

Generative artificial intelligence adoption among Generation Z students in Turkish higher education

Mestan Küçük^{1*} , Hasan Çalışkan¹ 

¹ Department of New Media and Communication, Faculty of Communication Sciences, Anadolu University, Eskişehir, TURKEY

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Abstract

This research examines how Generation Z students at a single large public university in Turkey intend to incorporate generative artificial intelligence (GenAI) into their studies. Drawing on the unified theory of acceptance and use of technology 2 (UTAUT2), a survey of 346 participants tested the seven core predictors of behavioral intention through covariance-based structural equation modeling. Hedonic motivation emerged as the strongest predictor ($\beta = 0.322$, $p < 0.001$), followed by performance expectancy, habit, and facilitating conditions, whereas effort expectancy, social influence, and price value showed no significant effect. Within this institutional context, students appear motivated by enjoyment, perceived usefulness, established habit, and institutional support rather than by peer pressure, affordability, or ease of use. The simultaneous non-significance of effort expectancy, social influence, and price value points to a culturally and contextually distinct adoption profile that warrants replication across institutions and cultures.

Keywords: generative AI, UTAUT2, technology acceptance, behavioral intention, higher education, Generation Z

INTRODUCTION

ChatGPT reached an often-cited adoption benchmark of approximately 100 million users within two months of its public release – a number that took Instagram approximately two and a half years to achieve (Strzelecki, 2024). As is often the case with new technology, university students were among the first to adopt this tool. Since then, other tools have continued to expand beyond ChatGPT: Google Gemini, Microsoft Copilot, and a developing list of discipline-specific applications (for example, Mathway) give students the ability to generate text, read summaries, and provide problem-solving assistance in almost every academic field (Dwivedi et al., 2023; Kasneci et al., 2023). Therefore, in terms of research about higher education, researchers should concentrate on understanding the reasons students choose to utilize these tools rather than simply determining if students are using them. During data collection, it was observed that students without formal GenAI training reported daily use and self-reported proficiency that often equaled or exceeded that of peers with formal exposure. Curiosity appeared to be the initial driver for student usage; however, the reason

students kept using the tools week after week appears to be a matter of habit (HB) rather than excitement.

The framework developed by Venkatesh et al. (2012), is called the unified theory of acceptance and use of technology 2 (UTAUT2) and it is a structured way of answering this question. The model consists of seven core constructs; two of these are considered “utilitarian” predictors – performance expectancy (PE) and effort expectancy (EE) – while two other predictors are considered “contextual” – social influence (SI) and facilitating conditions (FC). Additionally, three constructs were specifically included for the purpose of studying how consumer technologies would be adopted: hedonic motivation (HM), price value (PV), and HB. The model has been cited over 6,000 times within the literature and explains approximately 74% of variance in behavioral intention (BI). The 74% figure is consistent with the evaluation criteria proposed by Weber (2012) for information systems theories (Tamilmani et al., 2021b). The application of the UTAUT2 model to GenAI in education remains to be evaluated. According to findings made by Budhathoki et al. (2024), students from Nepal and the UK respond more to PE, EE, and SI compared with other types of motivation, while in

Contribution to the literature

- By applying the UTAUT2 model to generative artificial intelligence (GenAI) adoption within Turkish higher education, this study provides an empirical baseline for future comparative and longitudinal research in an under-researched area. In contrast to most of the studies in this literature which are based on PLS-SEM, this research uses covariance-based structural equation modeling (CB-SEM) and allows for the direct assessment of model-data fit using a two-step process where measurement validity is determined first through exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) and then by performing structural tests.
- To the best of the authors' knowledge, this study is among the first within the UTAUT2-GenAI literature reviewed to simultaneously document the non-significance of EE, SI, and PV within a single empirical investigation, offering a tentative diagnostic profile that warrants cross-institutional and cross-cultural replication.
- The emergence of HM as the predominant factor in predicting technology adoption challenges long-held beliefs regarding technology adoption and provides an avenue for creating culturally relevant context-aware AI adoption frameworks within the university context.

Uganda HB, SI, and LV are also important predictors of technology adoption, whereas PE was not found to be significant, as reported by Namatovu and Kyambade (2025). However, according to Aldreabi et al. (2025), the key deciding factors to adopt technology for many students were their EE; how they viewed artificial intelligence (AI) as an additional resource. These differences in the results show that acceptance of technology across various cultures varies (e.g., Ali et al., 2024; Xue et al., 2026) and thus continuing to replicate studies in new contexts remains an important consideration.

This body of work does not yet include Turkey; thus, that gap warrants attention. Turkey has over eight million enrolled university students and offers an academic system that fits between European and Middle East academic formats, making it a distinctive context in its own right rather than a substitute for either. Turkish students are from Generation Z, who have grown up accustomed to their use of smartphones and social networks; thus, they would describe themselves with some level of openness to AI tools. On the other hand, while Turkey is very much a collectivist culture, many of its students are on free tier versions of those same technologies; therefore, the factors affecting which of the UTAUT2 constructs will be important could be quite different. The host university has been using technology in its teaching for decades (mostly through distance learning) and therefore will not begin with a blank slate in implementing GenAI. Nonetheless, what is still lacking is the measurement of the reasons for the face-to-face students in these institutions making the choice to use these tools. No previous research has tested the full UTAUT2 framework concerning GenAI usage, and the present study addresses this gap.

Using the data from 346 undergraduate students, we performed CB-SEM and estimated the direct effects of all seven UTAUT2 constructs upon BI. A key methodological decision was testing Venkatesh et al.'s

(2012) original specification with no changes made to the model prior to testing. The rationale behind that decision is discussed in the rationale for testing the baseline UTAUT2 model section below. This design will have three contributions:

- (a) an empirical result of the complete UTAUT2 model as it pertains to the adoption of GenAI by Turkish higher education;
- (b) the use of CB-SEM as a data analysis technique instead of the more widely-used but less capable PLS-SEM, which does not allow for the determination of proper fit between a model and its data (Hair et al., 2011; Rönkkö & Evermann, 2013); and
- (c) that the number of significant versus non-significant paths in the model – in conjunction with items dropped in factor analysis – will provide diagnostic insight into how UTAUT2 constructs operate under different cultural and economic contexts.

THEORETICAL BACKGROUND AND LITERATURE REVIEW

The purpose of the UTAUT was to merge numerous disparate technology acceptance theories into a streamlined, useful, and cohesive framework (Venkatesh et al., 2003). Four variables are considered to be the principal predictors of an individual's intention: PE, EE, SI, and FC. Additional variables include age, sex, work experience, and whether the use of technology is elective [voluntary]. The original UTAUT accounted for approximately 70% of the variability in intention to use a technology. Venkatesh et al. (2012) added three additional variables – HM, PV, and HB – which were specifically targeted to voluntary consumer-oriented use of technology and accounted for an additional 4% of explained variance of intention to use technology, further sustaining and expanding UTAUT's paradigm,

which reached well beyond its original context in organizational behavior. Tamilmani et al. (2021a) conducted a meta-analysis of 60 studies with PE to BI being the most consistently statistically significant path between technology acceptance variables, while the path from EE to BI often fails to achieve statistical significance to a greater extent than many researchers expect. UTAUT2 has been utilized in education to assess e-learning platforms, mobile learning applications, and learning management systems, with generally positive results (Ain et al., 2016; Alanazi et al., 2026; Musa et al., 2022).

