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Research Article

Understanding the Adoption of Generative Artificial Intelligence in English Language Teaching: A UTAUT2 Perspective in Turkish Higher Education

Umut İPEKDAL [a] | **Gonca SUBAŞI** [b]

[*] *National Defence University, School of Foreign Languages, İstanbul, Türkiye*

[**] *Anadolu University, Faculty of Education, ELT Department, Eskişehir, Türkiye*

Corresponding Author: Gonca SUBAŞI (goncas@anadolu.edu.tr)

ABSTRACT

This study examined whether the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) could predict English language instructors' acceptance and use of generative artificial intelligence (GenAI) technologies in Turkish higher education. An explanatory sequential mixed-methods design was employed. Quantitative data were collected from 80 instructors through a structured questionnaire and analyzed using multiple regression, followed by qualitative data from 10 semi-structured interviews and 6 classroom observations, which were analyzed through thematic analysis. The findings showed that none of the UTAUT2 constructs significantly predicted behavioral intention or actual usage behavior. Although performance expectancy and hedonic motivation showed relatively high descriptive values, they did not reach statistical significance, with hedonic motivation only approaching significance. These results suggest that UTAUT2 demonstrated limited explanatory adequacy for GenAI adoption in this sample and context. Qualitative findings indicated that instructors recognized benefits such as time savings and enhanced student engagement, but also expressed concerns about academic integrity, the reliability of AI-generated content, and possible negative effects on critical thinking and language learning. Institutional support, professional identity, and pedagogical beliefs also shaped adoption decisions. Overall, GenAI adoption appears to be a complex, multidimensional process that may require broader explanatory frameworks incorporating trust, perceived risk, and pedagogical considerations. Quantitative findings should, however, be interpreted cautiously, given the sample size and model complexity.

Keywords: Generative artificial intelligence (GenAI), UTAUT2, Technology acceptance, English language teaching (ELT), Higher education

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Introduction

Technological advancements are occurring globally and rapidly transforming educational practices worldwide. These changes are prompting educators to rethink traditional pedagogical practices and integrate innovative technologies and tools into their daily teaching. Over the last few years, the educational sector has undergone a massive transformation, driven by technology in the ways knowledge is created, disseminated, and assessed (Selwyn, 2016; Zawacki-Richter et al., 2019). One of the most recent and exciting innovations in education is generative artificial intelligence (GenAI). It influences teaching and learning at various levels

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of education. These innovative tools powered by Large Language Models (LLMs), such as ChatGPT, Google Gemini, and Microsoft Copilot, have the potential to support a variety of teaching tasks and generate creative content on the fly. Human-like text can be generated in real time to provide feedback on student performance and facilitate pedagogical innovation (Kasneci et al., 2023; Dwivedi et al., 2023; Stokel-Walker & Van Noorden, 2023).

The emergence of new GenAI-based educational technologies has the potential to transform how teachers support learners' knowledge and skill acquisition. Unlike earlier generations of educational technologies, which were primarily designed to deliver information to students or distribute content, the new generation of tools is designed to actively participate in the construction of knowledge with learners (Al-Obaydi et al., 2025; Bin-Hady et al., 2023). They can generate text, converse with learners, and adapt their outputs to learners' inputs and interactions (Luckin et al., 2016; Holmes et al., 2019; Dong et al., 2024).

GenAI provides significant educational affordances in ELT environments that closely correspond with the fundamental goals of language learning. GenAI tools demonstrate significant strength in interaction, feedback, and ongoing practice, which are intrinsic to language acquisition. These tools can help students practice conversational English, expand their vocabulary, improve their writing skills, and receive quick feedback (Chapelle, 2009; Hubbard & Levy, 2016). To improve their communicative competence, students can, for instance, participate in simulated conversations, get real-time corrections, and investigate different language patterns. Teachers can devote more time to higher-order instructional activities by using GenAI to automate time-consuming processes such as lesson preparation, material development, and formative assessment (Cabero-Almenara et al., 2024; Chen et al., 2020). As a result, GenAI may improve student engagement and teaching effectiveness.

While GenAI promises many benefits, it poses complex challenges and raises many concerns among educators who intend to utilize the technology in their educational practice. At the same time, the number of educators who utilize AI is increasing steadily, raising questions about their concerns, expectations, and readiness for pedagogical integration. Academic integrity may be compromised when students use AI to complete assignments and earn better grades. It is, however, often difficult to determine the reliability and accuracy of AI-generated information, which may contain inherent biases or produce incomplete or incorrect information (Rudolph et al., 2023; Cotton et al., 2023; Bender et al., 2021; Floridi & Chiriatti, 2020). For English Language Teaching (ELT), particular issues include the potential for limited input authenticity, a decline in the priority given to cognitive ability, and decreased human interaction (Stockwell, 2013; Golonka et al., 2014).

Effective adoption and utilization of educational technologies in educational settings depend largely on instructors' acceptance and use behavior. Higher-education instructors, often described as gatekeepers of pedagogical innovation, are notoriously independent and frequently engage in self-directed learning as they decide which educational technologies to adopt, how to use them, and how to integrate them into instructional practices. Instructors' perceptions of technology are shaped by their prior experiences, developed knowledge structures and conceptual images of technology integration, and levels of technological, pedagogical, and content knowledge (Ertmer & Ottenbreit-Leftwich, 2010). Even if pedagogical applications of technology have the potential to positively shape learners' educational experience, educational innovations are unlikely to be adopted without teachers' and administrators' acceptance and effective use (Howard et al., 2020; Scherer et al., 2019; Viberg et al., 2020). The present study examines factors that contribute to instructors' acceptance of GenAI.

