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Motivational and appraisal factors shaping generative AI use and intention in Austrian higher education students and teachers

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This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine factors influencing generative AI (genAI) use among Austrian higher education students ($n = 3{,}094$) and teachers ($n = 1{,}767$). We applied confirmatory structural equation modeling (SEM) to replicate prior evidence on performance expectancy, effort expectancy, and social influence, and introduced partial least squares SEM (PLS-SEM) to examine challenge and threat appraisals as additional predictors. Behavioral intention strongly predicted genAI use ($\beta = 0.75$, $p < 0.001$ for students; $\beta = 0.48$, $p < 0.001$ for teachers), with performance expectancy, effort expectancy, and social influence as key positive predictors. Effort expectancy was particularly salient for teachers, reflecting time constraints. Gender differences emerged primarily among students: females reported lower subjective competence, intrinsic motivation, and challenge appraisals, but higher threat appraisals; differences were weaker in teachers. Linear regression analyses showed that challenge appraisals—predicted by intrinsic motivation, trust in genAI, and genAI-related subjective competence—positively influenced behavioral intention, whereas threat appraisals had a small negative impact ($\beta \approx -0.03$). The extended model explained substantial variance in behavioral intention ($R^2 \approx 0.8$) and genAI use (students $R^2 = 0.34$; teachers $R^2 = 0.18$). These findings highlight the importance of aligning AI integration with user needs, motivation, and affective responses to support meaningful and ethical genAI adoption in higher education. Future research should consider individual differences, institutional culture, and evolving AI landscapes to optimize adaptive AI use across diverse educational stakeholders.

KEYWORDS

genAI, motivation, UTAUT, students, teachers, appraisal

1 Introduction

The integration of artificial intelligence (AI) tools, particularly generative AI (genAI) like ChatGPT, into higher education (HE) has become a focal point of contemporary academic discourse. Despite challenges in data security and general concerns, such as the risk of losing certain basic competences—a concern particularly emphasized by teachers (cf. Tulis et al., 2024)—these tools have the potential to revolutionize teaching and learning methodologies, offering personalized learning experiences, instant feedback, and enhanced engagement for students (Lim et al., 2023; Hwang and Chen, 2023; Brandhofer and Tengler, 2025). However, acceptance as well as effective and adaptive utilization of such agents rely upon various structural and motivational factors, as identified in different models of AI adoption in higher education (Abulail et al., 2025). Recent evidence highlights concerns about the undermining of critical thinking through AI use (Gerlich, 2025), stressing the importance of understanding the underlying motivations to develop adaptive strategies in higher education, i.e., context-sensitive approaches that enable students and educators to flexibly adjust teaching, learning, and assessment practices in response to technological, motivational, and structural challenges, in higher education. While prior research has mainly focused on students' acceptance and use of genAI, little is known about the interplay between motivation and appraisal within an integrative model among both students and teachers in higher education. Evidence from Austrian higher education is lacking, leaving open questions about cross-context generalizability and the specific role of gender and study level across countries.

For teachers, empirical evidence on motivational predictors of genAI use is especially scarce in international literature (cf. Crompton and Burke, 2023). Yet, teachers' acceptance and didactic integration of AI are pivotal for shaping student experiences. Recent studies (Nikolic et al., 2024; Acosta-Enriquez et al., 2024) have highlighted the significance of supportive learning environments as well as motivational factors, such as expectancy-value beliefs (Eccles, 1983) in shaping students' motivations to engage with AI technologies, in particular genAI (Strzelecki, 2023; Strzelecki and ElArabawy, 2024). These models are based on the Unified Theory of Acceptance and Use of Technology (UTAUT), which is grounded in ongoing technological developments (Venkatesh et al., 2003; Patterson et al., 2024; Yakubu et al., 2025). Building on the motivational foundations (cf. Davis, 1989), adoption frameworks such as UTAUT provide a structured way to model how such beliefs translate into behavioral intention and use. The UTAUT provides a framework for understanding the acceptance and use of technology, encompassing constructs such as performance expectancy (the degree to which an individual believes that using AI will enhance their job performance), effort expectancy (the degree of ease associated with using AI), social influence (the extent to which an individual perceives the importance of others believing they should use AI), and facilitating conditions (the extent to which an individual believes that organizational and technical infrastructure supports the use of AI; cf. Venkatesh et al., 2012; Strzelecki, 2023) for technology in general as well as genAI use in particular (Strzelecki, 2023). Expectancy-value beliefs complement UTAUT constructs in that performance and effort expectancies align with perceived task value and cost, while expectancy beliefs closely parallel intrinsic motivation and self-efficacy as part of appraisal. For instance, supportive environments that provide accessible resources and positive social norms (cf. Lim et al., 2023) have been shown to enhance self-efficacy in students—that is, their belief in their ability to successfully learn how to use AI through sustained effort. This is an important factor in fostering motivation to learn about AI with implications for adaptive vs. problematic AI use, especially under stressful conditions, as the evidence suggests (Zhang et al., 2024). Empirical evidence suggests performance expectancy, i.e., the perceived usability of AI to be a central driver of (gen)AI use (Strzelecki, 2023; Strzelecki and ElArabawy, 2024; Patterson et al., 2024; Verma et al., 2025). Critical aspects of genAI usage should therefore be considered in usage models to counteract heavy reliance on what we call "genAI-utilitarianism," i.e., the tendency to reduce AI adoption to purely instrumental efficiency gains while neglecting critical reflection, creativity, and long-term competence development in higher education contexts where knowledge is being produced and transferred. Gender was found to significantly moderate the relationship between effort expectancy and behavioral intention to use AI in an Egyptian student sample, but not in a Polish student sample (Strzelecki and ElArabawy, 2024). However, the direction of the effect is not reported. In contrast, study level, i.e., which degree is being sought, moderated the relationship in the Polish sample but not in the Egypt sample. Study level is relevant because digital, in particular genAI, self-efficacy and knowledge are expected to increase over the course of higher education. Examining whether predictors of AI use vary by study level can therefore inform stage-specific interventions for undergraduates vs. advanced students. For teachers, we found similar gender effects regarding the subjective competence in AI use as well as the provided didactical and technical support in higher education in Austria (Tulis et al., 2025). This finding aligns with previous research on self-efficacy regarding technology use in general where males would score higher on subjective measures (cf. Janneck et al., 2013). Investigating gender effects in the Austrian context is particularly relevant given ongoing policy discussions about digital literacy gaps and gender equality in STEM education. Understanding whether motivational predictors operate differently across genders in Austria can inform targeted support for both students and teachers.

Challenge and threat appraisals are proposed as additional predictors in understanding the motivational dynamics surrounding AI use (Tulis et al., 2025). Challenge and threat appraisals extend beyond UTAUT's cognitive focus by capturing the affective quality of motivation for genAI engagement. Whereas, UTAUT emphasizes beliefs about usefulness, effort, and social influence, appraisal theory accounts for whether users approach AI with openness and engagement (challenge) or with anxiety and avoidance (threat), thus offering explanatory power for variance not captured by cognitive predictors alone. Individuals experience a challenge state when they perceive sufficient resources to cope with task demands (secondary appraisal), leading to increased engagement and thorough information processing (Blascovich and Mendes, 2000) as well as a sense of opportunity for growth (Drach-Zahavy and Erez, 2002). Conversely, a threat state arises when individuals feel they lack the resources to meet task demands, resulting in motivational disengagement and superficial processing when perceiving potential harm (Blascovich and Mendes, 2000). As we use the terms challenge and threat in two ways, it is important to differentiate: appraisals as incorporated in the analyses of this study are distinct motivational factors strongly associated with self-efficacy (and possibly other AI use predictors) rather than simply reflecting the (cognitive) evaluation of the potential benefits and problems related to AI use, such as data security or the loss of competences (cf. Tulis et al., 2024), and genAI use in particular (Walczak and Cellary, 2023; Chan and Hu, 2023). While the UTAUT traditionally focuses on cognitive evaluations such as performance and effort expectancies besides social influence, recent experimental evidence highlights the critical role of psychological appraisal processes in intention and use of genAI. For instance, Chan et al. (2024) demonstrated that genAI-supported revision reports, while enhancing engagement elicited mixed emotions among students. This finding underscores the necessity of incorporating constructs like challenge and threat appraisals, which offer significant explanatory power by capturing the nuanced emotional and motivational responses to genAI integration, thereby enriching our understanding beyond cognitive and social factors. We found that the perception of challenge, in contrast to threat, is correlated with AI use in higher education for students and teachers likewise (Tulis et al., 2024). In the context of AI adoption, challenge appraisals can enhance users' willingness to engage with AI tools, viewing them as opportunities for growth and efficiency. Threat perceptions can hinder adoption, as users may feel overwhelmed or fearful of the technology's implications (Chang et al., 2024). AI transparency in the workplace is associated with higher challenge appraisals (Yu et al., 2023), highlighting the influence of social norms and influence within a system, possibly introducing implications not only for the higher education within universities but also the administration involved in producing and storing knowledge. Lastly, gender differences were reported for anxiety in AI use associated with negative attitudes toward AI use, especially when AI usage was low (Russo et al., 2025). Compared to men, women reported higher levels of anxiety, more negative attitudes toward the use of artificial intelligence, and lower levels of subjective knowledge regarding its functioning. In contrast, we found a tendency for males to report higher challenge appraisals in AI use (Tulis et al., 2025). Regarding study level, we found no evidence to build on regarding differential effects of challenge and threat appraisals. However, as effort expectancy and knowledge are assumed to increase over the course of one's studies, the moderating effect of gender is hypothesized for both appraisals in line with the motivational predictors of AI use intention and behavior.