The introduction of generative AI marks a true turning point for this field of research. The dominant predictor for Strzelecki (2024) was HB ($\beta = .339$) in a survey with 503 Polish students and was followed by PE ($\beta = .260$) and HM ($\beta = .187$). In the case of Norwegian students however, Grassini et al. (2024) found the dominant driver for their sample to be PE. When looking at South Asia, however, Bahadur et al. (2024) showed that only HB, learning value (LV), and SI were significant predictors for students in Nepal; PE and HM were both not significant. Finally, Sergeeva et al. (2025) found HB, PE, HM, SI, and PV to be all significant in their sample, while Namatovu and Kyambade (2025) found the same three predictors (HB, SI, and LV) were significant in their study of students in Uganda, while PE was not significant. There have been two systematic reviews of this topic, Xue et al. (2026) and Ali et al. (2024), that demonstrate how variation occurs amongst studies on the same topic; both authors conclude that (on average) the strongest predictor of study outcomes is PE, but that studies have weak to moderate correlations with one another across the universe of cultural contexts. The observed degree of variance between these results, in general, demonstrates the need to evaluate the model in other cultural contexts that have yet to be studied.

The cross-national difference in the use of the UTAUT suggests that each UTAUT construct varies in importance according to the individual using the technology, the institutional environment of the technology, and the intended purpose for using the technology. Turkey combines a significant level of collectivist values (cultural), uneven levels of AI and institutional preparedness, and a student population the majority of whom taught themselves to use these tools – conditions that together provide an ideal environment in which the model would show a large prediction error based on previous models.

Rationale for Testing the Main-Effects Specification of UTAUT2

The question of whether to use pre-adapted or original models for cross-cultural technology-acceptance research has been debated for a number of years (Im et al., 2011; Straub et al., 1997). In the present work, we chose to test the structural-core (main-effects)

specification of UTAUT2 – the seven exogenous constructs predicting BI without the inclusion of the moderating variables (age, gender, experience, and voluntariness) originally proposed by Venkatesh et al. (2012). This is a deliberate scope decision rather than a position that moderators are theoretically irrelevant, and three considerations underline this choice (detailed further in the method section below).

Firstly, there is no previous UTAUT2 study on Turkish GenAI adoption therefore any changes made prior to data collection would need to be based upon assumptions rather than supporting evidence, which is debatable in an instance where comparable studies exist but unwarranted in this instance. Secondly, meta-analysis indicates that different UTAUT2 constructs have different levels of importance between settings, as opposed to existing cultural theory which can adequately predict these results (Ali et al., 2024; Tamilmani et al., 2021a). Lastly – and most importantly – the base model provides diagnostic value; if the factor structure holds but certain paths are non-significant, we know exactly where to adjust the model for the Turkish context. The base model supports this form of logic, which we return to in the section on context-specific diagnostic signals of the discussion.

Hypothesis Development

There are seven hypotheses based on the UTAUT2 framework and literature previously evaluated. Each specifies a direct, positive relationship between a UTAUT2 construct and the intention to use GenAI for education.

Performance expectancy

PE refers to the degree to which an individual believes that using a technology will enhance task performance (Venkatesh et al., 2003, 2012). Of all the paths in UTAUT2 research, PE → BI has the most reliable relationship (Ali et al., 2024). There has been strong evidence of the effect of PE on the intention to use GenAI (Alotaibi & Alayed, 2025; Grassini et al., 2024; Strzelecki, 2024) across countries.

H1. PE has a significant positive effect on BI to use generative AI.

Effort expectancy

When a technology is easy to use (Venkatesh et al., 2003, 2012) the EE is positive. However, there is uncertainty surrounding the relationship between ease of use and BI: EE → BI path has been frequently tested in both longitudinal and meta-analytical approaches with results indicating that these relationships are generally weak in nature; for example, Tamilmani et al.'s (2021a) meta-analytical results indicated that the results were frequently statistically non-significant, while Strzelecki (2024) found a small effect size (f^2) (< 0.02) and

Budhathoki et al. (2024) reported results of non-significant in their studies. One explanation for this phenomenon may mean that due to the nature of natural language interfaces, the ceiling for the perceptions of ease of use collapses, and therefore, the ability to differentiate between users based on their perception of ease of use becomes non-existent (Liu et al., 2025). Nevertheless, the theoretical framework continues to support a positive relationship between EE and BI (Budhathoki et al., 2024).

H2. EE has a significant positive effect on BI to use generative AI.

Social influence

SI is defined as the degree to which an individual perceives that important others believe they should use a technology (Venkatesh et al., 2003, 2012). According to Ali et al. (2024) meta-analysis; the effect of SI on acceptance of AI in educational settings is medium sized and the same SI variables have been Identified as significant for both the Polish and Egyptian datasets (Strzelecki & ElArabawy, 2024). However, SI effects were found to be less significant when an individual self-initiates the use of a technology or product versus when it is required by the institution (Polyportis & Pahos, 2024) which is the case for most of the users of GenAI.

H3. SI has a significant positive effect on BI to use generative AI.

Facilitating conditions

The extent to which organizations perceive that the infrastructure (both technical and organizational in nature) can be used to facilitate the use of technology is indexed by the FC (Venkatesh et al., 2003, 2012). The evidence for the relationship between FC and BI in the GenAI literature is rather inconsistent. For example, Strzelecki (2024) has reported a non-significant relationship, whereas Alotaibi and Alayed (2025) have reported a significant relationship. According to Xue et al. (2026), FC is likely to be more influential in contexts in which there is a disparity in the availability of digital access and support from the institution across departments - a description that holds true for higher education institutions in Turkey.

H4. FC have a significant positive effect on BI to use generative AI.

Hedonic motivation

The amount of pleasure one derives from the use of a certain technical device can be called HM (Venkatesh et al., 2012). In a study by Strzelecki (2024) with participants from Poland, HM ranked 3rd overall. Additionally, Aldreabi et al. (2025) confirmed that HM was significant in terms of communication and collaboration for Generation Z, who have grown up with interactive and gamified digital environments.

Therefore, for this cohort, the enjoyment created by using new tools may serve as a major attraction for that cohort.

H5. HM has a significant positive effect on BI to use generative AI.

Price value

The PV of technology adoption is a cost/benefit consideration (Venkatesh et al., 2012). According to Tamilmani et al. (2019), PV can be found in only 41% of published UTAUT2 studies, making it the least frequently considered construct in this framework. The way PV is characterized in terms of GenAI, however, is unique since most tools in this space are free to use. Nevertheless, PV has been found significant by Sergeeva et al. (2025).

H6. PV has a significant positive effect on BI to use generative AI.

Habit

The degree of automaticity of technology use as a result of prior use is called HB (Venkatesh et al., 2012). Even though HB is one of the most significant additions to the UTAUT2 model, it has been represented in only 35% of UTAUT2 studies (Tamilmani et al., 2019). Within GenAI studies, Strzelecki (2024) and Namatovu and Kyambade (2025) both found HB to be a strong predictor of different behavior in culturally diverse samples. This implies students are becoming habitual users of GenAI much sooner than expected by traditional adoption models.

