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Adoption of ChatGPT for Learning-Related Information Access: A Comparative UTAUT2 Analysis of Turkish and Polish University Students

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Abstract

This study examines ChatGPT adoption among higher education students in Türkiye and Poland through an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework that also includes personal innovativeness. It compares country-specific adoption patterns across the two samples and offers a cautious contextual interpretation of the observed differences. Survey data were collected from 634 students in Türkiye and 531 students in Poland, and the proposed relationships were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that the extended UTAUT2 framework was empirically useful in both samples, although the relative prominence of specific predictors differed across them. Descriptively, Performance Expectancy ($\beta = 0.258$, $p < 0.001$) and Personal Innovativeness showed larger coefficients in the Polish sample, whereas Effort Expectancy ($\beta = 0.104$, $p < 0.01$) and Social Influence ($\beta = 0.199$, $p < 0.001$) appeared more prominent in the Turkish sample. Price Value showed a statistically significant reversed association with Behavioral Intention in Türkiye ($\beta = -0.187$, $p < 0.001$), whereas the association was positive in Poland ($\beta = 0.094$, $p < 0.01$). Habit emerged as one of the strongest predictors in the model and was positively associated with both Behavioral Intention and Use Behavior in the two samples. Taken together, the findings suggest that ChatGPT adoption in higher education is shaped by a combination of perceived usefulness, ease of use, social and practical support, habitual use, and context-sensitive evaluations of value. The study contributes to the growing literature on generative AI in higher education by showing that the same theoretical framework can reveal different adoption patterns across two national samples, while also highlighting the need for context-sensitive implementation strategies. The findings offer practical implications for higher education institutions, educators, and policy developers seeking to support the responsible and effective use of ChatGPT.

Keywords ChatGPT · UTAUT2 · Information access · Cross-cultural comparison · Technology adoption · Higher education

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1 Introduction

The rapid expansion of generative artificial intelligence has brought ChatGPT to the center of current debates on higher education. As a conversational AI tool, ChatGPT is increasingly used by university students for learning-related information access, idea generation, explanation, and academic support. Recent educational research suggests that ChatGPT may enhance personalized learning, timely feedback, and instructional efficiency; however, its educational value also depends on contextual factors such as technological readiness, user preparedness, and ethical concerns (Uğraş et al., 2024). For this reason, understanding how students adopt ChatGPT requires attention not only to individual perceptions but also to the national and institutional contexts in which use takes place.

Advancements in artificial intelligence (AI) and natural language processing (NLP) technologies have paved the way for innovative applications in education. In this context, tools such as the Chat Generative Pre-Trained Transformer (ChatGPT), which possess human-like text generation and interaction capabilities, hold significant potential for personalized learning, academic support, and instant feedback in higher education fundamentally reshaping how students seek, access, and evaluate information (İpek et al., 2023; Lund & Wang, 2023). However, the adoption and effective use of such technologies are influenced by factors such as cultural context, technological infrastructure, and educational policies, which may vary substantially across countries. Therefore, conducting a comparative investigation of university students' acceptance and use of ChatGPT as a tool for academic information-seeking and problem-solving in two distinct socio-cultural contexts—Türkiye and Poland—emerges as a critical research need that can enrich the literature (Venkatesh et al., 2012).

The theoretical foundation of this comparative analysis is based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), one of the most comprehensive models explaining individuals' behavioral intentions and actual use of technology. The model's validity has been supported through empirical studies across diverse cultural contexts. For instance, Strzelecki (2024) found that habit, performance expectancy, and hedonic motivation were strong determinants of AI adoption in Poland. Budhathoki et al. (2024) demonstrated that anxiety exhibited different influences in a comparison between the United Kingdom and Nepal, while Arbulú Ballesteros et al. (2024) identified performance and effort expectancy as significant predictors in Peru. Similarly, research conducted in Germany (Kacperski et al., 2025; Dietrich & Grassini, 2025) and Hungary (Koteczki & Eisinger Balassa, 2025) indicated that demographic, cultural, and ethical contexts shape technology acceptance processes.

Nevertheless, most existing studies are based on the 2022–2023 versions of ChatGPT and do not capture the tool's most recent functionalities (Strzelecki & ElArabawy, 2024). The newer versions, with advanced text generation, user guidance, and analytical capabilities, are reshaping students' perceptions of usefulness, ease of use, and motivation (Ashraf et al., 2025). The ability to effectively utilize these advanced features is closely associated with users' levels of digital competence.

Comparative research on ChatGPT adoption remains limited, especially across national higher education contexts that differ in digital development and institutional conditions. Türkiye and Poland offer a meaningful comparison in this respect. Although both countries have large student populations and sustained engagement with digital platforms, they differ in terms of digital infrastructure, economic environment, and higher education settings. These contrasts make it possible to examine whether the determinants of ChatGPT adoption operate similarly or differently across two distinct national contexts. The comparison between Türkiye and Poland is also relevant at the level of higher education because the two countries are connected through academic exchange, student mobility, and broader educational interaction. At the same time, they are not identical contexts. Their differences in digital maturity, economic conditions, and institutional support structures make them especially suitable for comparing how students perceive and adopt ChatGPT in university settings.

Against this background, the present study investigates ChatGPT adoption among higher education students in Türkiye and Poland through an extended UTAUT2 framework that also includes personal innovativeness. The study contributes to the growing literature on generative AI in education by comparing the determinants of behavioral intention and use behavior across two national contexts rather than within a single-country sample. In doing so, it aims to provide context-sensitive evidence for how higher education institutions may better support students' responsible and effective use of ChatGPT.

Accordingly, the study addresses the following research questions:

RQ1. How do the UTAUT2 constructs and personal innovativeness explain higher education students' behavioral intention and use behavior toward ChatGPT in Türkiye and Poland?

RQ2. To what extent do these relationships differ between the two national contexts, and how can any observed differences be interpreted in light of country-level contextual conditions?

All in all, the purpose of this research is to comparatively examine Turkish and Polish higher education students' acceptance and use of ChatGPT within the UTAUT2 framework and to describe the observed country-specific patterns in ChatGPT adoption in this process. The study aims to analyze how constructs such as performance expectancy, effort expectancy, social influence, hedonic motivation, habit, price value, personal innovativeness, and facilitating conditions operate within two different cultural contexts.

2 Literature Review

2.1 Unified Theory of Acceptance and use of Technology 2 (UTAUT2)

Understanding why students adopt ChatGPT in higher education requires a framework that can explain not only whether the tool is perceived as useful, but also whether it is easy to use, socially acceptable, practically accessible, enjoyable, economically worthwhile, and ultimately capable of becoming part of routine academic behavior. For this reason, the present study is grounded in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) developed by Venkatesh et al. (2012), which remains one of the most widely used models for explaining technology acceptance and use at the individual level. UTAUT2 is particularly suitable for the present study because ChatGPT is not simply a technical system that students either accept or reject; rather, it is an interactive tool whose use is shaped simultaneously by perceived academic usefulness, ease of interaction, social expectations, access conditions, cost–benefit judgments, and repeated experience.

In its original formulation, UTAUT2 proposes that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit shape users' behavioral intention and use behavior (Venkatesh et al., 2012, 2016). In the present study, behavioral intention refers to students' willingness and readiness to use ChatGPT for learning-related purposes, whereas use behavior refers to their self-reported actual use of the tool. Because ChatGPT represents a relatively recent and rapidly diffusing technology in higher education, the model is further extended with personal innovativeness, an individual-difference variable that captures one's general openness to trying new technologies (Agarwal & Prasad, 1998; Dajani & Abu Hegleh, 2019; Farooq et al., 2017; Sitar-Taut & Mican, 2021; Twum et al., 2022).

The comparative dimension of the present study makes UTAUT2 especially useful. The model allows the researcher to begin from a stable theoretical core while examining whether the same relationships appear similarly or differently across two national higher education contexts. However, because the present study does not directly measure culture at the individual level, the hypotheses below are formulated as general structural expectations rather than as country-specific directional claims. The comparative value of the study therefore lies in examining how the same model operates across the Turkish and Polish samples and then interpreting the observed patterns cautiously in light of context.

From a conceptual point of view, the logic of the model unfolds in a coherent sequence. Students are first likely to ask whether ChatGPT is worth using for academic purposes. This leads naturally to performance expectancy. If the tool is seen as useful, the next question becomes whether it is easy enough to learn and use, which points to effort expectancy. Yet students do not make such decisions in isolation; their choices are often shaped by what peers, instructors, and institutions signal as legitimate or desirable, which introduces social influence. Even favorable intentions may not translate into real behavior unless students feel they have sufficient resources, guidance, and access, which makes facilitating conditions crucial. Adoption is also not purely instrumental: if interacting with ChatGPT is enjoyable, stimulating, or satisfying, hedonic motivation may further strengthen intention. Because ChatGPT exists within a free and paid ecosystem, students may additionally weigh perceived benefit against cost, which introduces price value. Over time, repeated use may become routinized, turning ChatGPT into an automatic part of academic practice; this is the role of habit. Finally, within UTAUT2, behavioral intention remains the most immediate antecedent of actual use behavior. Since not all students respond to emerging technologies in the same way, personal innovativeness is included to capture whether students who are more open to technological experimentation are also more inclined to adopt ChatGPT. Taken together, this logic offers a structured pathway from students' initial evaluations of ChatGPT to their eventual and repeated use of it. The subsections below develop each of these relationships in turn.