To explain and predict technology adoption behavior, a range of models have been proposed over the past few decades. These models have progressed from generalized theories of human behavior to more specialized models designed specifically for technology. One of the earliest models put forward was the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975). The TRA posits that behavior is determined by a person's behavioral intention, and that the best predictors of behavioral intention are the person's attitude towards the behavior and the subjective norm regarding the behavior. Attitude refers to an individual's belief about the consequences of behaving in a certain way (evaluation) and their evaluation of those consequences (attitude). Intention to adopt is enhanced when both evaluation and attitude are positive and when the subjective norm indicates support for adoption from others whom the individual values. The TRA has, however, been criticized for failing to consider the influence of factors outside an individual's control. In particular, it assumes that behavior is completely under the individual's control and, as such, is not suitable for explaining adoption behavior under external constraints.

Davis (1989) developed the Technology Acceptance Model (TAM), which has become the most influential research model for understanding user adoption of technology. It posits that users' intention to use a system is affected by their two perceptions: perceived usefulness and perceived ease of use. Many educational

studies have found that TAM is applicable in general education as well as in English Language Learning andTeaching contexts (King & He, 2006; Scherer & Siddiq, 2015). While widely applied and perceived as effective for predicting user behavior, it suffers from limitations because it focuses solely on individuals' cognition without adequately addressing social, organizational, and contextual influences on technology adoption (Bagozzi, 2007).

To overcome the limitations of the Theory of Reasoned Action, Ajzen (1991) offered the Theory of Planned Behavior (TPB). Unlike earlier models, TPB takes into account the construct of perceived behavioral control (PBC), which refers to individuals' perceptions of their ability to perform a behavior and the availability of opportunities or resources needed to do so. PBC relates to confidence and institutional support in the educational environment. The theory has gained significant support for predicting teachers' behavior through their intentions (Teo, 2011). As with the TRA and TAM, however, both models are generally applied and do not describe technology-specific beliefs.

Venkatesh et al. (2003) addressed these limitations by proposing a unified theory to predict information technology adoption and use behavior. The Unified Theory of Acceptance and Use of Technology (UTAUT) draws on key constructs from earlier acceptance models and integrates the variables from eight established models into a single, empirically validated framework. Technology adoption is predicted by four key determinants: performance expectancy (perceived benefits), effort expectancy (perceived ease of use), social influence (perceived expectations from others), and facilitating conditions (organizational and technical support). UTAUT provides a significant increase in the explanation of behavioral intention and usage behavior compared with the eight theories it integrates (Venkatesh et al., 2003).

On this basis, the UTAUT2 model (Venkatesh et al., 2012) expanded the previous model with three additional factors: hedonic motivation, price value, and habit. In a digital age, the drivers of technology adoption are increasingly influenced by users' enjoyment of interacting with technology (hedonic motivation), the relative value of the benefits they expect to achieve against the cost of investing in the technology (price value), and the degree to which they simply do something without conscious effort because they have done it before (habit). UTAUT2 has been validated across a wide range of applications and is particularly appropriate for studying voluntary technology adoption (Dwivedi et al., 2020; Scherer & Teo, 2019; Kimmons, 2020).

Given the rapid emergence of new technologies, UTAUT2 remains a useful starting point for explaining technology adoption behavior. Recent studies have found that technology adoption in the modern era is often influenced not only by technology's functionality but also by experiential and contextual factors. Recent AI-focused adoption research further suggests that performance expectancy, hedonic motivation, trust, self-efficacy, ethical concerns, and institutional support may influence acceptance in university contexts (Dwivedi et al., 2023; Acosta-Enriquez et al., 2024; Scherer & Teo, 2019; Karahan Adalı & Bilgili, 2025). When it comes to GenAI adoption, enjoyment, engagement, and institutional and organizational support are key drivers influencing users' decisions to adopt the technology.

Research on technology adoption in ELT classrooms has primarily focused on the attitudes, self-efficacy, and technological competence of English language instructors. Such studies assert that attitudes towards technology are crucial to its effective integration within the teaching context, where instances of technology resistance or shallow use are often attributed to negative attitudes held by instructors (Lawrence & Tar, 2018; Salleh, 2016). Moreover, instructors' technological adoption can be best predicted by their self-efficacy regarding technology use; when instructors feel competent with technology, they are more likely to adopt it than their less competent peers (Scherer & Siddiq, 2015; Ertmer & Ottenbreit-Leftwich, 2010).

Despite instructors' positive intentions for technology use, research has found that there is often a large gap between intended use and actual use, due to a variety of barriers, including limited technological infrastructure, insufficient training, and time constraints. To bridge the intention-behavior gap, a variety of facilitating conditions must be in place for actual use to occur. These conditions include access to and appropriate use of infrastructure, technical and troubleshooting support, and professional development (Liu et al., 2019; Mei et al., 2017; Koç et al., 2021). This gap may be even more pronounced in the case of GenAI, given its complexity and ethical implications (Leiker et al., 2023).