H7. HB has a significant positive effect on BI to use generative AI.

The Proposed Research Model

The research model is shown in **Figure 1**. Seven elements of the UTAUT2 model (PE, EE, SI, FC, HM, PV, and HB) are identified as predictors of BI. Consistent with the scope decision outlined in the rationale for testing the main-effects specification of UTAUT2 section, the present study estimates the structural-core effects without including UTAUT2's original moderating variables. Three considerations underline this scope of the decision. First, because no prior UTAUT2 investigation of GenAI in Turkish higher education exists, the present work is designed as a baseline-establishing study whose primary aim is to estimate the structural-core effects before adding moderating complexity that could only be interpreted against an as-yet-unestablished baseline. Second, the sample composition presents practical constraints for moderator estimation: the gender distribution (67.6% female, 32.1% male) and the proficiency-level distribution (with 14.5% beginners and 5.5% professional users) yield subgroup cell sizes that fall below the case-to-parameter ratios required for stable multi-group CB-SEM estimation in a

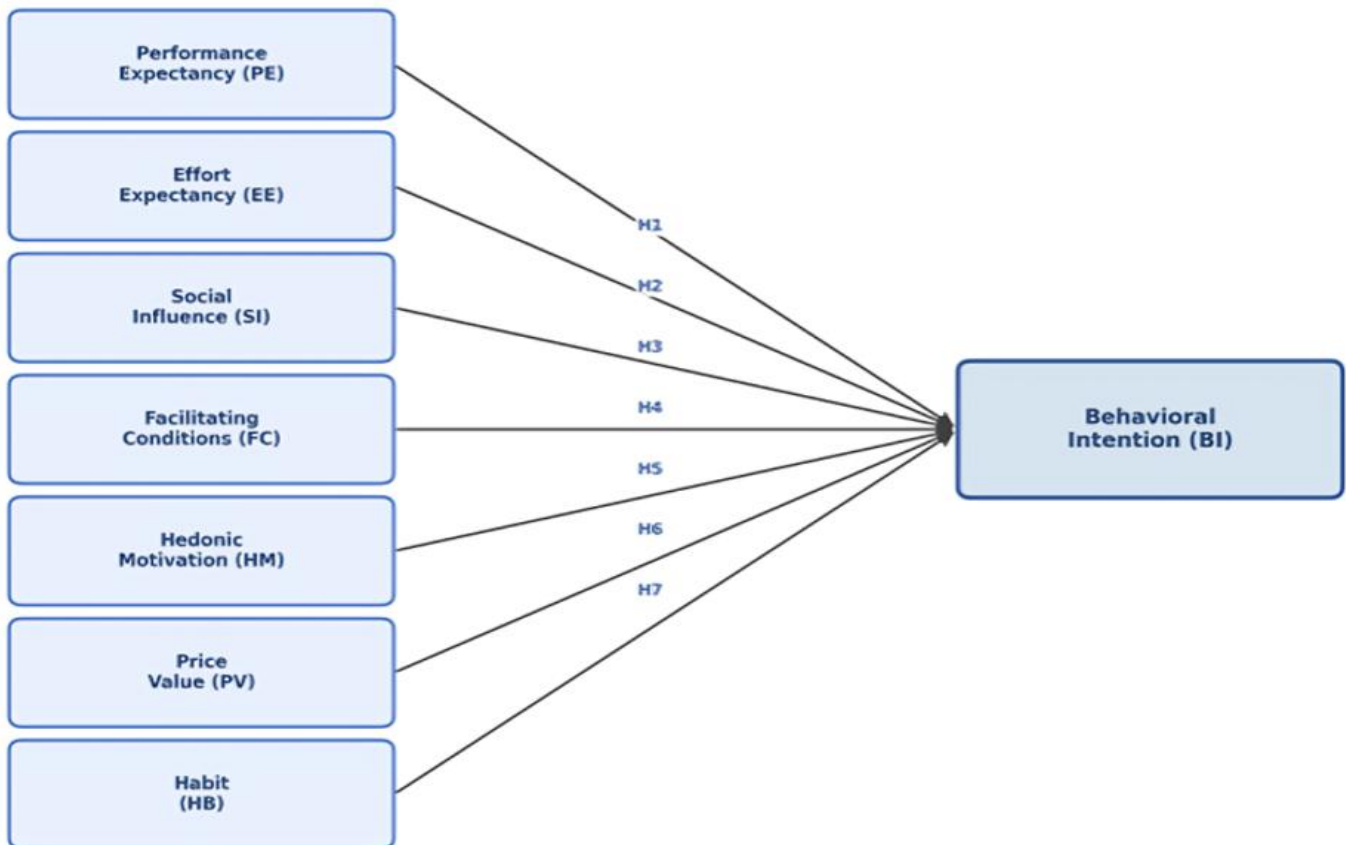


Figure 1. Proposed research model based on UTAUT2 framework (the authors' own elaboration based on Venkatesh et al., 2012)

seven-construct model with two-item PE and FC factors (Byrne, 2016; Kline, 2016). Attempting full multi-group invariance testing under these conditions would risk producing unstable estimates that obscure rather than clarify the structural-core findings. Third, the voluntariness moderator was not estimated because GenAI use within this sample was uniformly self-initiated (93.4% of students reported acquiring GenAI proficiency through informal trial-and-error rather than institutionally mandated training), rendering voluntariness non-varying for the present participants. We therefore frame the present results as a structural-core estimation for the Turkish GenAI context and treat moderator-conditioned UTAUT2 testing as a distinct future-research objective. The original moderating structure of UTAUT2 remains theoretically important; its omission here is a study-design decision, not a claim that the full model has been tested. The research model was tested using CFA with a CB-SEM based on the two-stage modelling approach described by Anderson and Gerbing (1988).

MATERIALS AND METHODS

Research Design

This research utilized a cross-sectional survey strategy that is based on the UTAUT2 model (Venkatesh et al., 2012). All of the seven constructs were treated as

“exogenous” predictors for a singular “endogenous” outcome, which is the BI.

Participants

Students were recruited in the 2024-2025 academic year using convenience sampling, which is standard in technology adoption research in higher education (Dwivedi et al., 2019). To be eligible for inclusion in the study, participants must have previously used at least one GenAI tool. Of 399 complete responses, 14 were eliminated due to insufficient data and 39 were excluded as multivariate outliers based on Mahalanobis distance ($p < .001$) resulting in $N = 346$ being included in the final sample. This number exceeds both Kline's (2016) 10:1 case-to-parameter ratio as well as Byrne's (2016) minimum of 200 cases needed for maximum likelihood (ML) estimation.

The demographics are shown in **Table 1**. 67.6% of the respondents were female ($N = 234$). The most frequent age range was 20 years old or younger (34.4%) and the second most frequent age range was 22 years of age to 23 years of age (30.1%). 45.4% of the respondents utilized GenAI tools on a daily basis, and another 42.8% of the respondents utilized these tools multiple times per week. The majority of participants rated their skill level as intermediate (52.9%). 93.4% of participants learned how to use GenAI tools mainly through trial and error and not through formalized education and training.

