ChatGPT adoption and its influence on faculty well-being: An empirical research in higher education

Abstract
Rapid technological advancements of recent decades have fueled, among other aspects, a global boom in the utilization of artificial intelligence (AI) tools across a variety of areas. Higher education, like other domains, has embraced these innovations, with ChatGPT emerging as one of the latest additions. Faculty perception, ability, and willingness to adopt these new tools remain fundamental factors in understanding their proliferation and adoption. However, it's equally important to strike a balance between reaping the benefits of technology and safeguarding the well-being of faculty members. Against this backdrop, this study assesses the impact of a series of factors on ChatGPT adoption among university faculty members, taking as reference the Technology Acceptance Model (TAM). Additionally, we analyze the impact of ChatGPT adoption on faculty well-being. All hypotheses are tested using covariance-based structural equation modeling (CB-SEM). The findings highlight the positive influence of perceived usefulness, ease of use and enjoyment on ChatGPT adoption. Moreover, ChatGPT adoption seems to boost faculty' happiness and energy, while diminishing their stress levels. Theoretical and practical implications are discussed in the last section.

Keywords ChatGPT · TAM framework · Faculty well-being · Perceived usefulness · Easy-of-use · Enjoyment · Happiness · Energy · Stress

The term "faculty" refers to the group of university educators. In the British context, the word "lecturer" is used, while in a North American context, "professor" is more common. To ensure consistency throughout the manuscript, we will use "faculty" to refer to all university faculty/ educator/ teacher, regardless of their rank or appointment.

1 Introduction

Higher education has undergone a profound shift in recent decades, mostly driven by technological advancements (e.g., Adams et al., 2024; Ali et al., 2024; Ansari et al., 2024; Mukul & Büyüközkan, 2023; Rawas, 2023). However, Adamson and Sloan (2022) highlight that higher education is currently facing unprecedented reorganization challenges to ensure an adequate implementation of cutting-edge teaching and learning methodologies. This is especially important as technology plays an increasingly significant role in shifting traditional pedagogies to a more up-to-date approach (Mukul & Büyüközkan, 2023). The development and widespread adoption of emerging technologies, including the proliferation of digital devices and the integration of artificial intelligence (AI), have sparked a profound transformation in educational resources and methodologies (Dwivedi et al., 2021). Most educational institutions have embraced this technological revolution, adapting to and implementing innovative tools. In this context, faculty's ability, willingness, and efforts to adopt these new tools and methods remain a fundamental factor. Hence, beliefs and attitudes of faculty members can wield significant influence over their practices (Bower et al., 2024; Velander et al., 2023; Bruggeman et al., 2022).

Specifically, AI has emerged as transformative force in education. At its core, AI refers to the development of computer systems capable of performing tasks simulating human intelligence (Du-Harpur et al., 2020). In education, AI manifests in various forms, such as tutoring systems, personalized learning platforms, adaptive assessment tools, among others (Bhutoria, 2022; Mousavinasab et al., 2021). Generative AI refers to a type of AI that is capable of creating human-like content (e.g., textual, narratives, visual artwork). This advanced system operates by interpreting specific instructions or prompts to generate original and contextually relevant output, mimicking the creative processes observed in human cognition (Lim et al., 2023).

Generative AI gained widespread recognition following the launch of ChatGPT in November 2022. As a leading example of generative AI, ChatGPT's introduction has sparked new conversations on its potential application and use in education (e.g., Li et al., 2024; Maheshwari, 2024; Baabdullah, 2024; Rawas, 2023; Roose, 2023; The Economist, 2023). Educational institutions and scholars have put forth arguments from diverse perspectives acknowledging both benefits and concerns related to ChatGPT (Adams et al., 2024; Ali et al., 2024; Ansari et al., 2024). Evidence suggests that some of its benefits are related to personalized learning, availability, or even support for special needs (Ansari et al., 2024; Korneeva et al., 2023; Lo, 2023). However, just as importantly, valid concerns were raised as regards the ethical implications of ChatGPT (Li et al., 2024; Korneeva et al., 2023), especially related to plagiarism, privacy concerns and security risks, among others (Ali et al., 2024; Tlili et al., 2023). In any case, it is acknowledged that the potential benefits may outweigh these concerns, and that ChatGPT's prevalent use makes it difficult to control (Li et al., 2024; Mucharraz and Cano et al., 2023).

The challenge associated with ChatGPT's potential in shaping the future of education remains significant (Ali et al., 2024; Baabdullah, 2024). With a view to assess institutional perceptions towards the use of ChatGPT, a set of strategies, policies and other structural issues taking faculty and student perspectives into account must be

considered (Ansari et al., 2024; Bower et al., 2024; Li et al., 2024). While the literature on ChatGPT is growing consistently, it remains relatively limited in providing a comprehensive understanding of how ChatGPT use evolves into adoption. In that regard, much of the existing research has taken a theoretical or exploratory approach, resulting in a need for more empirical evidence (Jeon & Lee, 2023; Lo, 2023).

Furthermore, with limited exceptions (e.g., Bower et al., 2024; Guo & Wang, 2023; Jeon & Lee, 2023; Veklander et al., 2023), most studies have predominantly centered on the student viewpoint (e.g., Adams et al., 2024; Maheshwari, 2024). From both theoretical and practical perspectives, it is essential to consider the impact of tools like ChatGPT on teaching in higher education, and educators must weigh the benefits and drawbacks of incorporating such technology into instruction (Regnier et al., 2023). Therefore, there is a pressing need to delve into determining what factors could influence ChatGPT adoption from faculty members' perspective. As in all educational technology adoption, the role of faculty is key. Their participation comprises more than the mere acquisition of knowledge or skills (Ansari et al., 2024; Philipsen et al., 2019). Authors such as Bruggeman et al. (2021) underscore the importance of comprehending faculty beliefs, attitudes, and perceptions concerning the technology or tool involved. This holds special significance, as ChatGPT can prove to be a useful tool for faculty members as well, including numerous benefits, such as assistance and support of teaching activities (Cooper, 2023). For this reason, to understand ChatGPT adoption, faculty perceptions are crucial; yet more research is needed on faculty's experiences concerning ChatGPT use.