The introduction of GenAI into the ELT classroom opens new possibilities for technology integration and raises questions about teachers' roles in the learning process. While earlier educational technologies were often used as supplementary tools for supporting listening, reading, speaking, and writing activities, GenAI can function as an interactive learning partner that generates texts, simulates conversations, provides feedback, and supports material design and facilitates interactive and engaging instructional activities (Holmes et al., 2019; Kasneci et al., 2023; Moorhouse et al., 2023). Recent work on GenAI and language teaching further emphasizes that these tools may support teacher productivity, learner interaction, feedback

provision, and AI literacy development, while also requiring critical and ethical pedagogical integration (Moorhouse & Wong, 2025). Recent research highlights that GenAI tools not only facilitate personalized language practice but also significantly reduce teacher workload by automating material generation and providing real-time diagnostic feedback (Dwivedi et al., 2023; Su & Yang, 2023). This transition from passive tools to active pedagogical agents underscores the transformative capacity of GenAI in modern ELT contexts. At the same time, GenAI may create challenges related to linguistic authenticity, assessment integrity, learner dependency, and the responsible interpretation of AI-generated feedback (Rudolph et al., 2023; Cotton et al., 2023; Stokel-Walker & Van Noorden, 2023). Therefore, GenAI should be understood not merely as a digital supplement but as a pedagogically consequential technology that may reshape classroom interactions, assessments, and teachers' decision-making.

In Turkish settings, educational technology adoption is shaped by a particular combination of institutional and cultural characteristics. While teachers tend to display optimism about the potential of technology, insufficient funding, limited training, and a lack of organizational and administrative support also shape the conditions in which they work (İçen, 2022; Koç et al., 2021). Research with Turkish EFL teachers has similarly shown that positive attitudes and self-confidence toward technology integration may coexist with limited institutional support, infrastructure-related difficulties, and the need for continuous professional development (Önalan & Kurt, 2020; Koç et al., 2021). Studies conducted in Turkish higher education contexts also highlight the role of teachers' beliefs, self-efficacy, and pedagogical orientations in shaping technology integration practices (Arslan, 2025; Çepni & Çepni, 2025; Yılmaz & Ağır, 2025). Furthermore, recent empirical investigations at Turkish universities indicate that, despite these challenges, ELT practitioners are willing to integrate AI when supported by adequate institutional training and clear policy frameworks (Özkan et al., 2024). Despite these developments, research specifically addressing the acceptance and pedagogical integration of GenAI among ELT instructors in Turkish higher education remains limited.

In addition, the adoption of GenAI raises several questions about professional identity and pedagogy. Teachers may see GenAI as useful but also as a threat to their practice, often holding negative attitudes towards technology due to perceived loss of control, uncertainty about how technology can enhance learning, and concerns about students' ethical use of technology (Ertmer et al., 2012).

Although there is an emerging academic interest in investigating the acceptance and use of educational technologies, the current study specifically aims to explore the applicability of the UTAUT2 model for predicting English language instructors' acceptance and use of GenAI tools in the Turkish higher education setting. The study seeks answers to the following research questions.

1. To what extent do UTAUT2 constructs predict instructors' behavioral intention to use GenAI tools?

2. To what extent do these constructs predict actual usage behavior?

3. How do instructors perceive the opportunities and challenges associated with GenAI?

4. How do institutional, professional, and pedagogical factors influence adoption decisions?

This study examines English language instructors' perspectives, analyzing their evolving roles as generative AI becomes more prominent in language learning and teaching. Answering these research questions contributes to the field in several ways. Firstly, the study does not merely seek to validate UTAUT2; rather, it critically interrogates its explanatory adequacy in the context of GenAI adoption. Secondly, it addresses the under-researched context of Turkish higher education. Finally, the findings of the present study provide practical implications for policymakers, teacher educators, and educational institutions regarding the responsible and effective integration of generative artificial intelligence into educational practices.

Methodology

The current study adopted an explanatory sequential mixed-methods design. Using this design method, quantitative data were collected and analyzed first, followed by qualitative data, and the qualitative data explained the results obtained from the quantitative data (Creswell & Plano Clark, 2018; Creswell, 2014). This approach enabled a broader quantitative analysis of the numerical data and an in-depth exploration of English language instructors' acceptance and adoption of generative artificial intelligence (GenAI) tools. The study consisted of two phases. In the first phase, quantitative data were collected via a structured online questionnaire, using items based on UTAUT2 (Venkatesh et al., 2012) to identify factors that predict behavioral intention and actual technology use. The second phase consisted of qualitative data, in which in-depth semi-structured interviews and classroom observations were conducted among a subset of the instructors. These qualitative methods enabled a deeper understanding of participants' experiences and the contextual factors that affect their adoption of GenAI. Combining quantitative and qualitative findings adds depth, validity, and completeness to the study through triangulation and analysis (Denzin, 1978).

Participants

This study was conducted at a public university in Türkiye, where students enroll in English preparatory programs to improve their English academic language proficiency. English language instructors in these programs engage in a variety of tasks, such as developing, evaluating, and using teaching materials; assessing and providing feedback on students' writing; and designing activities to help students practice English language skills. To support these tasks, adopting GenAI may offer pedagogical benefits and transform English language instructional practices.