2.2 Performance Expectancy (PE)

When students encounter a new academic technology, their first evaluative question is often pragmatic: *Will this help me perform better?* In UTAUT2, this evaluation is captured by performance expectancy, defined as the degree to which individuals believe that using a technology will help them attain gains in performance (Venkatesh et al., 2012). In the context of higher education, this idea is especially relevant for ChatGPT because the tool is often used for activities such as clarifying concepts, organizing information, generating ideas, drafting text, and supporting academic problem

solving. If students perceive these functions as academically beneficial, their willingness to adopt the tool should increase.

This expectation is well supported in the literature. Across technology acceptance research more broadly, performance expectancy has consistently emerged as one of the strongest predictors of behavioral intention (Venkatesh et al., 2012). Recent work on ChatGPT adoption among university students points in the same direction. Strzelecki (2024) shows that perceived usefulness is central to students' willingness to use ChatGPT, and Strzelecki and ElArabawy (2024) similarly report that students are more inclined to adopt the tool when they believe it contributes meaningfully to their academic work. Although older technology studies such as Lewis et al. (2013) did not examine ChatGPT specifically, they remain useful in showing that the perceived performance benefits of a learning-related technology often shape students' acceptance decisions. The ChatGPT literature extends this logic by suggesting that performance expectancy in this context may include not only speed and efficiency, but also support for explanation, idea generation, and cognitive work. Accordingly, if students believe that ChatGPT enhances their academic effectiveness, it is reasonable to expect a stronger intention to use it.

H1: *Performance Expectancy (PE) has a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*

2.3 Effort Expectancy (EE)

Perceived usefulness alone is rarely enough to sustain technology adoption. Even a highly useful system may remain underused if it feels difficult, confusing, or cognitively demanding. This is where effort expectancy becomes important. In UTAUT2, effort expectancy refers to the degree of ease associated with the use of a system (Venkatesh et al., 2012). Applied to ChatGPT, the construct concerns whether students perceive the tool as easy to learn, easy to interact with, and clear in its operation.

This construct is particularly relevant for a conversational AI tool because students do not simply "access" ChatGPT in the same way they access a static digital resource; they interact with it dynamically. Ease of use therefore involves both interface simplicity and the perceived ease of asking questions, understanding outputs, and integrating the tool into ongoing study practices. Previous research supports the importance of this factor. Strzelecki (2024) found that the intuitive and accessible nature of ChatGPT positively shaped students' willingness to adopt it. Similar evidence is reported by Strzelecki and ElArabawy (2024), who show that students' perceptions of ease and convenience remain an important part of adoption decisions. More generally, earlier educational technology studies have also shown that technologies perceived as easier to use are more likely to generate positive usage intentions, even if they were conducted outside the specific ChatGPT context (Bozorgkhou, 2015; Chatterjee & Bhattacharjee, 2020; Habibi et al., 2022). The logic here is straightforward: if students perceive ChatGPT as understandable, manageable, and easy to incorporate into their academic routines, they are more likely to intend continued use. In other words, effort expectancy can be seen as the condition that allows perceived usefulness to become actionable.

H2: *Effort Expectancy (EE) has a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*

2.4 Social Influence (SI)

Technology adoption in higher education rarely occurs in a purely individual vacuum. Students interpret new tools not only through their own experiences, but also through the expectations, practices, and judgments of the people around them. UTAUT2 captures this dynamic through social influence, defined as the degree to which an individual perceives that important others believe he or she should use a new system (Venkatesh et al., 2012). In the case of ChatGPT, these "important others" may include peers, classmates, instructors, supervisors, and the wider institutional climate.

This construct is especially relevant because the educational use of generative AI remains socially and normatively contested. Students may ask not only whether ChatGPT is useful, but also whether it is acceptable, encouraged, frowned upon, or risky in the eyes of others. The literature suggests that such perceptions matter. Strzelecki and ElArabawy (2024) report that peer and instructor influence plays a meaningful role in students' intentions to adopt ChatGPT. Earlier educational technology research also points to the importance of recommendations, visible usage norms, and socially transmitted expectations in shaping adoption behavior (Guggemos et al., 2020; Kang et al., 2015; Raffaghelli et al., 2022). Even where students personally recognize the utility of a tool, uncertainty about whether others regard its use as legitimate may weaken intention. Conversely, visible approval from peers or instructors may help normalize adoption. For this reason, social influence is not merely a peripheral construct. In a higher education environment where technology use is observed, discussed, and evaluated, social signals may directly strengthen students' behavioral intention toward ChatGPT.

H3: *Social Influence (SI) has a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*

2.5 Facilitating Conditions (FC)

Even when students perceive ChatGPT as useful, easy to use, and socially acceptable, actual adoption may still depend on whether they feel they have the practical means to use it effectively. UTAUT2 refers to these enabling circumstances as facilitating conditions, that is, the degree to which users believe that the necessary organizational and technical infrastructure exists to support system use (Venkatesh et al., 2012). In the present study, facilitating conditions refer to students' perceived access to the resources, knowledge, and support needed to use ChatGPT effectively in academic contexts.

The importance of facilitating conditions is particularly clear in higher education settings. Students may need reliable internet access, appropriate devices, familiarity with digital tools, and some degree of institutional or peer support in order to make regular and effective use of ChatGPT. Prior research suggests that such conditions matter both for intention and for actual use. Strzelecki (2024), for example, showed that facilitating conditions were positively associated with students' use-related outcomes in the context of ChatGPT. More broadly, technology adoption studies have repeatedly found that even strong intentions may fail to translate into actual behavior when users perceive gaps in infrastructure, support, or practical know-how (Cabrera-Sánchez et al., 2021; Chatterjee & Bhattacharjee, 2020).

Conceptually, facilitating conditions occupy a pivotal position in the model because they connect favorable perception to feasible action. A student may want to use ChatGPT, but if access, confidence, or support are lacking, that intention may not result in real use. For this reason, facilitating conditions are expected to play a role in shaping both behavioral intention and actual use behavior.

H4: *Facilitating Conditions (FC) have a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*
H5: *Facilitating Conditions (FC) have a direct and positive effect on higher education students' use behavior of ChatGPT.*

2.6 Hedonic Motivation (HM)

Not all technology use is driven solely by utility, efficiency, or necessity. Students may also adopt a tool because they find it enjoyable, engaging, stimulating, or satisfying. UTAUT2 conceptualizes this experiential dimension as hedonic motivation, defined as the fun or pleasure derived from using a technology (Venkatesh et al., 2012). In the context of ChatGPT, this may include the enjoyment of conversational interaction, the satisfaction of receiving immediate responses, the curiosity involved in exploring the system's capabilities, or the sense of fluency that comes from smooth interaction with the tool.

This construct is relevant because generative AI tools differ from many earlier educational technologies in their interactive and responsive character. ChatGPT does not simply present information; it engages users in a conversational process that may itself feel interesting or rewarding. Existing evidence supports this idea. Strzelecki (2024) found that hedonic motivation positively influenced students' willingness to use ChatGPT, suggesting that students may adopt the tool not only because it is useful, but also because interacting with it is experienced as interesting and enjoyable. Other technology adoption studies similarly show that enjoyment can strengthen intention, particularly when the technology provides a sense of novelty or intrinsically satisfying engagement (Arain et al., 2019; Gharrah & Aljaafreh, 2021). The role of hedonic motivation is therefore not trivial. In educational contexts, enjoyment can help transform an initially experimental interaction into a more stable willingness to use the tool. If students experience ChatGPT as satisfying and engaging rather than burdensome or purely mechanical, their behavioral intention should become stronger.

H6: *Hedonic Motivation (HM) has a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*

2.7 Price Value (PV)

Once students perceive a tool as useful, manageable, socially legitimate, and perhaps even enjoyable, another evaluative question may emerge: *Is it worth it?* UTAUT2 captures this cost–benefit judgment through price value, which reflects users' cognitive trade-off between the perceived benefits of a technology and the costs of using it (Venkatesh et al., 2012; Tamilmani et al., 2021). In the case of ChatGPT, this construct is especially relevant because the technology exists in both free and premium forms, and students may weigh its benefits against actual or perceived monetary cost.

Price value is important because adoption is rarely based on utility alone. Even a highly useful tool may be judged negatively if the cost is experienced as excessive relative to expected benefit. In the ChatGPT context, this calculation may involve not only direct financial cost, but also perceptions of whether the tool is sufficiently useful, reliable, and worthwhile for academic tasks. Strzelecki (2024) shows

that price value plays a role in students' adoption decisions, and the general UTAUT2 literature consistently treats this construct as a relevant predictor when users must assess whether the benefits of a system justify its cost (Tamilmani et al., 2021; Venkatesh et al., 2012). The relevance of this construct is heightened in higher education because students often operate under budget constraints while simultaneously seeking tools that can save time, improve output quality, and support academic performance. If the perceived benefits of ChatGPT outweigh the perceived costs, students should be more inclined to adopt it.