Table 1. Demographic characteristics of sample (N = 346)

Variable	Category	n	P (%)
Gender	Female	234	67.6
	Male	111	32.1
	Missing	1	0.3
Age (years)	≤ 20	119	34.4
	21	65	18.8
	22-23	104	30.1
	≥ 24	58	16.8
	GenAI usage frequency	Daily	157
	Several times a week	148	42.8
	Several times a month	22	6.4
	Rarely	7	2.0
	Missing	12	3.5
Self-reported proficiency	Beginner	50	14.5
	Intermediate	183	52.9
	Experienced	94	27.2
	Professional	19	5.5
GenAI learning method	Trial and error	323	93.4
	School courses	9	2.6
	Other	10	2.9
	External training	4	1.2

Note. P: Percentage

Instrument Development

Scale adaptation

The GenAI-in-education context required modifying UTAUT2 items (Venkatesh et al., 2012) in three ways:

1. Two bilingual researchers independently prepared translations of all items from English to Turkish; then they reconciled two versions of all items.
2. A third, independent translator, who had not seen the original items, prepared a back-translation (Brislin, 1970).
3. Finally, specific changes were made to content by replacing terms such as “mobile Internet” to “AI applications in coursework” to provide an educational context for survey participants when responding about the GenAI tools used for academic purposes.

Content validity

In this study, the procedures established by Lawshe (1975) were used to evaluate the content validity of an assessment instrument. Twenty-eight items were evaluated by five experts (three from the field of educational technology and two from the field of communication sciences) using a three-point rating scale (essential, useful but not essential, and not essential). The CVR for each item was calculated using Lawshe’s (1975) formula: $(ne - N/2)/(N/2)$, where *ne* is the number of experts who thought the item was essential and *N* is the total number of experts evaluating that item. The minimum CVR required for a five-member panel is .99

Table 2. EFA pattern matrix and descriptive statistics (N = 346)

Construct/item	Code	M	SD	Loading	α
EE					.89
EE1	EE1	3.89	1.014	.828	
EE2	EE2	4.02	0.917	.817	
EE3	EE3	3.98	0.894	.662	
HB					.81
HB2	HB2	2.66	1.239	.937	
HB3	HB3	2.53	1.137	.662	
HB1	HB1	3.51	1.168	.489	
SI					.89
SI2	SI2	3.32	1.037	.913	
SI3	SI3	3.28	1.018	.866	
SI1	SI1	3.42	1.036	.729	
PV					.80
PV3	PV3	3.34	0.991	.851	
PV2	PV2	3.38	1.027	.791	
PV1	PV1	2.72	1.209	.562	
HM					.97
HM2	HM2	4.06	0.958	.916	
HM3	HM3	4.06	0.955	.898	
HM1	HM1	4.06	0.943	.865	
BI					.94
BI2	BI2	4.01	0.996	.856	
BI3	BI3	3.98	1.071	.824	
BI1	BI1	4.20	0.940	.767	
FC					.83
FC1	FC1	3.99	0.966	.785	
FC2	FC2	3.83	1.006	.687	
PE					.75
PE4	PE4	3.77	1.085	.797	
PE3	PE3	4.03	0.992	.457	

Note. PAF (EFA) extraction with Kaiser normalized oblimin rotation; all loadings represent primary factor only; M, standard deviation (SD), and α provided for all variables; & with the exception of PE items 1 and 2, which were excluded based on loadings < .40

(Wilson et al., 2012). Seven items had CVR values below .99, four of which were modified based on the experts’ ratings and re-evaluated; all re-evaluated items achieved CVR = 1.00. Three items were removed because they were redundant. The 25 items that exceeded the minimum CVR of .99 produced an overall CVI of 1.00.

Exploratory factor analysis

Principal axis factoring (PAF) with an oblimin rotation was conducted on the data set and produced 8 factors that were in accordance with UTAUT2’s theoretical structure. Three items were excluded due to their factor loadings (λ) being less than .40 (Stevens, 2002) which were two PE items (PE1 & PE2) and one FC item (FC3). The final instrument was made up of 22 items across 8 constructs (PE: 2; EE: 3; SI: 3; FC: 2; HM: 3; PV: 3; HB: 3; and BI: 3) rated on 5-point Likert type scales. Results of the pattern matrix loadings along with descriptive statistics can be found in **Table 2**.

An important methodological issue is that EFA and CFA were performed with a single dataset ($N = 346$). Ideally, the second phase should involve a different sample for analysis to avoid CFA exploiting covariance that is unique to that data (Hinkin, 1998; Worthington & Whittaker, 2006). Several safeguards were implemented within this study to mitigate this concern. First, the criteria for deleting items were pre-specified before EFA and CFA (λ below .40) and were strictly adhered to throughout both phases. Thus, no opportunity existed for modifying analyses (e.g., increasing λ) based on a review of the data, which could have resulted in enhanced CFA results. Second, CFA was conducted without re-specification or the use of modification indices to adjust the factor structure derived from EFA – a deliberately conservative approach. Third, EFA and CFA λ show close correspondence, providing support for the stability of the factor solution because each item loaded on its respective factor in both EFA and CFA. Discriminant validity was assessed via the HTMT approach (Henseler et al., 2015); this method is more rigorous than the Fornell and Larcker (1981) criterion. Split-sample validation (e.g., $N = 173 + 173$) was considered but not pursued because the resulting per-subsample case-to-parameter ratio would fall below recommended thresholds for stable CFA estimation in a seven-construct model that includes two-item PE and FC factors (Kline, 2016; Worthington & Whittaker, 2006). To complement the standard ML estimates, the explanatory power of the structural model is additionally indexed via R^2 for the endogenous construct, the unique contribution of each predictor via Cohen's (1988) f^2 , and the stability of each structural path coefficient via 95% bias-corrected percentile bootstrap confidence intervals (CIs) based on 2,000 bootstrap resamples. The CFA findings should therefore be interpreted as initial psychometric support rather than absolute proof; in particular, the PE and FC findings – both measured with two items – should be validated on a separate Turkish sample before being accepted as a basis for conclusion (Kline, 2016).

Data Collection Procedure

Ethics approval has been granted by the university (ethics committee approval number 155247/05-03-2026) for conducting this research project. The participant survey data collection occurred over four weeks in the spring semester of the 2024 to 2025 academic year. Surveys were collected via in-person data collection ($N = 304$) and via on-line Google Form. All data collected were obtained voluntarily and anonymously. In an effort to prevent common method bias (CMB) within the dataset; five CMB control measures were utilized as well as two statistical tests, Harman's one-factor test and a complete collinearity variable inflation factor (VIF) test (Kock, 2015; Podsakoff et al., 2003).