In this study, we explore perceptions among university faculty members, constructing our model based on the foundational framework of the classic Technology Acceptance Model (TAM) (Davies, 1989). This framework is widely acknowledged and is particularly relevant in educational settings (e.g., Wojciechowski and Vellary, 2013; Shroff et al., 2011), offering insights into the adoption of new technologies such as generative AI by elucidating user attitudes and behaviors. We study perceptions of usefulness, ease of use and enjoyment and determine their influence on ChatGPT adoption. Furthermore, authors such as Mehta et al. (2019) and Ukpabi and Karlajuoto (2017) suggest that TAM may be excessively simplistic. Hence, we also consider enjoyment as an additional factor influencing ChatGPT adoption. While the utilitarian aspects of technology (i.e., usefulness and ease of use) traditionally explain adoption, the emotional and pleasurable aspects can also play a significant role in influencing users to embrace a new technology (Chin & Gopal, 1995; Davis et al., 1992; Teo et al., 1999).

At the same time, the resulting outcomes of ChatGPT adoption are still to be explored. When implementing new tools, educational institutions face challenges not just from the perspective of technical knowledge or skills but also within the realm of human resource management. For this reason, it becomes imperative to strike a balance between harnessing the benefits of adopting new technology tools and safeguarding the well-being of faculty members. Well-being at work plays a central role, not just for employees, but also for organizations (Franco-Santos & Doherty, 2017). This is also evident in the very dynamic context of higher education. As Kinman and Court (2010) already indicated more than a decade ago, staff well-being has been shown to be continuously impacted by changes in the sector. Universities have

been subject to a number of challenges over the past 20 years, including proliferation of new learning approaches, technologies and tools. Therefore, due to the dynamic nature of the context, academic staff may find several challenges related with their performance and well-being (Marshall & Morris, 2015), including those related with psychosocial hazards (Kinman & Court, 2010). In this sense, Franco-Santos and Doherty (2017) analyze the aggregated level of well-being perceived by their academic staff in UK universities from a global perspective. However, they overlooked the potential influence of new technology adoption. Additionally, Stojanov and Daniel (2023) highlighted the need for future research to delve deeper into the well-being of staff members when integrating new tools. This underscores a relevant gap that our research aims to address. Besides, Caprara and Caprara (2022) pointed out that many of the studies related with faculty well-being relied on qualitative data, highlighting another significant gap in the literature.

Therefore, a differentiating aspect is that our study also assesses faculty well-being as a potential consequence of ChatGPT adoption from a quantitative perspective. We take a closer look at faculty happiness, energy and stress levels to examine how their well-being can be enhanced by ChatGPT adoption. Identifying these consequences may reveal key theoretical contributions to the current literature and relevant practical implications for higher education institutions.

The remaining of our paper is structured as follows. In the next section, we explain our theoretical background and conceptual framework. Section 3 presents methodological issues related to the empirical study carried out on a sample of 401 university faculty members. We then present our findings, followed by the final section where key theoretical implications, practical recommendations and proposals for future research are discussed.

2 Conceptual framework and hypotheses development

2.1 Technology adoption: The TAM framework

In the realm of technology adoption, it is widely acknowledged that the processes involved are fundamentally non-uniform, with users exhibiting a wide range of different behaviors. Within this context, literature puts forth several reference models that explain the factors influencing the **adoption**—or sustained and continued usage and integration into existing routines—of new technology tools. The model proposed by Davies (1989), TAM, stands out as one of widely recognized frameworks and has served as a reference for studies in the field of education (e.g., Wojciechowski and Vellary, 2013; Shroff et al., 2011). TAM is based on the premise that perceived usefulness and ease of use are key factors in predicting user attitudes towards adoption of a given technology (Davies, 1989).

In educational contexts, this framework holds significant relevance for understanding and predicting the adoption of new technologies, and it can be applied in the context of technologies like ChatGPT. TAM can be useful to assess the perceived usefulness and ease of use of educational technologies, enabling faculty to strategically integrate these tools into teaching practices (Scherer et al., 2019). In this line,

TAM can inform the design and implementation of professional development programs aimed at enhancing educators' technological competencies and confidence (Antonietti et al., 2022). Addressing factors influencing technology acceptance, such as perceived usefulness and ease of use, is critical for professional development initiatives, as they can empower educators to effectively integrate technology into their instructional practices and adapt to evolving educational trends (Persico et al., 2014). Recent studies have underscored the convenience and applicability of TAM to explain the adoption of e-learning methodologies, technologies and tools within educational contexts (e.g., Al-Adwan et al., 2023; He et al., 2023; Mailizar et al., 2021; Al-Qaysi et al., 2020). These studies have shown that TAM provides a robust analytical framework for assessing the perceived usefulness and ease of use educational technologies, thereby facilitating a deeper understanding of users' attitudes and intentions towards technology adoption. Considering this evidence, TAM enables researchers to identify critical determinants of technology acceptance and adoption behavior among stakeholders in educational settings (Scherer et al., 2019).

2.2 Faculty´s well-being: The key role of happiness, energy and stress

Additionally, our framework suggests that technology adoption (i.e., ChatGPT adoption) may affect faculty's well-being. In this sense, literature shows a lack of a unique definition of well-being. However, there is some consensus that well-being at work is often related to positive feelings, emotions and thoughts about life, happiness, satisfaction, and a sense of meaning, while also being linked to the absence of negative aspects such as stress, anxiety and depression (Xanthopoulou et al., 2012; Bakker & Oerlemans, 2011; Ryan & Deci, 2001). From a global perspective, well-being represents the evaluations that employees make about workplace experiences (Xanthopoulou et al., 2012). Baker and Oerlemans (2011) indicate that employees who find satisfaction in their job and derive positive feelings whilst doing it, tends are more likely to exhibit high levels of well-being at work, with negative emotions being less prevalent.