H7: *Price Value (PV) has a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*

2.8 Habit (HT)

Technology use does not remain at the level of deliberate evaluation forever. Once a system is used repeatedly, that use may become routinized and increasingly automatic. UTAUT2 conceptualizes this process through habit, defined as the extent to which people tend to perform behaviors automatically because of learning and repetition (Venkatesh et al., 2012). In the present study, habit refers to the degree to which students' use of ChatGPT has become a regular or automatic part of their academic behavior.

Habit matters because the logic of technology use changes over time. A student may first adopt ChatGPT because it is useful or easy to use, but repeated successful experience may gradually shift use from intention-driven to routine-driven. Earlier studies have long shown that habitual engagement with technology is an important predictor of continued use (El-Masri & Tarhini, 2017; Tseng et al., 2022). In the specific context of ChatGPT, Strzelecki (2024) similarly found that habit plays an important role in students' usage patterns. This is especially plausible for a tool that can be incorporated into recurring academic activities such as brainstorming, summarizing, revising, translating, or checking information.

Theoretically, habit should matter in two related ways. First, repeated use may directly support actual use behavior, since routinized interaction makes continued use more likely. Second, habit may also reinforce behavioral intention, because a student who has already incorporated ChatGPT into everyday practice may be more inclined to continue using it in the future. This dual role is central to the UTAUT2 model and is particularly relevant for a tool whose academic use can quickly become normalized through repetition.

H8: *Habit (HT) has a direct and positive effect on higher education students' use behavior of ChatGPT.*
H9: *Habit (HT) has a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*

2.9 Behavioral Intention (BI)

In UTAUT2, behavioral intention occupies a central place because it represents the most immediate motivational antecedent of actual technology use (Venkatesh et al., 2012). Put differently, if the preceding constructs explain why students want to use ChatGPT, behavioral intention explains whether that motivation is likely to result in use behavior. This is why BI functions not merely as another construct in the model, but as a key bridge between evaluation and action.

This relationship is also well established in both general technology acceptance research and recent work on ChatGPT. Strzelecki (2024) found that students' intention to use ChatGPT was positively associated with their actual use behavior. Similar patterns have long been observed in related digital learning contexts, where intention consistently predicts enacted technology use even when users face varying levels of support or constraint (Maican et al., 2019; Hoi, 2020; Zwain, 2019). The theoretical implication is that behavioral intention summarizes the cumulative influence of earlier evaluative and contextual factors and channels them into actual practice. For that reason, the final structural path of the model follows directly from the UTAUT2 logic: students who report stronger intention to use ChatGPT should also report greater actual use.

H10: *Higher education students' behavioral intention to use ChatGPT has a direct and positive effect on their use behavior.*

2.10 Personal Innovativeness (PI)

Although UTAUT2 already captures several major determinants of technology adoption, emerging tools such as ChatGPT may also be shaped by stable individual differences in users' willingness to experiment with new technologies. This is why the present study includes personal innovativeness, defined as an individual's general tendency to try out and adopt new information technologies (Agarwal & Prasad, 1998). In higher education, this construct is especially relevant because students differ in their comfort with novelty, experimentation, and technological uncertainty.

The inclusion of personal innovativeness is supported by both theoretical and empirical work. Agarwal and Prasad (1998) originally showed that more innovative individuals tend to be more open to unfamiliar technologies. Later studies extended this logic to digital learning and emerging systems, finding that personal innovativeness strengthens openness to experimentation and adoption intentions (Dajani & Abu Hegleh, 2019; Farooq et al., 2017; Sitar-Taut & Mican, 2021; Twum et al., 2022). In the context of ChatGPT, this implies that students who are generally more willing to experiment with new tools may also be more likely to perceive ChatGPT as worth trying, exploring, and incorporating into their academic practices.

At a theoretical level, personal innovativeness complements the UTAUT2 framework by acknowledging that not all adoption decisions are driven purely by system characteristics or social context. Some students approach new technologies with a more exploratory disposition from the outset. This does not replace the core UTAUT2 constructs, but it can add explanatory power, particularly in a context where generative AI tools are still relatively new and students vary in their willingness to engage with them.

H11: *Personal Innovativeness (PI) has a direct and positive effect on higher education students' behavioral intention to use ChatGPT.*

Overall, the proposed model assumes that students' adoption of ChatGPT is shaped by a layered process rather than by a single factor. They first evaluate whether the tool is useful, manageable, socially legitimate, enjoyable, and worthwhile; they then act within the limits of their available resources and support; over time, repeated use may become habitual; and their general openness to technological innovation may further strengthen intention. Figure 1 presents the final conceptual model tested in the study.

3 Method

3.1 Research Design and Participants

This study employed a cross-sectional, web-based survey design to examine ChatGPT adoption among higher education students in Türkiye and Poland within an extended UTAUT2 framework. A cross-sectional survey design was appropriate because the study aimed to compare students' self-reported perceptions, behavioral intention, and use behavior across two national higher education contexts at a single point in time. Data were collected during the 2023–2024 academic year through an online questionnaire administered via Google Forms. Table 1 presents the demographic and academic profile of the participants included in the Turkish and Polish samples.

The final sample consisted of 1,165 higher education students, including 634 respondents from Türkiye and 531 respondents from Poland. Table 1 presents the demographic and academic profile of the two national samples. Because the respondents were recruited through an open online survey, the study relied on convenience sampling. The two samples were not compositionally identical, particularly with regard to gender and academic level, and these differences should be considered when interpreting between-country comparisons.

3.2 Data Analysis Strategy

Data analysis was conducted using SmartPLS 4 (Version 4.0.9.2). The Turkish and Polish samples were analyzed

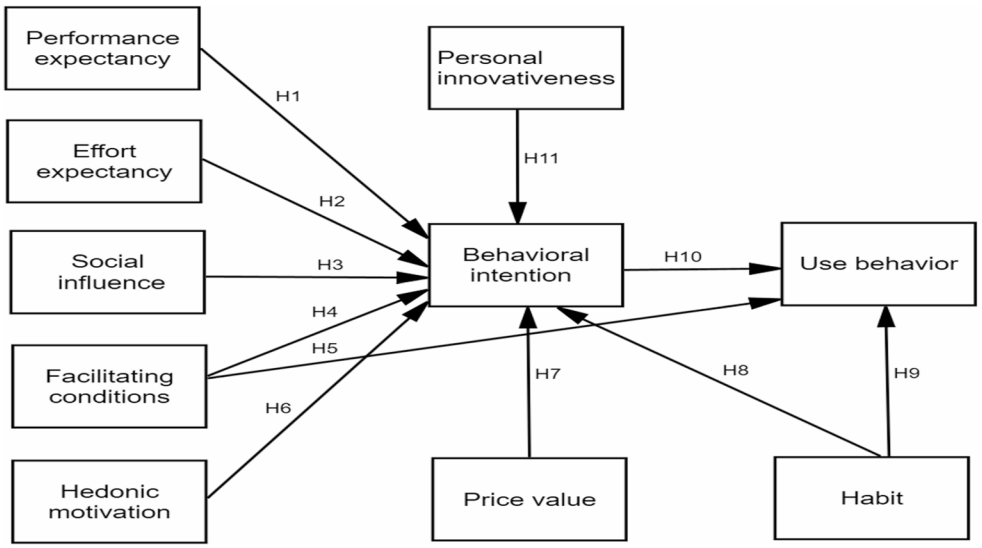


Fig. 1 Integrated UTAUT2 model for ChatGPT adoption among higher education students in Türkiye and Poland

Table 1 Demographic and academic profile of survey participants

Demographic Characteristics		Türkiye		Poland	
		N	%	*N*	%
Gender	Female	458	72.2	280	52.7
	Male	176	27.8	228	42.9
	Not mentioned	0	0	23	4.3
	Total	634	100	531	100
Academic Level	Preparatory Class	4	0.6	0	0
	1 st year	153	24.1	29	5.5
	2nd year	145	22.9	169	31.8
	3rd year	88	13.9	198	37.3
	4th year	188	29.7	57	10.7
	Master's student	31	6.5	69	13.0
	PhD student	15	2.4	9	1.7

separately through Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model was evaluated using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), variance inflation factor (VIF), and heterotrait–monotrait ratios (HTMT). The structural model was assessed through path coefficients, t values, p values, effect sizes (f^2), and explained variance (R^2), based on non-parametric bootstrapping with 5,000 resamples (Sarstedt et al., 2022). Because formal measurement invariance testing and multi-group difference testing were not conducted, between-country differences in path coefficients were interpreted descriptively rather than as formally confirmed cross-group differences. Supplementary checks were also conducted to examine the robustness of the main findings after excluding the low-loading FC4 item and after considering gender and academic level.

