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Are university teachers ready for generative artificial intelligence? Unpacking faculty anxiety in the ChatGPT era

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Abstract
This study investigates the role of technology-related anxiety in shaping university teachers' behavioral intention to adopt ChatGPT. Three distinct types of anxiety are examined: (a) anxiety about the future of the academic profession, (b) anxiety regarding the personal misuse of ChatGPT, and (c) anxiety concerning negative impacts on student learning. A structured questionnaire was administered to 249 faculty members from Spanish public universities. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess both the direct effects of each type of anxiety on behavioral intention and the mediating roles of effort expectancy (EE) and performance expectancy (PE). Results indicate that anxiety about student learning exhibits a significant negative direct effect on behavioral intention and an indirect effect through performance expectancy. Similarly, anxiety related to the misuse of ChatGPT is negatively associated with behavioral intention, with significant mediation through both EE and PE. In contrast, anxiety concerning the future of the academic profession does not show a statistically significant relationship with behavioral intention. The findings underscore the importance of addressing specific psychological barriers—particularly those linked to concerns over student learning and technology misuse—to facilitate ChatGPT integration in higher education. The study suggests that effective implementation strategies should combine technical training with targeted interventions aimed at managing technology-related anxiety, enhancing ethical practices, and improving perceptions of the tool's utility and ease of use.

Keywords Generative artificial intelligence · Anxiety · Technology adoption · Higher education · Teachers

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1 Introduction

Generative artificial intelligence (GAI) tools like ChatGPT are rapidly transforming the landscape of higher education. These technologies challenge traditional academic practices by introducing capabilities that go far beyond previous innovations. ChatGPT, for instance, can generate human-like text, offer personalized tutoring, and automate intricate educational tasks (Pasupuleti & Thiyyagura, 2024). Unlike earlier tools, its influence is not limited to assisting in isolated tasks; rather, it has the potential to fundamentally reshape pedagogical relationships, instructional strategies, and even the core roles of university teachers. Concerns about the displacement or diminishing value of university teachers is a psychological and professional challenge that can affect the adoption of this technology. This transformative power compels universities to reconsider how technology integrates into the teaching–learning process, presenting both opportunities and challenges for faculty (Henderson & Corry, 2021; Jain & Raghuram, 2024).

While significant research has explored technology adoption in education, there is a notable lack of focus on the psychological dimensions of incorporating tools like ChatGPT. Research on ChatGPT adoption has predominantly focused on undergraduate students (e.g., Pasupuleti & Thiyyagura, 2024; Strzelecki & ElArabawy, 2024), leaving university teachers as a relatively understudied group. This gap is evident in the lack of research, particularly empirical studies, examining faculty engagement with ChatGPT. While some recent studies have explored this topic, they do not specifically focus on the university context (Al Darayseh, 2023; Chocarro et al., 2023). This study explores the anxiety experienced by university teachers in adopting GAI tools and investigates the different types of anxiety according to their underlying cause. In addition, previous work has addressed anxiety in technology adoption (e.g., Chiu & Churchill, 2016; Duong et al., 2024; Gunasinghe & Nanayakkara, 2021; Lakhal & Khechine, 2021 and Mac Callum et al., 2014). However, according to the literature review conducted, there is no evidence that the various causes of anxiety have been empirically addressed. Specifically, this study examines three critical kinds of anxiety related to the adoption of GAI technologies: (1) concerns about how ChatGPT may drive significant professional changes, including shifts in university teachers'roles and responsibilities; (2) fears about university teachers'ability to effectively manage and use ChatGPT in their own work; and (3) university teachers' apprehensions regarding its potential impact on students'learning outcomes, such as diminished effort or increased dependence on artificial intelligence (AI) tools. Addressing these kinds of anxiety is crucial, as they highlight previously unexplored barriers that university teachers face in adapting to these disruptive technologies.

Two of these kinds of anxiety, namely the professional changes and the impact on student learning, are particularly noteworthy because, to the best of our knowledge, they have not been studied in an academic context. By exploring these issues, this study contributes to literature by filling a gap in the understanding of how teachers perceive and respond to GAI technologies. These concerns go beyond technical usability to encompass deeper professional and ethical challenges, such as fears of devaluation of the teachers's role and skepticism about the long-term effects of AI integration on student engagement and learning outcomes.

To study how technology is adopted, as is the case with this work, literature uses intention models, including the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT is a well-known framework for analyzing technology adoption, especially in business and educational settings (Xue et al., 2024). The model identifies the factors that influence whether people will use technology or not, such as social influence, facility conditions, performance expectancy and effort expectancy (Farooq et al., 2017; Venkatesh et al., 2003). Social influence refers to the extent to which individuals perceive that important others (e.g., colleagues, supervisors, peers) expect them to use the technology. Facilitating conditions refers to the degree to which individuals believe that organizational and technical infrastructure supports their use of the technology. Performance expectancy is defined as the degree to which using technology will provide benefits to users when performing certain activities. Effort expectancy is the belief that a specific technology will be easy to use. UTAUT provides a structured approach to examine how anxiety affects technology adoption. It highlights how psychological barriers can influence how university teachers evaluate the usefulness and ease of use of AI-driven tools. This paper focuses on two of the UTAUT variables: performance expectancy and effort expectancy. Given that this study aims to examine how technology-related anxiety affects university teachers'behavioral intention to adopt ChatGPT, the performance expectancy and effort expectancy variables are the most direct predictors of behavioral intention. This is because they directly reflect users'perceptions of a technology's usefulness and ease of use (Venkatesh et al., 2003). Considering that anxiety is likely to influence these cognitive evaluations by altering both perceived benefits and expected effort, focusing on performance expectancy and effort expectancy allows to capture the core mechanisms through which anxiety affects technology adoption. Furthermore, the conceptualization of anxiety in this study specifically addresses the emotional and cognitive barriers that shape university teachers'evaluations of the usability and effectiveness of ChatGPT. Prior literature suggests that anxiety may distort perceptions of a technology's ease of use and its potential to improve performance (e.g., Chiu & Churchill, 2016; Gunasinghe & Nanayakkara, 2021). In contrast, other UTAUT dimensions, such as social influence and facilitating conditions, are less directly related to these psychological processes, especially in the autonomous context of higher education. On the other hand, university teachers typically operate in environments where individual expertise and professional autonomy reduce the impact of external social pressures and variable facilitating conditions. In such settings, the primary concerns focus on whether a new technology increases productivity and whether it can be seamlessly integrated into existing teaching practices.

Based on the above arguments, this research has two objectives. First, it aims to identify and analyze the types of anxiety that influence university teachers' adoption of ChatGPT, with a focus on its novel aspects of professional transformation and student-related impacts. Secondly, it explores how the types of anxiety indirectly affect behavioral intention (BI) through the expectancy of effort (EE) and the expectancy of performance (PE).