The quantitative phase of the study involved 80 English language instructors from a wide range of institutional backgrounds. Participants were selected using convenience sampling; this method was appropriate for the current study because the researchers were able to recruit teachers from diverse contexts. Although the method may limit the generalizability of findings, it is widely used in exploratory and mixed-methods research to gather preliminary data (Etikan et al., 2015; Creswell & Plano Clark, 2018). The participants had varying degrees of teaching experience, from newly qualified to established educators, and differed in their exposure to GenAI tools.

Table 1. *Participant Demographic Overview*

Demographic Variable	Category	Frequency (n=80)	Percentage (%)
Gender	Male	42	52.5%
	Female	38	47.5%
Qualification	Bachelor's Degree	35	43.75%
	Master's Degree	45	56.25%
Teaching Experience	0-5 years	27	33.75%
	6-10 years	43	53.75%
	11-15 years	7	8.75%
	More than 15 years	3	3.75%

The demographic characteristics of the participants are presented in Table 1. The sample is primarily composed of moderately experienced instructors with relatively high academic qualifications. This profile is particularly relevant to examining technology adoption, as mid-career instructors are often actively integrating new pedagogical tools while balancing established teaching practices.

Qualitative data were collected using semi-structured interviews. For the qualitative phase, a purposive sampling strategy was used to select 10 participants from the quantitative dataset. Participants were selected based on variation in behavioral intention scores, variation in GenAI use levels, and willingness to participate in additional data collection. This strategy allowed for an in-depth examination of selected cases with diverse characteristics related to decisions to adopt GenAI. In addition to the interviews, six classroom observations were conducted to examine the actual use of GenAI tools in teaching practices. The observations were used to triangulate instructors' self-reported perceptions with their classroom practices and to identify whether stated attitudes toward GenAI were reflected in pedagogical behavior. Observation notes informed the refinement of qualitative themes, particularly those related to instructional caution, practical use patterns, and contextual constraints. An observation checklist was used to document the frequency, purpose, and pedagogical context of GenAI-related practices.

Data Collection Instruments

In the quantitative phase, a structured questionnaire was used to collect data. This questionnaire was based on UTAUT2 (Venkatesh et al., 2012) and included items on performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, and usage behavior. Items from validated UTAUT2 scales were adapted for this study on GenAI in English-language teaching contexts. Participants responded to items on a Likert scale, ranging from strongly disagree (1) to strongly agree (5).

The qualitative data were collected through semi-structured video interviews. Instructors were asked about their perceptions and experiences regarding the implementation of GenAI tools and features in their teaching practices. The semi-structured protocol included open-ended questions exploring experiences with specific tools, perceptions of benefits and challenges, and institutional and pedagogical factors that inform

instructors' GenAI-related practices and decisions.

Classroom observations further supported triangulation by allowing the researcher to compare interview-based accounts with observed classroom practices. These observations also provided contextual evidence regarding how GenAI tools were used in teaching, the frequency of use, and the nature of teacher–student interactions, thereby strengthening the credibility of the findings.

Data Collection Procedure and Analysis

In accordance with the mixed-methods design, data were collected in two consecutive phases. In the first phase, a paper questionnaire was distributed to a group of instructors. Participation was voluntary, and potential participants were informed of the research aims and the anonymity of the data collected. The data collection phase lasted a set period, during which instructors had sufficient time to participate. Participants for the second phase were selected for an interview based on criteria derived from the quantitative analysis. Once selected, instructors were contacted and invited to participate in an interview. The interviews were conducted individually and, with the participant's permission, recorded and transcribed for analysis. In addition to the interviews, instructors' classrooms were observed in a non-intrusive manner and scheduled with participating instructors. Ethical principles were followed throughout the data collection process. Participants had the right to decide whether to take part in the survey, to withdraw at any stage of the research, to remain anonymous, to maintain confidentiality, to clarify any points, and to seek advice from others. The recorded and written data were securely stored and anonymized.

The quantitative data were analyzed using SPSS (Version 28). Descriptive statistics were computed to describe the participants' perceptions of GenAI. The scales' reliability was then assessed using Cronbach's alpha. Finally, multiple regression analyses were conducted to examine the relationships between the UTAUT2 constructs and behavioral intention and usage behavior.

The quantitative analysis examined whether UTAUT2 constructs predicted instructors' behavioral intention and usage behavior. The qualitative data were analyzed using thematic analysis as described by Braun and Clarke (2006). The analysis proceeded through several stages. First, the researcher repeatedly read and returned to the data, using the transcripts to develop initial codes. These initial codes were then sorted into themes, which were reviewed and refined. Finally, the themes were interpreted in light of the quantitative results and the theory underpinning the research to provide a comprehensive interpretation of instructors' experiences and perspectives in the study.

In the quantitative phase of this study, the validity was ensured using established scales drawn from UTAUT2. The reliability results reveal that all measurement items exhibit satisfactory reliability, as indicated by Cronbach's alpha coefficients. Construct validity is also supported by the measurement model. Qualitative methods were used to establish a believable representation of the phenomenon under study. Strategies were employed to establish trustworthiness in the qualitative phase: credibility was established through data triangulation (interviews and classroom observations); transferability was increased by providing a detailed description of the research setting, participants, and context; dependability was established by following a systematic coding process throughout the data analysis, and confirmability was ensured by accurately documenting the steps taken during analysis.