3.3 Instrument and Data Collection Procedure

The study used the University Students' ChatGPT Application Usage Scale (USCAUS) developed by Strzelecki (2024) as the main survey instrument. The research model included the seven UTAUT2 constructs employed in the present study—performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit—together with behavioral intention, use behavior, and personal innovativeness. Attitudinal items were measured on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), whereas use behavior was measured on a seven-point frequency scale ranging from 1 (never) to 7 (several times a day). To address transparency concerns regarding the questionnaire content, representative examples of the scale items are reported here. The instrument included 32 attitudinal items and one separate frequency item for actual ChatGPT use. Performance expectancy was represented by items such as "I believe ChatGPT is beneficial for my studies" and "Using ChatGPT increases my chances of achieving important success in my studies." Effort expectancy included items such as "Learning how to use ChatGPT was easy for me." Social influence included items such as "Important people in my life say that it is good for me to use ChatGPT." Facilitating conditions included items such as "I have sufficient infrastructure to use ChatGPT" and "My knowledge is sufficient to use ChatGPT." Hedonic motivation included items such as "Using ChatGPT is fun." Price value included items such as "The price of ChatGPT Plus (USD 20 per month) is reasonable." In the price value construct, the items explicitly referred to the perceived reasonableness and worth of ChatGPT Plus at a stated monthly cost of USD 20, which should be kept in mind when interpreting the country-specific findings for this construct. Habit included items such as "Using ChatGPT has become a habit for me." Behavioral intention included items such as "I intend to continue using ChatGPT in the future." Personal innovativeness included items such as "I like trying new information technologies." Actual use behavior was measured separately through a frequency item ranging from "never" to "several times a day." The survey form used in the study preserved the original construct structure of the scale and its item distribution. The Turkish and Polish administrations were prepared as parallel versions of the same questionnaire in order to ensure comparability across the two samples. To support semantic consistency across language versions, the wording was reviewed through translation checking and expert evaluation. In addition, a pilot administration with 42 Turkish higher education students was conducted to identify possible wording problems and improve clarity. The final questionnaire retained the original 32-item attitudinal structure and required approximately 5 min to complete. The questionnaire was distributed through email, social media, and WhatsApp in order to reach higher education students in both countries. Because the survey link was distributed through multiple open channels, an exact response rate could not be calculated (Lavidas et al., 2022). Before accessing the questionnaire items, respondents were presented with a short introductory page explaining the purpose of the study, the approximate completion time, the voluntary nature of participation, the assurance of anonymity, and the handling of the collected data. Only those who provided informed consent proceeded to the questionnaire. No personally identifying information was collected, and the responses were used only for research purposes.

3.4 Measurement Model Assessment

Table 2 reports the indicator loadings, descriptive statistics, and collinearity diagnostics for the Turkish and Polish samples. Internal consistency was evaluated through Cronbach's alpha and composite reliability, convergent validity through AVE, and discriminant validity through HTMT values

Table 2 Comparative analysis of the USCAUS: factor loadings, means, standard deviations, and VIF values for higher education students in Türkiye and Poland

	Türkiye				Poland				Factor
Item	Loading	Mean	SD	VIF	Loading	Mean	SD	VIF	Source
BI1	0.898	4.83	1.513	2.169	0.910	5.38	1.774	2.902	Behavioral Intention (Venkatesh et al., 2012)
BI2	0.817	4.65	1.501	1.718	0.821	3.38	1.923	1.874	
BI3	0.887	4.96	1.469	2.178	0.939	4.44	2.037	3.576	
EE1	0.836	4.69	1.501	1.918	0.863	5.70	1.505	2.312	Effort Expectancy (Venkatesh et al., 2012)
EE2	0.800	5.26	1.441	1.814	0.886	5.63	1.444	3.110	
EE3	0.889	5.12	1.473	2.523	0.887	5.82	1.396	3.301	
EE4	0.838	5.29	1.403	2.102	0.907	5.73	1.428	2.894	
FC1	0.940	4.96	1.393	3.579	0.822	5.95	1.393	1.917	Facilitating Conditions (Venkatesh et al., 2012)
FC2	0.955	4.34	1.661	3.553	0.884	5.60	1.500	2.300	
FC3	0.918	4.23	1.716	3.222	0.819	5.16	1.586	1.698	
FC4	0.227	4.25	1.683	1.053	0.572	4.97	1.736	1.240	
HM1	0.894	4.71	1.583	3.071	0.954	5.81	1.533	3.210	Hedonic Motivation (Venkatesh et al., 2012)
HM2	0.893	4.68	1.574	3.078	0.961	5.75	1.490	3.399	
HM3	0.783	5.05	1.439	1.366	0.712	5.21	1.702	1.490	
HT1	0.844	5.01	1.544	2.296	0.893	2.97	1.983	2.621	Habit (Venkatesh et al., 2012)
HT2	0.785	4.96	1.446	3.119	0.846	1.96	1.522	2.497	
HT3	0.847	4.92	1.481	3.575	0.782	1.98	1.517	2.036	
HT4	0.724	4.67	1.511	1.214	0.890	3.08	1.982	2.450	
PE1	0.906	3.07	1.685	3.272	0.902	5.13	1.714	2.400	Performance Expectancy (Venkatesh et al., 2012)
PE2	0.928	3.83	1.573	3.192	0.866	4.69	1.807	2.814	
PE3	0.918	3.90	1.548	3.715	0.891	5.52	1.633	2.423	
PE4	0.915	3.63	1.729	3.494	0.863	4.85	1.874	3.404	
PI1	0.830	2.87	1.639	2.430	0.910	5.75	1.587	3.372	Personal Innovativeness (Agarwal & Prasad, 1998)
PI2	0.842	2.92	1.728	3.344	0.907	5.38	1.671	1.908	
PI3	0.859	3.33	1.782	3.406	0.815	5.36	1.773	1.701	
PI4	0.664	4.45	1.623	1.118	0.777	5.29	1.763	3.141	
PV1	0.873	3.97	1.637	2.877	0.937	5.12	1.671	3.131	Price Value (Venkatesh et al., 2012)
PV2	0.906	4.06	1.674	3.444	0.969	5.24	1.658	2.234	
PV3	0.929	5.41	1.465	2.292	0.960	5.22	1.629	3.918	
SI1	0.806	5.13	1.478	1.590	0.938	3.94	1.586	4.264	Social Influence (Venkatesh et al., 2012)
SI2	0.898	4.49	1.728	2.025	0.942	3.91	1.593	3.565	
SI3	0.727	5.25	1.536	1.414	0.936	3.92	1.640	2.902	

Item codes correspond to the original scale structure as follows: PE1–PE4 = performance expectancy (Items 1–4), EE1–EE4 = effort expectancy (Items 5–8), SI1–SI3 = social influence (Items 9–11), FC1–FC4 = facilitating conditions (Items 12–15), HM1–HM3 = hedonic motivation (Items 16–18), PV1–PV3 = price value (Items 19–21), HT1–HT4 = habit (Items 22–25), BI1–BI3 = behavioral intention (Items 26–28), and PI1–PI4 = personal innovativeness (Items 29–32). Actual use behavior was measured with a separate frequency item

reported in Table 4 and 5. BI and UB were treated as endogenous latent constructs and were therefore included in the measurement assessment together with the predictor constructs. One facilitating conditions item (FC4), corresponding to the statement "If I have difficulty using ChatGPT, I can get help from others," displayed weaker loadings than the other facilitating conditions indicators, especially in the Turkish sample. The original scale structure was retained to preserve comparability with the source instrument; however, because FC4 appeared to function less consistently across the two samples, an additional sensitivity check was conducted by re-estimating the model after excluding this item. The results of this check are reported briefly in the Findings section and were used to guide the cautious

interpretation of facilitating conditions. As noted above, the survey procedure was designed to reduce response pressure and support honest self-reporting.

Table 3 encompasses fundamental statistical metrics for each factor, including Cronbach's alpha, composite reliability (rho_a and rho_c), and average variance extracted (AVE), for the USCAUS scale. This allows for a robust assessment of the integrity and internal consistency of the factors (Strzelecki, 2024). The examination conducted in the Turkish and Polish participants indicates that the reliability and validity levels of the USCAUS align with standard benchmarks. Particularly, the Cronbach's alpha values for both countries exceed the 0.70 threshold, indicating reliable internal consistency (Hair et al., 2022). Additionally, composite reliability scores (rho_a and rho_c) generally surpass accepted criteria, affirming the reliability of the factors (Hair et al., 2022; Dijkstra & Henseler, 2015). Moreover, composite reliability scores for all factors in both samples are above 0.70. Construct validity, especially convergent validity assessed through the AVE metric, meets minimum requirements for all factors in both countries (Sarstedt et al., 2022).

Discriminant validity was assessed using the heterotrait–monotrait ratio of correlations (HTMT), following Henseler et al. (2015). As shown in Tables 4 and 5, all HTMT values in both the Turkish and Polish samples were below the conservative threshold of 0.85, indicating adequate discriminant validity among the constructs.

3.5 Findings

This section reports the country-specific PLS-SEM results for the Turkish and Polish samples. In line with the analytical strategy described in the Method section, the two models are presented side by side and compared descriptively. Because formal multi-group difference testing was not conducted, any between-sample differences in path coefficients should be interpreted as descriptive patterns rather than statistically confirmed cross-group differences. To improve readability and maintain a clear link with the conceptual model, the structural paths are reported below using both hypothesis labels and construct names.

Figure 2 visually summarizes the country-specific structural estimates reported in Table 7 and is provided to facilitate descriptive comparison across the two samples.