University teachers' perceptions are central to the success or failure of technology integration in education (Liu et al., 2020). Teachers serve as the primary agents of implementation, bridging the gap between institutional strategies and classroom practices. Their concerns—whether regarding professional identity, technological complexity, or pedagogical impact—cannot be overlooked. Failure to address these issues risks alienating university teachers, creating resistance to adoption, and undermining the potential benefits of GAI technologies.

This study's contributions are both theoretical and practical. Theoretically, it advances the understanding of the psychological and professional barriers to adopting GAI tools by focusing on previously unexplored kinds of university teachers' anxiety. Practically, it offers actionable insights for higher education institutions, enabling them to design targeted interventions that address university teachers´ concerns and ensure a smoother integration of ChatGPT. By focusing on how EE and PE mediate these types of anxiety, the research highlights specific factors that institutions can leverage to encourage adoption while minimizing resistance.

2 Literature review

2.1 Anxiety and intention to adopt ChatGPT by university teachers

Anxiety is defined as an emotional response that negatively influences an individual's intention to engage in certain behaviors (Bandura, 1986). In the context of technology adoption, it can manifest as a temporary feeling of unease, fear, or discomfort regarding the implications of using a technology (Debasa et al., 2023; Duong et al., 2024; Gunasinghe & Nanayakkara, 2021; Venkatesh et al., 2012), and research has consistently shown that such anxiety can be a significant barrier to adopting new technologies (Gunasinghe et al., 2019; Holzmann et al., 2020; Lakhal & Khechine, 2021; Maican et al., 2019).

This paper explores anxiety in a more comprehensive manner than is common in literature. This approach allows us to examine how individual, ethical, and professional considerations shape the adoption of GAI in higher education. Specifically, the study investigates the anxiety experienced by university teachers when adopting technology and focuses on the causes of this anxiety. The kinds of anxiety studied in this paper are related to (a) the potential impact of ChatGPT on the academic profession, (b) the challenges associated with using this technological tool, and (c) the impact of ChatGPT on student learning outcomes. Together, these elements capture the interplay between teachers' personal experiences and the broader ethical and structural implications of technology in their professional contexts. It is worth noting that, of these three kinds of anxiety, the first two are novel in the area of technology adoption by university teachers.

2.1.1 Anxiety about the future of the academic profession (ANXP)

The development of AI is expected to transform—and, in some cases, threaten—certain jobs, both quantitatively and qualitatively (Dwivedi et al., 2023; Wang & Wang, 2022). Educators, in particular, may express concern that tools like ChatGPT could replace human intelligence (Hazzan-Bishara et al., 2025; Sampson, 2021). Research by Felten et al. (2023) highlights that university teachers in disciplines such as English, literature, and history are among those most at risk from the rise of GAI technologies.

ChatGPT has demonstrated its ability to create assignments, generate assessment questions, grade various types of student work, and produce learning materials. These capabilities may lead university teachers to redefine their professional roles. In this evolving landscape, teachers will need to focus more on monitoring and critically evaluating the output generated by GAI tools (Hu et al., 2025).

For instance, AI-driven bots are being presented as alternatives to human tutors, with the notable advantage of being accessible to students at any time. In some cases, these tools can even produce results comparable to those of human instructors (Edwards & Cheok, 2018; Ilieva et al., 2023; Li et al., 2024). ChatGPT's ability to offer student support, address questions instantly, and provide personalized tutoring may reduce the significance of teachers'roles in the educational process (Bae et al., 2024).

The integration of GAI tools into education may, therefore, require teachers to acquire new competencies to adapt effectively to these technologies (Dwivedi et al., 2023; Sampson, 2021; Van Dis et al., 2023). This shift and the rapid pace of technological change may lead teachers to feel less effective, less useful in their roles, and in some cases, fear job displacement. This situation, that can cause discomfort and anxiety among university teachers, is already becoming a reality (Bae et al., 2024; Zhang & Aslan, 2021).

2.1.2 Anxiety about misusing ChatGPT (ANXU)

Academic integrity has a significantly negative direct effect on university teachers' adoption of ChatGPT (Bin-Nashwan et al., 2023). This suggests that higher levels of academic integrity among academics correspond to lower use of ChatGPT in their work. This aligns with concerns about technology anxiety, a feeling of apprehension that arises when individuals face the possibility of using new technologies (Gelbrich & Sattler, 2014).

While ChatGPT has demonstrated value in generating educational and research materials, its use raises significant uncertainties (Dowling & Lucey, 2023; Hu et al., 2025). For instance, questions about whether it is necessary to disclose ChatGPT usage, how such disclosure might affect the legitimacy of the materials produced, and concerns over authorship persist (Bae et al., 2024; Thorp, 2023). These doubts are particularly salient for university teachers, who may question the ethical implications, accuracy, and potential reputational risks associated with using ChatGPT in teaching and research (Bae et al., 2024; Else, 2023; Hu et al., 2025; Yu, 2024). The interplay between academic integrity and technology anxiety underscores the complex challenges teachers face in integrating GAI into their professional practices.

2.1.3 Anxiety about student learning (ANXS)

In the light of ChatGPT's demonstration of its ability to generate text, a debate has arisen as to whether AI tools, and ChatGPT in particular, should be restricted in academic settings. Concerns such as student plagiarism, the creation of fake content, and legal ramifications are central to these discussions. University teachers have expressed concerns about maintaining academic integrity and ensuring effective student learning, as reflected in the limited academic research available (e.g., Bae et al., 2024; Cotton et al., 2023; Dwivedi et al., 2023; García-Peñalvo, 2023; Sullivan et al., 2023).

A particular concern is that students may become overly reliant on ChatGPT, potentially compromising their ability to complete academic tasks independently. Detecting whether students have used ChatGPT for assignments presents a significant challenge due to the tool's ability to closely mimic human-generated content (Dwivedi et al., 2023). This ability complicates traditional approaches to assessing originality and contributes to university teachers'concerns about the potential erosion of the authenticity of the learning process.

As a result of these concerns, university teachers may be reluctant to incorporate ChatGPT into their classroom practices (Jain & Raghuram, 2024), based on the belief that the tool may undermine the core principles of education and hinder meaningful student engagement (Bae et al., 2024; Yu, 2024).

Accordingly, the following hypothesis is proposed:

H1 Anxiety has a direct and significant negative association with the intention to use ChatGPT by university teachers (BI).

H1a Anxiety regarding the impact that ChatGPT may have on the academic profession (ANXP) has a direct and significant negative association with the intention to use ChatGPT by university teachers (BI).

H1b Anxiety regarding the misuse of technology (ANXU) has a direct and significant negative association with the intention to use ChatGPT by university teachers (BI).

H1c Anxiety regarding the student learning (ANXS) has a direct and significant negative association with the intention to use ChatGPT by university teachers (BI).

2.2 Mediating effects on the relationship between anxiety and intention

In the previous section, it was argued that technology-related anxiety is both directly and negatively related to the intention to use ChatGPT. In this section, the indirect effect of anxiety on behavioral intention is analyzed through the EE and PE variables. For intention models, like UTAUT, these two variables are critical.