In their examination of well-being, Van de Voorde et al. (2012) recommend considering various components, although they do not explicitly specify them. Similarly, Peccei (2004) takes a comparable approach, defining well-being as the balance between levels of satisfaction (e.g., positive) and stress (e.g., negative, potentially affecting health). However, both Peccei (2004) and Van de Voorde et al. (2012) acknowledge limitations in their frameworks, recognizing that their proposals do not include the full range of work experiences that could influence well-being. Nonetheless, they lay the groundwork for future research agendas in employee well-being, suggesting the need of considering a trade-off between positive and negative elements affecting well-being.

Taking as reference the work of Peccei (2004), happiness well-being can be defined as subjective experiences and feelings at work such as satisfaction, energy and commitment. **Happiness** is widely regarded as an internal state, residing within individuals, characterized by a profound sense of satisfaction and inner harmony that extends to the relationship with their surroundings (Lu, 2001). On the other hand, health-related well-being is determined by stressors such as workload, strain, and

burnout, as well as by employees' coping mechanisms. In this context, **energy** represents the degree of mental vigor, vitality and resilience experienced by employees throughout their workday (Buil et al., 2019; Schaufeli et al., 2002). **Stress** is usually referred to as a response to external pressures that exceed the ability of an individual to cope effectively, often manifesting as feelings of feelings of tension and anxiety (Szabó & Lovibond, 2006).

Finally, Peccei (2004) also defines relationship well-being, as the interactions and quality of relationships between employees, employees-supervisors, and within employees-organization dynamics. However, given that our research only considers the effect of individual ChatGPT adoption, we exclusively focus on happiness and health-related well-being (energy, as positive components; stress, as negative component) as our reference points for the empirical research. Therefore, as shown in Fig. 1 our casual model links the basis of technology adoption with the well-being perceived by faculty.

2.3 Hypotheses development

From a conceptual standpoint, we take into account the foundational research underpinning the TAM framework. **Perceived usefulness**, a critical aspect of this model, is defined as the extent to which a user believes that employing a particular technology enhances their overall performance (Davis et al., 1989). A significant amount of research has been devoted to understanding how perceived uselessness explains adoption processes within the educational context (e.g., Ansari et al., 2024; Xiao et al., 2023; Shen et al., 2022; Mehta et al., 2019; Padilla-Meléndez et al., 2013). Based on prior work, we propose that when individuals perceive a new tool or technology as useful in fulfilling their needs and improving their performance, they are more likely to continue to engage with it, and thus the probability of adoption is higher. As a result, we put forth the first hypothesis:

Hypothesis 1 *Perceived usefulness of university faculty members has a positive impact on ChatGPT adoption.*

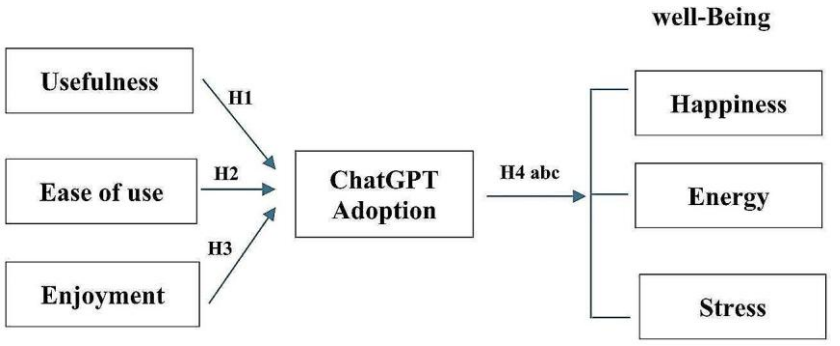

Fig. 1 Conceptual model

Ease of use is usually defined as the degree to which a user perceives a specific tool as user-friendly and requiring minimal effort to employ (Venkatesh, 2000). This concept can play a fundamental role in the adoption of a new technology by reducing the barriers to adoption and facilitating a quicker learning curve, allowing users to become proficient in a timely manner (Xiao et al., 2023; Sheppard & Vibert, 2019). All these aspects present critical influences on the users' attitudes and can encourage a sustained adoption of ChatGPT. For these reasons, we propose the following:

Hypothesis 2 *Perceived ease of use of university faculty members has a positive impact on ChatGPT adoption.*

On the other hand, authors like Mehta et al. (2019) and Ukpabi and Karlajuoto (2017) suggest that TAM may be overly basic and general. Therefore, they recommend including additional variables, adapted to the study context. To this end, as suggested by literature, enjoyment becomes relevant when engaging with a new technology or tool, especially in a context characterized by uncertainty, as it is the case surrounding the emergence of ChatGPT (Agarwal & Karahanna, 2000). **Enjoyment** encapsulates the sensation of pleasure or satisfaction as a reaction to a pleasant experience (Fang & Zhao, 2010; Moon & Kim, 2001). It is also characterized by the expectation of psychological reward and feelings of joy and satisfaction (Lin et al., 2020; Barak et al., 2016; Padilla-Meléndez et al., 2013; Agarwal & Karahanna, 2000). Obtaining high levels of enjoyment could be fundamental to determining a sustained usage and a commitment to continuing to employ a tool (Nabi and Krecmar, 2004). For this reason, we highlight that, even though the utilitarian aspects of technology are relevant and can drive adoption, the emotional and pleasurable aspects can also play a major influence in users' decision to embrace a new technology. As a result, we hypothesize that enjoyment presents a relevant impact on the adoption of ChatGPT, and we put forth the following:

Hypothesis 3 *Perceived enjoyment of university faculty members has a positive impact on ChatGPT adoption.*

Conversely, through the lens of human resource management, it becomes imperative to assess how ChatGPT adoption can contribute to improving faculty members' well-being. Our evaluation of well-being places emphasis on key components by focusing on happiness, energy and stress, all of which being crucial for fostering a fulfilling work environment. As previously mentioned, Peccei (2004) suggests defining employee well-being as the balance between levels of positive moods and negative feelings with potential effects on health. In alignment with this perspective, Lu (2001) views happiness as an intrinsic condition in individuals, characterized by profound feelings of pleasure and inner peace. Authors such as Buil et al. (2019) and Schaufeli et al. (2002) consider energy as the level of mental strength, liveliness, and adaptability of employees, complementing happiness as facet of positive moods. On the contrary, stress, characterized by potential negative feelings, represents a reaction to external demands that surpass an individual's capacity to cope effectively, often resulting in sensations of tension and anxiety (Szabó & Lovibond, 2006).

Scholars have recognized that the success or failure of a given tool should also be assessed based on the emotional responses elicited in faculty members (Shetu et al., 2021). In the specific case of ChatGPT, continuous usage and integration of this tool have the potential to notably enhance faculty productivity and reduce their workload (Jeon & Lee, 2023; Tlili et al., 2023). Such improvements can, in turn, benefit employees by promoting a healthier work-life balance and encouraging a supportive workplace environment. Therefore, the adoption of a new tool (i.e., ChatGPT) can significantly contribute to an enhancement of quality of life and personal experiences, thus affecting happiness, energy and stress levels. Hence, we put forth our last set of hypotheses:

Hypothesis 4 *ChatGPT adoption influences faculty well-being, by having a positive impact on (a) happiness and (b) energy, and a negative impact on (c) stress.*

3 Method

3.1 Measurement instrument

To test our hypotheses, we developed a questionnaire by adapting scales previously employed in the specialized literature. The measurement of perceived usefulness relied on five items from Davies' (1989) proposal, while the assessment of ease-of-use encompassed five items based on Venkatesh's (2000) perspective. For measuring enjoyment, we utilized four items in alignment with the propositions by Luo et al. (2011). ChatGPT adoption was measured through three items following Ajzen's well-established recommendations (1991), and our happiness scale, consisting of three items, drew upon recent concepts introduced by Shetu et al. (2021). Lastly, the scales for energy (three items) and stress (four items) were adapted from Buil et al. (2019) and Schaufeli et al. (2002) proposals. Initially, we adapted the scales to the study context. All items were measured on a seven-point Likert-type scale ranging from 1 (completely disagree) to 7 (completely agree). Subsequently, we conducted a pretest to guarantee clarity and mitigate potential misunderstandings. All the measurement scales are included in the Appendix at the end of the manuscript.

3.2 Fieldwork and sample characteristics

The empirical research was conducted within the context of Business Administration and Management degrees, specifically targeting university faculty members in Spain. During the academic year 2022-23, the total population consists of 2,606 university faculty members associated with Business and Management fields. The fieldwork took place during the month of July 2023. This timeframe was selected due to the absence of teaching activities during this month, which is normally used for evaluation and planning of the upcoming academic year. All the population was contacted by email and the distribution of the survey occurred through the professors' corporate email addresses, with a follow-up reminder sent to non-respondents two weeks after

the initial mailing. The final sample is composed by the complete and valid responses of 401 professors (15.4% response rate). Among the respondents, 51.9% identified as male (48.1% as female; no other gender options were selected by the participants in their responses to the questionnaire). The average age was of 45.9 years old (Stand. Deviation = 1.3). 80% of professors have a full-time contract, with a mean length of service of 17.1 years (Stand. Deviation = 1.0). Regarding the utilization of ChatGPT, 12.7% of the sample reported using it at least once every week, 47.4% use it occasionally, and 28.4% had never used it.

The final sample size (n = 401) exceeds the minimum recommended size (n = 119) for SEM estimation, considering the structural complexity of the model: 26 observable variables + 7 latent constructs, and an anticipated absolute effect size (small = 0.1), with alpha = 0.05 and (1-beta) = 0.8, as calculated using the *'A-priori Sample Size Calculator for Structural Equation Models*' (Soper, 2024). Following Preacher and Coffman (2006)'s procedure, a similar minimum sample size of $n = 118$ is necessary for RMSEA testing, with alpha = 0.01, desired power (1-beta) = 0.8, H_0: RMSEA = 0.000, and H_1: RMSEA = 0.05, taking into account the causal model's degrees of freedom (df) = 290.

4 Findings

4.1 Analysis of measurement scales

The first step to study the psychometric properties of the measurement scales was to perform an exploratory factor analysis (EFA) using the criterion of extraction of eigenvalues greater than one with IBM SPSS Statiestics 27. The results confirm that the items load onto their latent construct excellently—factor loadings > 0.7[1] (Tabachnick & Fidell, 2007)— and that the reliability of the scales is optimal, as shown in Table 1—Cronbach's α > 0.8 (Taber, 2018)—. This analysis was completed with the estimation of a first-order measurement model (or confirmatory factor analysis, CFA) with Robust Maximum Likelihood using Eq. 6.2. The model fit is appropriate: χ^2_{Sat-B}. (df = 278) = 601.17; χ^2_{Sat-B}./df = 2.16 < 3.0 (Schermelleh-Engel et al., 2003); RMSEA = 0.054 < 0.08 (Hu & Bentler, 1995); CFI = 0.961; BB-NFI = 0.930; BB-NNFI = 0.954; IFI = 0.954 > 0.9 (Hair et al., 2019), indicating that the results are reliable for analyzing internal consistency and scale validity. The composite reliability values—CR > 0.7 (Anderson & Gerbing, 1988)—and the average variance extracted associated with each latent construct—AVE > 0.5 (Fornell & Larcker, 1981)—clearly exceed the established limits. Therefore, we can conclude that all the scales present optimal levels of internal consistency. Regarding validity analysis, the standardized factor loadings (see Table 1) also exceeded the recommended minimum threshold of 0.6 and were significant at their latent factor—t-Stat > 2.58 (Steenkamp & Van Trijp, 1991)—, concluding that the scales are endowed with convergent validity.