Table 6 presents the explained variance values for behavioral intention (BI) and use behavior (UB) in the two samples. The model explained 52.1% of the variance in BI and 28.1% of the variance in UB in the Turkish sample, compared with 73.1% and 54.2%, respectively, in the Polish sample. These values indicate that the model accounted for a larger proportion of variance in both endogenous constructs

Table 3 Reliability and validity metrics for constructs in the Turkish (TR) and Polish (PL) participants

Constructs	Cronbach's Alpha		Composite reliability (rho_a)		Composite reliability (rho_c)		Average variance extracted (AVE)	
	TR	PL	TR	PL	TR	PL	TR	PL
Behavioral intention	0.837	0.870	0.853	0.888	0.902	0.920	0.754	0.794
Effort expectancy	0.862	0.909	0.870	0.923	0.907	0.936	0.708	0.785
Facilitating conditions	0.796	0.786	0.935	0.830	0.876	0.861	0.672	0.614
Habit	0.822	0.878	0.840	0.916	0.877	0.915	0.642	0.729
Hedonic motivation	0.818	0.859	0.817	0.950	0.893	0.913	0.736	0.780
Performance expectancy	0.937	0.904	0.937	0.906	0.955	0.933	0.841	0.776
Personal innovativeness	0.816	0.876	0.813	0.892	0.878	0.915	0.644	0.730
Price value	0.893	0.952	1.021	0.957	0.930	0.969	0.816	0.913
Social influence	0.741	0.933	0.759	0.935	0.853	0.957	0.662	0.881

Table 4 Discriminant validity assessment via HTMT ratios for the Turkish participants

HTMT values (Turkish Sample)										
Constructs	1	2	3	4	5	6	7	8	9	10
Behavioral intention										
Effort expectancy	0.402									
Facilitating conditions	0.620	0.400								
Habit	0.710	0.298	0.812							
Hedonic motivation	0.482	0.196	0.836	0.778						
Performance expectancy	0.493	0.363	0.820	0.742	0.588					
Personal innovativeness	0.546	0.289	0.787	0.750	0.632	0.695				
Price value	0.161	0.080	0.381	0.562	0.702	0.228	0.396			
Social influence	0.658	0.490	0.838	0.639	0.454	0.751	0.803	0.080		
Use behavior	0.423	0.412	0.507	0.510	0.378	0.525	0.414	0.165	0.500	

Table 5 Discriminant validity assessment via HTMT ratios for the Polish participants

HTMT values (Polish Sample)										
Constructs	1	2	3	4	5	6	7	8	9	10
Behavioral intention										
Effort expectancy	0.624									
Facilitating conditions	0.619	0.791								
Habit	0.766	0.370	0.383							
Hedonic motivation	0.733	0.724	0.776	0.408						
Performance expectancy	0.836	0.573	0.604	0.611	0.711					
Personal innovativeness	0.608	0.569	0.584	0.396	0.615	0.565				
Price value	0.601	0.530	0.638	0.406	0.617	0.536	0.427			
Social influence	0.603	0.398	0.507	0.499	0.443	0.571	0.387	0.392		
Use behavior	0.744	0.531	0.527	0.626	0.486	0.569	0.507	0.432	0.441	

in the Polish sample. However, this pattern should be interpreted descriptively and does not by itself establish formal between-country differences in model fit.

Table 7 reports the structural path coefficients for the Turkish and Polish samples. In the Turkish sample, performance expectancy ($\beta = 0.181$, $p = 0.001$), effort expectancy ($\beta = 0.104$, $p = 0.006$), social influence ($\beta = 0.199$, $p = 0.001$), facilitating conditions ($\beta = 0.035$, $p = 0.001$), hedonic motivation ($\beta = 0.098$, $p = 0.043$), habit on behavioral intention ($\beta = 0.627$, $p = 0.001$), and personal innovativeness ($\beta = 0.031$, $p = 0.001$) were positively associated with behavioral intention. In the same sample, facilitating conditions ($\beta = 0.305$, $p < 0.001$), habit on use behavior ($\beta = 0.204$, $p = 0.001$), and behavioral intention ($\beta = 0.090$, $p = 0.028$) were positively associated with use behavior. Contrary to the hypothesized positive direction, H7: Price Value (PV) → Behavioral Intention (BI) showed a statistically significant negative association in the Turkish sample ($\beta = -0.187$, $p = 0.001$). Thus, H7 was not supported in Türkiye; however, the result should be interpreted as a significant reversed relationship rather than merely as a non-supported hypothesis.

When the two samples are viewed descriptively, several coefficient patterns stand out. H1: Performance Expectancy (PE) → Behavioral Intention (BI), H6: Hedonic Motivation (HM) → Behavioral Intention (BI), H7: Price Value (PV) → Behavioral Intention (BI), H8: Habit (HT) → Use Behavior (UB), H10: Behavioral Intention (BI) → Use Behavior (UB), and H11: Personal Innovativeness (PI) → Behavioral Intention (BI) showed larger coefficients in the Polish sample. By contrast, H2: Effort Expectancy (EE) → Behavioral Intention (BI), H3: Social Influence (SI) → Behavioral Intention (BI), H5: Facilitating Conditions (FC) → Use Behavior (UB), and H9: Habit (HT) → Behavioral Intention (BI) were larger in the Turkish sample. These differences are reported as descriptive coefficient patterns and should not be interpreted as statistically confirmed between-country differences. The effect size values also suggest that not all statistically significant relationships carry the same practical weight. In particular, H4: Facilitating Conditions (FC) → Behavioral Intention (BI) showed very small effect sizes in both samples ($f^2 = 0.001$ in Türkiye; $f^2 = 0.002$ in Poland), and personal innovativeness → behavioral intention remained practically negligible in the Turkish sample ($f^2 = 0.001$). By contrast, Habit (HT) → Behavioral Intention (BI) was the strongest predictor of behavioral intention in both samples, while Behavioral Intention (BI) → Use Behavior (UB) showed a notably stronger effect in the Polish sample ($f^2 = 0.177$) than in the Turkish sample ($f^2 = 0.006$).

A supplementary sensitivity check was conducted by re-estimating the model after excluding FC4 from the Facilitating Conditions construct. The direction and substantive interpretation of the main structural paths remained stable in both samples, including H4: FC → BI and H5: FC → UB. The explained variance values for BI and UB also showed no meaningful change. Therefore, the original item was retained to preserve comparability with the source instrument, but the facilitating conditions findings are interpreted cautiously because FC4 performed less consistently across the two samples.

A second supplementary check was conducted by adding gender and academic level as control variables. The main descriptive patterns highlighted in the study, particularly H7: PV → BI, H8: HT → UB, H9: HT → BI, and H10: BI → UB, remained substantively stable after these controls were considered. This suggests that the observed coefficient patterns are not simply attributable to the compositional differences between the Turkish and Polish samples in terms of gender and academic level.

Taken together, the results indicate that the extended UTAUT2 framework was empirically useful in both samples, but the relative salience of specific predictors differed descriptively across the Turkish and Polish groups. The most notable pattern concerned price value, which changed direction across the two samples, and habit, which emerged as a strong predictor of behavioral intention in both contexts. These findings are used in the next section as a basis for cautious contextual interpretation rather than as evidence of formally established cross-national moderation.