To promote a useful and ethical AI incorporation into higher education and to make its advantages accessible to teachers and students, it is important to improve our understanding of the underlying motivational dynamics. This might contribute to the development of successful implementation strategies. Therefore, this study aims to (1) replicate the UTAUT-based model of Strzelecki and ElArabawy (2024) in an Austrian student and teacher sample, (2) test the predictors for challenge and threat appraisals, and (3) extend the model by including challenge and threat appraisals as motivational predictors for genAI intention and use of students and teachers in higher education. We hypothesized:

H1: Performance expectancy, effort expectancy, and social influence positively predict behavioral intention, which mediates their effect on genAI use in students and teachers.
H2: Facilitating conditions directly positively predict genAI use in students and teachers.
H3: Higher genAI-related subjective competence, intrinsic motivation and trust in genAI negatively predict threat appraisal in students and teachers.
H4: Higher genAI-related subjective competence and intrinsic motivation positively predict challenge appraisal in students and teachers.
H5: Higher trust in genAI negatively predict challenge appraisal in students and teachers.
H6: Challenge appraisals positively predict behavioral intention, whereas threat appraisals negatively predict behavioral intention in students and teachers.
H7: Gender moderates the relationship between predictors and behavioral intention, with stronger effects for males in students and teachers.
H8: Study level moderates the relationship between predictors and behavioral intention as well as use, with stronger effects at higher study levels.

2 Method

A total of $N = 4,861$ respondents (3,094 students, of whom 39% were male, 59% female, and 2% non-binary; 1,767 teachers, of whom 51% were male, 47% female, and 2% non-binary) were included in the analyses. The majority of students (42%) belonged mainly to the age group of 21–25 years, as well as the age groups of 26–30 years (23%) and 31–45 years (16%). The participating teachers were primarily between the ages of 31 and 60 years (80%). A detailed description and information of the representativeness of the sample and the data acquisition can be found in Tulis et al. (2024). Please note that for the current study, only German-speaking students undergoing their bachelor, diploma, master, and doctoral program were included in the analyses, resulting in a final sample of $N = 3,094$ students (compared to 3,195 students in the original project report the dataset was first introduced).

By replicating and extending the model from Strzelecki and ElArabawy (2024), this study seeks to validate the findings in the Austrian educational context, thereby contributing to the generalizability of the UTAUT model in the realm of AI adoption in higher education. Furthermore, this study will test the model for HE teachers, providing a comprehensive understanding of the factors that drive the acceptance and effective use of AI tools among both students and teachers. We therefore focused on three lines of research in this study:

1) Replicating the structural model of Strzelecki and ElArabawy (2024) in an Austrian student and teacher sample using confirmatory SEM analysis.
2) Investigating differential effects of the predictors of challenge and threat appraisals, i.e., genAI-related subjective competence, trust in genAI, and intrinsic motivation among students and teachers. Different pathways are proposed to predict threat and challenge appraisals: for threat appraisals the first model contained genAI-related subjective competence, as the subjective believe in knowing how to deal with AI is proposed to shape the subsequent anxiety related appraisal. Next, intrinsic motivation to use AI as initial point to start using AI is added, before trust in genAI, i.e., the subjective trust in the correctness of answers (which should be seen critically) is added. For challenge appraisal intrinsic motivation is expected to be the main predictor, followed by differential trust development and a genAI-related subjective trust.

3) Incorporating challenge and threat appraisals into an exploratory PLS-SEM analysis to the previously tested SEM model for students and teachers (see Figure 1).

Covariance-based SEM was used to test theory-driven models with an emphasis on global model fit, while PLS-SEM was chosen to explore predictive extensions of the UTAUT framework. The inclusion of new constructs (challenge and threat appraisals) and potential formative relationships justified the use of PLS-SEM, which is robust for prediction-oriented analyses and does not rely on multivariate normality (Sarstedt et al., 2022). This stepwise SEM approach, combined with differential linear regression analyses of new predictors prior to their incorporation into the model, offers a comprehensive analysis of the factors influencing genAI use in academic settings.

Statistical analyses were carried out using R (version 4.3.1; R Core Team, 2023) in RStudio (version 2023.03.0+386; RStudio Team, 2023) for SEM and PLS-SEM, and JASP (version 0.18.3; JASP Team, 2023) for linear regression. SEM was conducted using the *lavaan* package (Rosseel, 2012), and PLS-SEM analyses were performed using the *plspm* (Sanchez et al., 2017) and *seminr* (Hair et al., 2021) packages. The methodology involves a survey-based approach, utilizing the SEM as well as the partial least squares structural equation modeling (PLS-SEM) approach to analyze the data collected from Austrian university students and teachers. Unlike covariance-based SEM, which focuses on model fit and theory confirmation, partial least squares SEM (PLS-SEM) is prediction-oriented and well-suited for exploring complex relationships and extending existing models. The survey measured the key constructs of the UTAUT model, including performance expectancy, effort expectancy, social influence, and facilitating conditions, along with moderating variables, such as gender and study level for students, and technological literacy and trust in AI for teachers.

The descriptives for the sample characteristics and of each variable including reliability for students and teachers separately can be found in Supplementary Table 1. Please note that a detailed description of the UTAUT-questionnaire scales can be found in Strzelecki and ElArabawy (2024) as well as Tulis et al. (2024) for adaptations. The UTAUT scales were measured on a 5-point Likert scale and three to four items each, i.e., Performance expectancy (usefulness, success, efficiency, productivity), effort expectancy (adopting, communication, ease of use, skillful handling), and social influence (important people, influencing people, valued people). AI use behavior was operationalized as use frequency in winter term 2023/2024 for genAI (we also measured other types of AI) as well as the intention to use AI in the future (continued use, planned use, planned frequency of use). GenAI is defined as a type of artificial intelligence that produces new content—such as text, images, audio, or video—based on provided prompts and pre-existing data. This category includes AI chatbots like ChatGPT, Gemini/Bard, and Bing, as well as creative tools such as DALL·E, Murf AI, Simplified, and Midjourney. These systems generate novel outputs rather than simply retrieving or restructuring existing information. Challenge and threat appraisals were measured with four items each on a 5-point Likert scale, i.e., challenge (overcoming obstacles, increase skills, increase self-esteem, mastering) and threat (threat, exposing weaknesses, not mastering, lack of skills; items adopted to the context of AI from Feldhammer-Kahr et al., 2021). GenAI-related subjective competence and trust in genAI were measured with a single item on a 6-point and 5-point Likert scale. Intrinsic motivation was measured on a 5-point Likert scale (fun, desire, appreciation, interest, productivity; Tulis and Dresel, 2018).