Data Analysis Strategy

The analysis process was completed in four distinct phases. First, data screening included removing incomplete cases as well as eliminating multivariate outliers by using Mahalanobis distances and checking for distributional properties in SPSS v.28. The second step involved assessing CMB through Harman's single-factor test and the VIF of collinearity. The third step included evaluating the measurement model via CFA conducted with maximum likelihood estimation (MLE) based on AMOS 24 software; fit was evaluated with commonly used thresholds (i.e., $\chi^2/df \leq 3.0$; CFI ≥ 0.90 ; TLI ≥ 0.90 ; RMSEA ≤ 0.08), reliability was estimated using Cronbach's alpha (α) (≥ 0.70) and composite reliability (CR) (≥ 0.70), convergent validity was established via $\lambda \geq 0.50$ and average variance extracted (AVE) (≥ 0.50), and discriminant validity was assessed both via the Fornell-Larcker criterion and HTMT (i.e., < 0.85). Finally, the fourth phase involved testing the structural model by using structural equation modeling (SEM) with MLE; levels of statistical significance were assessed as a function of $p < 0.05$.

In addition to standardized path coefficients and critical ratios, the explanatory power of the structural model was indexed via R^2 for the endogenous construct (BI), and the unique contribution of each predictor via Cohen's (1988) f^2 – computed as squared semi-partial correlations relative to the residual variance of the outcome. Conventional Cohen (1988) thresholds ($f^2 \geq .02$ small, $\geq .15$ medium, $\geq .35$ large) were used to characterize practical significance alongside statistical significance. To provide an inferential robustness check independent of the same-sample EFA-CFA design, 95% bias-corrected percentile bootstrap CIs were additionally computed for all structural path coefficients using 2,000 bootstrap resamples in AMOS 24 (Efron & Tibshirani, 1993). Based on Kline (2016) and Byrne (2016), it has been established that the use of CB-SEM versus PLS-SEM was determined by the ability of CB-SEM to provide model fit indices; that the objectives of the study were of a theory-testing nature rather than of a predictive nature; and that the sample size met the criteria for ML estimation purposes.

Ethical Considerations

This research adhered to the Declaration of Helsinki and the ethical standards set by Turkey's Higher Education Board, and all volunteer research subjects were informed that they could participate in this study and that their results would be kept completely confidential and private. Researchers did not store any identifying data from respondents, and all data were stored in a secure location using encrypted databases.

Table 3. The results of CFA analyses which include λ , CR, and convergent validity of each construct

Construct/item	λ	CR	AVE	$\sqrt{\text{AVE}}$
EE		.887	.724	0.851
EE1	.845			
EE2	.864			
EE3	.842			
BI		.943	.848	0.921
BI1	.883			
BI2	.940			
BI3	.942			
HB		.824	.611	0.782
HB1	.721			
HB2	.856			
HB3	.759			
SI		.890	.733	0.856
SI1	.780			
SI2	.913			
SI3	.867			
PV		.822	.612	0.782
PV1	.623			
PV2	.876			
PV3	.836			
HM		.970	.916	0.957
HM1	.942			
HM2	.981			
HM3	.958			
FC		.825	.702	0.838
FC1	.849			
FC2	.830			
PE		.744	.595	0.771
PE3	.842			
PE4	.718			

Note. It is important to acknowledge that all the λ s are statistically significant at $p < .001$ with the following criteria for thresholds established (Fornell & Larcker, 1981; Hair et al., 2010, 2011): $\lambda \geq .50$, CR $\geq .70$, AVE $\geq .50$ & α values corresponding to the factors are also included in Table 2

RESULTS

Preliminary Analysis

Out of the total number of 399 participants who answered the survey, 14 had incomplete data or had produced straight-line responses, and 39 provided multivariate outlier data (Mahalanobis D^2 statistic of each value at $p < .001$). Thus, the final sample size for the analysis cohort was $N = 346$. The skewness values for all items had values less than $|2|$ and the kurtosis values for all items had values less than $|7|$. The KMO value was .934; Bartlett's test of sphericity was significant (χ^2 value = 7,170.80, $df = 300$, and $p < .001$). The results of the CMB analysis were also within acceptable limits with Harman's first factor accounts for 44.32% variance, below the cut-off point of 50%, and the VIF ranged from 1.41 to 2.59, below the established cut-off point of 3.3 by Kock (2015).

Table 4. Fornell-Larcker discriminant validity matrix

	EE	BI	HB	SI	PV	HM	FC	PE
EE	.851							
BI	.702	.921						
HB	.449	.524	.782					
SI	.460	.472	.482	.856				
PV	.520	.423	.465	.374	.782			
HM	.700	.721	.417	.527	.481	.957		
FC	.756	.660	.383	.443	.442	.647	.838	
PE	.763	.696	.463	.429	.494	.686	.616	.771

Note. The diagonal values (**bold**) are equal to the square root of the average variance extracted ($\sqrt{\text{AVE}}$); the off-diagonal values show the standardized inter-construct correlations; & for evidence to establish discriminant validity, the $\sqrt{\text{AVE}}$ value must be greater than each of its corresponding correlations (Fornell & Larcker, 1981)

Measurement Model Assessment

Fit statistics for the 8-factor, 22-indicator CFA model included: $\chi^2 (181) = 401.77$ $p < .001$; $\chi^2/df = 2.22$; GFI = .905, CFI = .964, TLI = .955, NFI = .938, RMSEA = .059 90% CI [.052,.067], SRMR = .060. Each index met their standard thresholds (Hu & Bentler, 1999) with CFI & TLI exceeding .95 and RMSEA in the ideal range of $\leq .06$.

All factor loadings (λ) were statistically significant ($p < .001$) with loadings ranging from .623 (PV1) to .981 (HM2). From a total of 22 λ s, 20 had values > 0.70 and therefore met the minimum requirement of > 0.70 with two loadings, PV1 of 0.623 and PE4 of 0.718, still being > 0.50 . CR values ranged from 0.744 for PE to 0.970 for HM, with 100% meeting the minimum requirement of > 0.70 (Table 3). AVE values ranged from .595 (PE) to .916 (HM), all exceeding the minimum acceptable value of .50 (see Table 3). α coefficients were between 0.75 for PE to 0.97 for HM.

Discriminant validity was confirmed via two separate criteria (refer to Table 4). The Fornell-Larcker criterion demonstrated that the square root of the AVE along the diagonal was greater than all of the off-diagonal correlations in every comparison. The closest pair of values was between EE and PE ($\sqrt{\text{AVE}}_{\text{PE}} = .771$ and the correlation $r = .763$). This pair also met the requirement to be discriminant against one another. All 28 HTMT values ranged from .407 to .771, well below the .85 threshold, established by Henseler et al. (2015).

Structural Model and Hypothesis Testing

The structural model, with all seven exogenous constructs predicting one endogenous construct, has the same structure as the saturated CFA model and has the same fit indices (Kline, 2016). Hypothesis testing therefore rests on path coefficients, significance levels, and f^2 , not on model-fit indices; the model's overall explanatory power is indexed via R^2 for BI. The results are reported in Table 5.