Discriminant validity was assessed through correlations between latent constructs following Fornell and Larcker's (1981) criteria. As shown in Table 2, the linear cor-

[1] One item of the stress scale was eliminated due to a low factor loading ($\lambda_{STRESS1} = 0.395 < 0.7$).

Table 1 Measurement model estimation (internal consistency and validity of the measurement scales)

Latent Construct	Observable variable	Mean (SD)	λ (t-Stat)	α	CR	AVE
Usefulness	USE1	5.53 (1.44)	*0.78*	0.94	0.94	0.77
Mean (SD) = 5.09 (1.39)	USE2	4.66 (1.57)	0.85** (17.60)			
	USE3	4.98 (1.62)	0.95** (17.86)			
	USE4	4.85 (1.59)	0.94** (16.69)			
	USE5	5.42 (1.50)	0.84** (22.05)			
Ease of use	EAS1	5.16 (1.57)	*0.82*	0.92	0.92	0.71
Mean (SD) = 5.30 (1.32)	EAS2	5.47 (1.48)	0.89** (22.85)			
	EAS3	5.46 (1.44)	0.92** (23.31)			
	EAS4	5.43 (1.45)	0.92** (24.34)			
	EAS5	4.99 (1.69)	0.64** (12.74)			
Enjoyment	ENJ1	4.01 (1.62)	*0.92*	0.94	0.95	0.81
Mean (SD) = 3.90 (1.50)	ENJ2	3.93 (1.65)	0.93** (37.73)			
	ENJ3	3.98 (1.59)	0.94** (38.89)			
	ENJ4	3.67 (1.65)	0.80** (21.75)			
ChatGPT adoption	CHAP1	5.08 (1.57)	*0.90*	0.87	0.87	0.69
Mean (SD) = 4.83 (1.49)	CHAP2	4.86 (1.67)	0.77** (20.46)			
	CHAP3	4.53 (1.77)	0.82** (22.25)			
Happiness	HAP1	4.08 (1.99)	*0.89*	0.94	0.94	0.84
Mean (SD) = 4.02 (1.83)	HAP2	3.90 (1.95)	0.95** (38.03)			
	HAP3	4.09 (1.89)	0.90** (29.15)			
Energy	ENE1	3.30 (1.87)	*0.82*	0.91	0.91	0.77
Mean (SD) = 3.53 (1.86)	ENE2	3.73 (2.19)	0.86** (21.60)			
	ENE3	3.56 (2.00)	0.94** (25.45)			
Stress	STR2	2.62 (1.65)	*0.82*	0.87	0.87	0.69
Mean (SD) = 2.48 (1.43)	STR3	2.45 (1.61)	0.86** (16.95)			
	STR4	2.37 (1.56)	0.80** (15.73)			

SD: Standard deviation; λ: Standardized factor loading; α: Cronbach's alpha (> 0.7); CR: composite reliability (> 0.7); AVE: average variance extracted (> 0.5)

In italics, parameters fixed before estimation
** $p < 0.01$

Table 2 Discriminant validity analysis (linear correlation between latent constructs)

	1.	2.	3.	4.	5.	6.	7.
1. Usefulness	*0.87*						
2. Ease of use	0.411**	*0.84*					
3. Enjoyment	0.689**	0.53**	*0.90*				
4. ChatGPT adoption	0.682**	0.52**	0.67**	*0.83*			
5. Happiness	0.511**	0.44**	0.58**	0.73**	*0.91*		
6. Energy	0.362**	0.36**	0.47**	0.55**	0.84**	*0.88*	
7. Stress	-0.18**	-0.14*	-0.14*	-0.30**	-0.21**	-0.06	*0.83*

In Italics, square root of AVE (main diagonal); below diagonal, correlations between latent factors
* $p < 0.05$; ** $p < 0.01$

relation between each pair of latent constructs was lower than the square root of the Average Variance Extracted (AVE) for each scale. Additionally, the χ^2 difference-test —χ^2 (df = 21) = 564.28; $p < 0.0001$— between the estimation of the theoretical measurement model with the seven latent factors and the model restricting correlations to unity (χ^2_{Sat-B}.(df = 299) = 1092.77; RMSEA = 0.082; CFI = 0.904; BB-NFI = 0.873; BB-NNFI = 0.895; IFI = 0.904) is significant. Therefore, we can conclude that each dimension is measuring a different construct (Anderson & Gerbing, 1988).

Finally, it was verified that there were no common bias method problems. Following the recommendations of Podsakoff et al. (2003), the estimation of the proposed measurement model was compared with the estimation of a measurement model where all items load on a single latent factor (χ^2_{Sat-B}.(df = 299) = 4274.25; RMSEA = 0.183; CFI = 0.519; BB-NFI = 0.502; BB-NNFI = 0.477; IFI = 0.520). The increase in the $\Delta\chi^2_{Sat-B}$.(df = 21) = 5172.35 statistic is significant at 0.01 ($p < 0.0001$), concluding that the fit of the theoretical measurement model showing the seven latent factors is significantly better.