Gender effects were examined descriptively and via group comparisons prior to moderation tests in SEM/PLS-SEM to (a) provide a clearer picture of mean-level differences, and (b) avoid conflating structural moderation with baseline disparities. This stepwise approach helps disentangle whether possible moderation effects reflect structural differences or are simply due to mean differences across groups. As the number of non-binary respondents (2% of the sample) was too small for reliable group-based inference, they were excluded from Mann–Whitney U-tests and moderation, but retained in descriptive analyses and in the overall SEM/PLS-SEM models to avoid sample bias. To formally test moderation, categorical variables were dummy coded. Gender was coded as a binary variable (male = 0, female = 1), allowing creation of interaction terms with centered continuous predictors (e.g., perceived effort, self-efficacy, social influence). Study level, an ordinal variable with four categories (bachelor, diploma, magister/master, promotion), was dummy coded using bachelor as the reference category, yielding three dummy variables (diploma, master, promotion). Interaction terms between each centered predictor and each dummy-coded category were included in the SEM to estimate whether structural paths differed across gender or study levels. This stepwise approach helps disentangle whether observed moderation effects reflect genuine structural differences or are merely due to mean-level disparities across groups.

As gender effects are found in various predictors of technology and AI use (cf. Tulis et al., 2024, 2025; Russo et al., 2025), we analyzed gender effects for genAI related subjective competence, trust in AI, intrinsic motivation as well as challenge and threat appraisals in the Austrian students and teacher sample before reporting the results for the hypotheses. We computed Mann Whitney U-Tests as assumptions for parametric testing were not met, Shapiro Wilk test for normality distribution significant for all dependent variables in both samples. Levene's test for equality of variances was significant for all dependent variables except challenge appraisal for students. For teachers, the test was non-significant, indicating that the variances across male and female are equal for teachers in all dependent variables (descriptives are found in Table 1).

The results for students indicated a significant difference in genAI-related subjective competence between groups, $U = 1{,}321$, $p < 0.001$, with a small to moderate effect size ($r_{rb} = 0.21$, $SE = 0.021$). Similarly, intrinsic motivation differed significantly between groups, $U = 1{,}287$, $p < 0.001$, $r_{rb} = 0.17$, $SE = 0.021$, as did challenge appraisal, $U = 1{,}176$, $p < 0.001$, $r_{rb} = 0.07$, $SE = 0.021$, and threat appraisal, $U = 1{,}006$, $p < 0.001$, $r_{rb} = -0.08$, $SE = 0.021$.

No significant difference was found in trust in genAI, $U = 1{,}074$, $p = 0.319$, $r_{rb} = -0.02$, $SE = 0.021$.

A series of Mann–Whitney U tests were conducted to examine group differences across the five psychological constructs related to AI use for teachers. A significant difference was found in genAI-related subjective competence, $U = 422{,}938.5$, $p < 0.001$, with a small effect size ($r_{rb} = 0.12$, $SE = 0.028$). Additionally, intrinsic

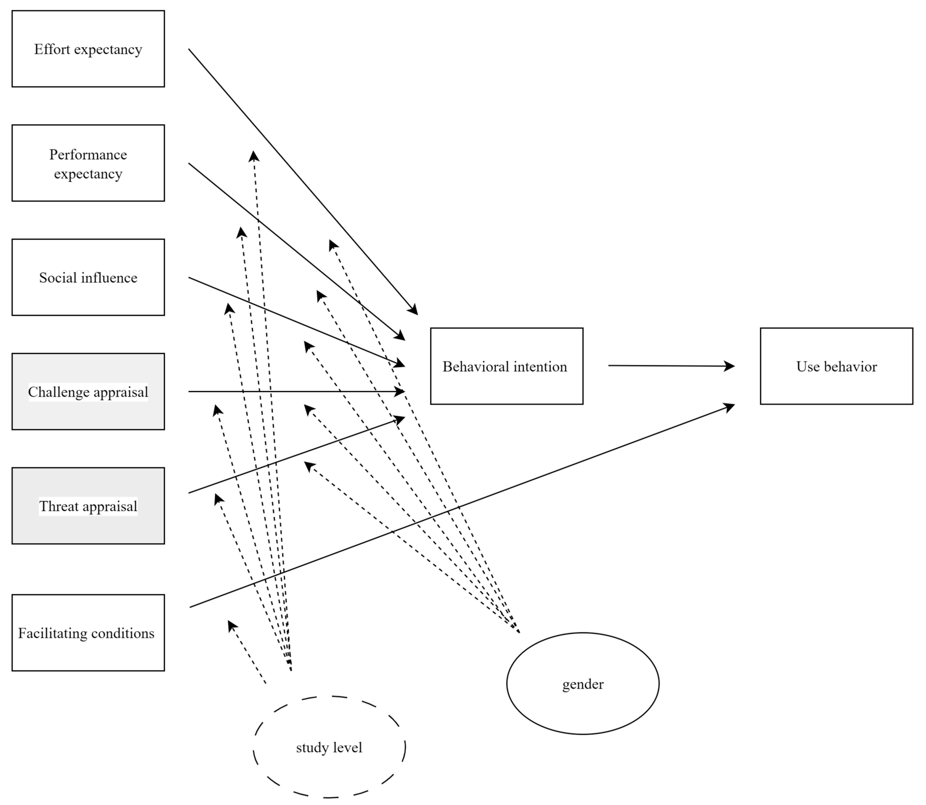

FIGURE 1
Proposed PLS structural equation model for students (study level, gender) and teachers (gender). The model represents the replication of Strzelecki and ElArabawy (2024) and incorporates additional predictors, namely challenge and threat appraisals.

motivation differed significantly between groups, U = 399,577.5, $p = 0.035$, $r_{rb} = 0.06$, $SE = 0.028$.

No significant differences were found in trust in genAI, U = 393,190.5, $p = 0.113$, $r_{rb} = 0.04$, $SE = 0.028$; challenge appraisal, U = 396,960.5, $p = 0.062$, $r_{rb} = 0.05$, $SE = 0.028$; or threat appraisal, U = 370,220.5, $p = 0.477$, $r_{rb} = -0.02$, $SE = 0.028$.

3 Results

Next, the results of the proposed SEM, regression and PLS-SEM models are reported. First, the replication for students and extension for teachers based on the PLS-SEM model (Strzelecki and ElArabawy, 2024) found in Poland and Egypt will be reported using confirmatory SEM analyses. Next, the regression model testing the predictive values of genAI subjective competence, trust in genAI, intrinsic motivation to use AI for challenge, and threat appraisals will be reported. Lastly, an exploratory PLS-SEM model incorporating challenge and threat appraisals to the structural equation will be reported. The correlation coefficients of the variables of interest for students and teachers can be found in Figure 2. Correlation heatmaps visualize the overall association patterns between constructs for students and teachers. Beyond descriptive reporting, they highlight theoretically meaningful clustering (e.g., performance expectancy and social influence correlating more strongly with challenge appraisals than with threat appraisals), which guided subsequent model specification and final interpretation.

3.1 Replicating the structural model of Strzelecki and ElArabawy in an Austrian student as well as teacher sample using confirmatory SEM analysis

We first tested the replicated SEM model to validate UTAUT predictors in Austrian students and teachers. A SEM (see Figure 1) was estimated using maximum likelihood with robust standard errors and a Yuan–Bentler correction for students. The model demonstrated excellent fit to the data: $\chi^2(12) = 51.29$, $p < 0.001$, robust CFI = 0.993, robust TLI = 0.985, robust RMSEA = 0.034, 90% CI [0.026, 0.044], and SRMR = 0.006. The model explained a substantial portion of variance in behavioral intention ($R^2 = 0.79$) and a moderate portion in use behavior (UB) ($R^2 = 0.34$). All three predictors—performance expectancy ($b = 0.67$, $p < 0.001$), effort expectancy ($b = 0.23$, $p < 0.001$), and social influence ($b = 0.15$, $p < 0.001$)—had significant positive effects on behavioral intention. In turn, behavioral intention strongly predicted genAI use ($b = 0.91$, $p < 0.001$), while facilitating conditions had a significant negative direct effect on *UB* ($b = -0.47$, $p < 0.001$).

TABLE 1 Group descriptives for students and teachers for the gender effects.