Of the seven hypotheses tested, four were supported. The seven UTAUT2 predictors collectively explained $R^2 = .662$ (66.2%) of the variance in BI. This value sits

Table 5. Structural model results: hypothesis testing with f^2 values

H	Path	β	SE	CR	p	95% bias-corrected CI	f^2	Magnitude	Result
H1	PE → BI	.209	.083	2.503	.012	[.034, .510]	.046	Small	Supported
H2	EE → BI	.128	.088	1.415	.157	[-.122, .338]	.013	Trivial	Not supported
H3	SI → BI	.007	.050	0.139	.890	[-.100, .094]	.000	Trivial	Not supported
H4	FC → BI	.180	.073	2.504	.012	[.002, .357]	.038	Small	Supported
H5	HM → BI	.322	.057	5.239	< .001	[.171, .483]	.121	Small-medium	Supported
H6	PV → BI	-.076	.055	-1.528	.127	[-.193, .046]	.011	Trivial	Not supported
H7	HB → BI	.199	.051	3.813	< .001	[.073, .339]	.075	Small	Supported

Note. β : Standardized path coefficient; SE: Standard error; p: Significance level; 95% bias-corrected CI = 95% bias-corrected percentile bootstrap CI based on 2,000 bootstrap resamples; CIs that exclude zero corroborate the significance of the path; f^2 values were computed as squared semi-partial correlations (sr^2) divided by $(1 - R^2)$ – mathematically equivalent to Cohen's (1988) f^2 index for individual predictors; conventional Cohen thresholds: $\geq .02$ small, $\geq .15$ medium, $\geq .35$ large; values below .02 are reported as trivial; & significance threshold: $p < .05$

modestly below the approximately 74% benchmark reported for UTAUT2 in the original consumer-technology context (Venkatesh et al., 2012) and is consistent with R^2 values reported in comparable UTAUT2-GenAI investigations (e.g., Sergeeva et al., 2025; Strzelecki, 2024), in which explained variance has typically ranged between .55 and .70. The somewhat lower R^2 obtained here, relative to the original UTAUT2 benchmark, is consistent with a cross-cultural pattern in which the relative contributions of UTAUT2 constructs become more dispersed in contexts where social-normative and economic predictors lose explanatory force, while affective and habitual predictors retain or expand it. The largest effect ($\beta = .322$, $CR = 5.239$, $p < .001$) was produced by HM, with the largest associated f^2 in the model ($f^2 = .121$, approaching Cohen's (1988) medium-effect threshold), thereby supporting H5. PE was also significant ($\beta = .209$, $CR = 2.503$, $p = .012$; $f^2 = .046$, small effect), supporting H1. HB had a significant effect ($\beta = .199$, $CR = 3.813$, $p < .001$; $f^2 = .075$, small effect), confirming H7. FC was significant ($\beta = .180$, $CR = 2.504$, $p = .012$; $f^2 = .038$, small effect), confirming H4. The PE and FC findings are nevertheless interpreted as provisional in light of the two-item operationalization of these constructs (see limitations).

Three paths showed no statistical significance: EE ($\beta = .128$, $CR = 1.415$, $p = .157$; H2 was not supported), SI ($\beta = .007$, $CR = 0.139$, $p = .890$; H3 was not supported), and PV ($\beta = -.076$, $CR = -1.528$, $p = .127$; H6 was not supported). All three non-significant paths additionally fell below Cohen's (1988) threshold for a small effect (EE: $f^2 = .013$; PV: $f^2 = .011$; SI: $f^2 \approx .000$), indicating that their non-significance is not merely an artefact of statistical power but reflects substantively trivial unique contributions to BI. The EE → BI f^2 is closely consistent with Strzelecki's (2024) report of $f^2 < .02$ for the same path among Polish students, suggesting that the non-significance of EE in GenAI adoption may extend beyond a single-study artefact toward a more generalizable pattern in this technology context. The 95% bias-corrected bootstrap CIs for these three paths all included zero (EE: [-.122, .338]; SI: [-.100, .094]; PV: [-.193, .046]), corroborating the inferential conclusion through a resampling-based procedure independent of the

maximum-likelihood standard errors. Conversely, the bootstrap CIs for the four significant paths (PE, HM, FC, and HB) all excluded zero, supporting the robustness of these estimates under the same-sample EFA-CFA design.

DISCUSSION AND CONCLUSION

What motivates Turkish Generation Z students to use generative AI for their studies? In answering this question through our data, four constructs provided insight: HM ($\beta = .322$), PE ($\beta = .209$), HB ($\beta = .199$), and FC ($\beta = .180$). Three constructs did not – EE, SI, and PV all had non-significant values. Considering the above, students in Turkey will use GenAI because of their enjoyment, perceived usefulness, established habits, and availability of resources provided by the institution. However, the other three constructs do not relate to whether or not the students will adopt GenAI. Therefore, social norm pressure, ease-of-use expectations, and cost-benefit decisions do not contribute to the student's decision to adopt or not to adopt GenAI. Additionally, the host university has established itself as a leader in distance education; therefore, the students have an experiential basis from which to view digital technologies as an integral part of the education process, and it seems to have lowered the threshold for face-to-face students to adopt GenAI. Because SI was found to be statistically non-significant, it indicates that these students did not rely on social validation from their peers or teachers to accept GenAI. Their decisions related to the use of GenAI were based entirely on personal preference and direct interaction with the technology, rather than being influenced by established norms of using the technology in the classroom.

However, the construct-by-construct summary does not fully capture the configural pattern of significant and non-significant paths. We therefore propose – as a conceptual framing rather than as an established analytical practice – that the overall pattern be read as a tentative diagnostic profile of UTAUT2's operation under the institutional and cultural conditions of the present sample. We do not claim methodological grounding for this framing within an existing literature on configural SEM interpretation; we offer it as a

heuristic device for future replication studies. For the diagnostic-profile framing to acquire empirical traction, three falsifiable conditions would need to hold across future research:

- (a) the configural pattern (HM, PE, HB, FC significant; EE, SI, PV non-significant) should approximately replicate in independently sampled Turkish higher-education populations under comparable institutional conditions;
- (b) deviations in any single construct's significance should be theoretically traceable to identifiable institutional or cultural differences (for example, a paid-tier adoption mandate would be expected to recover PV significance); and
- (c) the pattern should differ in predictable directions from patterns observed in dissimilar contexts (for example, institutional-mandate contexts in which SI would be expected to recover significance).

Should these conditions not be met across replications, the present pattern should be reinterpreted as sample-specific rather than as a substantive diagnostic signal. Three aspects of this profile merit particular attention.

The EFA eliminated two productive efficiency questions from Turkish Generation Z participants, namely PE1 ("increasing my productivity") and PE2 ("helping me get tasks completed more quickly"). That is to say, they did not see the general improvement in productivity versus specific task completion speed as two significantly different aspects of evaluating GenAI's usage in their lives. When Venkatesh et al. (2012) originally investigated mobile Internet usage, they view these two PE items as independently classified. Therefore, the remaining two items, PE3 and PE4, were classified as assessment categories that utilize a considerably larger definition of performance. That said, is it now necessary to redefine how we use the concept of PE with conversational AIs, given the difficulty in drawing the lines between productivity, creativity, and learning use when using earlier technologies?