2.2.1 Mediating effect of effort expectancy (EE) on the relationship between anxiety and intention to use ChatGPT (BI)

Effort expectancy (EE) is defined as the degree to which individuals perceive a technology as easy to use. In the context of this study, EE refers to the extent to which academics perceive ChatGPT as an accessible and user-friendly tool that can be seamlessly integrated into their teaching practices. This includes an assessment of the complexity of the system, the perceived ease or difficulty of its operation, and the amount of effort required to effectively use ChatGPT within an educational setting. The importance of EE in influencing BI has been highlighted by previous research. Literature shows that the ease of use of technology (Xue et al., 2024), particularly GAI tools (Jain & Raghuram, 2024) and ChatGPT specifically (Hidayat-ur-Rehman & Ibrahim, 2024), is a critical factor for university teachers in determining their willingness to adopt such innovations. In this context, the perception of ease of use (defined as the degree to which teachers believe the technology minimizes effort) is paramount in shaping their intention to integrate these tools.

The influence of anxiety on EE has been extensively documented in the literature. For example, Gunasinghe and Nanayakkara (2021) report that technology-related anxiety negatively affects users'perceptions of technological usability. Similarly, Chiu and Churchill (2016) and Mac Callum et al. (2014) find that teachers who experience elevated levels of anxiety when using technology as a learning and teaching tool are less likely to perceive such technology as user-friendly. This diminished perception of usability subsequently inhibits the likelihood of adoption. Anxiety exacerbates perceptions of complexity and reinforces concerns about the effort required to learn and use the technology effectively.

Moreover, in the specific context of ChatGPT and other GAI tools, anxiety may arise from fears that these technologies could potentially displace the role of the university teacher, compromise the quality of the learning process for students, or lead to errors due to misuse. Such concerns may reinforce the perception that the tool is inherently difficult to use, further reducing EE. As a result, university teachers who experience heightened anxiety are more likely to negatively evaluate the usability of ChatGPT and other GAI tools, reducing their willingness to adopt these innovations (Mac Callum et al., 2014).

In this context, technology-related anxiety, by altering university teachers' perceptions of usability, plays a significant role in determining their intention to adopt new technologies. These arguments, supported by existing empirical evidence, lead to the formulation of the following hypothesis:

H2 Effort expectancy (EE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety.

H2a Effort expectancy (EE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety regarding the impact that ChatGPT may have on the academic profession (ANXP).

H2b Effort expectancy (EE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety regarding the misuse of technology (ANXU).

H2c Effort expectancy (EE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety regarding the student learning (ANXS).

2.2.2 Mediating effect of performance expectancy (PE) on the relationship between anxiety and behavioral intention (BI)

Performance expectancy (PE) is defined as the degree to which using technology will provide benefits to users when performing certain activities, which in this study refers to the degree to which academics believe that using ChatGPT would help them to attain gains and increase opportunities, achievements, and productivity in their teaching practice.

Anxiety related to the use of GAI can negatively impact PE, as university teachers may perceive less utility in a technology that elicits significant concern. When the adoption of GAI technologies necessitates profound changes in established academic practices and diminishes the perceived value of the teacher's contribution, it can lead to a reduced perception of PE. University teachers may view such technologies as less beneficial if they perceive that their professional role is being undermined or devalued.

Additionally, concerns about the potential for unethical use by students—such as relying on GAI tools for academic dishonesty—or the perception that students are exerting less effort in learning and becoming overly dependent on technology for completing academic tasks may further reduce the perceived usefulness of GAI tools. Teachers might interpret such dependencies as detrimental to the overall educational process, thereby diminishing their belief in the value of these technologies.

Furthermore, anxiety has been found to negatively influence individuals' performance expectations related to technology use (Celik, 2016; Gunasinghe & Nanayakkara, 2021; Gunasinghe et al., 2019). This suggests that teachers who experience higher levels of anxiety regarding GAI may be less likely to perceive its utility in improving their teaching outcomes. Anxiety also affects the perceived effort required to complete a task using technology, as it amplifies fears and concerns about complexity and usability (Celik, 2016; Gunasinghe & Nanayakkara, 2021). These negative emotions—such as worry, fear, or uneasiness—not only affect how university teachers perceive the usefulness of GAI but also trigger withdrawal behaviors. For instance, anxiety can lead to physical withdrawal, where teachers avoid using the technology altogether, or mental withdrawal, where they engage in nonproductive tasks unrelated to their professional goals (Huang et al., 2024). Both forms of withdrawal impede effective task performance and further reinforce negative perceptions of GAI tools.

Finally, if university teachers perceive that they lack sufficient control over their own use of GAI tools or question whether their outputs generated with these technologies are appropriately executed, their perception of the tool's utility may also decline (Gunasinghe & Nanayakkara, 2021). These factors collectively suggest that anxiety and associated concerns significantly undermine the perception of GAI as a valuable resource in the academic context, highlighting the importance of addressing these psychological barriers to promote effective adoption (Arpaci & Basol, 2020).

Given that the relationship between PE and BI has been extensively validated in the literature (Hu et al., 2020; Lee et al., 2024; Xue et al., 2024), the following hypothesis is proposed:

H3 Performance expectancy (PE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety.
H3a Performance expectancy (PE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety regarding the impact that ChatGPT may have on the academic profession (ANXP).
H3b Performance expectancy (PE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety regarding the misuse of technology (ANXU).
H3c Performance expectancy (PE) mediates the relationship between the intention to use ChatGPT by university teachers (BI) and anxiety regarding the student learning (ANXS).

2.3 ChatGPT´s behavioral intention and use behavior

As established in intention models, such as those proposed by Venkatesh et al. (2003), BI is a critical determinant of technology use behavior (UB). These models consistently demonstrate that higher levels of BI positively and significantly influence actual usage behavior.

In the context of higher education, the BI-UB relationship has been shown to be particularly strong, surpassing its predictive power in other educational settings (Strzelecki & ElArabawy, 2024; Xue et al., 2024). The following hypothesis is proposed:

H4 Intention to use ChatGPT (BI) by university teachers is positively, directly, and significantly associated with actual use of ChatGPT (UB).

With these rationales in mind, a research model was designed to analyze the direct effect of anxiety types on intention to use ChatGPT (BI), its indirect effect through effort expectancy (EE) and performance expectancy (PE), and the BI-UB relationship (Fig. 1).