Table 2.*Quantitative Data Collection Instrument (UTAUT2 Survey)*

Constructs	**Items in Questionnaire**	**Reliability (Cronbach's α)**
Performance Expectancy	PE1-PE4	$\alpha > 0.80$
Effort Expectancy	EE1-EE4	$\alpha > 0.75$
Social Influence	SI1-SI3	$\alpha > 0.70$
Facilitating Conditions	FC1-FC4	$\alpha > 0.75$
Hedonic Motivation	HM1-HM3	$\alpha > 0.80$
Price Value	PV1-PV3	$\alpha > 0.75$
Habit	HT1-HT4	$\alpha > 0.75$
Behavioral Intention	BI1-BI3	$\alpha > 0.80$
Usage Behavior	UB1-UB3	$\alpha > 0.70$

The internal consistency reliability of the measurement constructs was assessed using Cronbach's alpha coefficients. As presented in Table 2, all constructs demonstrated acceptable to high levels of reliability. Specifically, performance expectancy, hedonic motivation, and behavioral intention showed strong internal consistency, with Cronbach's alpha values exceeding .80. Effort expectancy, facilitating conditions, price value, and habit also demonstrated satisfactory reliability, with values above .75. Social influence and usage behavior met the acceptable threshold of .70, indicating adequate reliability for exploratory research (Hair et al., 2010).

Overall, these results confirm that the measurement scales used in this study are reliable and suitable for further statistical analysis. The satisfactory reliability levels support the validity of subsequent regression analyses examining the relationships between UTAUT2 constructs and instructors' behavioral intention and usage behavior.

Findings

This section presents findings on the research questions, drawing on both quantitative and qualitative data from the study. The findings from the quantitative data offer insights into the relationships between the UTAUT2 constructs and instructors' behavioral intention and usage behavior, while the qualitative findings provide deeper insights into instructors' perceptions, experiences, and contextual factors that may influence their adoption of generative artificial intelligence (GenAI) tools.

The quantitative data analysis began with descriptive statistics in order to better understand instructors' perceptions of GenAI. The results indicated that participants were generally positive toward the use of GenAI in English language teaching. Both performance expectancy and hedonic motivation demonstrated relatively high mean values, suggesting that instructors perceive GenAI tools as useful and engaging. Participants also reported relatively high levels of behavioral intention to use GenAI. In contrast, moderate levels were observed for facilitating conditions and habits, indicating that although instructors recognize the potential of GenAI to enhance teaching and learning, consistent and supported use has not yet been fully established.

To address the first research question, a multiple regression analysis was conducted to examine the extent to which UTAUT2 constructs predict instructors' behavioral intention to use GenAI tools.

Table 3. *Multiple Regression Analysis Predicting Behavioral Intention (BI)*

Predictor Variable	B (Coefficient)	Std. Error	t-value	p-value	Significance (p<0.05)
Constant	6.058	1.124	5.388	<0.001	**Yes**
Performance Expectancy	-0.221	0.139	-1.588	0.117	No
Effort Expectancy	-0.182	0.128	-1.427	0.158	No
Social Influence	-0.077	0.117	-0.661	0.511	No
Facilitating Conditions	-0.117	0.112	-1.042	0.301	No
Hedonic Motivation	-0.203	0.114	-1.785	0.078	No (marginal)
Price Value	-0.073	0.107	-0.687	0.495	No
Habit	-0.119	0.125	-0.952	0.344	No

The results revealed that none of the independent variables significantly predicted behavioral intention at the conventional significance level of $p < .05$. As shown in Table 3, performance expectancy ($B = -0.221$, $SE = 0.139$, $t = -1.588$, $p = .117$), effort expectancy ($B = -0.182$, $SE = 0.128$, $t = -1.427$, $p = .158$), social influence ($B = -0.077$, $SE = 0.117$, $t = -0.661$, $p = .511$), facilitating conditions ($B = -0.117$, $SE = 0.112$, $t = -1.042$, $p = .301$), price value ($B = -0.073$, $SE = 0.107$, $t = -0.687$, $p = .495$), and habit ($B = -0.119$, $SE = 0.125$, $t = -0.952$, $p = .344$) did not demonstrate statistically significant effects. Hedonic motivation approached statistical significance ($B = -0.203$, $SE = 0.114$, $t = -1.785$, $p = .078$), indicating a marginal tendency to influence behavioral intention. The overall model was not statistically significant, $F(7, 72) = 1.52$, $p > .05$, $R^2 = .13$ (adjusted $R^2 = .04$), indicating that the UTAUT2 constructs do not significantly predict behavioral intention. These findings raise questions about the explanatory adequacy of UTAUT2 for instructors' behavioral intention in the context of GenAI adoption. However, given the sample size and number of predictors included in the model, the non-significant results should be interpreted cautiously rather than as definitive evidence of model failure.

To address the second research question regarding predictors of actual usage behavior, a separate regression analysis was conducted.