The second order of importance of the four major factors influencing technology acceptance may be vastly different from previous research in western cultures, where "perceived ease of use", "HB", or "heavy use" has had the highest rank previously (and most commonly). In western acceptability research, the "utility" of a product is predominant and therefore: we initially expected our study to align with this perception; however, we found that the "hedonic" motivation for use of a product is of the highest importance to our subjects. This agrees with Im et al. (2011), who found that in cultural settings with a positive collectivist orientation, affective involvement had a greater effect than in well-documented cultural settings with individualistic orientations. Nonetheless, the precise mechanism for this difference remains to be assessed

further using longitudinal or multi-site designs, rather than the cross-sectional/one-sample feature of the current study.

Third – and the most theoretically significant result – EE, SI, and PV were all simultaneously non-significant. Each of these three constructs operationalizes a distinct decision rationale: perceived effort cost, social-normative pressure, and economic cost-benefit assessment. Their joint null results suggest that, within this sample, GenAI adoption does not appear to be governed by rational cost-benefit calculation or by peer-conformity dynamics. To the best of the authors' knowledge, this particular three-way null pattern has not been previously reported within the UTAUT2-GenAI literature reviewed. We frame this not as a definitive absence of finding but as a tentative diagnostic signal regarding the kind of adoption process operating in this specific institutional and cultural context.

Significant Findings

Hedonic motivation as the dominant driver

HM has been established as the strongest predictor ($\beta = .322$) and represents a potentially significant theoretical contribution. Contrary to Strzelecki's (2024) study, in which HM ranked third ($\beta = .187$), and to Grassini et al. (2024), who reported that PE had the largest total effect, the present investigation aligns with Sergeeva et al. (2025) in evidencing substantial hedonic impacts. The strength of the HM effect is plausibly attributable to Turkish Generation Z's affective orientation toward GenAI tools: as digital natives raised within gamified and interactive environments, these students are likely to engage with conversational AI as an intellectually stimulating experience rather than a purely utilitarian one. This interpretation aligns with Aldreabi et al.'s (2025) observation that, among Generation Z learners socialized within interactive and gamified digital environments, the affective dimensions of GenAI engagement carry particular weight in shaping adoption intentions. Tamilmani et al.'s (2019) meta-analysis of HM across UTAUT2 studies similarly indicates that HM's predictive strength varies systematically with the consumer-experience orientation of the user population. In short, the results suggest that Generation Z's use of GenAI cannot be fully explained through cost-benefit rationale alone; an affective dimension is centrally involved.

Performance expectancy

Findings indicate that PE had a statistically significant effect ($\beta = .209$), supporting previous research identifying PE \rightarrow BI as the most robust relationship identified across all UTAUT2-related studies reviewed (Ali et al., 2024; Tamilmani et al., 2021a). PE also significantly influenced BIs for Turkish undergraduate

students, as demonstrated by Strzelecki (2024) and Alotaibi and Alayed (2025), as well as Grassini et al. (2024), providing an additional basis to extend these previous studies to Turkish undergraduate samples; however, the value of β in the current research was lower than that of the other studies cited. Whether this was due to differences between disciplines, the unique institutional characteristics of the university or how Turkish students define performance of GenAI; two of the original PE items were not included in our EFA, is unknown and warrants investigation by future research on the same or other populations and for future research in general.

Habit

HB was shown to be significant at $\beta = .199$ within our sample in a manner that replicates Strzelecki (2024) and Namatovu and Kyambade (2025) in other cultures. Unlike SI and PV, whose effectiveness is affected by local context, HB operates through a cognitive mechanism whereby repeated behaviors eventually become automatic and therefore are relatively culture-independent. GenAI has clearly produced such patterns in our sample – particularly among intermediate-level users. The coefficient will probably be affected by the wider range of experience levels for students in this study than in Strzelecki's (2024), possibly decreasing the value of HB as a predictor; for example, 14.5% of our sample were new users, thus reducing any potential for HBs of experienced users to show clear predictive patterns.

Facilitating conditions

The establishment of an FC access ($\beta = .180$) indicates a significant relative weight for perceptions of infrastructure, consistent with Xue et al. (2026) as being of greater importance among those who have less access digitally and/or less support institutionally. Alotaibi and Alayed (2025) showed this same trend in Saudi Arabia. While Turkey has significant Internet and smartphone usage overall, the differences between how much one department has the ability to access paid subscriptions to GenAI and how developed the policies of that institution are regarding use of GenAI, are considerable (Albayrak & Çetin, 2025; Ateş & Gündüzalp, 2025; Dalgıç-Tetikol et al., 2022; Mohammadi et al., 2026). As such, perceived institutional support is likely to act as an actual restriction on the adoption decision of potential users as opposed to simply being a supporting condition.

As of the time of collecting this data, the host university had not established a formal institutional policy to govern the use of GenAI in academic work. This absence of formal policy is a gap for this institution, but this gap exists at other institutions as well, especially where an institution has many years of experience with

technology-enabled education and yet has not addressed the use of generative AI in that same way. Despite the lack of formal policy guidelines, students have relied on their own judgement as to whether they have received permission to use the tools. The FC construct indicates that any indicators of institutional willingness to accept use of generative AI, whether informal (e.g., a professor mentioning generative AI in class) or formal (e.g., access to the necessary university hardware, software, etc.), may be sufficient to alter a student's decision regarding whether to adopt and use generative AI tools.

Non-Significant Findings

Effort expectancy

The EE variable did not achieve significance ($\beta = .128$, $p = .157$). This finding corroborates those of Namatovu and Kyambade (2025) as well as the findings of Tamilmani et al. (2021a), who conducted a meta-analysis showing that the causal relationship between perceived ease of use and behavioral intent to use is more often violated than the framework's theoretical proposition suggests. An explanation could be that there was a ceiling effect; because GenAI tools are used via natural language, very little technical skill is needed to use them. In our sample, 93.4% of students achieved their level of proficiency using random experimentation alone. Thus, when a technology is considered easy to use by all users, EE cannot distinguish between users who will adopt and those who will not (Bilos & Budimir, 2024; Caffaratti et al., 2025). Therefore, it is probable that EE has simply exhausted its variability as an explanatory variable.

Social influence

SI found no significant direct relationship between SI and use of the GenAI. An evaluation of the data reported a path coefficient of zero ($\beta = .007$, $p = .890$); this finding stands in contrast to the medium-sized effect reported in Ali et al.'s (2024) meta-analysis; however, it is consistent with Venkatesh et al.'s (2003) theoretical argument as well as Grassini et al.'s (2024) empirical observation that SI diminishes with spontaneous initiation as opposed to institutionally mandated initiation. In our current sample, 93.4% of students began using the GenAI independently and at least 88.2% utilized the tool several times per week or more; thus, with such frequent usage HBs being established, the need for social validation may have been rendered unnecessary, as all participants considered the tool to be acceptable based on their previous experiences and/or the current use of the tool is common enough that participants do not seek validation through peer approval.

Another important detail adds clarity to our analysis. Our sample contained 67.6% females; Venkatesh and Morris (2000) also found that SI is stronger for females than males. Therefore, the fact that we have a majority

female sample would probably strengthen the SI signal. Given that the SI signal in our sample was effectively 0, we cannot rule out the possibility that the null result is due to sampling noise.