3 Method

3.1 Instrument

To collect the data to test the formulated hypotheses, a questionnaire was developed. The questionnaire was divided into three sections: the first section contained an introduction and general information about the subject of the study, while the

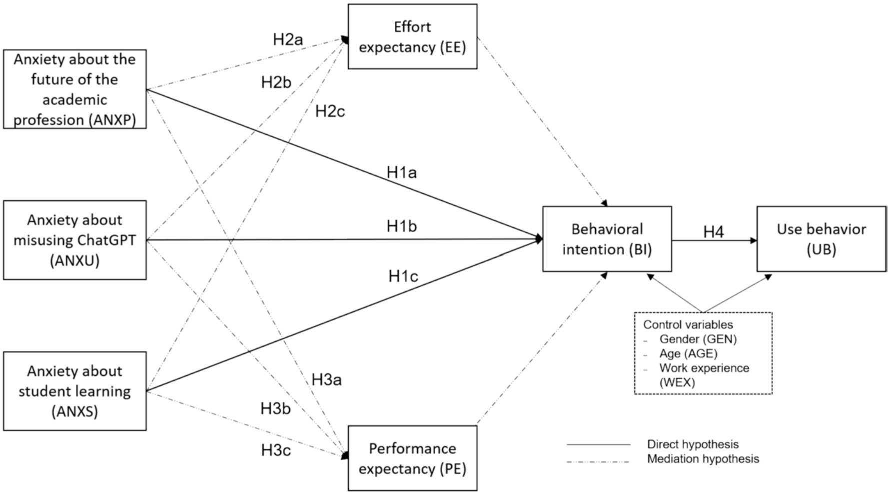

Fig. 1 Proposed model to explain the adoption of ChatGPT by university teachers

second section consisted of 23 items measuring seven factors (ANXP, ANXU, ANXS, EE, PE, BI, UB). The items are listed in the Appendix. The constructs were modelled as reflective measures. The scales related to the UTAUT model (EE, PE, BI, and UB) were based on the works of Farooq et al. (2017) and Venkatesh et al. (2003). The scale for anxiety about misusing ChatGPT (ANXU) was adapted from the work of Garone et al. (2019). The scale addressing anxiety about the future of the academic profession (ANXP) was developed from the work of Sampson (2021) and Felten et al. (2023). Finally, the scale for anxiety about student learning (ANXS) was constructed based on the concerns and issues raised in works such as Cotton et al. (2023) and Dwivedi et al. (2023). All scales were modified to include specific references to ChatGPT.

Scales were translated into Spanish. Statements were measured on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree), except for use behavior, which would be a frequency scale (1 = never; 5 = continuously). The third section collected demographic information, including gender (male, female, other), age, work experience and work schedule (full-time or part-time). The variables of age, work experience, and gender were used as control variables, following precedents set in previous research on technology adoption (Jo, 2023).

3.2 Procedure

The study population comprised the teaching staff employed at the 50 public universities within the Spanish university system.

Because the data were collected from a single source, several procedural precautions were taken to mitigate common method bias. These measures, as recommended by Podsakoff et al. (2003, 2012), included the following: (a) providing clear instructions emphasizing that there are no correct answers and ensuring confidentiality of responses to minimize response bias; (b) designing a concise questionnaire and avoiding redundant items to reduce respondent fatigue and demotivation; (c) including both positively and negatively worded items; (d) separating the presentation of independent and dependent variables within the questionnaire to prevent respondents from inferring the researcher's interest in specific variable relationships; and (e) conducting a pretest to identify and address potential response bias.

Data collection was conducted using Microsoft Forms. The survey tool was configured to automatically validate responses by requiring all questions to be completed before submission and by preventing multiple submissions from the same participant. Considering that the items of the scales were translated from English to Spanish and in order to guarantee their comprehensibility, and that the questionnaire was addressed to teachers, a pretest was conducted with 10 university teachers. Based on the feedback from the pretest, modifications were made to improve the clarity and comprehensibility of the questionnaire. No items were introduced or eliminated as a result of this pretest.

The final questionnaire was distributed to a random sample of 100 unit directors at Spanish public universities, with the request that they disseminate it to their teachers. The survey was carried out between March and April 2023. In May 2023, a follow-up reminder was sent to the same unit directors in order to improve the response rate. All participants had to give their informed consent to participate. The data collected were processed following the Spanish data protection regulations (Organic Law 3/2018 of 5 December on Personal Data Protection and Digital Rights Guarantees). Finally, 249 valid questionnaires were received.

3.3 Data analysis

The structural equation modelling (SEM) technique is applied, using Smart-PLS-4.0.9.6 software. The variance-based PLS-SEM method, commonly employed in empirical research on technology adoption (Ringle et al., 2022) for its explanatory, predictive and complex model estimation capabilities (Guenther et al., 2023), is applied to test the hypotheses. Moreover, as Hair et al. (2019) point out, this technique works well with both large and small samples and does not assume any particular distribution of the data. The data in this research follow a non-normal distribution, as all skewness and kurtosis values are less than 2 in absolute value.

Before conducting the SEM, the adequacy of the sample, the absence of multicollinearity and the lack of common method bias (CMB) were verified (Ooi, 2014). G*Power 3.3 software was used, with parameters of 0.9 for the power test (Cohen, 1988) and 0.15 for the effect size (Faul et al., 2007) to determine the minimum sample size, obtaining a result of 116 cases. This research includes 249 individuals, which makes it appropriate for PLS-SEM. Secondly, a full multicollinearity test was performed, and all variance inflation factors (VIFs) were below the established cutoff point of 5 (Becker et al., 2015; Hair et al., 2019). Finally, to control common method variance (CMB), in addition to following the recommendations in the questionnaire design, a Harman´s single factor test was performed. The unrotated first factor explains 44.63% of the variance, below the 50% threshold established by Podsakoff et al. (2003). These results indicate that CMB is not an issue in this research.

4 Results

Table 1 shows the sample characteristics. As can be seen, the percentage of men and women is similar. The majority of the teachers surveyed are between 41 and 60 years old, have more than 20 years of work experience and work for the university on a full-time basis.

In line with Hair et al. (2017), the two-stage procedure, characteristic of PLS-SEM analyses, was adopted: evaluation of the measurement model (outer model) and evaluation of the inner or structural model.

4.1 Assessment of the outer model

The outer model is made up of reflectively measured constructs. For its assessment, both indicator and construct reliability are evaluated, as well as convergent and discriminant validity (Hair et al., 2021). Thus, the validity of the measurement model

Table 1 Sample characteristics

Variable	Frequency	%
Gender		
Man	132	53.0
Woman	117	47.0
Other	--	--
Age (years)		
20–25	10	4.0
26–30	15	6.0
31–35	15	6.0
36–40	10	4.0
41–50	62	24.9
51–60	112	45.0
61–65	19	7.6
More than 65	6	2.4
Work experience (years)		
Less than 1	11	4.4
1–5	28	11.2
6–10	22	8.8
11–20	44	17.7
More than 20	144	57.8
Work schedule		
Full time	195	78.3
Part time	54	21.7

was tested by adopting the following criteria (Tables 2 and 3): a) loadings above 0.708, i.e., at least 50% of the variance of each indicator must be explained by the construct, suggested by Hair et al. (2019); b) reliability of the measurement scales with Cronbach's Alpha > 0.7 recommended by Peterson (1994); internal consistency through composite reliability (CR), when exceeding the value 0.7 according to Nunnally and Bernstein (1994), and Dijkstra and Henseler's rho_A, also exceeding 0.7 (Dijkstra & Henseler, 2015); c) convergent validity with Average Variance Extracted (AVE) greater than 0.5 (Fornell & Larcker, 1981); and d) discriminant validity with HTMT ratio less than 1 (Henseler et al., 2015) and upper limit of the confidence interval is less than 0.90 (Guenther et al., 2023). Consequently, the proposed