Table 4. *Multiple Regression Analysis Predicting Usage Behavior (UB)*

Predictor Variable	B (Coefficient)	Std. Error	t-value	p-value	Significance (p<0.05)
Constant	3.289	0.556	5.912	<0.001	**Yes**
Behavioral Intention	-0.007	0.100	-0.069	0.945	No
Facilitating Conditions	-0.093	0.096	-0.963	0.338	No
Habit	0.006	0.110	0.053	0.958	No

The results similarly indicated that none of the predictors significantly explained usage behavior. As presented in Table 4, behavioral intention ($B = -0.007$, $SE = 0.100$, $t = -0.069$, $p = .945$), facilitating conditions ($B = -0.093$, $SE = 0.096$, $t = -0.963$, $p = .338$), and habit ($B = 0.006$, $SE = 0.110$, $t = 0.053$, $p = .958$) were not statistically significant predictors. The overall model was not statistically significant, $F(3, 76) = 0.31$, $p > .05$, $R^2 = .01$ (adjusted $R^2 = -.03$), indicating that behavioral intention, facilitating conditions, and habit do not significantly predict usage behavior. This finding raises questions about the assumption that behavioral intention predicts actual use in this context and suggests a possible intention–behavior gap in GenAI adoption.

The qualitative findings provide additional insights into instructors' experiences with GenAI and help explain the patterns observed in the quantitative results. Thematic analysis of interview and observation data revealed three main themes: perceived opportunities, perceived challenges, and contextual influences on adoption.

Table 5. *Main Themes of Qualitative Findings*

Theme	Main Focus	Representative Issues
Perceived opportunities	Positive uses of GenAI in ELT	Time-saving, material development, feedback, student engagement
Perceived challenges	Concerns limiting adoption	Academic integrity, reliability of AI-generated content, reduced critical thinking, limited authentic interaction
Contextual influences	Institutional and professional factors shaping adoption	Training guidelines, infrastructure, professional identity, pedagogical beliefs

As shown in Table 5, the qualitative findings indicate that instructors' GenAI adoption was shaped not only by perceived usefulness and engagement but also by ethical, pedagogical, institutional, and professional considerations. This thematic structure helps clarify why the quantitative model did not identify statistically significant predictors of behavioral intention or usage behavior.

The first theme concerns the perceived opportunities that GenAI presents for language-teaching instructors. The majority of participants highlighted the benefits of GenAI, including increased efficiency, particularly through automation of tasks such as lesson planning, content generation, and grading. Instructors reported that these efficiencies allow them to allocate more time to communicative and interactive aspects of teaching. In addition, participants noted that GenAI has the potential to enhance student engagement by offering interactive learning opportunities and real-time feedback. These perceptions align with the relatively high levels of performance expectancy and hedonic motivation identified in the quantitative data. For example, one instructor stated, "I saved so much time generating materials that actually teach my students." Another instructor reported, "My students were more engaged with what we were doing in class, as they saw the demos and tried them out." These quotations illustrate how instructors associated GenAI with instructional efficiency and learner engagement.

The second theme identified was perceived challenges. Participants expressed several concerns that influenced their decisions regarding the use of GenAI in teaching and learning. A major concern was academic integrity, with instructors worrying that students might misuse GenAI tools to complete assignments without fully engaging with the learning process. Participants also raised concerns about thereliability and accuracy of AI-generated content, emphasizing the need for critical evaluation. Furthermore, pedagogical concerns were highlighted, including the potential reduction of authentic

interaction and opportunities for critical thinking. These concerns may help explain why the quantitative analysis did not identify strong predictors of behavioral intention. One instructor explained, “Students can easily use AI to complete assignments without actually learning any material, which is a serious issue for us.” Another participant stated, “Sometimes the information that is generated by AI is not accurate. I don’t fully trust it, so I always have to double-check.” These statements show that ethical concerns and trust in AI-generated outputs played an important role in instructors’ cautious attitudes toward GenAI adoption.

The third theme, contextual influences, examined the role of institutional, professional, and pedagogical factors in shaping the adoption of GenAI. Instructors emphasized that institutional support, including training, guidelines, and technological infrastructure, plays a crucial role in facilitating adoption. In some cases, a lack of support hindered the use of GenAI, even when instructors expressed interest in using it. Professional identity also emerged as an important factor: some instructors viewed GenAI as a supportive tool, while others saw it as a potential threat to their expertise. Additionally, pedagogical beliefs influenced adoption decisions, with instructors who prioritized student autonomy and critical thinking adopting a more cautious approach. One instructor stated, “If the institution provides proper training and clear guidelines, I will feel more comfortable using AI tools.” Another participant commented, “I see AI as a helpful assistant that can support my teaching, not replace it,” whereas another expressed concern by stating, “I feel like AI might replace some parts of our job in the future, and that worries me.” These quotations demonstrate the importance of institutional support and professional identity in shaping instructors’ adoption decisions.

While presenting a range of findings through the integration of qualitative and quantitative data, the study finds that, descriptively, instructors have mostly positive views of adopting GenAI in their teaching. However, regression analysis shows that traditional UTAUT2 predictors did not significantly explain intention to use GenAI or reported GenAI usage in the present sample. The qualitative insights gained from the study suggest that factors influencing instructors’ adoption decisions may not be fully captured in the UTAUT2 model, including ethical concerns, pedagogical issues, and operational constraints.