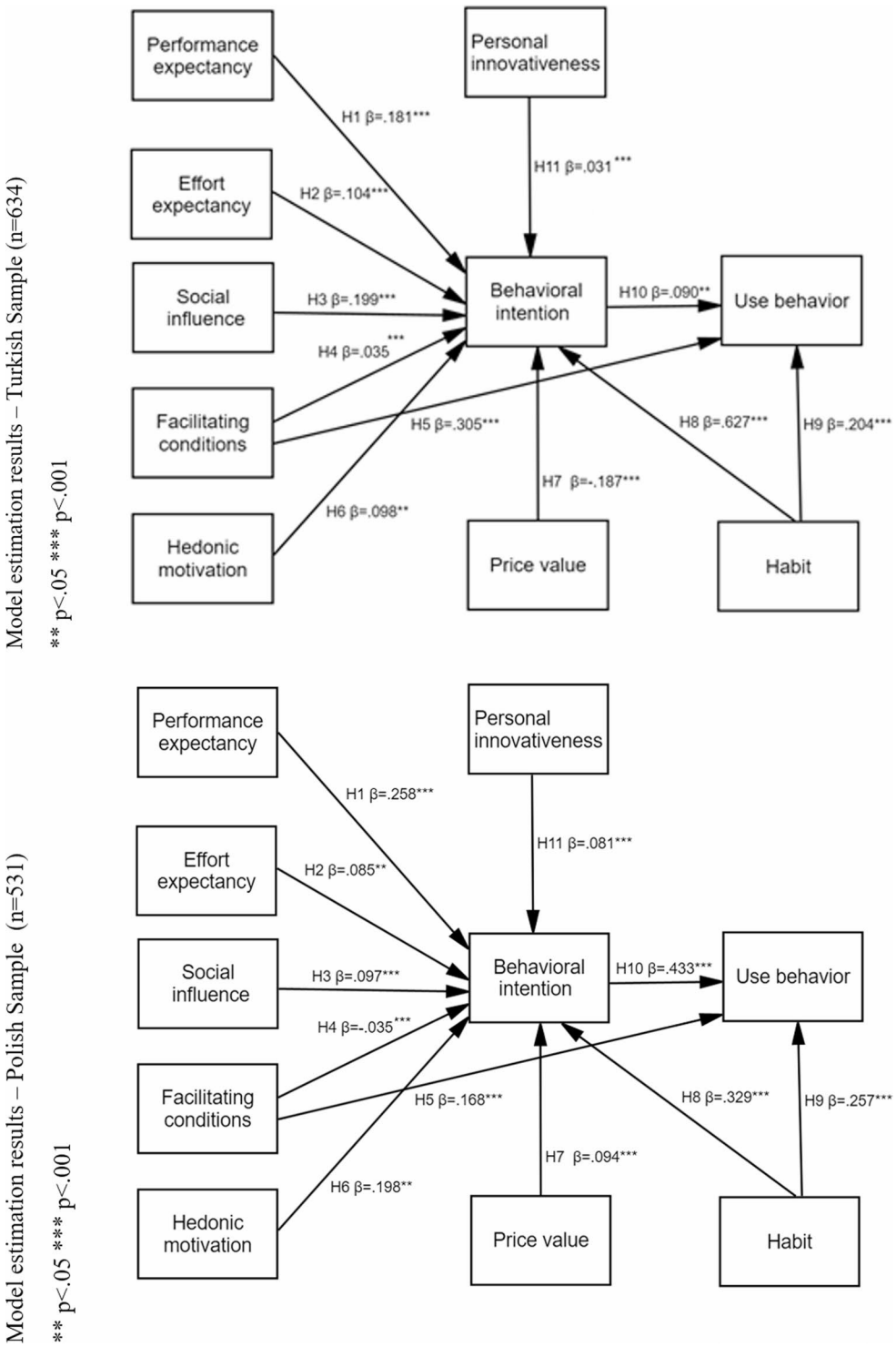


Fig. 2 Visual summary of the structural model results for the Turkish and Polish samples. Note. The figure provides a visual summary of the country-specific model estimates. The Turkish and Polish coefficients are shown side by side for descriptive comparison only. Because formal multi-group difference testing was not conducted, visual differences between coefficients should not be interpreted as statistically confirmed between-country differences

Table 6 Comparative analysis of coefficients of determination for behavioral constructs in Türkiye and Poland

Constructs	Türkiye		Poland	
	R^2	Adjusted R^2	R^2	Adjusted R^2
Behavioral intention	0.521	0.515	0.731	0.727
Use behavior	0.281	0.278	0.542	0.539

4 Discussion

This study comparatively examined ChatGPT adoption among higher education students in Türkiye and Poland through an extended UTAUT2 framework that also included personal innovativeness. Overall, the findings indicate that the model was empirically useful in both samples, but that

Table 7 Structural path coefficients for the Turkish and Polish samples

	Variables	Türkiye				Poland			
	Predictive ➞ Outcome	β	f^2	t	*p*	β	f^2	t	*p*
H1	Performance expectancy ➞ Behavioral intention	0.181	0.026	3.598	0.001	0.258	0.102	6.855	0.001
H2	Effort expectancy ➞ Behavioral intention	0.104	0.018	2.735	0.006	0.085	0.012	2.273	0.023
H3	Social influence ➞ Behavioral intention	0.199	0.033	3.992	0.001	0.097	0.023	3.106	0.002
H4	Facilitating conditions ➞ Behavioral intention	0.035	0.001	3.612	0.001	0.035	0.002	3.925	0.001
H5	Facilitating conditions ➞ Use behavior	0.305	0.068	7.409	0.001	0.168	0.044	4.853	0.001
H6	Hedonic motivation ➞ Behavioral intention	0.098	0.008	2.024	0.043	0.198	0.052	4.804	0.001
H7	Price value ➞ Behavioral intention	−0.187	0.040	4.743	0.001	0.094	0.019	2.821	0.005
H8	Habit ➞ Use behavior	0.204	0.024	4.074	0.001	0.257	0.076	5.788	0.001
H9	Habit ➞ Behavioral intention	0.627	0.317	12.296	0.001	0.329	0.251	12.393	0.001
H10	Behavioral intention ➞ Use behavior	0.090	0.006	2.197	0.028	0.433	0.177	9.834	0.001
H11	Personal innovativeness ➞ Behavioral intention	0.031	0.001	7.602	0.001	0.081	0.016	7.862	0.001

Coefficients for the Turkish and Polish samples are presented side by side for descriptive comparison. Because formal multi-group difference testing was not conducted, differences in coefficient magnitude across samples should not be interpreted as statistically confirmed between-country differences

the relative prominence of specific predictors varied across them. At the same time, these variations should be interpreted cautiously. Because formal multi group difference testing was not conducted, the present discussion treats the Turkish and Polish findings as country specific patterns and descriptive contrasts rather than statistically confirmed between country differences. Within that boundary, however, the results still provide a meaningful basis for contextual interpretation and for situating the two samples within the rapidly expanding literature on ChatGPT adoption in higher education.

One of the clearest findings concerns the role of performance expectancy. In both samples, students were more likely to express behavioral intention toward ChatGPT when they perceived the tool as useful for their academic work. This result is highly consistent with the growing literature showing that perceived usefulness remains one of the most stable determinants of ChatGPT adoption across diverse higher education settings, including Poland, Norway, Croatia, and Jordan (Strzelecki, 2024; Strzelecki & ElArabawy, 2024; Grassini et al., 2024; Biloš & Budimir, 2024; Al-Okaily et al., 2025). In descriptive terms, the coefficient was larger in the Polish sample, suggesting that expected academic gains may have played a somewhat more central role there. This pattern can be interpreted in a careful and non deterministic way. In contexts where digital tools are more readily integrated into students' everyday academic routines, ChatGPT may be assessed more directly in terms of productivity, clarity, task support, and efficiency. The present findings also resonate with Romero-Rodríguez et al. (2023), who argue that students often perceive ChatGPT not merely as a time saving device but as a form of cognitive support that can assist them in explanation, idea development, and intellectual processing. Read in that light, performance expectancy in the present study may reflect not only instrumental utility but also a broader perception of ChatGPT as a helpful academic partner. Even so, the stronger descriptive effect observed in Poland should not be overstated. The Turkish sample also showed a clearly significant path, meaning that usefulness mattered in both settings. The more appropriate conclusion is therefore that performance expectancy appears to function as a robust cross sample driver, while its relative weight may shift depending on the local educational and technological context.

A second important pattern concerns effort expectancy. Ease of use was significant in both samples, but its coefficient was descriptively larger in Türkiye. This is an important finding precisely because it resists simplistic assumptions that more digitally advantaged settings will always produce stronger effort expectancy effects. Prior work has shown that effort expectancy can remain an important predictor in technology acceptance, but its role is not uniform across contexts, and in some studies it has even become secondary to other concerns (Strzelecki, 2024; Biloš & Budimir, 2024). The present results suggest that in the Turkish sample, students' intention to use ChatGPT depended more strongly on whether the tool felt easy to learn, easy to navigate, and cognitively manageable. One possible interpretation is that in settings where students may encounter more variability in experience, support, or confidence, a system's immediate usability becomes especially salient. In such contexts, ease of use may function not as a convenience but as a threshold condition for adoption. Romero-Rodríguez et al. (2023) indirectly support this interpretation by emphasizing that students engage with ChatGPT as part of a broader cognitive workflow rather than as a simple interface. From this perspective, effort expectancy may refer not only to technical simplicity but also to the ease with which the tool can be meaningfully incorporated into academic thinking. In the Polish sample, the path remained significant, but its smaller

coefficient may indicate that ease of use was less central relative to other evaluative factors, such as perceived usefulness, enjoyment, and intention driven actual use.

A related pattern emerged for social influence, which was significant in both samples but descriptively stronger in Türkiye. This finding suggests that the perceived expectations of peers, instructors, or the broader academic environment may have mattered more strongly in the Turkish sample. Existing research has repeatedly shown that social influence can play a meaningful role in ChatGPT adoption, especially when the use of the tool becomes publicly visible, socially discussed, or institutionally signaled (Strzelecki & ElArabawy, 2024; Faraon et al., 2025). In the present study, the Turkish result may indicate that adoption was more closely tied to social legitimacy. In other words, students may have been more inclined to intend continued use when they believed that relevant others viewed ChatGPT favorably or at least as acceptable. This does not require a deterministic cultural explanation. It is enough to observe that in some academic environments, the social meaning of AI use can become highly consequential. When a tool is new, normatively contested, or associated with concerns about fairness and academic integrity, endorsement from instructors and peer groups may matter a great deal. The present results therefore point to a practical implication that is stronger than a purely technical recommendation: if institutions want students to use ChatGPT responsibly, they may need not only guidelines and infrastructure but also clear signals about when, how, and under what conditions such use is legitimate.