Table 2 Measurement model. Reliability and convergent validity

Constructs	Indicators	Loadings (t-value)	Construct Reliability and Validity			
			Alpha de Cronbach	CR (rho_C)	rho_A	AVE
Performance expectancy (PE)	PE1	0.921 (71.821)	0.943	0.959	0.947	0.854
	PE2	0.935 (70.598)				
	PE3	0.916 (60.411)				
	PE4	0.925 (63.928)				
Effort expectancy (EE)	EE1	0.875 (47.598)	0.866	0.907	0.899	0.712
	EE2	0.923 (79.748)				
	EE3	0.718 (11.833)				
	EE4	0.844 (33.003)				
Anxiety about the future of the academic profession (ANXP)	ANXP1	0.951 (10.701)	0.901	0.953	0.903	0.910
	ANXP2	0.957 (11.083)				
Anxiety about misusing ChatGPT (ANXU)	ANXU1	0.872 (29.491)	0.879	0.916	0.899	0.732
	ANXU2	0.851 (25.235)				
	ANXU3	0.821 (18.551)				
	ANXU4	0.879 (35.414)				
Anxiety about student learning (ANXS)	ANXS1	0.870 (29.015)	0.909	0.942	0.938	0.845
	ANXS2	0.948 (95.493)				
	ANXS3	0.937 (69.516)				
Behavioral intention (BI)	BI1	0.922 (65.232)	0.957	0.967	0.957	0.853
	BI2	0.942 (103.599)				
	BI3	0.907 (60.834)				
	BI4	0.946 (105.589)				
	BI5	0.900 (51.580)				
Use behavior (UB)*	UB	1				

Note(s): AVE: Average Variance Extracted; *Single-item construct; bootstrapping based on n = 10,000 subsamples; all t-values are significant at p-value < 0.001

Table 3 Measurement model. Discriminant validity

	PE	EE	ANXP	ANXU	ANXS	BI	UB
PE		0.640	0.211	0.336	0.358	0.875	0.695
EE	0.536		0.238	0.361	0.353	0.675	0.590
ANXP	0.083	0.105		0.627	0.415	0.225	0.215
ANXU	0.216	0.242	0.506		0.516	0.438	0.353
ANXS	0.240	0.228	0.312	0.415		0.470	0.443
BI	0.832	0.583	0.104	0.324	0.366		0.832
UB	0.633	0.507	0.108	0.255	0.338	0.793	

Note(s): HTMT values are shown below the diagonal, and the upper 95% confidence interval limit (bootstrapped with n= 10,000 subsamples) is above the diagonal. PE: performance expectancy; EE: effort expectancy; ANXP: anxiety about the future of the academic profession; ANXU: anxiety about misusing ChatGPT; ANXS: anxiety about student learning; BI: behavioral intention; UB: use behavior

measurement model has a satisfactory degree of reliability, internal consistency, convergent and discriminant validity.

4.2 Assessment of the inner model

The assessment of the structural model requires the study of multicollinearity and the analysis of the explicative and predictive power of the model. All VIFs of the constructs report a value below 3, so no multicollinearity problems are apparent (Becker et al., 2015; Hair et al., 2019). The model fit is analyzed using the most widely used bootstrap-based test for model fit: the standardized root mean square residual (SRMR), with recommended thresholds of 0.08 (Hair et al., 2022). The SRMR obtained (0.067) ensures a good model fit. Figure 2 shows the results of the PLS-SEM analysis, with the standardized regression coefficients (β) and p-value, subject of discussion in the hypothesis evaluation section, and R^2 values of the constructs to evaluate the explicative capacity. 70.6% of the variance of BI is explained by its predictors. In addition, BI has a significant impact on UB ($\beta = 0.753$), accounting for 60.7% of its variance. In both cases the R^2 value is considered moderate (Hair et al., 2019).

The predictive ability of the model is examined with the PLSpredict algorithm developed by Shmueli et al. (2016). The results (Table 4) show positive Q^2 values, as required by Hair et al. (2017), and root mean square error (RMSE) values in PLS lower than those obtained in LM in all indicators, so the model has a high predictive ability (Shmueli et al., 2019).

4.3 Assessment of the proposed hypotheses

Table 5 presents the significance tests for the path coefficients of the structural model (β), the confirmation of the hypotheses and the effect size (f^2) of the direct

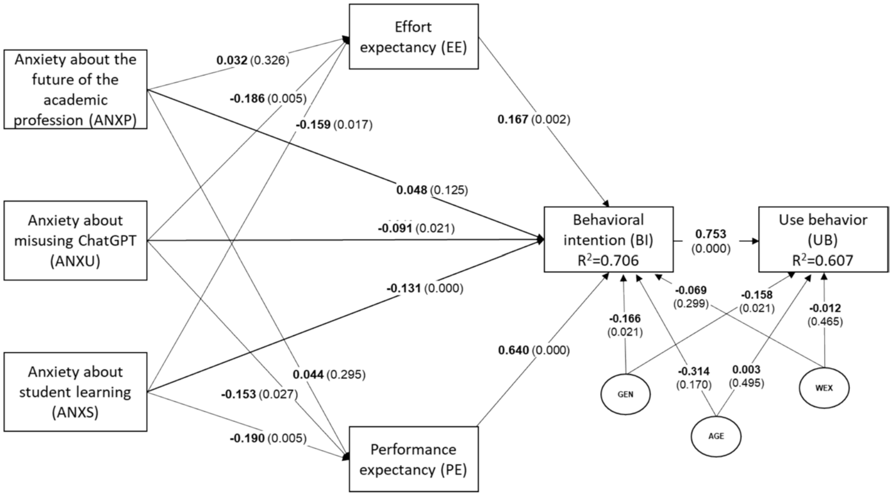

Fig. 2 Results of the proposed model to explain the adoption of ChatGPT by university teachers. Note: SRMR: standardized root mean square residual bootstrapped with 10,000 subsamples =0.067. GEN: Gender; AGE: Age; WEX: Work experience

Table 4 Predictive relevance of the model

	Q^2	PLS-SEM_RMSE	LM_RMSE
BI1	0.093	1.327	1.351
BI2	0.141	1.323	1.362
BI3	0.187	1.155	1.162
BI4	0.159	1.239	1.266
BI5	0.100	1.308	1.353
UB	0.127	1.081	1.125