Variable	Group	N		Mean		SD		SE		r_{rb}	
		Students	Teachers	Students	Teachers	Students	Teachers	Students	Teachers	Students	Teachers
genAI- related competence	Male	1,210	900	4.21	3.76	1.49	1.6	0.043	0.053	0.21	0.12
	Female	1,811	839	3.66	3.43	1.55	1.58	0.036	0.055		
Trust in genAI	Male	1,210	900	2.59	2.34	0.91	0.87	0.026	0.029	-	-
	Female	1,811	839	2.63	2.27	0.88	0.85	0.021	0.029		
Intrinsic motivation	Male	1,210	900	3.71	17.83	1.08	5.33	0.031	0.178	0.17	0.06
	Female	1,811	839	3.37	17.34	1.14	5.33	0.027	0.184		
Challenge appraisal	Male	1,210	900	3.22	3.07	0.84	0.74	0.024	0.025	0.07	-
	Female	1,811	839	3.11	3	0.86	0.78	0.02	0.027		
Threat appraisal	Male	1,210	900	1.72	1.69	0.68	0.7	0.02	0.023	−0.08	-
	Female	1,811	839	1.83	1.72	0.74	0.71	0.017	0.025		

Effect sizes (rank-biserial correlation, r_{rb}) are reported only for significant test statistics.
For this analysis, only participants identifying as male or female were included, as the number of individuals identifying as non-binary was insufficient for reliable statistical inference. Effect sizes are interpreted according to Cohen's (1988) conventions, where $r_{rb} < 0.1$ indicates a small effect, $r_{rb} < 0.3$ a medium effect, and $r_{rb} > 0.5$ a large effect.

Significant indirect effects were found for performance expectancy ($b = 0.62$, $p < 0.001$), effort expectancy ($b = 0.21$, $p < 0.001$), and social influence ($b = 0.14$, $p < 0.001$) on genAI use via behavioral intention, indicating that behavioral intention fully mediated these effects. Moderation effects (e.g., by gender and study level) on the structural paths were not statistically significant (all $p > 0.05$), though the path from effort expectancy × study level to behavioral intention approached significance ($b = 0.03$, $p = 0.071$). The standardized coefficients and effect sizes for students and teachers are found in Supplementary Table 2.

For the teacher sample, a SEM was estimated using maximum likelihood with robust standard errors and a Yuan–Bentler correction. The hypothesized model demonstrated excellent fit to the data, $\chi^2(7) = 81.2$, $p < 0.001$, with a robust comparative fit index (CFI) of 0.974 and a robust Tucker–Lewis index (TLI) of 0.944. The robust root mean square error of approximation (RMSEA) was 0.077, 90% CI [0.063, 0.093]. The standardized root mean square residual (SRMR) was 0.013, indicating excellent fit. The model explained 80% ($R^2 = 0.8$) of the variance in behavioral intention and 18% ($R^2 = 0.18$) in genAI use behavior. All hypothesized paths were statistically significant except for the gender moderation paths (all $p > 0.68$). Performance expectancy ($b = 0.63$, $p < 0.001$), effort expectancy ($b = 0.37$, $p < 0.001$), and social influence ($b = 0.11$, $p < 0.001$) significantly predicted behavioral intention, with standardized coefficients. In turn, behavioral intention significantly predicted genAI use behavior ($b = 0.6$, $p < 0.001$), while facilitating conditions showed a small negative effect on genAI use behavior ($b = -0.11$, $p = 0.019$). Significant indirect effects on genAI use behavior were found for performance expectancy ($b = 0.38$, $p < 0.001$), effort expectancy ($b = 0.22$, $p < 0.001$), and social influence ($b = 0.07$, $p < 0.001$), indicating that behavioral intention fully mediated these effects.

3.2 Investigating differential effects of the predictors of challenge and threat appraisals, i.e., genAI-related subjective competence, trust in genAI, and intrinsic motivation for students and teachers

A series of hierarchical linear regression analyses were conducted to examine predictors of threat appraisal and challenge appraisal in students. For threat appraisal, the final model explains 20.7% of the variance. For challenge appraisal, the final model accounted for 55.9% of the variance. Durbin-Watson statistics indicated no significant autocorrelation issues in either regression (all values between 1.937 and 2.043). Multicollinearity diagnostics showed acceptable variance inflation factors (all VIFs < 2), suggesting that multicollinearity was not a concern.

A series of hierarchical linear regression analyses were conducted to examine the predictive effects of genAI-related subjective competence, trust in genAI, intrinsic motivation on threat, and challenge appraisals in teachers. For threat appraisal, the final model explained 18.8% of the variance. The Durbin-Watson statistic (1.96) suggested no autocorrelation concerns, and variance inflation factors (VIFs ≤ 1.59) indicated no multicollinearity issues. For challenge appraisal, the final model with the same predictors in the proposed order explained 48.3% of the variance. The Durbin-Watson statistic (2.03) indicated no autocorrelation, and VIF values ($\leq$ 1.48) confirmed no multicollinearity. Intrinsic motivation was the strongest positive predictor of challenge appraisal (β = 0.58, p < 0.001), followed by trust in genAI (β = 0.17, p < 0.001), and genAI-related subjective competence (β = 0.06, p = 0.003).

In summary, while higher genAI-related subjective competence and intrinsic motivation were associated with reduced threat appraisal, higher trust in genAI slightly increased threat appraisals. All three predictors positively contributed to challenge appraisal, with intrinsic motivation showing the largest effect (Standardized Regression coefficients are found in Supplementary Table 3).

3.3 Exploratory PLS-SEM analysis incorporating challenge and threat appraisals into the previously tested SEM model for students and teachers

Finally, PLS-SEM integrated these appraisals into the structural model to predict behavioral intention and use behavior. A partial least squares path modeling (PLS-PM) analysis with 500 bootstrap samples was conducted to examine factors predicting students' intention to use and use behavior of genAI. The model revealed significant positive effects of performance expectancy [β = 0.58, 95% CI (0.52, 0.64)], effort expectancy [β = 0.19, 95% CI (0.14, 0.24)], social influence [β = 0.12, 95% CI (0.07, 0.17)], and challenge appraisal [β = 0.13, 95% CI (0.11, 0.15)] on the behavioral intention to use generative AI. Conversely, threat appraisal was significantly negatively associated with behavioral intention [β = −0.03, 95% CI (−0.04, −0.01)]. Behavioral intention strongly predicted actual use frequency [β = 0.74, 95% CI (0.70, 0.77)], while facilitating conditions had a significant negative effect on use frequency [β = −0.29, 95% CI (−0.33, −0.25)]. Interaction terms modeling moderation by gender and study level were all statistically non-significant. For example, the interaction between performance expectancy and gender was negligible [β = −0.01, 95% CI (−0.08, 0.07)], and the interaction between effort expectancy and study level was also non-significant [β = 0.03, 95% CI (−0.04, 0.10)]. Thus, no evidence was found for moderation either by gender or educational level. The model accounted for a substantial proportion of the variance in behavioral intention to use AI tools [R^2 = 0.81, 95% CI (0.79, 0.82)] and a moderate proportion of variance in actual usage frequency [R^2 = 0.32, 95% CI (0.29, 0.35)]. These results suggest that the proposed predictors account for 81% of the variance in usage intention and 32% in generative AI usage behavior. A summary of both models can be found in Figure 3.

A PLS-PM analysis with 500 bootstrap samples was conducted to examine factors predicting behavioral intention and use behavior of genAI among teachers. The model accounted for a substantial amount of variance in behavioral intention [R^2 = 0.81, 95% CI (0.79, 0.83)] and a moderate amount of variance in generative AI usage frequency [R^2 = 0.18, 95% CI (0.15, 0.22)]. Regarding the structural paths predicting behavioral intention, performance expectancy was a strong positive predictor [β = 0.53, 95% CI (0.48, 0.59)], as was effort expectancy [β = 0.32, 95% CI (0.27, 0.37)]. Social influence showed a smaller but significant positive effect [β = 0.09, 95% CI (0.05, 0.13)], and challenge appraisal also positively predicted behavioral intention [β = 0.08, 95% CI (0.06, 0.11)]. In contrast, threat appraisal had a small but significant negative effect [β = −0.03, 95% CI (−0.05, −0.01)]. Interaction terms involving gender were not significant predictors of behavioral intention. Behavioral intention significantly predicted use behavior of genAI [β = 0.41, 95% CI (0.35, 0.47)], whereas facilitating conditions did not show a significant effect. Figure 3 summarizes the PLS-PM results for students and teachers. All standardized coefficients for students and teachers are found in Supplementary Table 4.