Facilitating conditions generated one of the most revealing patterns in the study. Their path to behavioral intention was statistically significant but practically negligible in both samples, whereas their path to actual use behavior was much more substantial, especially in Türkiye. This distinction is theoretically and practically important. It suggests that resources, knowledge, and support may not strongly determine whether students *want* to use ChatGPT, but they do matter for whether students *actually use* it in practice. This interpretation is strongly aligned with Guillén-Yparrea and Hernández-Rodríguez (2024), who show that students' practical difficulties with AI tools often revolve around access, prompting competence, and the ability to judge outputs. Such concerns are not abstract preferences; they are enabling or constraining conditions of use. In this sense, facilitating conditions are better understood as implementation variables than as motivational variables. The pattern is particularly notable in the Turkish sample, where the H5: Facilitating Conditions (FC) → Use Behavior (UB) path was descriptively stronger. When read together with the relatively weak H10: Behavioral Intention (BI) → Use Behavior (UB) path in Türkiye, the implication becomes even clearer: positive intention alone may not translate into sustained use unless students also possess the material, technical, and procedural conditions needed to act on that intention. This finding is important for policy. Universities often assume that once students see AI tools as useful, adoption will naturally follow. The present results suggest otherwise. Institutions may need to invest not only in awareness or attitude formation but also in support structures that enable actual use, including guidance, skill development, and accessible institutional frameworks. Because FC4 showed weaker and less consistent loading, especially in the Turkish sample, the facilitating conditions findings should be interpreted with additional caution. The sensitivity check suggests that the main structural interpretation remains stable after excluding FC4, but the construct-level comparison should still be read as descriptive rather than definitive.

The results for hedonic motivation further enrich the picture. Hedonic motivation significantly predicted behavioral intention in both samples and was descriptively stronger in Poland. This suggests that enjoyment, curiosity, and the intrinsically engaging side of ChatGPT were more visible in the Polish sample. This pattern is compatible with previous studies showing that enjoyment can function as a meaningful predictor of emerging technology use, including ChatGPT and related AI tools in higher education (Biloš & Budimir, 2024; Faraon et al., 2025). De Martino et al. (2025) are especially useful here because they frame enjoyment not merely as superficial entertainment but as a potential bridge to more sustained engagement, self regulation, and higher order learning. Read in this light, the present findings do not imply that Polish students were simply using ChatGPT because it was amusing. Rather, they suggest that the pleasurable and exploratory aspects of interacting with the tool may have supported stronger willingness to adopt it. In the Turkish sample, hedonic motivation also mattered, but its lower coefficient implies that intention may have depended more on pragmatic and social conditions than on enjoyment alone. From a pedagogical standpoint, this distinction matters. If enjoyment can support experimentation and sustained engagement, then instructional designs that channel curiosity into academically meaningful use may be especially valuable. At the same time, as both De Martino et al. (2025) and Dietrich and Grassini (2025) suggest in different ways, enjoyable engagement with AI also requires ethical scaffolding. Otherwise, a highly engaging tool may be adopted rapidly without a corresponding growth in critical awareness.

The most theoretically distinctive finding concerns H7: Price Value (PV) → Behavioral Intention (BI). In Türkiye, this path was statistically significant but negative, indicating a reversed relationship rather than a merely unsupported

hypothesis; in Poland, the same path was positive and significant. This opposite directional pattern is one of the most important contributions of the study because it shows that cost benefit reasoning did not operate similarly across the two samples. At the same time, the interpretation must remain careful. The price value items in the questionnaire explicitly referred to ChatGPT Plus at a stated cost of USD 20 per month, but respondents' actual subscription status and access conditions were not measured. Thus, the result should not be read as direct evidence about payment behavior. Rather, it indicates that the *perceived worth* of paid ChatGPT access was evaluated differently across the two groups. In the Polish sample, the positive path suggests that the perceived benefits of premium access were more likely to outweigh the stated monetary cost. In the Turkish sample, the negative path suggests the opposite. Rawas (2024) helps explain why this difference may matter beyond simple price sensitivity. The value of a paid AI service is shaped not only by direct cost but also by time savings, quality of output, access limitations in free versions, and the user's broader sense of whether the investment is worthwhile. In contexts where the cost is more likely to be experienced as burdensome, the evaluative balance may tilt away from adoption. The current findings cannot prove a macroeconomic explanation, but they do justify the cautious interpretation that affordability and perceived worth may be more problematic in some settings than in others. For higher education institutions, this result is especially important because it suggests that equitable access to AI tools cannot be treated as a purely individual matter. If premium functionality substantially affects perceived usefulness, then affordability may become a real part of digital inequality.

Habit emerged as one of the strongest constructs in the model. It significantly predicted both behavioral intention and use behavior in both samples, and the H9: Habit (HT) → Behavioral Intention (BI) path was by far the strongest predictor of behavioral intention in each group. This result is consistent with a growing international literature showing that repeated exposure and routinized use are central to the incorporation of ChatGPT and other AI tools into everyday student practice (Strzelecki, 2024; Grassini et al., 2024; Biloš & Budimir, 2024; Faraon et al., 2025). However, the pattern differed in its configuration. H9: Habit (HT) → Behavioral Intention (BI) path was descriptively much larger in Türkiye, whereas H8: Habit (HT) → Use Behavior (UB) was somewhat larger in Poland. This combination is theoretically interesting. In the Turkish sample, routinized use may have been more tightly linked to students' stated willingness to continue using ChatGPT in the future. In the Polish sample, habit may have translated more directly into regular enacted behavior. This interpretation becomes particularly compelling when read alongside the H10: Behavioral Intention (BI) → Use Behavior (UB) path. In Poland, intention strongly predicted actual use, whereas in Türkiye the path, though significant, was much weaker. Together, these results point to a more visible intention behavior gap in the Turkish sample. Students may express willingness, develop positive routines, and still face barriers that reduce the translation of intention into enacted practice. In this sense, habit is not merely a positive force. As Karkoulian, Sayegh, and Sayegh (2025) caution, routinization can increase efficiency but may also diminish reflective control if use becomes automatic. The present study does not directly test ethical outcomes, but the strength of habit suggests that institutions should not only encourage effective use but also support reflective and responsible use before routines become normalized in uncritical ways.

The findings for H10: Behavioral Intention (BI) → Use Behavior (UB) deserve special emphasis because they speak directly to the difference between wanting to use ChatGPT and actually using it. The path was significant in both samples, but it was much stronger in Poland. This suggests a clearer intention action linkage there. In the Turkish sample, by contrast, the path was comparatively weak, which may indicate that intention alone was not enough to ensure use. This interpretation is also compatible with the lower R^2 values observed in Türkiye for both behavioral intention and use behavior. In other words, the extended UTAUT2 model explained meaningful variance in both settings, but it explained substantially more in Poland. This does not invalidate the model for the Turkish sample. Rather, it suggests that additional contextual predictors not captured in the present study may be more relevant there. Blahopoulou and Ortiz-Bonnin (2025) offer a useful lens for this issue by showing that users and non users can differ sharply in their attitudes toward AI tools, including resistance, uncertainty, and even support for restrictive positions. Similarly, Ortiz-Bonnin and Blahopoulou (2025) emphasize that perceived academic dishonesty risks can suppress both intention and actual use. Read together with the present results, these studies suggest that intention behavior gaps may emerge not because students lack motivation, but because the practical, normative, or institutional environment makes implementation less straightforward. Thus, the weaker H10: Behavioral Intention (BI) → Use Behavior (UB) path in Türkiye should be read not as a deficit of students, but as a sign that intention can be interrupted by contextual friction. The supplementary control check also indicated that the main patterns emphasized in the discussion, especially those concerning H7: PV → BI, H8/H9 habit-related paths, and H10: BI → UB, remained substantively stable after gender and academic level were considered. Nevertheless, these controls do not eliminate the need for caution, since the samples were convenience-based and not nationally representative.

Finally, personal innovativeness was significant in both samples, but its practical role remained modest. The path coefficient was descriptively larger in Poland, and the effect size was also somewhat larger there, yet in both groups personal innovativeness was clearly weaker than predictors such as habit, performance expectancy, and, depending on the sample, social influence or hedonic motivation. This is an important corrective to overly individualistic narratives of AI adoption. Students' openness to trying new technologies matters, but it does not override the broader structure of expectations, support, and routine use. Foroughi et al. (2025) argue that UTAUT based models benefit from including individual difference variables such as innovativeness and risk orientation, and the present findings support that view, but only in a measured sense. The contribution of personal innovativeness here is not transformative; it is supplementary. Chuah and Sumintono (2024) are especially relevant because they show that readiness to use ChatGPT in academic assessment contexts varies considerably and depends on institutional clarity as much as on personal predisposition. Likewise, Ortiz-Bonnin and Blahopoulou (2025) show that risk perceptions can suppress use even when students are otherwise open to innovation. In the present study, the small effect sizes suggest that being innovative may help students move toward intention, but only within limits set by the wider educational environment. Therefore, universities should not assume that innovation minded students will naturally self regulate their AI use without institutional support. Clear guidance, transparent rules, and trustworthy pedagogical integration remain necessary even for those most ready to experiment.