4.2 Estimation of structural equation model and hypotheses testing

The hypotheses were tested through the estimation of the structural equation model, which includes the seven latent constructs corresponding to the validated scales. The fit obtained from the estimation of the causal model is appropriate (χ^2_{Sat-B}. (df = 290) = 851.95; χ^2_{Sat-B}./df = 2.94; RMSEA = 0.071; CFI = 0.929; BB-NFI = 0.898; BB-NNFI = 0.920; IFI = 0.929).

Considering the estimated coefficients (see Table 3), we can conclude that the utilitarian ($\gamma_{usefulness} = 0.35^{**}$ and $\gamma_{ease\_of\_use} = 0.21^{**}$) and hedonic ($\gamma_{enjoyment} = 0.34^{**}$) antecedents significantly and positively impact ChatGPT adoption by university faculty ($R^2 = 0.59$), confirming H1, H2 and H3.

Furthermore, ChatGPT adoption has a significant effect on the studied outcomes. Specifically, adoption exerts a strong positive influence on happiness ($\beta_{happiness} = 0.81^{**}$; $R^2 = 0.65$) and energy ($\beta_{energy} = 0.66^{**}$; $R^2 = 0.43$), while demonstrating a negative impact on stress ($\beta_{stress} = -0.28^{**}$; $R^2 = 0.08$). The proportion of variance uniquely explained by adopting ChatGPT on happiness ($f^2 = 0.779$), energy ($f^2 = 0.300$), and stress ($f^2 = 0.074$) is noteworthy. Following Cohen's (1988) guidelines, ChatGPT adoption demonstrates a large effect size on happiness ($f^2 \geq 0.35$), a moderate effect on energy ($0.15 \leq f^2 < 0.35$), and a small effect on stress ($0.02 \leq f^2 < 0.15$). The afore-

Table 3 Hypotheses testing (causal relationships estimation)

Hypothesis	Relationship (direct effect)	Stand. Coeff	Stand. error	t-Stat	Support
H1.	Usefulness→ChatGPT adoption	0.35^{**}	0.09	4.68	Yes
H2.	Ease of use→ChatGPT adoption	0.21^{**}	0.06	4.07	Yes
H3.	Enjoyment→ChatGPT adoption	0.34^{**}	0.07	4.77	Yes
H4a.	ChatGPT adoption→Happiness	0.81^{**}	0.06	18.40	Yes
H4b.	ChatGPT adoption→Energy	0.66^{**}	0.06	12.33	Yes
H4c.	ChatGPT adoption→Stress	-0.28^{**}	0.06	-4.34	Yes

Stand. Coeff: Standardized Coeficient; Stand. error: Standard error
$^{**}p < 0.01$

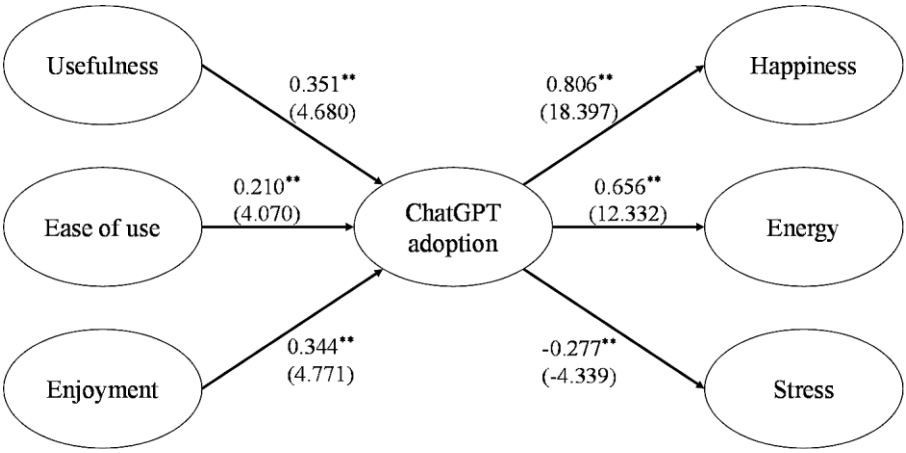

Fig. 2 Structural model estimation of the causal relationships. ** $p<0.01$. *Note* t-Stat values shown in brackets

mentioned results confirm the set of hypotheses H4a, b, c. Figure 2 graphically illustrates the non-standardized coefficients of the causal relationships. In conclusion, we can state that faculty well-being depends indirectly and significantly on the constructs of the TAM framework through ChatGPT adoption.

5 Discussion

The changing nature of the university context and workplace may affect the faculty well-being. For instance, Franco-Santos and Doherty (2017) highlight how academic staff are increasingly expected to demonstrate individual responsibility, self-sufficiency, market orientation, efficiency, and competitiveness to meet quality standards in their teaching endeavors. In addition, faculty must navigate the pursuit of research and knowledge generation within a context where normative and technological issues are continuously evolving. Therefore, research on how and to what extent human resource management practices and technology adoption relate to well-being is still inconclusive.

As technology advances, educators must adapt to new developments in the field. AI tools hold significant promise for both students and faculty members (Ansari et al., 2024; Regnier et al., 2023). As an example of disruptive dynamism, since its emergence in November 2022, ChatGPT has sparked extensive debate, and a broader discussion has also flourished regarding its possible use in education in general, and in higher education in particular (Adams et al., 2024; Ali et al., 2024). This study took a fresh perspective by focusing on faculty members and looked at how their perceptions of ChatGPT affect the tool adoption, subsequently impacting outcomes related to faculty well-being. Our empirical analysis reveals compelling insights, from which several theoretical contributions and practical implications can be derived and elaborated in further detail.

5.1 Theoretical contributions

The evolution of technology in education has significantly reshaped learning dynamics over the past decade (Mukul & Büyüközkan, 2023). Recent insights from Ali et al. (2024) and Rawas (2023) emphasize the profound potential of AI technologies to revolutionize higher education teaching. ChatGPT stands out as prime example of AI's ability to cultivate a more motivating and prolific learning environment by tailoring responses to each individual's unique requirements. Moreover, its integration can alleviate faculty burdens and workload, allowing them to concentrate on other responsibilities (Rawas, 2023), potentially enhancing their overall well-being (Marshall & Morris, 2015).