Outer loadings for the measurement model were evaluated separately for students and teachers. The construct performance expectancy showed high loadings across its indicators for students: usefulness (0.94), success (0.93), efficiency (0.93), and productivity (0.93). Similarly, effort expectancy indicators—learning success (0.95), clear communication (0.95), easy handling (0.95), and skillful handling (0.95)—all demonstrated strong loadings above 0.94. Indicators for social influence ranged from 0.95 to 0.97, and facilitating conditions showed loadings from 0.64 to 0.94, except for support of the university at 0.64. For challenge appraisal, students' loadings varied: overcoming obstacles (0.88), increase skills (0.88), increase self-esteem (0.62), and mastering (0.52). For threat appraisal, student loadings were threat (0.73), exposing weaknesses (0.53), not mastering (0.83), and lack of skills (0.73). Behavioral intention indicators were robust, with loadings between 0.95 and 0.97.

For teachers, performance expectancy indicators ranged from 0.92 to 0.93, and effort expectancy indicators ranged from 0.94 to 0.95. Social influence loadings were similarly high (0.96), and facilitating conditions ranged from 0.6 to 0.94, with support of the university at 0.6. For challenge appraisal, teacher loadings were overcoming obstacles (0.87), increase skills (0.87), increase self-esteem (0.51), and mastering (0.51). In threat appraisal, teacher loadings were threat (0.74), exposing weaknesses (0.49), not mastering (0.84), and lack of skills (0.8). Behavioral intention indicators had high loadings (0.94 to 0.96). All loadings met or exceeded the recommended cutoff of 0.5, supporting the reliability of the indicators for both samples. However, implications regarding challenge and threat appraisal measurement will be addressed in the discussion.

4 Discussion

To promote the meaningful and ethical integration of AI in higher education, it is essential to understand the motivational dynamics that shape how both students and teachers engage with genAI tools. A deeper grasp of these motivational mechanisms and providing facilitating conditions can inform strategies that not only enhance adoption but also ensure that AI is used in a responsible, pedagogically sound and didactically meaningful manner. Evidence indicates that potential concerns —such as ethical use and legal standards, which are crucial aspects in developing guidelines for AI usage in higher education—are of particular interest for the users (cf. Brandhofer and Tengler, 2025). These concerns were also

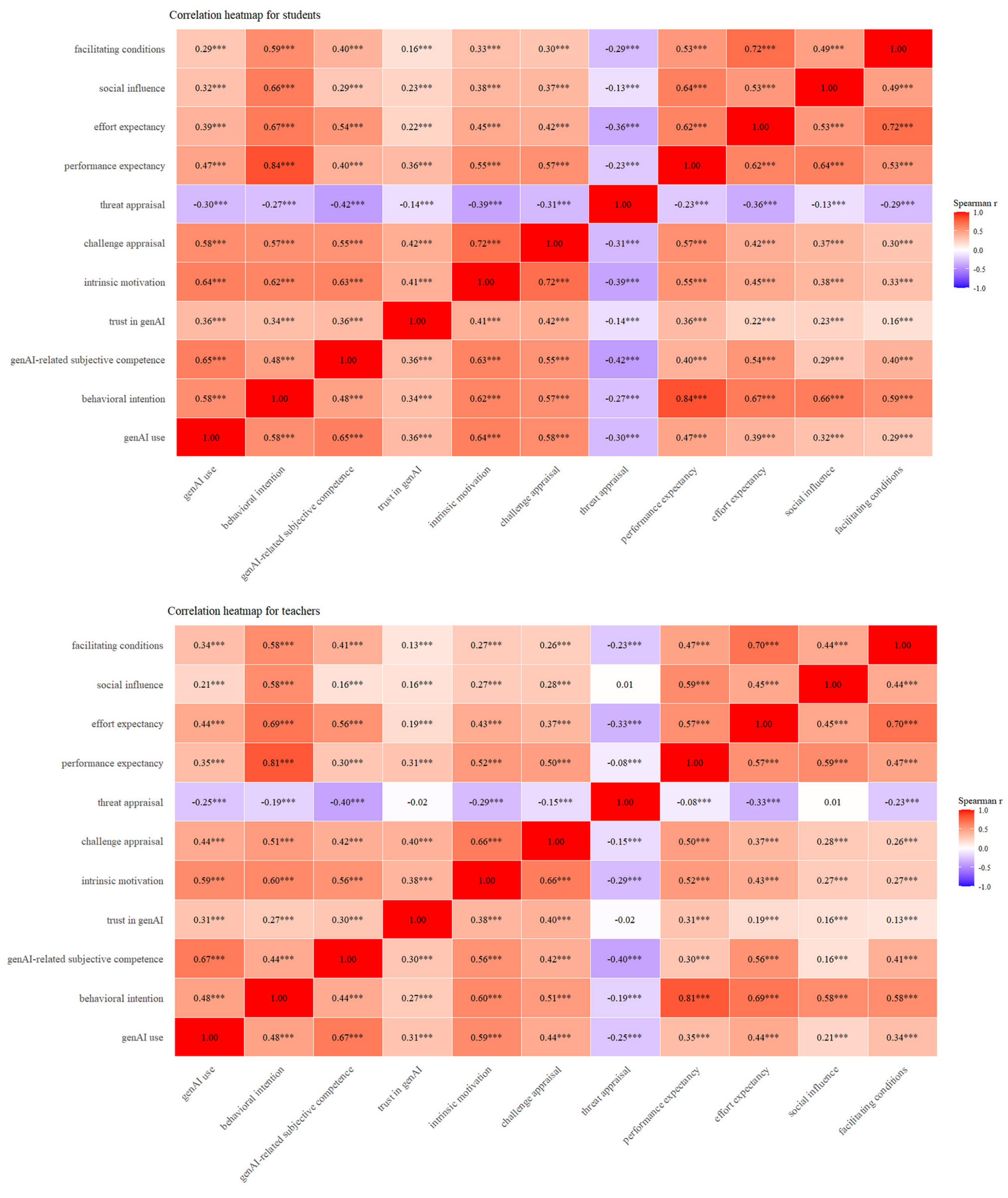

FIGURE 2
Correlation coefficients for the variables of interest for students and teachers. The asterisk indicates the significance level of <0.05 (*), <0.01 (**), and <0.001 (***).

reflected in the current sample as previously reported in the highest scoring for data security and copyright challenges in AI adoption (Tulis et al., 2024). This study contributes to the understanding of the underlying motivational dynamics regarding AI usage in higher education from students and teachers by replicating and extending the UTAUT model developed by Strzelecki and

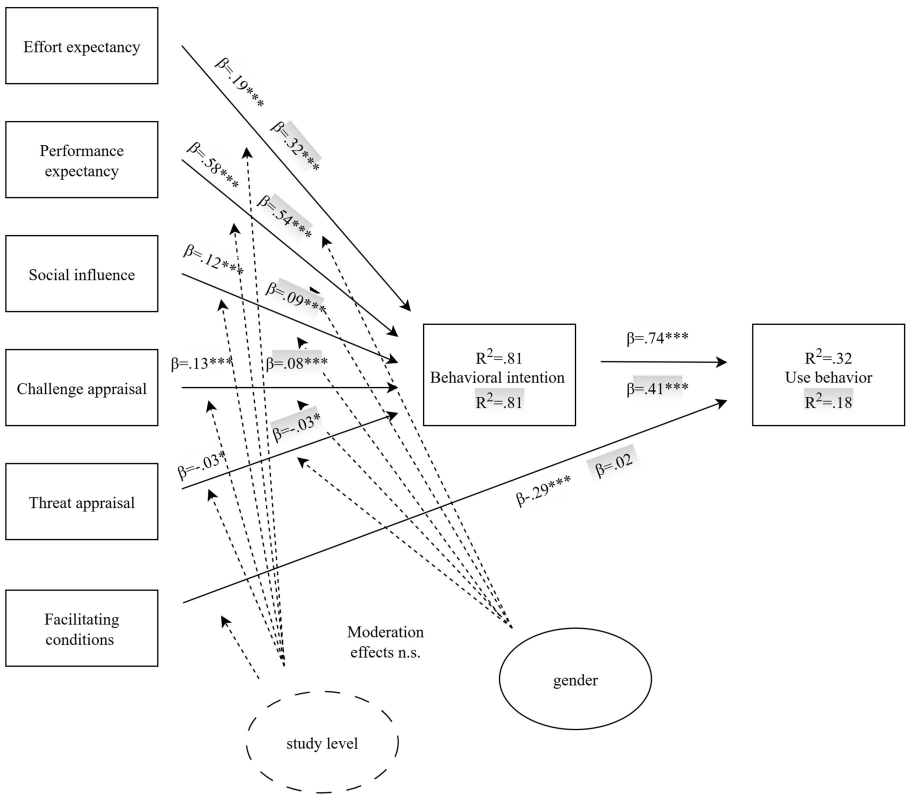

FIGURE 3
Model estimation results in students (blank) and teachers (gray background). Non-significant moderations effects are not shown, please find the coefficients in Supplementary Table 4.