Note: RMSE: root mean square error; LM: linear regression model

Table 5 Direct Hypothesis testing

Hypothesis	Path	β	t	95% CI	f^2	Confirmed
H1a	ANXP → BI	0.048 ns	1.152	[– 0.018; 0.119]	0.006	No
H1b	ANXU → BI	– 0.091**	2.037	[– 0.163; – 0.015]	0.020	Yes
H1c	ANXS → BI	– 0.131***	3.394	[– 0.196; – 0.068]	0.048	Yes
H4	BI → UB	0.753 ***	25.459	[0.229; 0.493]	1.293	Yes

Note: bootstrapping based on 10,000 subsamples; ***p <0.001; **p <0.05; *p <0.01; ns: non-significant

hypotheses. The negative and significant effects of ANXU ($\beta = -0.091$, $p < 0.05$) and ANXS ($\beta = -0.131$, $p < 0.001$) on BI are confirmed, supporting H1b and H1c respectively. The ANXP-BI relation is not significant, so H1a is not supported. UB is positive, direct and significantly influenced by BI ($\beta = 0.753$, $p < 0.001$), thus confirming H4. According to Cohen's proposal (Cohen, 1988), BI contributes greatly to explaining UB ($f^2 \geq 0.35$).

The conditions established by Baron and Kenny (1986) for mediation analysis require, firstly, direct significant relations between the variables being mediated and the mediators. Figure 2 shows the significant relationship of ANXU with EE ($\beta = -0.186$, $p < 0.05$) and with PE ($\beta = -0.153$, $p < 0.05$), as well as that of ANXS with EE ($\beta = -0.159$, $p < 0.05$) and with PE ($\beta = -0.190$, $p < 0.05$). Significant effects of EE ($\beta = 0.167$, $p < 0.05$) and PE ($\beta = 0.640$, $p < 0.001$) on BI are also confirmed. The ANXP relationships are not significant.

Furthermore, the analysis of indirect effects determines whether there is mediation (Cepeda et al., 2017). As shown in Table 6, the simple indirect effect of EE on the relations ANXU-BI ($\beta = -0.031$, $p < 0.05$) and ANXS-BI ($\beta = -0.027$, $p < 0.001$) are significant and negative, indicating the same direction of the direct effect (partial complementary mediation). The same occurs with the simple indirect effects of PE in these relationships ($\beta = -0.098$, $p < 0.05$; $\beta = -0.122$, $p < 0.05$), thus confirming the complementary partial mediating effect. This means that both EE and PE explain part of the observed relationship between the different kinds of anxiety and BI (Hair et al., 2017), while anxiety also explains part of BI, independently of EE and PE. However, the mediating effect of EE and PE in the ANXP-BI relationship is not significant, so H2b and H3b are not confirmed. In addition, the multiple indirect effect of EE and PE on ANXU-BI is significant, suggesting that EE and PE jointly influence the relationship between ANXU and BI, with PE ($\beta = -0.098$) being the primary driver of the mediation (44.29% of the total effect). This phenomenon is also observed in the ANXS-BI relationship, where PE ($\beta = -0.122$) accounts for 43.64% of the total effect.

To confirm the hypotheses of partial mediations, the explained variance (VAF) is calculated. VAF determines the ratio between the indirect effect and the total effect (Nitzl et al., 2016) and its value should be between 0.2 and 0.8 (Hair et al., 2017). The calculated VAFs (Table 7) corroborate the partial mediation of EE and PE in

Table 6 Mediation test

Simple	Specific indirect effects	β	t	95% CI
H2a	ANXP-EE-BI	0.005 ns	0.415	– 0.0150.027
H2b	ANXU-EE-BI	– 0.031**	1.828	– 0.063–0.008
H2c	ANXS-EE-BI	– 0.027*	1.559	– 0.059–0.004
H3a	ANXP-PE-BI	0.028 ns	0.538	– 0.0530.120
H3b	ANXU-PE-BI	– 0.098 **	1.919	– 0.184–0.016
H3c	ANXS-PE-BI	– 0.122**	2.541	– 0.200–0.043
	Total indirect effects	β	t	95% CI
Multiple	ANXP-BI	0.034 ns	0.570	– 0.059 0.134
	ANXU-BI	– 0.129**	2.246	– 0.227 – 0.036
	ANXS-BI	– 0.148**	2.736	– 0.236 – 0.059

Note: bootstrapping based on 10,000 subsamples; ***p <0.001; **p <0.05; *p <0.01; ns: non-significant

Table 7 Indirect effects' and total effects' variance accounted (VAF)

Effects	H2b ANXU→ BI	H2c ANXS→ BI	Effects	H3b ANXU→ BI	H3c ANXS→ BI
Direct	$\beta = -0.091$	$\beta = -0.131$	Direct	$\beta = -0.091$	$\beta = -0.131$
EE Indirect	$\beta = -0.031$	$\beta = -0.027$	PE Indirect	$\beta = -0.098$	$\beta = -0.122$
EE Total	$\beta = -0.122$	$\beta = -0.158$	PE Total	$\beta = -0.189$	$\beta = -0.253$
VAF	0.254	0.17	VAF	0.518	0.48

the ANXU-BI relationship, and that of PE in the ANXS-BI relationship. This supports hypotheses H2b, H3b and H3c. The VAF = 0.17 in the ANXS-EE-BI relationship indicates that no mediation occurs due to its irrelevant impact, so H2c is not confirmed.

In terms of the control variables, the results show that gender has a significant effect on BI ($\beta = -0.166$, $p < 0.05$) and on UB ($\beta = -0.158$, $p < 0.05$). In this sense, women have lower BI and UB than their male colleagues. Neither age nor work experience have a significant effect on BI and UB.

5 Discussion

This study sets out to address two objectives. Regarding the first objective, the existence of three types of anxiety that may influence the behavioral intention to adopt ChatGPT was explored. This behavioral intention is a key variable in UTAUT model. While previous studies have addressed technological anxiety or technostress, this work makes a distinct effort to detail the specific sources of anxiety that university teachers experience when considering the use of ChatGPT and, by extension, other GAI tools. The findings supported that anxiety directly and negatively impacts teachers' intention to adopt the tool. This is especially true for anxiety about student learning according to previous literature (e.g., Cotton et al., 2023; Dwivedi et al., 2023). This means that, in the context of the use of GAI, it has been observed that when teachers feel anxious about the possibility of students misusing this technology (for example, plagiarism or excessive dependence on automated answers), this anxiety directly reduces their willingness to use the tool in their classes (Bae et al., 2024; Sullivan et al., 2023).

A direct negative association was also observed between anxiety about university teachers' misusing ChatGPT and behavioral intention. This means that when teachers are afraid that ChatGPT could produce inaccurate, misused or even plagiarized information, they are less willing to adopt it, as the use of GAI generated content can compromise the academic integrity of the materials produced. This finding is consistent with previous work that indicates that ethical or professional doubts about technological tools tend to undermine their acceptance (e.g., Bin-Nashwan et al., 2023; Hu et al., 2025).