Evidence indicates that utilization of ChatGPT into students' workflow is a reality across all academic levels (e.g., Adams et al., 2024; LI et al., 2024; Maheshwari, 2024). Consequently, educators and educational institutions—whether compelled by necessity or driven by conviction—need to adapt and integrate this tool as well. In this light, it seems opportune to leverage the advantages and opportunities ChatGPT has to offer (Ali et al., 2024; Baabdullah, 2024; Li et al., 2024; Tlili et al., 2023). Nevertheless, to ensure optimal implementation and use of ChatGPT, it is necessary to consider the perspectives of faculty members' (Guo & Wang, 2023).

This paper represents a significant milestone within the education field, as it conducts empirical research specifically centered on the adoption of ChatGPT from the viewpoint of university faculty members. Faculty members face distinctive challenges when it comes to adoption of new technologies. At the same time, ChatGPT also offers different benefits for faculty members when compared to students (Jeon & Lee, 2023). In this context, it becomes imperative to delve into the specific adoption process of faculty. By focusing on the faculty perspective, we contribute to the existing literature, as the majority of previous studies have primarily centered on the experiences of students (Tlili et al., 2023). This shift in focus enables us to offer fresh insights and a novel understanding of the dynamics at play when it comes to the integration of ChatGPT within teaching activities.

Additionally, while previous research has extensively explored new technologies and adoption of tools in educational contexts (e.g., Wojciechowski and Vellary, 2013; Shroff et al., 2011), this study sheds light on the unique adoption process in the context of ChatGPT. In line with the established TAM framework, we contribute to the literature by empirically confirming the significant roles of perceived usefulness and ease of use on faculty's decisions to adopt ChatGPT. These findings highlight key factors of ChatGPT acceptance behavior among faculty members (Scherer et al., 2019). Moreover, they can empower faculty to strategically incorporate new tools into their teaching methodologies, facilitating adaptation to changing educational trends (Persico et al., 2014).

However, a differentiating aspect of this study and one of the factors that sets this investigation apart is the introduction of enjoyment as a novel determinant of ChatGPT adoption. The research underscores that the utilitarian aspects of ChatGPT influence adoption, yet they are not exclusively significant. The emotional aspect also plays a significant role. For this reason, this paper highlights the multifaceted nature of user attitudes, as the affective dimension also shapes the specific context

of adoption of ChatGPT. These findings extend the current understanding of the psychological processes underlying adoption by demonstrating that a positive emotional state fosters adoption. Thus, our research enriches the current understanding of the emotional aspect inherent in the adoption of ChatGPT by faculty members.

Moreover, this study underscores a significant relationship between faculty ChatGPT adoption and the constructs utilized to describe faculty well-being. Faculty well-being represents one of the key concerns for educational institutions, carrying both a moral significance and a strategic imperative. However, we must recognize its complex and multidimensional nature (Peccei & Van de Voorde, 2019). Our findings reveal that ChatGPT adoption not only enhances overall happiness and energy but also enables the reduction of stress in faculty members. These findings are in line with ideas of Ogbonnaya and Messersmith (2019) who highlight the link between changes, innovation, behavior and well-being. ChatGPT adoption increases positive feelings related with well-being, while reducing potential negative effects related with stress. These results can be attributed to the beneficial effects of ChatGPT. When used effectively, ChatGPT has the potential to introduce novel methodologies, streamline processes, diminish time and energy expenditures, alleviate faculty workload, and yield various other favorable outcomes. This connection extends far beyond the realm of academia and presents potential contributions and implications for the design of educational technologies by emphasizing the importance of faculty well-being in the digital age.

In line with this, the significance of fostering a positive workplace environment cannot be overstated. When faculty members experience high levels of well-being, its influence extends throughout the entire educational system, influencing the quality of education and student achievements (Mudrak et al., 2018). Emotionally content faculty members are more inclined to actively engage with students, offering them the requisite guidance and support. Such an environment encourages academic excellence and personal growth. The implications of prioritizing well-being extend to an institution's reputation and standing.

5.2 Practical implications

Given the proliferation of AI tools, it becomes clear that a careful and responsible strategy for implementing ChatGPT in higher education is required, as potential difficulties with user acceptability may influence teaching and learning experiences. Responsible ChatGPT implementation in higher education involves careful planning and taking into account a number of factors and actors (i.e., students, faculty members). It also requires a thoughtful approach that considers both the potential benefits and challenges associated with this technology (Li et al., 2024). Our findings also present significant practical implications. Considering this, we can suggest a series of actions for enhancing best practice with ChatGPT from faculty's perspective.

Firstly, developers and designers should focus on enhancing the usefulness, ease of use, and enjoyment of ChatGPT to encourage its adoption among users. This could involve refining the user interface, improving response accuracy, and incorporating features that align with user preferences and needs. Technical difficulties can cause disruptions and negative feelings such as irritation and stress for faculty. For this rea-

son, faculty may need to be trained on how to efficiently use the tool. Rawas (2023) recognizes the relevance of training and support, as well as to assess the scalability and sustainability of using the tool. In the same line, to enhance ChatGPT's perceived usefulness, we recommend implementing initiatives such as presentations, seminars and objective data studies. These initiatives could help faculty members to better comprehend the applications of ChatGPT in their teaching activities, while highlighting the practical benefits of this tool. Additionally, as regards ease of use, we suggest the development of new resources including courses, tutorials or practical manuals. These could also be focused on streamlining the integration of ChatGPT in educator-student interaction, that could potentially lead to a more efficient and extensive use of this technology.