ElArabawy (2024), assessed its validity in a new educational system: Austrian higher education. Moreover, we expand the scope of the original model by applying it to higher education instructors, a group for which empirical data on AI use remains scarce. Our research was guided by three aims: (1) to replicate the structural model of Strzelecki and ElArabawy (2024) using confirmatory SEM analyses in Austrian student and teacher samples; (2) to explore how individual predictors—specifically, genAI-related subjective competence, trust in genAI and intrinsic motivation—relate to challenge and threat appraisals in both groups; and (3) to extend the original SEM model by incorporating these appraisals through exploratory PLS-SEM analyses. The following section integrates our findings along these lines and considers their theoretical and practical implications.

We conducted preliminary analyses prior to test our main hypotheses and explore potential gender-related patterns in psychological antecedents of genAI use. Given that gender differences have been repeatedly observed in predictors of technology acceptance and AI-use related variables (cf. Tulis et al., 2024, 2025), we investigated whether these effects extend to the motivational prerequisites of AI use in Austrian students and teacher samples. Specifically, we examined genAI-related subjective competence, trust in AI, intrinsic motivation, and challenge and threat appraisals. The results revealed several significant gender differences in the student sample, with females reporting lower subjective competence, intrinsic motivation, and challenge appraisal, but higher threat appraisal (cf. Russo et al., 2025), all with small to moderate effect sizes. No significant gender difference was found in trust in genAI among both males and females, showing moderate trust in answers generated by AI. In contrast, gender effects were more limited in the teacher sample. Female teachers reported significantly lower subjective competence and intrinsic motivation, but no differences were observed for trust, challenge, or threat appraisals. These results suggest that gender disparities are more pronounced among students than teachers, particularly regarding perceptions of genAI's potential for oneself—either as a manageable challenge and even personal enrichment, or as a threat. Importantly, these pre-analytical findings underscore the necessity to consider gender as a relevant covariate in subsequent regression models to avoid confounded interpretations of the main predictors.

The structural equation model (SEM) replicated in this study demonstrated excellent fit and confirmed the key pathways proposed by the UTAUT framework among higher education students. Notably, the predictors explained a substantial proportion of the variance in behavioral intention ($R^2 = 0.79$), exceeding the variance explained in the Polish ($R^2 = 0.65$) and Egyptian ($R^2 = 0.38$) student models. The particularly high explained variance for behavioral intention ($R^2 > 0.79$) indicates that the core predictors—performance expectancy, effort expectancy, and social influence—account for a substantial proportion of variance in students' behavioral intention to use genAI. While this finding reflects the theoretical coherence and robustness of the UTAUT framework in capturing key motivational dynamics, it also raises the possibility of overfitting, particularly given the inclusion of multiple interaction terms and many predictors relative to unique patterns in the data. Accordingly, the strength of these effects should be interpreted with caution. Behavioral intention had a strong positive direct effect on genAI use ($\beta = 0.91$). This finding confirms behavioral intention as the key driver of actual genAI use behavior, which is consistent with UTAUT theory regarding their motivational antecedents. Behavioral intention was strongly predicted by performance expectancy, effort expectancy (for students cf. Saxena and Doleck, 2023), and social influence, with performance expectancy exerting the most substantial influence ($\beta = 0.63$), consistent with findings from Poland ($\beta = 0.50$) and Egypt ($\beta = 0.29$; Strzelecki and ElArabawy, 2024; Patterson et al., 2024). However, in Egypt, social influence showed the strongest predictive value on behavioral intention as a mediator for genAI use ($\beta = 0.4$). Indirect effects further supported full mediation of the three core predictors through behavioral intention, reinforcing the centrality of differentiating intentional factors in supporting adaptive usage behavior. Especially as problematic usage behavior was found to increase in stressful settings (Zhang et al., 2024), higher education and university management should promote awareness of adaptive usage values in terms of performance expectancies. Interestingly, the predictive value of behavioral intention in genAI use was comparable to Poland, whereas in Egypt it was lower. In addition, while facilitating conditions had a significant *negative* effect on genAI use ($\beta = -0.32$), a stronger contrast emerges when compared to the modest but *positive* effects observed in Poland ($\beta = 0.17$) and Egypt ($\beta = 0.21$), suggesting contextual differences in how students perceive institutional and technical support within different educational contexts despite suppressor effects interpreted in the next section. Evidence from Arab universities indicates that social influence and technology readiness strongly predict educators' perceptions of genAI usefulness and effectiveness, whereas anxiety serves as a negative predictor (Sallam et al., 2025). No significant moderation by gender was observed in the present model, consistent with partial moderation findings from the original replication study. In that study, only selected paths were moderated by gender in specific contexts, such as social influence × gender and effort expectancy × gender on behavioral intention in Egypt. In contrast, our findings suggest that the predictive relationships of performance expectancy, effort expectancy, social influence, and challenge/threat appraisals operate similarly for male and female students and teachers in Austria. This indicates that, at the structural level, gender does not substantially alter the motivational mechanisms driving genAI adoption in Austrian higher education. Nonetheless, preliminary analyses showed that gender differences may emerge in antecedent and complementary motivational factors among students, including genAI-related subjective competence, intrinsic motivation, and challenge appraisals, highlighting that gender may still play a role at a descriptive or preparatory level rather than as a structural moderator. The lack of moderation also suggests that interventions to enhance AI use can be broadly applied without tailoring to specific subgroups based on these demographics and that support and training programs should consider gender-sensitive approaches at the preparatory stage: for example, providing confidence-building workshops and fostering intrinsic motivation for female students may reduce threat perceptions and enhance engagement, even though structural adoption patterns do not differ significantly by gender. Study level significantly moderated several pathways among students. Specifically, the effects of performance expectancy, effort expectancy, and social influence on behavioral intention were stronger at higher study levels, with all dummy-coded interactions (diploma, master, promotion) reaching statistical significance. For example, the performance expectancy × master interaction had a $\beta = 0.79$, indicating that the positive influence of perceived usefulness on behavioral intention is particularly pronounced among master's students compared to bachelor students. Similarly, effort expectancy and social influence effects were enhanced at higher study levels. These findings suggest that students' motivational responsiveness to core predictors of genAI adoption is not uniform across educational stages: students in advanced programs appear more sensitive to perceived usefulness, ease of use, and social endorsement, possibly reflecting greater experience with independent learning and academic self-regulation. Overall, this replication reinforces the robustness of the UTAUT model for the predictive effects of performance expectancy, effort expectancy, and social influence mediated by behavioral intention in explaining genAI usage among students, while highlighting contextual divergences, particularly in the role of facilitating conditions.

Contrary to both theoretical expectations and most of the previous empirical findings—with some exceptions (cf. Zaim et al., 2024)—we found a significant negative effect of facilitating conditions on genAI use behavior. This contrasts sharply to the findings in Poland and Egypt (Strzelecki and ElArabawy, 2024), where facilitating conditions had *positive* effects on genAI use. According to UTAUT, facilitating conditions should promote usage by reducing external barriers, such as lack of access to technology or insufficient support (Venkatesh et al., 2003). Initial correlational analyses revealed a significant positive association between facilitating conditions and genAI use among students ($r = 0.29$) and teachers ($r = 0.34$), suggesting that as facilitating conditions improve, genAI use tends to increase. However, within the comprehensive structural model, the direct path from facilitating conditions to genAI use was significantly negative for students, indicating a strong effect ($\beta = -0.32$, $p < 0.001$, $SE = 0.032$, $z = -14.593$) and a small, albeit significant for teachers ($\beta = -0.07$, $p < 0.019$, $SE = 0.045$, $z = -2.344$). This indicates that, after accounting for the influence of other variables in the model, an increase in facilitating conditions is associated with a decrease in genAI use. This counterintuitive finding can be explained by a suppressor effect, where performance expectancy, effort expectancy and social influence masking the true relationship between facilitating conditions and genAI use. The seemingly counterintuitive negative direct effect of facilitating conditions among students in our study warrants further interpretation through the lens of constructively aligned AI integration. The formative use case presented by Chan et al. (2024), where AI provided targeted feedback within authentic writing tasks, demonstrates that when facilitation is meticulously designed and oriented toward enhancing feedback quality, positive learning outcomes are fostered, possibly increasing the performance expectancy. This suggests that the efficacy of facilitating conditions is not merely about the presence of resources but critically depends on their pedagogical alignment and integration within meaningful learning activities. Facilitation that enhances intrinsic motivation and challenge, as well as adaptive threat appraisals (in terms of being aware of the limits of one's competence or the functions of genAI), can be characterized by several factors. First, *task-embedded support* means that AI tools and resources are seamlessly integrated into authentic, relevant learning tasks, making their utility immediately apparent. Second, *autonomy-supportive design* empowers students to leverage AI as a tool for self-directed learning and exploration, rather than imposing rigid usage protocols.

