.077, 0.180]	0.003	Not Supported
H4	HM → BI	0.212	2.626	0.009**	[0.049, 0.362]	0.048	Supported
H5	PV → BI	0.278	2.869	0.004**	[0.091, 0.468]	0.116	Supported
H6	HT → BI	0.332	3.719	0.000***	[0.161, 0.505]	0.151	Supported
H7	FC → UB	0.135	2.393	0.017*	[0.031, 0.252]	0.030	Supported
H8	HT → UB	0.368	3.863	0.000***	[0.184, 0.557]	0.197	Supported
H9	BI → UB	0.451	4.716	0.000***	[0.271, 0.637]	0.257	Supported

Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001. Effect size (f^2): 0.02 = small, 0.15 = medium, 0.35 = large [49].

Seven of the nine hypotheses were supported (77.8% support rate). The following sections provide detailed interpretations of each hypothesis.

Predictors of Behavioral Intention

H1. *Performance Expectancy → Behavioral Intention (Supported)*

Performance Expectancy positively influenced Behavioral Intention (β = 0.132, t = 2.117, p = 0.034), supporting H1. The effect size was small (f^2 = 0.024). Students who believed that AI tools would enhance their English learning performance were more likely to intend to use these tools. While significant, this effect was smaller than typically reported in UTAUT2 studies [4,17], possibly due to the presence of stronger competing predictors in the model.

H2. *Effort Expectancy → Behavioral Intention (Not Supported)*

Effort Expectancy did not significantly influence Behavioral Intention (β = −0.014, t = 0.227, p = 0.821), failing to support H2. The 95% confidence interval included zero [−0.133, 0.107], and the effect size was negligible (f^2 = 0.000). This finding is consistent with recent research suggesting that Effort Expectancy has diminishing importance among digitally competent students who find contemporary AI tools inherently easy to use [4,16].

H3. *Social Influence → Behavioral Intention (Not Supported)*

Social Influence did not significantly predict Behavioral Intention (β = 0.046, t = 0.703, p = 0.482), thus H3 was not supported. The confidence interval included zero [−0.077, 0.180], and the effect size was negligible (f^2 = 0.003). This finding was unexpected, as prior research in Saudi Arabia has shown Social Influence to be a significant predictor of technology adoption [50]. The non-significant effect may reflect the highly personal and voluntary nature of AI tool adoption for individual language learning.

H4. *Hedonic Motivation → Behavioral Intention (Supported)*

Hedonic Motivation positively influenced Behavioral Intention (β = 0.212, t = 2.626, p = 0.009), supporting H4. The effect size was small (f^2 = 0.048). Students who found AI tools enjoyable and fun were more likely to intend to use them for English learning. This finding aligns with research emphasizing the role of enjoyment in voluntary technology adoption [2,11].

H5. *Price Value → Behavioral Intention (Supported)*

Price Value demonstrated a positive and significant effect on Behavioral Intention (β = 0.278, t = 2.869, p = 0.004), supporting H5. Notably, this was the second-strongest predictor of intention, with a small-to-medium effect size (f^2 = 0.116). This finding was unexpected, as most AI tools are freely available. The strong effect suggests that students are evaluating value in terms of time and effort investment rather than monetary cost. This represents an important theoretical contribution, suggesting that Price Value in UTAUT2 should be conceptualized more broadly as encompassing time and effort value, not merely monetary considerations.

H6. *Habit → Behavioral Intention (Supported)*

Habit emerged as the strongest predictor of Behavioral Intention (β = 0.332, t = 3.719, p < 0.001), supporting H6. The effect size was medium (f^2 = 0.151). Students who had developed routinized AI usage patterns demonstrated significantly stronger intentions to continue using these tools. This finding aligns with recent research emphasizing habit as the primary driver of AI adoption [4,16].

Predictors of Use Behavior

H7. *Facilitating Conditions → Use Behavior (Supported)*

Facilitating Conditions positively influenced Use Behavior (β = 0.135, t = 2.393, p = 0.017), supporting H7. The effect size was small (f^2 = 0.030). Students with better access to resources, infrastructure, and support demonstrated higher actual usage of AI tools. This finding confirms that while infrastructure is necessary for enabling usage, it is not sufficient on its own, motivational factors play a larger role.

H8. *Habit → Use Behavior (Supported)*

Habit demonstrated a strong direct effect on Use Behavior (β = 0.368, t = 3.863, p < 0.001), supporting H8. The effect size was medium (f^2 = 0.197). This finding confirms the dual-pathway nature of habit in UTAUT2: habit influences behavior both directly (through automatic processes) and indirectly through intention [17,27]. The total effect of habit on behavior (combining direct and indirect effects through intention) was 0.518 (0.368 direct + 0.332 × 0.451 indirect), making it the strongest overall influence on AI tool usage.