Taken together, the discussion points to three broader conclusions. First, the extended UTAUT2 framework appears useful for explaining ChatGPT adoption in both samples, but the explanatory structure is not identical across them. Second, not all significant predictors are equally important in practical terms. Facilitating Conditions (FC) → Behavioral Intention (BI) and Personal Innovativeness (PI) → Behavioral Intention (BI), for example, were statistically significant yet weak in practical magnitude, whereas habit, performance expectancy, and, in the Polish sample, Behavioral Intention (BI) → Use Behavior (UB) played a much stronger role. Third, the findings support the need for context sensitive implementation strategies in higher education. Institutions that want to promote responsible and effective ChatGPT use should not focus only on attitudes or only on technical access. They should simultaneously consider usefulness, usability, social legitimacy, support conditions, affordability, and the possibility that intention may not automatically become use.

At the same time, the study's interpretive boundaries should remain explicit. The comparison between Türkiye and Poland is informative, but it does not establish formal cross national moderation effects. Culture was not measured at the individual level, and formal multi group difference testing was not conducted. For that reason, the present study does not claim that the observed coefficient differences represent statistically confirmed national contrasts. What it offers instead is a cautious comparative reading of two country specific adoption patterns. Within those limits, the contribution remains meaningful. The study shows that ChatGPT adoption in higher education is not governed by a single universal mechanism. Similar constructs matter in both settings, but their relative prominence differs, and these differences have practical implications for policy, pedagogy, and institutional support. In that sense, the present findings contribute to the international literature not by claiming definitive causal differences between countries, but by demonstrating how a comparative design can reveal important variation in the structure of AI adoption across higher education contexts.

4.1 Conclusion and Practical Implications

This study comparatively examined ChatGPT adoption among higher education students in Türkiye and Poland through an extended UTAUT2 framework that also included personal innovativeness. Overall, the findings indicate that the model was empirically useful in both samples, but that the relative prominence of specific predictors was not identical across them. Performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and personal innovativeness were all positively associated with behavioral intention in both groups, while facilitating conditions and behavioral intention were associated with actual use behavior. At the same time, the descriptive comparison of coefficients showed that some factors appeared more salient in one sample than in the other. In particular, price value differed in direction across the two groups, habit emerged as a particularly strong predictor of behavioral intention in both samples, and the behavioral intention–use behavior link appeared more substantial in Poland than in Türkiye.

These results suggest that ChatGPT adoption in higher education cannot be reduced to a single universal mechanism. The same core constructs may matter in different settings, yet their relative weight and practical implications may vary depending on local educational, institutional, and economic conditions. In this respect, the study contributes to the growing literature on generative AI in higher education by showing that comparative designs can reveal meaningful variation in adoption patterns even when the same theoretical framework is applied across national samples. The contribution of the study, therefore, lies not in claiming formally established cross-national moderation, but in offering a cautious comparative account of how the extended UTAUT2 model operates in two different higher education contexts.

The findings carry several implications for higher education institutions seeking to support the responsible and effective use of ChatGPT and related generative AI tools. First, universities should move beyond a purely attitudinal approach to technology adoption. Positive perceptions of usefulness are important, but they are not sufficient on their own. The results suggest that actual use also depends on whether students have the practical conditions needed to translate intention into behavior. Institutions should therefore invest not only in awareness raising, but also in the concrete supports that make AI use feasible in everyday academic practice. These supports may include guidance on prompting, critical evaluation of outputs, and accessible technical assistance.

Second, universities should develop clear and explicit policies regarding the appropriate academic use of generative AI. Students are more likely to engage with tools such as ChatGPT when institutional expectations are visible and understandable. Clear rules can reduce uncertainty, support academic integrity, and help students distinguish acceptable assistance from problematic dependence. In this sense, ethical guidance should not be treated as an external add on. It should be incorporated into the broader support structure surrounding AI use in higher education.

Third, the findings indicate that institutions should pay attention to the gap that may emerge between intention and actual use. Where students express willingness to use ChatGPT but do not consistently translate that willingness into behavior, the problem may lie less in motivation and more in practical or structural barriers. For this reason, implementation strategies should include not only policy statements but also training opportunities, instructor guidance, and efforts to reduce friction in actual use. Faculty members are particularly important here, as their visible modeling of responsible AI use may shape the legitimacy of these tools within the learning environment.

Finally, the opposite direction of H7: PV → BI across the two samples suggests that affordability and perceived worth should be considered carefully when universities develop policies for student access to generative AI tools. When access to premium AI services is perceived as costly or inequitable, this may weaken adoption even when students recognize potential academic benefits. Institutions should therefore remain attentive to the relationship between access, cost, and educational equity. Where possible, they should consider how students' lived economic conditions may influence their willingness to adopt paid AI tools and whether institutional support mechanisms can reduce this burden.

4.2 Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the research employed a cross-sectional survey design. As a result, the study cannot establish causal relationships among the constructs, nor can it capture how students' perceptions and usage patterns may change over time as generative AI tools continue to evolve. Second, the study relied on self-reported data for both behavioral intention and use behavior. Such data are inherently vulnerable to response-related limitations, including recall bias and social desirability bias. Although procedural steps were taken to reduce these risks, common method bias cannot be entirely ruled out.

Third, the comparative design itself involves important constraints. Formal measurement invariance testing and formal multi-group difference testing were not conducted. For that reason, coefficient differences between the Turkish and Polish samples should be interpreted descriptively rather than as statistically confirmed between-country differences. Relatedly, culture was not measured at the individual level. The study therefore does not claim to test cultural mechanisms directly; instead, it offers a cautious contextual interpretation of country-specific patterns. Future comparative research should therefore prioritize measurement invariance testing and formal multi-group analysis before making stronger claims about statistically confirmed country-level differences.

Fourth, the two national samples were not compositionally identical. In particular, differences in gender distribution and academic level may have influenced the observed patterns and may partially overlap with country-level variation. Although supplementary checks indicated that the main descriptive patterns remained substantively stable after considering gender and academic level, these checks do not fully remove the limitations associated with non-equivalent convenience samples. The results should therefore be interpreted as evidence from two specific higher education samples rather than as nationally representative estimates.

Finally, some measurement and contextual limitations should be acknowledged. One facilitating conditions item, FC4, performed more weakly than the other indicators, especially in the Turkish sample. Although the sensitivity check suggested that the main conclusions did not change after excluding this item, FC4 did not function equally strongly across the two samples. Therefore, the facilitating conditions comparison should be interpreted with this measurement limitation in mind. In addition, the study did not directly measure respondents' subscription status, actual access conditions, or the specific version of ChatGPT they were using. This is especially relevant for interpreting the price value findings, since perceived worth may differ depending on whether students relied on free or paid access and under what conditions they encountered the tool.

Future research can build on the present study in several ways. From a methodological perspective, longitudinal and experimental designs would be especially valuable.

Longitudinal research could show how initial intention develops into sustained or discontinued use over time, while experimental designs could test whether specific interventions—such as structured training, policy clarification, or guided prompting support—strengthen the translation of intention into actual behavior. Comparative studies should also incorporate formal measurement invariance procedures and multi-group testing when the aim is to establish statistically confirmed differences between national or subgroup samples.

Future studies would also benefit from extending the range of measured variables. Because the present study interpreted the results contextually rather than through direct measurement of culture, future models could include individual-level indicators such as perceived academic risk, institutional trust, policy clarity, or orientations toward technology and uncertainty. Similarly, direct measures of access conditions, subscription status, and patterns of free versus paid use would help clarify how students evaluate the cost and worth of ChatGPT in different settings. It may also be useful to examine subgroup variation more directly, including differences by gender, academic discipline, and study level.

A further direction concerns the combination of methods. Mixed-method designs could provide a deeper understanding of why some students translate intention into action more easily than others. Interviews, focus groups, or reflective accounts could help identify the practical and normative barriers underlying the intention–behavior gap observed in some contexts. Where ethically and technically feasible, future studies may also combine self-report data with trace-based indicators of actual use in order to produce a more robust picture of students' interactions with generative AI tools. In particular, formal measurement invariance testing and multi-group analysis should be treated as methodological priorities in future comparative studies that aim to establish whether observed coefficient differences represent statistically significant cross-group differences. Finally, expanding the comparison to additional countries and disciplinary fields would help clarify which findings are likely to be context-specific and which may generalize more broadly across higher education environments.

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Data Availability The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics Approval Ethical approval for this study was obtained from the Afyon Kocatepe University Social and Human Sciences Scientific Research and Publication Ethics Committee (Decision No: 2023/377, Date: 20.12.2023). Prior to data collection, all participants were presented with a digital informed consent form on the first page of the Google Form. They were informed that their participation was voluntary, anonymous, and that they could withdraw at any time without penalty. No personal identifying information (e.g., names, student IDs) was collected to ensure strict confidentiality.

Consent to Participate All participants provided informed consent prior to participating in the study.

AI Declarations In preparing this manuscript, the authors used the ChatGPT- 5.4 tool solely for language refinement and text editing purposes (e.g., improving grammar, clarity, and academic tone). The intellectual content, structure, arguments, data analysis, and interpretation were entirely developed by the authors. All outputs generated by the AI tool were thoroughly reviewed, revised, and verified by the authors before submission, and full responsibility for the final content lies with the authors.

Conflict of interest The authors declare no conflict of interest related to this study.

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