Third, *feedback-centric quality* emphasizes improving the quality and interpretability of AI-generated feedback. This enables students to transparently and critically engage with it and refine their work, thereby addressing threat appraisals. Finally, *adaptive scaffolding* involves support mechanisms that evolve with student proficiency, offering more guidance to novices and fostering independent exploration for advanced users to help develop self-efficacy. Maladaptive threat appraisals might be fostered by inadequate facilitation in turn. For instance, an overabundance of AI tools without clear guidance, or a perceived pressure to use AI without adequate training, can lead to feelings of being overwhelmed or inadequate, lowering intrinsic motivation and genAI-related subjective competence, thereby fostering threat. On the other hand, if a critical evaluation is not being done and anxiety is low, trust in genAI might lead to an overestimation of performance expectancy fostering maladaptive genAI use. Therefore, while a broad measure of facilitating conditions might not always show a direct positive impact, context-specific and design-sensitive facilitation, particularly in formative assessment, is crucial for optimizing AI adoption and its benefits, by fostering a sense of challenge and intrinsic motivation, while carefully mitigating the potential for threat.

Specifically, perceived usefulness and ease of learning AI together with social influence suppress the effect of facilitating conditions. The negative pathway may suggest a potential mismatch between the formal availability of resources and their perceived usefulness or usability in real-world educational settings in Austria. The current sample contains students and teachers from all across Austria, encompassing different higher education systems. In the Austrian higher education system, universities are traditional, research-oriented institutions that offer a broad range of academic degrees, including doctoral programs, with a strong focus on theoretical knowledge and academic research. Universities of applied sciences are more practice-oriented and emphasize applied skills and professional training, typically offering Bachelor's and Master's degrees but not PhDs. Finally, university colleges of teacher education are specialized institutions focused on preparing student teachers and prospective educators, with an emphasis on pedagogical training and practical teaching experience, primarily awarding Bachelor's and Master's degrees in education. For both students and teachers, it is plausible that the presence of institutional or technical "support" may feel prescriptive, overwhelming, or insufficiently tailored to the actual learning and didactical needs, thereby undermining—rather than enabling—effective engagement with genAI, especially as genAI is perceived to be more useful. These findings underscore the importance of examining multivariate relationships beyond simple bivariate correlations. The negative direct effect of facilitating conditions, once other factors are accounted for, suggests that the effectiveness of such conditions is highly contingent on motivational factors (cf. Zaim et al., 2024). Importantly, these findings signal that simply providing access to AI tools or offering general training is not enough; effective facilitation must be aligned with users' expectations and contexts to avoid inadvertently reducing motivation or usage.

Building upon these theoretical foundations, the results of our study extend the application of the UTAUT model to higher education teachers and provide novel empirical insights into the motivational determinants of the genAI adoption. The SEM demonstrated excellent fit, and the core predictors—performance expectancy, effort expectancy, and social influence—were all significant positive predictors of teachers' behavioral intention to use genAI, explaining 80% of the variance in intention. Notably, effort expectancy exerted a stronger influence among teachers ($\beta = 0.34$) than in the student sample ($\beta = 0.21$), suggesting that perceived ease of use plays a particularly salient role in motivating faculty engagement. This finding resonates with expectancy × value theory, where perceived cost (e.g., complexity) can inhibit motivation to adopt new tools (cf. Eccles, 1983) and the particularly limited time of teachers in higher education to learn how to use new technologies. In line with the importance of lowering efforts to learn about adaptive genAI use, both teachers and students ranked the challenge of finding time to learn about new tools as top challenge in the same sample (Tulis et al., 2024), followed by privacy and author's rights issues on the individual level (top challenge on an institutional level). In line with the findings in students, behavioral intention robustly predicted actual genAI use behavior, highlighting intention as a central mediator in both groups, consistent with the UTAUT. We previously found that higher education instructors training should be tailored to individual factors, i.e., female preferring didactical and male preferring technical support (Tulis et al., 2025). However, gender did not significantly moderate any structural path on a motivational level regarding behavioral intention in the teacher sample, differing from the student results in Egypt but remaining consistent with findings from Poland and prior studies on e-learning (Dečman, 2015). These results underscore the importance of designing AI training and support that not only lowers perceived effort but also actively enhances perceived usefulness and social endorsement, which are critical drivers of adoption in academic contexts. These findings imply that training programs should be tailored to user needs: for students, programs might focus on enhancing intrinsic motivation, competence, and awareness of AI's pedagogical potential, whereas for teachers, emphasis should be placed on reducing perceived effort, offering time-efficient training, and integrating AI tools into existing workflows as indicated above. Gender-sensitive preparatory interventions may further optimize engagement, particularly among female students who reported higher threat appraisals. Future research should explore how individual background, institutional culture, workload, and subject area further shape teachers' motivational orientations toward AI in education (see Limitations and Implications).

Prior to incorporating new predictors into the model, we computed stepwise multiple regression models to study the underlying motivational dynamic of challenge and threat appraisals. Our findings highlight the proposed distinct psychological pathways that predict challenge and threat appraisals in the context of genAI use among students and teachers in higher education. Challenge and threat appraisals are not merely cognitive evaluations of AI's potential risks and benefits (cf. Tulis et al., 2024), but rather motivational-affective states that reflect users' perceived capacity to cope with AI demands in relation to their personal goals in AI adoption. Consistent with theoretical background in goal-pursuit research (cf. Drach-Zahavy and Erez, 2002), we found that challenge appraisals were primarily predicted by intrinsic motivation in both students and teachers. Incorporating trust in genAI and subjective competence added significantly to the model, suggesting that the perception of AI as an opportunity for personal growth is closely tied to autonomous engagement and self-determined learning goals. These findings suggest that students and teachers who feel competent and motivated perceive genAI as an opportunity rather than a threat, consistent with challenge vs. threat theory (Blascovich and Mendes, 2000; Drach-Zahavy and Erez, 2002). Trust in AI has a dual role: it can enhance engagement (challenge) but may also generate overconfidence, slightly increasing threat perceptions when outcomes are uncertain. This highlights the importance of fostering intrinsic motivation along with critical thinking, i.e., raising awareness of the purpose and error-proneness of genAI for highly intrinsically motivated users. Trust in genAI answers should remain low for competent use. If intrinsic motivation is high, then guidance at university can focus on fostering critical thing toward genAI outputs by increasing AI literacy. In contrast, threat appraisals were best predicted by low subjective competence and low intrinsic motivation, supporting the notion that perceived insufficiency of personal resources fosters avoidance tendencies. Interestingly, trust in genAI showed a dual role—while it positively contributed to challenge appraisals, it also slightly increased threat appraisals, particularly in teachers. This finding could reflect an ambivalence toward the reliability and control over AI systems (cf. Chang et al., 2024) that teachers, in their responsible didactical role, are particularly aware of. Taken together, fostering subjective competence might be a key factor in promoting challenge appraisals and genAI use while threat appraisals, i.e., the awareness of possibly exposing mistakes and not mastering a tool (also in terms of misuse) might help to maintain a critical distance and should be linked in cases where intrinsic motivation is high. Thus, both challenge and threat appraisals might be part of fostering adaptive AI use in higher education.