However, no significant association was found between anxiety related to profound changes in teaching tasks and the potential devaluation of the teaching profession as it is currently conceived. A plausible explanation for this finding is the high level of job security prevalent among most teachers in the Spanish public university system (Ministerio de Universidades, 2024). Under Spanish legislation, teachers who have obtained stable positions generally enjoy permanent contracts that are protected by law. This legal framework greatly diminishes concerns about possible layoffs or forced obsolescence due to technological advancements. Consequently, although some teachers might feel apprehensive about how artificial intelligence could redefine their roles, these concerns do not seem to significantly affect their overall intention to adopt new technologies; their employment status is safeguarded. Additionally, the stability afforded by these positions may foster a professional environment in which teachers can experiment with innovations and navigate pedagogical shifts without fear of immediate professional repercussions. Such certainty effectively mitigates any anxiety rooted in the idea that GAI might displace or drastically reduce their role, which explains why this particular form of anxiety does not have a significant effect on their intention to use ChatGPT.

Furthermore, university teachers perceive themselves not only as technically capable of adapting to and mastering new artificial intelligence-based tools, but also as bringing unique human qualities that distinguish them from GAI (Chan & Tsi, 2024). Their ability to foster creativity, demonstrate empathy, and engage in critical thinking enables them to provide sophisticated insight, ethical judgment, and personalized guidance that technology alone cannot replicate. These distinctly human attributes make their role in higher education essential, ensuring that GAI functions as a complement rather than a replacement in academic and pedagogical contexts (Dwivedi et al., 2023).

The second objective aimed to analyze how effort expectancy and performance expectancy mediate the relationship between the kinds of anxiety and behavioral intention. To the best of our knowledge, these mediation relations have not been addressed in previous research. However, both effort expectancy and performance expectancy are variables specific to UTAUT and their direct effect on both behavioral intention and use behavior have been widely validated (Farooq et al., 2017).

In this work, no mediation effect was found for anxiety related to changes affecting the profession. Although university teachers may consider the effort expectancy or the performance expectancy, these perceptions do not explain how preoccupation with professional transformation affects (or not) the intention to use ChatGPT. These results suggest that anxiety about changes in the teaching profession is not a determining factor in the decision to use technology such as ChatGPT. As with the direct relationship, it is expected that contextual factors such as job security and the regulatory framework, as well as the intrinsic characteristic of university teachers to be able to adapt to change, will mean that this type of anxiety will not have an indirect relationship with behavioral intention.

Regarding anxiety about teachers' misuse of ChatGPT, as previously mentioned, negatively and directly influences their intention to use it. In addition, if university teachers are worried because they believe that ChatGPT may generate errors or achieve poor results, they are more likely to perceive that efficiently mastering this tool requires a lot of effort (effort expectancy) and to think that it is not useful in their teaching (performance expectancy), which will lower their intention to use it (Gunasinghe & Nanayakkara, 2021). Therefore, both effort expectancy and performance expectancy are mediators in the relationship between teacher misuse anxiety and intention to use ChatGPT.

Finally, teachers' anxiety related to student misuse of ChatGPT, in addition to having a direct and negative relationship with teacher behavioral intention, indirectly affects teacher intention to use through performance expectancy, but not through effort expectancy. Therefore, this type of anxiety also has an indirect effect through performance expectancy. That is, the greater the teachers' anxiety generated by the possibility of misuse by students, the lower the expectation of good performance with ChatGPT by teachers, and thus the lower the intention to use it. Since performance expectancy is one of the most influential factors in technology adoption according to the UTAUT model (Farooq et al., 2017; Venkatesh et al., 2003), the reduction of this perception leads to a lower interest in using the tool. However, the effect of this same type of anxiety on intention to use the tool through perceived ease of use is irrelevant, so effort expectancy cannot be considered a mediating variable in this relationship.

5.1 Implications

The results of this study offer relevant implications for both theoretical and practical aspects. From a theoretical perspective, this work explores the adoption of GAI in a group that has received limited research attention: university teachers. Given the significance of this group in implementing new teaching tools and methodologies, it is crucial to understand their motivations and interests regarding the adoption of GAI.

A salient concern among university teachers is the potential implications of GAI adoption for the future of their profession, its misuse, and the subsequent impact on student learning. This study addresses this concern by examining the three types of anxiety that shape the adoption of GAI in academic settings. The findings of this study support the notion that technology-related anxiety hinders the intention to adopt and subsequently implement GAI in university classrooms. Moreover, a significant theoretical implication of this work is that when examining the role of anxiety in technology adoption, it is essential to consider the concept in a multifaceted manner, as anxiety can stem from diverse causes. As articulated in the paper, the influence of anxiety on technology adoption varies across different types. Notably, the study underscores the notion that the impact of anxiety on technology adoption is operating both directly and indirectly through other variables, such as effort expectancy and performance expectancy. These results reinforce the contributions of the UTAUT model, by showing how affective factors can impact the expectation of performance to a greater extent than the expectation of effort.

From the point of view of practical application, significant implications can also be drawn. University teachers' development programs should focus on teaching the practical applications of GAI tools, which can reduce usage anxiety, and how to use them ethically and responsibly without compromising academic integrity (Yu, 2024). Such training programs must include strategies to address anxiety stemming from concerns over students' misuse of these tools and their potential effects on learning outcomes. For instance, these programs could demonstrate how to create and implement student-oriented codes of conduct. Every training initiative should incorporate a practical component, allowing university teachers to reflect on and implement GAI tools in their own disciplines.

An analysis of the sociodemographic variables revealed noteworthy differences in the adoption of GAI tools. The results indicate that while age and work experience did not significantly influence behavioral intention or use behavior, gender emerged as a significant factor. Specifically, female teachers exhibited lower levels of behavioral intention compared to their male counterparts. These differences suggest that female teachers may experience unique barriers or concerns regarding the adoption of GAI technologies. In light of these findings, it is imperative that educational guidance and training interventions be tailored to address these gender-specific challenges. Targeted interventions could include dedicated training sessions, mentorship programs, and resources that focus on both enhancing technical proficiency and mitigating anxiety associated with the use of GAI tools. Such tailored support is likely to increase overall university teachers' confidence and promote a more balanced and effective integration of these emerging technologies into the academic environment.

Additionally, initiatives should be undertaken to encourage reflection on the appropriate use of GAI tools in the academic context. It is crucial for the university community to be aware of both the opportunities and risks associated with these technologies. Sharing best practices, case studies, and research findings can accelerate the adoption and implementation of GAI in higher education (Bin-Nashwan et al., 2023). Regarding the risks, targeted actions should be directed toward university teachers who, due to prior negative experiences, are reluctant to adopt these tools. Such teachers must be made aware of the full range of functionalities these tools offer, so that even if they choose not to apply them in their courses, they understand how others, including students, might utilize them (Hazzan-Bishara et al., 2025).