H9. *Behavioral Intention → Use Behavior (Supported)*

Behavioral Intention was the strongest direct predictor of Use Behavior (β = 0.451, t = 4.716, p < 0.001), supporting H9. The effect size was medium-to-large (f^2 = 0.257). This validates the core UTAUT2 mechanism: students who intend to use AI tools do indeed use them. The strong intention-behavior link confirms that conscious adoption decisions translate effectively into actual usage behavior.

4.3.4. Effect Sizes

Effect sizes (f^2) assess the substantive impact of predictor variables on endogenous constructs. Following Cohen's [49] guidelines (0.02 = small, 0.15 = medium, 0.35 = large), the strongest effects were observed for Behavioral Intention → Use Behavior (f^2 = 0.257, medium-large), Habit → Use Behavior (f^2 = 0.197, medium), and Habit → Behavioral Intention (f^2 = 0.151, medium). Price Value also demonstrated a notable effect (f^2 = 0.116, small-to-medium). The multiple small-to-medium effects combined to produce the substantial R^2 values observed for both endogenous constructs.

4.4. Summary of Results

The analysis yielded several key findings. First, the model demonstrated exceptional explanatory and predictive power, explaining over 80% of the variance in both behavioral intention and actual usage. Second, Habit emerged as the dominant factor, showing the strongest effects on both intention and behavior, with a total effect of 0.518 on usage. Third, Price Value unexpectedly emerged as the second-strongest predictor of intention, suggesting that students highly value the time-saving and efficiency benefits of AI tools even when they are freely available. Fourth, traditional UTAUT predictors showed mixed results: Performance Expectancy was significant but weaker than expected, while Effort Expectancy and Social Influence were non-significant, likely reflecting high digital literacy and the personal nature of learning tool adoption. Finally, the strong intention-behavior link (β = 0.451) validated the core UTAUT2 theoretical mechanism.

These results provide strong empirical support for the UTAUT2 framework in explaining AI tool adoption among English learners, while also highlighting the central importance of habit formation and value perception in sustaining technology use for language learning.

5. Discussion

This study investigated the determinants of generative AI adoption among undergraduate English learners at the University of Hail, Saudi Arabia, using the UTAUT2 framework. The structural model demonstrated exceptional explanatory power, accounting for 80.1% of the variance in behavioral intention and 80.9% of the variance in use behavior, figures substantially exceeding those typically reported in UTAUT2 studies [17,42]. Seven of the nine hypothesized relationships were supported. Habit emerged as the dominant predictor, followed by price value (reconceptualized for free technologies), hedonic motivation, and performance expectancy. Contrary to theoretical expectations, effort expectancy and social influence were non-significant. This discussion interprets these findings in relation to prior research, theoretical expectations, and the Saudi higher education context.

5.1. The Primacy of Habit in Sustained AI Adoption

Habit demonstrated the strongest influence on both behavioral intention (β = 0.332, p < 0.001) and use behavior (β = 0.368, p < 0.001), confirming its dual-pathway role as specified in UTAUT2 [17,27]. The total effect of habit on use behavior reached 0.518, establishing it as the dominant mechanism driving AI adoption.

This finding aligns closely with recent international research. Moradi [16] similarly identified habit as the primary determinant of ChatGPT usage among Chinese EFL learners, while Zheng et al. [4] confirmed habit's significance in predicting behavioral intention. The convergence of evidence across diverse contexts suggests a fundamental pattern: once students integrate AI tools into recurrent academic tasks, usage becomes increasingly automatic through strengthened cue–response associations [51].

Importantly, the primacy of habit over performance expectancy indicates that sustained AI use is less a matter of continued rational evaluation and more a function of behavioral embedding. This extends recent Saudi-based findings [1,18], which emphasized perceived usefulness but did not model habit explicitly. The present study advances the regional literature by demonstrating that routinization, not merely perceived benefit, is central to understanding long-term AI adoption patterns.

5.2. Reconceptualizing Price Value in Zero-Cost AI Ecosystems

Price value demonstrated a strong effect on behavioral intention ($\beta = 0.278$, $p = 0.004$), emerging as the second-strongest predictor. This finding was unexpected, as leading AI tools are freely available, and previous research has reported non-significant price value effects [4,16].

The discrepancy can be explained through theoretical reconceptualization. In free-access environments, monetary cost is negligible, but students incur non-monetary costs—time investment, cognitive effort, and attention allocation. Drawing on Becker's [25] economic theory of time allocation, this study reconceptualized price value as an efficiency-based trade-off between learning gains and time investment. When perceived benefits exceed non-monetary costs, price value is positive and adoption intentions strengthen.

The strong effect suggests that Saudi EFL students are particularly sensitive to efficiency-enhancing tools, likely reflecting the high-stakes nature of English proficiency in Saudi higher education. Theoretically, this finding refines UTAUT2 by demonstrating that price value retains predictive salience in zero-price digital ecosystems when operationalized beyond financial cost.