Using a partial least squares path modeling (PLS-PM) approach with bootstrap validation, we extended the UTAUT framework by incorporating challenge and threat appraisals as additional predictors of behavioral intention. Our findings demonstrate strong support for the relevance of expectancy-value beliefs and social influence in shaping genAI acceptance, while revealing nuanced effects of challenge and threat appraisals on motivation to use AI tools. Consistent with prior research (Strzelecki, 2023; Venkatesh et al., 2012), performance expectancy emerged as the most robust predictor of behavioral intention for both students and teachers. This underscores the centrality of perceived usefulness in driving AI adoption in educational contexts. The difference in magnitude for effort expectancy among students ($\beta = 0.19$) compared to teachers ($\beta = 0.32$) was even more pronounced, suggesting that perceived ease of use may be particularly salient for educators who often balance multiple professional demands alongside technology adoption if appraisal is being accounted for. Social influence positively influenced intention in both samples, albeit with smaller effect sizes, highlighting the role of normative beliefs and institutional culture in supporting AI integration. In addition to the traditional UTAUT predictors, challenge appraisal positively predicted behavioral intention in students and teachers, while threat appraisal showed a small negative association. These findings align with the theoretical framing of challenge and threat states in motivational psychology (Blascovich and Mendes, 2000; Drach-Zahavy and Erez, 2002) and suggest that perceiving genAI use as an opportunity rather than a risk enhances engagement and willingness to use it.

Interestingly, facilitating conditions showed divergent effects: a negative impact on genAI usage frequency among students ($\beta = -0.29$), but no significant effect among teachers was observed. Therefore, the negative impact of facilitating conditions found in the SEM without challenge and threat appraisals as additional predictors was no longer present when these motivational components were added to the equation. This is an indication of the importance of subjective factors in the change management process and implementation of adaptive and ethical genAI usage as explained before. We found no moderation effects of gender consistent with the first SEM analyses and no significant moderation effects of study level. This suggests that in our sample, motivational dynamics around genAI use operate similarly across gender and educational stages in Austria compared to Poland and Egypt (Strzelecki and ElArabawy, 2024) if challenge and threat appraisals are considered. The model explained a substantial proportion of variance in behavioral intention and a moderate amount in actual usage frequency, indicating a strong fit and practical relevance of the extended UTAUT model including challenge and threat appraisals.

From a practical perspective, these results highlight the value of designing supportive learning environments that enhance performance and effort expectancy, promote positive social norms around AI, and address users' appraisals of challenge vs. threat. For educators and institutions, this could mean providing accessible, well-structured training, clear communication about AI benefits and risks, and fostering peer support networks to reduce anxiety and increase confidence. Given the strong influence of challenge appraisal, framing AI as a tool for growth and innovation may further motivate its adoption. Universities should design interventions that enhance challenge appraisals while mitigating threat perceptions. For example, integrating AI tools into authentic, task-embedded learning activities can promote perceived opportunities for skill development (challenge), while structured guidance and feedback mechanisms can reduce anxiety and perceived risks (threat). Adaptive scaffolding, autonomy-supportive designs, and formative feedback ensure that facilitation strengthens intrinsic motivation and subjective competence without overwhelming users. These recommendations are directly supported by our PLS-SEM findings, where challenge positively predicted behavioral intention, and threat negatively predicted it, albeit with smaller effect sizes. In conclusion, this study contributes to the growing literature on AI adoption in higher education by replicating and extending the UTAUT framework with motivational constructs grounded in appraisal theory. The findings underscore the complex interplay of expectancy-value beliefs, social influence, and affective appraisals in shaping genAI acceptance and use among students and teachers alike. By deepening our understanding of these factors, educators and policymakers can better support meaningful and ethical integration of the adaptive use of genAI technologies in academic settings.

4.1 Limitations and implications

The current results should be interpreted in the light of some limiting factors. First, data was collected in summer semester 2024 and collected solely in Austrian higher education. Considering the fast development of academic AI and the dynamic interactions of AI emergence as well as HE regulation concerning AI, motivational factors might strongly fluctuate and adapt to its practical and institutional surrounding. The latter in turn seems to rely on specific cultural, political and institutional factors limiting generalizability of our results. Second, the results are based on self-reported measures only, therefore focusing on subjective components of AI use only. Participation was voluntary, potentially overrepresenting individuals favorable toward genAI. The cross-sectional design precludes causal inference, and different genAI tools were not specifically addressed. Variables such as institutional policies, availability of AI training, and disciplinary differences were not controlled. Objective causal assumptions should not be made, for example, in terms of specific genAI tools and their causal effects on intention and usage. Lastly, appraisals, in particular challenge appraisals, were found to add value to existing models, therefore specialized surveys tailored to the context of AI-adoptions should be developed. Investigating how students or teachers who show both a high behavioral intention and extensive use of AI differ from students and teachers who do not want to learn and use genAI could help to differentiate challenge and threat appraisals in academic settings.

Future studies should adopt longitudinal and multi-context designs to capture dynamic changes in motivation and usage patterns and investigate how the intention to use and actual usage of different AI systems, such as processing AI and—of particular importance in higher education—learning analytics, can be explained by the UTAUT operationalized by the SEM. In addition, age effects might be included into the model, considering the distinct effects for students vs. teachers as well as migration history, considering the cultural effects across three different samples. For example, we previously found that among teachers, the subjective understanding of one's role as a teacher in relation to AI was ranked in the top 5 individual challenges (Tulis et al., 2024). The current results underscore the ambivalence of teachers regarding the usefulness of AI—and its potential to increase efficient administrative workflows and didactical chances—while also being aware of their knowledge-based role as responsible role models in fostering adaptive and subject-related use of resources in general, as well as genAI-related use in particular. Future research might focus on the differential aspects and interplay of affective, motivational, and cognitive factors contributing to responsible and adaptive AI use in different areas while focusing on developing tailored educational programs for teachers in particular who act as multipliers (see also Strzelecki and ElArabawy, 2024). Given mixed previous findings and documented gender differences in AI-related anxiety (Russo et al., 2025; Tulis et al., 2025), future research should also continue to investigate these potential subgroup differences with larger and more diverse samples. Incorporating complementary motivational factors, i.e., genAI-related subjective competence, intrinsic motivation, in investigating behavioral intention and genAI use could provide additional insights on differential effects of gender, study level, and age. Lastly, future studies could shed light on how individual socioeconomic differences, a history of migration, educational background, institutional culture and regulations, workload and subjective stress, and different university systems (down to subject areas) may shape students' and teachers' motivational orientations toward AI in education in order to draw evidence-based conclusions about adaptive regulation on genAI use in higher education. Methodological extensions could involve combining a survey-based SEM approach with empirical paradigms such as course-embedded writing tasks (Chang et al., 2024) that collect objective performance indicators and appraisal measures before and after AI-supported revision. This would enable testing whether shifts in appraisals and UTAUT predictors mediate objective learning gains, providing a more comprehensive understanding of AI's impact on educational outcomes.

In conclusion, this study extends the UTAUT framework by incorporating challenge and threat appraisals, providing novel insights into the motivational dynamics shaping genAI adoption among students and teachers in Austrian higher education. Core predictors—performance expectancy, effort expectancy, and social influence—robustly predicted behavioral intention, with intrinsic motivation and subjective competence shaping challenge and threat appraisals. Trust in genAI exhibited a dual role, enhancing engagement while slightly increasing threat perceptions. Gender differences were evident in determinant measures, though not in structural pathways, highlighting the importance of preparatory, gender-sensitive support. Practical implications include designing tailored training programs, reducing perceived effort for teachers, embedding genAI in meaningful learning tasks, and fostering critical yet engaged use. By deepening understanding of these factors, institutions can promote adaptive, ethical, and context-sensitive AI integration, with attention to both opportunity and risk, ultimately enhancing educational outcomes in higher education genAI use.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: Austrian Neurocloud doi: 10.60817/x9pe-d595.

Ethics statement

Ethical approval was not required for the studies involving humans because the study involved a pseudonymous online survey from healthy adult participants. Participation was voluntary, and discontinuation was possible at any time by closing the browser window. Furthermore, the survey was part of a study commissioned by the Austrian Federal Ministry of Education, Science and Research. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

FK: Investigation, Software, Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Data curation, Resources, Formal analysis, Methodology. MT: Investigation, Funding acquisition, Project administration, Conceptualization, Methodology, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that Gen AI was used in the creation of this manuscript. The analyses code will be shared upon request. GenAI was partly used to set up the R codes for this study.

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