Overall, the findings show that while teachers perceived several benefits of GenAI, their adoption appeared to be shaped by perceived risks, organizational and instructional factors, and pedagogical beliefs about language learning. These findings suggest implications for UTAUT2, which may need to be refined or extended to capture the complexities of technology adoption involving emerging categories of innovative artificial intelligence technologies, such as GenAI.

Discussion and Conclusion

This study investigated English language instructors’ adoption of generative artificial intelligence (GenAI) tools in Turkish higher education settings using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. To gain deeper insights into the findings, an explanatory sequential mixed-methods design was employed. The results suggest that, although the UTAUT2 model accounted for some variance in behavioral intention and usage behavior, its explanatory adequacy was limited in this sample and context. Rather than validating UTAUT2, the present study critically examines the model's boundaries when applied to the adoption of GenAI in English language teaching. Unlike the findings of Venkatesh et al. (2012), which supported the applicability of the UTAUT2 model, the current study’s findings align with emerging critiques of traditional technology acceptance models (Dwivedi et al., 2023). None of the UTAUT2 constructs examined were statistically significant predictors of behavioral intention or usage behavior in the present sample. Moreover, the correlation between behavioral intention and usage behavior was not significant, suggesting a possible intention–behavior gap (Liu et al., 2019).

Importantly, these findings align with evolving research on the determinants of educational technology adoption and use. While existing research suggests that the Unified Theory of Acceptance and Use of Technology (UTAUT2) can explain a significant amount of variance in behavioral intention across multiple technology contexts, including those within education (Venkatesh et al., 2012; Dwivedi et al., 2019), this raises questions about the extent to which UTAUT2 can explain intentions to use emerging AI-driven technologies such as GenAI. This is because there are significant differences between established educational technologies and GenAI, which function not only as technology tools but also as cognitive agents, generating content, simulating interactions, and influencing epistemic processes (Holmes et al., 2019; Kasneci et al., 2023). The findings, particularly those related to teacher trust, ethical concerns, and pedagogical alignment, suggest that acceptance theories may need to be extended to address new issues arising when educational technology has the potential to change teaching practice.

Even though no significant predictors accounted for the variance in intention to use, the results showed generally positive means for instructors’ perceptions of several GenAI tools across performance expectancy and hedonic motivation. There is precedent in the education sector, where teachers report positive views of

AI regarding efficiency (Chen et al., 2020; Cabero-Almenara et al., 2024) and student engagement (Cabero-Almenara et al., 2024). The findings, however, point to a possible limitation of the UTAUT2 model: it explains usage intention in terms of facilitating factors but tends to ignore the role of barriers or inhibiting factors.

The qualitative findings provide critical depth and insight into the reasons underpinning the reported gap. The study conducted a thematic analysis of interviews with English language instructors to identify perceived opportunities and challenges and examine the potential influence of contextual and professional factors on the adoption of GenAI. Three themes emerged from the data, demonstrating that the adoption process for GenAI is complex and multifaceted.

The first theme centered on the perceived opportunities for GenAI to support language teaching. Instructors perceived the potential of GenAI tools to increase efficiency, for example, by automating parts of teachers' workloads in lesson planning, material design, and feedback. Instructors perceived that GenAI would save time on lesson and material design, for example, by generating repetitive exercises or texts. Similarly, they saw potential in increasing student engagement. These findings suggest that instructors' positive perceptions of GenAI were strongly associated with greater efficiency, reduced workload, and enhanced student engagement. Participants generally viewed GenAI as a practical tool that could support lesson preparation, material development, and interactive learning activities. These findings are consistent with existing research on the impact of AI tools such as GenAI on teachers' workload and lesson design (Cabero-Almenara et al., 2024), as well as on AI's potential to increase learner interaction and motivation (Chen et al., 2020).

Yet these perceived benefits do not appear to be significant predictors of instructors' behavioral intentions to adopt GenAI. This suggests that practical usefulness and enjoyable interaction alone may not be sufficient to motivate instructors to adopt GenAI tools and activities in the language classroom. Indeed, CALL research documents that the potential of technology is often limited by its integration into regular classroom pedagogy (Stockwell, 2013; Golonka et al., 2014). Instructors seem to consider far more than simple efficiency and student engagement when deciding which GenAI tools and activities to introduce into their teaching practice.

The second theme highlights instructors' concerns regarding trust, academic integrity, and pedagogical quality. Participants questioned the accuracy of AI-generated outputs, worried that students might misuse GenAI tools for assignments, and expressed concern that overreliance on automation could reduce authentic interaction and opportunities for critical thinking. These concerns may help explain why positive perceptions of usefulness and engagement did not translate into statistically significant predictors of intention or use. Similar concerns have been identified in recent studies (Rudolph et al., 2023; Cotton et al., 2023; Dwivedi et al., 2023). Previous CALL research has likewise shown that technologies may not improve learning outcomes unless they are carefully integrated into pedagogy (Stockwell, 2013; Golonka et al., 2014).