5.3. Hedonic Motivation and Performance Expectancy

Hedonic motivation significantly predicted behavioral intention ($\beta = 0.212$, $p = 0.009$), corroborating research emphasizing the role of intrinsic enjoyment in voluntary technology adoption [2,4,11]. The interactive, conversational affordances of generative AI generate engagement, curiosity, and satisfaction through dynamic dialogue. By incorporating UTAUT2's hedonic motivation construct, this study demonstrates that AI adoption is not solely utilitarian but also experiential, a dimension less systematically examined in prior Saudi-based TAM studies.

Performance expectancy positively influenced behavioral intention ($\beta = 0.132$, $p = 0.034$), aligning with extensive technology acceptance research [17,21]. However, its effect size was small relative to habit and price value. This pattern suggests a shifting adoption hierarchy in generative AI contexts: as awareness of AI's functional benefits becomes widespread, usefulness may transition from a differentiating factor to an assumed baseline.

5.4. Non-Significant Predictors: Effort Expectancy and Social Influence

Effort expectancy did not significantly influence behavioral intention ($\beta = -0.014$, $p = 0.821$). This finding, while surprising from a traditional technology acceptance perspective, mirrors recent research [16] and likely reflects technological normalization. Generative AI platforms utilize natural-language interfaces requiring minimal technical training. For digitally literate university students, usability may no longer represent a barrier.

Contrary to expectations grounded in collectivist cultural theory [52], social influence did not significantly predict behavioral intention ($\beta = 0.046$, $p = 0.482$). This finding may reflect the private, individual nature of AI tool adoption. Students use AI tools privately on personal devices, often outside classroom contexts, insulating decisions from social norms. The voluntary nature of adoption further reduces normative pressure.

5.5. Use Behavior: Intention and Facilitating Conditions

Behavioral intention was the strongest direct predictor of use behavior ($\beta = 0.451$, $p < 0.001$), validating the core UTAUT2 mechanism that conscious adoption decisions translate into actual usage. The medium-to-large effect size confirms that interventions targeting intention are likely to influence behavior.

Facilitating conditions also positively influenced use behavior ($\beta = 0.135$, $p = 0.017$), confirming that resource availability enables behavioral enactment. The importance of infrastructural and institutional support is a recurring theme in the literature. For example, Almutairi et al. [36] argued that for universities to effectively respond to the fourth industrial revolution, they must improve the quality of teaching and learning, which includes ensuring the necessary conditions for technology adoption. Similarly, Alshammari [53] found that while technical and administrative support significantly impacted technology use among faculty, the role of institutional policy was less clear, highlighting the complex interplay of facilitating conditions.

5.6. Theoretical Integration and Implications

This study extends previous Saudi Arabian research in several significant ways. Prior studies employing TAM [1, 12, 18] established the importance of perceived usefulness and ease of use. This study advances understanding by revealing that adoption decisions are influenced by a broader range of factors, particularly habit and value perceptions, that exceed the explanatory power of TAM alone. The exceptional explanatory power of UTAUT2 ($R^2 > 0.80$) confirms its robustness in this novel context.

Several theoretical implications emerge. First, habit should be recognized as a central mechanism in sustained AI use, potentially superseding continued cognitive evaluation. Second, price value remains salient in zero-cost environments when reconceptualized to encompass time and effort costs. Third, effort expectancy and social influence may weaken as technologies mature and use becomes private and voluntary.

The findings also offer practical implications. Educators should focus on supporting habit formation through consistent classroom integration. Training should emphasize efficiency gains to enhance value perceptions. The non-significance of effort expectancy suggests institutions can focus less on basic training and more on advanced applications. The dominance of ChatGPT (58.5%) suggests developing expertise with this platform while remaining aware of alternatives. Finally, the relatively low usage intensity (47.5% using less than 1 h/week) indicates substantial untapped potential for deeper integration.

5.7. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design captures adoption at a single point in time, which limits the ability to draw causal inferences and to examine how adoption behaviors evolve. Longitudinal studies would provide a clearer understanding of how factors such as habit develop and how the relative importance of predictors may shift over time. In addition, the sample was drawn from a single Saudi university, which may limit the generalizability of the findings. Future research may examine whether these results hold across different institutions and cultural contexts.

Second, this study relied on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. While the model demonstrated strong explanatory power, other potentially relevant factors were not included. In particular, AI literacy, trust in AI-generated outputs, and ethical concerns—such as academic integrity, data privacy, and potential bias—may also influence adoption decisions. The omission of these constructs may limit the overall comprehensiveness of the model. Future studies are encouraged to extend the framework by incorporating these variables to provide a more holistic understanding of AI adoption in language learning contexts.