Secondly, institutions and individuals seeking to promote well-being could consider integrating ChatGPT into wellness initiatives or daily routines. As ChatGPT adoption is associated with increased happiness and energy levels, organizations can leverage this technology to boost productivity and efficiency in various domains. Integrating ChatGPT into workflow processes can determine users to experience a positive impact on their mood and energy, leading to enhanced performance and output. In accordance with this, institutions should consider running pilot tests of ChatGPT with a small number of faculty before integrating it completely. This is helpful in finding potential difficulties and tracking evaluations to see how ChatGPT affects faculty workload, which may affect their well-being. Consistent with this and considering the educational institution perspective, institutions should consider the development of peer support networks where faculty members can share best practices and, thus, also foster a sense of community. Moreover, considering the usefulness impact on adoption, institutions are encouraged to foster the integration of ChatGPT into existing workflows. ChatGPT is a tool that is highly complementary to established practices (Jeon & Lee, 2023), and it can help faculty members to work more efficiently. If faculty acknowledge this complementarity, it becomes more likely to reap the benefits of employing it.

Finally, these measures may also enhance faculty productivity, apart from their overall well-being. As faculty members become increasingly more proficient and confident in their usage of ChatGPT, they are more likely to benefit from a boost of happiness and energy, while decreasing their stress levels. This has significant practical implications as faculty can thus experience an increased job satisfaction and a more positive work environment. ChatGPT can be positioned as a valuable tool for stress management and mental health support. Educators, employers, and healthcare providers could incorporate ChatGPT into stress reduction programs or provide access to ChatGPT as a resource for individuals seeking support in managing stress and maintaining mental well-being. However, managers must consider the individual idiosyncratic experiences of employees, understanding their profiles, skills, motivations, and feelings for a better use, technology adoption and positive outcomes (e.g., well-being).

5.3 Conclusions, limitations and future research

ChatGPT has the potential to have a substantial impact on education in general, and on higher education in particular. We hold the opinion that this technology will continue to be crucial in determining the direction of education. Academia must work toward a more equitable and productive educational system to both students and teachers by investigating the opportunities and challenges related with ChatGPT in higher education, while also establishing appropriate implementation strategies. Although our research is focused on the effect of ChatGPT adoption on faculty well-being, there are a number of issues that deserve future research.

Besides, despite the relevance of our findings, our study presents a series of limitations. First, working with survey data makes us more susceptible to potential response bias. To minimize this risk, we have followed procedural guidelines proposed by Podsakokk et al. (2003). For this reason, we have employed scales previously validated by the literature and adapted to the context under study, and then we carried out a pretest to clarify possible misunderstandings. Hence, we have adjusted the questionnaire length and informed respondents that there are no correct or incorrect answers, guaranteeing anonymity. All these actions ensured that response bias is substantially diminished.

Moreover, this study has exclusively focused on university faculty within a particular context, Business and Management degrees. Further research could be expanded across primary, secondary and university education using multilevel models to assess the relationships proposed in other settings. Besides, we are analyzing a global adoption of ChatGPT, not related with any specific activity. Future studies may analyze potential differences in ChatGPT adoption depending of specific academic tasks. By doing so, the applicability of our model could be enhanced beyond our context. This way, we can obtain a more in-depth understanding of professors' attitudes and adoption of ChatGPT. In line with this, our model could be further enriched by including other variables related to stress and anxiety as counterbalances to enjoyment and happiness. This could boost the model's robustness and explanatory capacity.

Future research endeavors could be broadened to also encompass a wider array of countries and cultures, thereby allowing us to observe the potential impact of multiculturalism. This approach would enable researcher to analyze the interplay of cultural diversity and, thus, provide invaluable insights in a multinational context.

We believe that this paper not only advances our knowledge of ChatGPT adoption but also paves the way for new avenues for research and application. We hope our findings will serve to shape the trajectory of future research on ChatGPT integration in education while prioritizing the well-being of those at its forefront.

Appendix measurement scales [1]

Scale	Item Statement
Usefulness	USE1. ChatGPT allows me to perform certain tasks more quickly
	USE2. ChatGPT would enhance my performance as a teacher
	USE3. ChatGPT would increase my productivity
	USE4. ChatGPT would improve my effectiveness
	USE5. Using ChatGPT can be helpful
Ease-of-use	EAS1. I believe that interacting with ChatGPT is straightforward and easy to understand
	EAS2. I think using ChatGPT is easy
	EAS3. I believe one can quickly grasp the mechanics of ChatGPT
	EAS4. I find the interaction with ChatGPT clear and understandable
	EAS5. I believe that interacting with ChatGPT does not require much mental effort
Enjoyment	ENJ1. Using ChatGPT is a pleasure
	ENJ2. I enjoy using ChatGPT
	ENJ3. The time spent using ChatGPT is enjoyable
	ENJ4. ChatGPT provides me with entertainment
ChatGPT adoption	CHAP1. I believe that ChatGPT can help improve thing
	CHAP2. I believe that interesting opportunities can arise with the use of ChatGPT
	CHAP3. I am sure that using ChatGPT is a good choice
Happiness	HAP1. I am proud to be able to use ChatGPT in my classes
	HAP2. I am excited to be able to use ChatGPT in my classes
	HAP3. I am inspired by the potential use of ChatGPT for my classes
Energy	ENE1. I feel energized when I consider using ChatGPT
	ENE2. I look forward to going to work when I think about using ChatGPT
	ENE3. I feel empowered when I think about using ChatGPT
Stress	*STR1. I feel sensitive when people talk about using ChatGPT*[*]
	STR2. I find it difficult to relax when using ChatGPT
	STR3. I think I tend to overreact when someone mentions using ChatGPT
	STR4. I feel unsettled when someone talks about using ChatGPT

[1] Translated from the Spanish version.
[*] As explained in sub-Sect. 4.1, this item was eliminated.

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