It is important to distinguish between factors that emerged empirically from the qualitative data and constructs proposed as theoretical implications. Trust concerns, academic integrity, pedagogical beliefs, institutional guidance, and professional identity emerged directly from interviews with instructors and classroom observations. By contrast, constructs such as perceived risk (Featherman & Pavlou, 2003), trust in AI systems (Gefen, 2003), technostress (Tarafdar et al., 2010), and pedagogical compatibility (Ertmer et al., 2012) may be considered as possible extensions to future technology acceptance models based on the interpretation of the present findings. These constructs were not directly tested in the quantitative phase of this study.

The third theme, contextual and professional influences, foregrounds how institutional and identity-related characteristics shape instructors' adoption decisions. The theme suggests that contextual elements such as training, available infrastructure, and institutional policies, together with their implementation, play a decisive role in selecting AI tools for educational environments. Similar findings have been reported in the literature, highlighting the enabling role of facilitating conditions for technology adoption (Mei et al., 2017; Koç et al., 2021). Although the theme suggests a mediating role, the findings did not reach statistical significance for facilitating conditions in the regression model.

In addition, participants' professional identities influenced their perceptions of GenAI's potential as a teaching tool. Some viewed AI as a helpful tool or addition to their teaching, whereas others saw it as a possible threat to teachers' professionalism. Taken together, these findings indicate that instructors' willingness to adopt GenAI depended not only on available institutional support but also on whether the technology aligned with their professional identities and views of teaching. These attitudes reflect research on teachers' beliefs and identity, which shows that professionals' conceptions of teaching are shaped by their values and pedagogical beliefs (Ertmer & Ottenbreit-Leftwich, 2010; Ertmer et al., 2012).

This study investigated factors influencing GenAI adoption decisions among academic staff and found thatcurrent technology acceptance models, such as UTAUT2, may be insufficient to explain GenAI adoption intentions. Although UTAUT2 provides a useful structure for examining use behavior and motivation, the present findings suggest that other critical factors, such as perceived risk, trust, ethical considerations, pedagogical issues, and professional identity, may also influence adoption. These findings support recent calls to develop extended or alternative models to explain AI adoption (Dwivedi et al., 2023; Holmes et al., 2019).

The study contributes to theory and practice by critically evaluating UTAUT2's explanatory power as a predictive model of instructors' adoption of generative AI in education. In particular, the findings have implications for future models of technology adoption by suggesting that constructs such as perceived risk (Featherman & Pavlou, 2003), trust (Gefen, 2003), and technostress (Tarafdar et al., 2010) could be incorporated into future models, as well as pedagogical and contextual variables that influence technology adoption decisions.

Based on the findings, several key implications for higher education institutions emerge. First, any professional development for instructors on GenAI should focus on both the technology itself and its pedagogical and ethical implications. This means providing support to help instructors learn to use GenAI effectively to enhance learning outcomes while upholding academic integrity. Furthermore, it is crucial for higher education institutions to establish policies and guidelines for the use of GenAI in teaching and assessment, as the absence of such frameworks can hinder adoption. Finally, adopting GenAI requires an inclusive institutional culture that encourages experimentation and collaboration among academic and support staff.

Although this research sought to address the needs of educators and learners within a single institution of higher education, it has some notable limitations. First, the study was conducted in a single institutional context. Technology adoption is influenced by institutional culture, available resources, and local policy conditions; therefore, findings from one public university context should be applied to other settings with caution. A further limitation concerns the quantitative sample size relative to model complexity. Although the sample was appropriate for exploratory analysis, the inclusion of multiple predictors may have reduced statistical power and limited the ability to detect smaller effects. Therefore, the non-significant regression results should be interpreted as raising questions about UTAUT2’s explanatory adequacy in this context rather than as definitive evidence that the model is invalid. Additionally, the study relied on self-reported survey items and may therefore be subject to biases and errors associated with participant recall and reporting. The study is cross-sectional, limiting its findings to a single point in time. Finally, while UTAUT2 provides a useful framework for examining technology acceptance, it does not explicitly include GenAI-specific factors such as trust in AI-generated outputs, perceived ethical risk, algorithmic transparency, or pedagogical compatibility.

Future research should address these limitations by employing a longitudinal design, a larger sample, and a more comprehensive theoretical framework that incorporates additional AI-related variables. Comparative studies across cultures and institutions would also provide a richer understanding of the adoption of GenAI. While generative artificial intelligence has vast potential to revolutionize English language teaching and learning, its implementation is complicated by a variety of technological, pedagogical, social, ethical, and contextual considerations.

In conclusion, while generative artificial intelligence holds considerable potential to transform English language teaching, its implementation is influenced by numerous technological, pedagogical, ethical, and contextual factors. The contribution of this study lies not in validating UTAUT2, but in critically examining its explanatory boundaries in the context of GenAI adoption. The findings suggest that UTAUT2 may not fully capture the complexities of GenAI integration in English-language teaching contexts, particularly where trust, academic integrity, professional identity, and pedagogical beliefs shape instructors’ decisions. Future research and practice should therefore address these dimensions through more comprehensive, context-sensitive models of AI adoption.

Declarations

The researchers declare that the data were collected prior to 2026. In accordance with internationally accepted ethical standards, they confirm that no unlawful methods or materials were used during the research process. The study was conducted after obtaining the necessary permissions, including voluntary and written informed consent from all participants, and these approvals were secured prior to publication. This manuscript is based on an MA thesis prepared and defended by the first author under the supervision of the second author.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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