Price value

PV yielded a non-significant negative coefficient ($\beta = -.076$, $p = .127$). The construct mean (M) across the three retained items (PV1 = 2.72; PV2 = 3.38; PV3 = 3.34) trended toward the midpoint of the response scale rather than toward perceived affordability, indicating that students did not strongly endorse the value-for-money framing as written. In fact, this is predictable when considering that most GenAI tools have a freemium model. This null result is interpretable in two distinct ways that future research should be disentangled. The first interpretation is substantive: Turkish Generation Z students may genuinely not weigh cost-benefit considerations when adopting GenAI tools, because the tools they predominantly encounter (ChatGPT free tier, Google Gemini, Microsoft Copilot academic access) operate on freemium models that present no salient monetary trade-off at the point of adoption. The second interpretation is instrumental: the PV items originally validated for paid mobile Internet services by Venkatesh et al. (2012) may lack content validity in freemium technology contexts, in which case the null result reflects measurement-construct mismatch rather than a substantive behavioral finding. The present study cannot adjudicate between these interpretations from its data alone. PV might need to be reconceptualized for use with free-access technology, as suggested by Tamilmani et al. (2019) and further iterated by Xue et al. (2026). We therefore propose that future UTAUT2-GenAI investigations consider operationalizing the cost dimension through items more conceptually aligned with freemium adoption decisions. Three candidate item directions are worth exploring: opportunity-cost framing (e.g., "Using GenAI saves time that I could otherwise spend on valuable academic activities"), data-privacy cost framing (e.g., "The personal information I share with GenAI tools represents a meaningful cost to me"), and premium-upgrade framing (e.g., "The capabilities offered by paid GenAI subscriptions justify their cost"). Until such reconceptualization is empirically validated, PV findings within freemium GenAI contexts should be interpreted with caution rather than treated as definitive evidence of cost-insensitivity among student users.

Limitations

The present study has several limitations that constrain the scope of its conclusions. The cross-sectional design limits inference about the transition from BI to behavioral enactment and the subsequent crystallization of HB; longitudinal designs would offer stronger leverage on the HB construct. Interpretability is further

constrained by data collection at a single large public university with a multi-decade legacy of distance education; the configuration of FC and SI reported here may not generalize to institutions with different infrastructural or cultural characteristics. Multi-institutional and cross-cultural replication is therefore required before any conclusions can be extended to Turkish higher education more broadly, much less to other national contexts. Although the common-method-variance diagnostics were acceptable (Harman's first factor = 44.32%; VIF range = 1.41-2.59), time-separated measurement or behavioral-trace data would provide stronger protection against CMB (Podsakoff et al., 2003). The same-sample EFA-CFA design, while mitigated by the safeguards described in the method, remains a limitation; the PE and FC findings are particularly tentative given the two-item operationalization of these constructs and require split-sample validation on an independent Turkish sample (Kline, 2016; Worthington & Whittaker, 2006). The moderating structure of UTAUT2 (age, gender, experience, voluntariness) was not estimated; the rationale for this scope decision is detailed in the method, but its consequence is that the present study tests only the structural-core specification, not the full moderated UTAUT2 model. The pronounced gender imbalance (67.6% female) further indicates that any future moderator-conditioned testing of UTAUT2 in Turkish higher education should incorporate stratified or quota-based sampling. Finally, the baseline UTAUT2 model does not capture variables of particular contemporary relevance to GenAI - most notably AI literacy, trust, and academic integrity concerns - which limits the model's explanatory power for the specific affordances and risks of conversational AI in education.

Implications for Practice

According to research by the instructional design (ID) community, HM can be one of the most important factors when it comes to how people learn through technology. So, from an ID perspective, framing GenAI as merely a productivity tool is likely to undermine engagement and result in poor adoption. In contrast, course activities that allow the learner to experiment with using GenAI for open-ended, creative or exploratory activities are more likely to provide opportunities for continuing to use GenAI than course activities where GenAI is just being used as a way of helping the learner to write faster. Furthermore, having instructors model how to use GenAI in their academic discipline provides the learner with confirmation of the academic worth of GenAI, which provides reassurance that GenAI can continue to be used by the learner. Additionally, one of the findings related to FC suggests that universities must not only provide learners with access to GenAI but also provide coherent use policy and training to faculty on how to use GenAI. Finally, with regard to the SI findings, peer awareness campaigns are

unlikely to raise much awareness of GenAI; therefore, it's recommended that universities spend their resources on removing the barriers to using GenAI and improving the quality of the GenAI experience.

Implications for Future Research

Several directions emerge from the present findings. First, multi-institutional and multi-disciplinary studies are needed to investigate the variability that single-institution designs cannot resolve – including institution-level policy environments, faculty-level adoption rates, and department-level infrastructure differences. Second, longitudinal designs employing digital-trace data would enable tracking of the intention-to-HB transition and a more direct empirical test of the HB construct's theoretical implications. Third, qualitative inquiry into the near-zero SI coefficient would help adjudicate between alternative explanations (saturated norm vs. independent self-initiation vs. measurement effects) that cross-sectional survey data alone cannot distinguish. Fourth, cross-disciplinary comparisons could clarify the mechanisms underlying HM's dominance, potentially drawing on Deci and Ryan's (1985) self-determination theory to specify the affordances driving enjoyment. Fifth, and most consequential for model development, future UTAUT2 extensions in Turkish higher education should incorporate GenAI-specific constructs that the baseline model does not capture: AI literacy (the user's capacity to understand and critically evaluate GenAI outputs); algorithmic awareness (the user's mental model of how generative systems produce responses); trust (both in the tool's reliability and in the institution's policies governing its use); and academic integrity concerns (perceived risk of policy violation or misuse). Given that the present study's non-significant findings cluster around social-normative (SI) and economic (PV) constructs while affective and habitual constructs (HM, HB) carried the explanatory weight, models that integrate affect, identity, and AI-specific cognitive constructs are likely to offer stronger explanatory traction than further extensions on the utilitarian or social-normative side. Sixth, the PV reconceptualization proposed in the Discussion (opportunity cost, privacy cost, premium-upgrade framing) requires dedicated validation work before being integrated into UTAUT2-style frameworks.

This study evaluated the main-effects specification of the UTAUT2 model in the context of GenAI adoption among Generation Z students at a single large public university in Turkey. Within the scope of this institutional setting, our results offer a tentative baseline that may inform future replication studies on UTAUT2 and GenAI adoption in Turkish higher education; generalization beyond institutions with comparable digital-education legacies and student demographics should await multi-institutional replication. Within this

scope, the adoption of GenAI by students relies predominantly on enjoyment, perceived usefulness, habitual usage, and institutional support. For universities, engaging students through exploratory and creative GenAI activities, together with the provision of a clear institutional framework, will be more effective than top-down directives or peer-awareness campaigns. The degree to which the affective and habitual drivers identified here will continue to be the primary motivators as students transition toward routine GenAI use is an empirical question that only longitudinal investigation can answer.

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AI statement: The authors used ChatGPT and Grammarly solely for language editing/grammar checking during the preparation of this manuscript. The authors reviewed and edited all content and took full responsibility for the work. No AI tool was used to generate data, analyses, or scholarly interpretations.

Declaration of interest: No conflict of interest is declared by the authors.

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