Third, the construct of price value was reconceptualized to reflect non-monetary costs, including time and cognitive effort, rather than financial cost. This approach is appropriate given that many AI tools are freely available; however, it may reduce comparability with prior UTAUT2 studies that operationalize price value in monetary terms. Further research is needed to validate this reconceptualization across different contexts and to develop measurement approaches suited to zero-cost digital environments.

Fourth, the study relied on self-reported data, which may be subject to biases such as social desirability and common method variance, although statistical tests suggested that this was not a major concern. Future research could complement self-report measures with objective usage data and qualitative methods to gain deeper insights into learners' experiences.

Fifth, the study did not examine potential moderating variables such as age, gender, and prior experience due to sample characteristics. These factors may play an important role in shaping AI adoption and should be explored in future research, particularly within the Saudi higher education context.

Sixth, the non-significant effect of social influence is noteworthy, especially given the collectivist cultural context. Further investigation using qualitative or mixed-method approaches may help explain how learners perceive social norms and external expectations regarding AI use.

Seventh, this study examined AI adoption in a general sense rather than focusing on specific tools or learning tasks. Future research could explore whether adoption patterns differ across various AI platforms and language learning activities, such as writing, vocabulary development, or speaking practice.

Overall, while the study provides strong empirical support for the UTAUT2 framework in this context, further research across diverse settings and with expanded models is needed to build a more comprehensive understanding of AI adoption in language learning.

6. Conclusion

This study investigated factors influencing English learners' adoption of generative AI tools at the University of Hail, Saudi Arabia, using the UTAUT2 framework. The model explained over 80% of the variance in both behavioral intention and use behavior, confirming the framework's robustness. Habit emerged as the dominant factor, followed by price value (reconceptualized for free technologies), hedonic motivation, and performance expectancy. Effort expectancy and social influence were non-significant, reflecting technological normalization and the private nature of AI engagement.

The findings contribute theoretically by extending UTAUT2 to generative AI in language learning, demonstrating that habit and value perceptions exceed TAM's explanatory power. The strong predictive power of price value, despite monetary costlessness, suggests students evaluate value in terms of time and effort investment, a refinement relevant to contemporary freemium ecosystems. The non-significant effects for effort expectancy and social influence identify boundary conditions for UTAUT2's applicability as technologies mature.

The findings portray generative AI tools as embedded learning companions whose adoption depends critically on routinization, efficiency perception, and intrinsic engagement. In the Saudi higher education context, students appear to adopt AI primarily for pragmatic and experiential reasons, habitual integration into routine tasks, favorable time-benefit trade-offs, and enjoyable interaction, rather than normative compliance or usability considerations.

Future research should employ longitudinal designs to examine habit development, investigate moderators with balanced samples, validate reconceptualized price value measures, and explore tool-specific adoption patterns using mixed methods.

As generative AI continues to transform educational landscapes, understanding factors that drive or inhibit adoption becomes increasingly essential for harnessing these tools in the service of language development and academic success. This study contributes theoretically grounded insights into the evolving dynamics of human–AI interaction in language learning, offering a foundation for future research and practice in this rapidly developing field.

The datasets generated and/or analysed during the current study are not publicly available due to privacy and ethical restrictions (to protect participant confidentiality) but are available from the corresponding author on reasonable request.

Author Contributions

O.I.M.A. and R.Q.G.R. conceptualized the study, led the literature review, designed the theoretical framework, and supervised data collection across participating institutions. S.A. conducted the Partial Least Squares Structural Equation Modeling analysis, interpreted the structural findings, and led the statistical reporting. A.A.M.B. and H.M.E. contributed to manuscript preparation, critical revision of theoretical sections, and overall quality assurance. All authors reviewed and approved the final manuscript for submission.

Funding

This research has been funded by the Scientific Research Deanship at the University of Ha'il–Saudi Arabia through project number [RCP-25 066].

Institutional Review Board Statement

Ethical approval for this study was granted by the Research Ethics Committee (REC) at the University of Hail (Approval No. H-2025-1005; December 8, 2025).

Informed Consent Statement

Written informed consent was obtained from all participants prior to data collection. Participation was voluntary, and anonymity and confidentiality were ensured.

Data Availability Statement

The data supporting this study are not publicly available to protect participant confidentiality under ethical approval H-2025-1005. De-identified data may be requested from the corresponding author and will be shared subject to REC approval.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the study design, data collection, analysis, interpretation, manuscript writing, or decision to publish.

AI Use Statement

During the preparation of this manuscript, the authors used Claude (Anthropic) solely for language refinement, including grammar, spelling, and phrasing improvements. No AI tools were used for data analysis, interpretation, hypothesis generation, or the development of scientific conclusions. All AI-generated suggestions were critically reviewed, fact-checked, and edited by the authors. The authors take full and sole responsibility for the integrity, accuracy, and originality of the work.

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