Institutional leaders should also promote collaboration and knowledge sharing among stakeholders within the GAI educational community (Jain & Raghuram, 2024). Collaborative initiatives can foster innovation and drive the development of advanced GAI solutions tailored to the specific needs of academia (Zhang & Aslan, 2021). These efforts will not only enhance the integration of GAI but also ensure that its implementation aligns with the broader objectives of higher education.

Finally, it is essential to establish a clear framework to fully leverage the opportunities offered by GAI. Institutions should develop and disseminate explicit guidelines for the use of GAI among members of the academic community, provide comprehensive training on these guidelines, and ensure their adherence through consistent monitoring (Bae et al., 2024).

5.2 Limitations and future research lines

This study presents limitations that should be addressed in future research. First, it adopts a cross-sectional design, which limits the ability to capture how perceptions of performance expectancy, effort expectancy, and anxiety evolve over time. For instance, as teachers receive more training and exposure to GAI tools, their technological literacy is likely to improve, potentially reducing usage anxiety and increasing performance expectancy and effort expectancy. This longitudinal study would provide a more dynamic understanding of these relationships and offer deeper insights into how training and experience shape behavioral intention to adopt GAI tools. Specifically, this research would provide insights into the long-term effects of targeted interventions and the evolution of perceptions as teachers become more familiar with these technologies. Additionally, this study could use a mixed-methods design to assess both quantitative differences and qualitative perceptions, thereby providing targeted insights for the design of specialized training programs.

Additionally, the study focuses exclusively on a sample of Spanish public university teachers, limiting the generalizability of the findings to other cultural and institutional contexts. While the results provide valuable insights into this specific setting, comparative studies with samples from different countries and educational systems are needed to assess the universality of the identified patterns and to explore cultural nuances in the adoption of GAI tools. Comparative studies could uncover how cultural and organizational differences shape anxiety, performance expectancy, effort expectancy, and behavioral intention regarding GAI adoption. For example, a cross-cultural study could be conducted in universities with very different regulatory and cultural environments. In this sense, it could clarify the relationship between anxiety and the adoption of ChatGPT and the perception of job security shown by the participants. This research could be applied in public and private universities, or in universities in countries with different levels of development, or between universities with different positions in academic rankings (e.g., Shanghai).

Investigating the role of institutional policies on the adoption of GAI tools is critical. Future research could examine how the clarity, dissemination, and enforcement of university regulations influence teachers' confidence and behavior regarding GAI use. In this sense, it would be useful to carry out a comparative analysis of universities with different levels of policy clarity, dissemination and enforcement regarding the use of GAI. Such research should examine how institutional regulatory maturity affects faculty confidence and usage patterns, potentially highlighting best practices that enhance adoption rates across diverse academic settings. Additionally, investigate how the broader organizational culture and leadership practices within universities influence teachers' anxiety and the adoption of GAI tools. This study might focus on how supportive leadership and a culture of innovation can mitigate resistance and promote effective technology integration.

University teachers' concerns about the ethical implications of GAI usage warrant further exploration. Research should examine how teachers' ethical apprehensions, such as fears of academic dishonesty or the erosion of academic integrity, affect the integration of these tools into their teaching practices. This study could employ a mixed-methods approach to identify the specific ethical dilemmas that drive university teachers' anxiety and propose frameworks for addressing them.

The emergence of GAI tools raises important questions about how these technologies are transforming the teaching profession. Future studies should delve deeper into the evolving roles and responsibilities of teachers in response to these disruptive technologies, as well as how these changes influence professional identity and pedagogical strategies. Consequently, a more exhaustive examination of the relationship between this particular kind of anxiety and behavioral intention is imperative, particularly in light of the absence of substantial findings in this study. A comprehensive understanding of the mechanisms underlying the direct influence of this kind of anxiety on behavioral intention could potentially reveal novel factors or mediators that shape this relationship.

Additionally, future research could explore whether different types of university teachers-such as those with different areas of expertise or academic disciplines, those at different stages of their careers, those with different levels of experience with GAI tools, or those of different genders-exhibit different levels of behavioral intention. In particular, examining gender differences could provide valuable insights into how perceptions, attitudes, or levels of anxiety toward GAI tools may vary by gender. Understanding these differences would allow for the development of more refined and equitable strategies to promote the responsible and effective integration of GAI tools across different segments of the academic community.

By addressing these limitations and pursuing these research directions, future studies can provide a more comprehensive understanding of the complex interplay between anxiety, perceptions of GAI tools, and behavioral intention, thereby informing more effective strategies for their integration into higher education.

6 Conclusions

This study examines how anxiety influences university teachers'intentions to adopt GAI tools like ChatGPT. By analyzing three distinct types of anxiety—concerns about professional change, worries about student learning, and fears of misusing ChatGPT—the research deepens the understanding of the psychological barriers to GAI adoption in higher education. The findings of this study indicate that teachers' anxiety negatively impacts behavioral intention, primarily by reducing performance and effort expectancies, especially concerning student misuse and reliance on inaccurate GAI outputs. In contrast, teachers' anxiety about the impact of ChatGPT on the academic profession did not significantly affect behavioral intention.

These results highlight the need for a comprehensive adoption strategy that goes beyond technical training. It is crucial to address anxiety through ethical awareness, academic integrity initiatives, and clear demonstrations of the tool's effectiveness in improving performance. The enhancement of confidence in GAI tools, as well as the promotion of their responsible and productive use, is only possible through the combination of these measures.

Appendix

Scales used

Variable	Description
ANXP1	I am concerned that ChatGPT and other artificial intelligence systems may make me less useful as a teacher
ANXP2	I am afraid that ChatGPT and other artificial intelligence systems will replace teachers
ANXU1	I am afraid of using ChatGPT
ANXU2	I am afraid to misuse the information I generate with ChatGPT
ANXU3	I am hesitant to use ChatGPT for fear of making mistakes that I can't correct
ANXU4	I am intimidated by using ChatGPT
ANXS1	I worry that my students may use ChatGPT in their assignments without me being aware of it
ANXS2	I fear that my students'learning will be of poorer quality if they use ChatGPT
ANXS3	I am concerned that my students will put less effort into learning if they use ChatGPT
BI1	I will continue to use ChatGPT for the foreseeable future
BI2	I will recommend ChatGPT to my peers and friends
BI3	I have a positive perception of ChatGPT
BI4	I intend to use or continue using ChatGPT for teaching purposes
BI5	I intend to use or continue to use ChatGPT in the research setting
EE1	I can easily interact with ChatGPT
EE2	It is easy for me to use ChatGPT
EE3	ChatGPT does not require much effort
EE4	It is easy for me to understand the different possibilities of using ChatGPT
PE1	ChatGPT is useful for my academic activity
PE2	ChatGPT helps me to do my work better
PE3	ChatGPT helps me to get my work done faster
PE4	ChatGPT helps me to be more productive
UB	Frequency of use

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Code availability Not Applicable.

Declarations

Competing interests The authors declare that they have no competing interests.

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