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THE IMPACT OF GENDER AND AGE ON HEI TEACHERS' INTENTIONS TO USE GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS

Abstract. While existing research has identified key determinants of Generative Artificial Intelligence (Gen-AI) tool usage by Higher Education Institution (HEI) teachers, the moderating effects of individual characteristics such as gender and age remain underexplored. Many studies assume a homogeneous population, thereby overlooking the diverse behavioral intentions and technology perceptions among individuals, particularly in the context of higher education.

This study addresses this critical gap by examining how gender and age influence the relationships between perceived utility, perceived ease of use, attitude, and subjective norms on HEI teachers' intention to adopt Gen-AI tools. By integrating these moderating factors within the frameworks of the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), this research offers a nuanced understanding of the differential impacts of gender and age on technology adoption.

The findings of this study contribute significantly to the Gen-AI literature by highlighting the importance of considering individual differences in demographic characteristics when investigating technology adoption behaviors. Specifically, the study reveals that gender and age not only affect the direct determinants of Gen-AI tool usage but also moderate the strength and direction of these relationships. For instance, younger teachers may perceive Gen-AI tools as more useful and easier to use compared to their older counterparts.

Practically, the study provides HEI practitioners with actionable recommendations to enhance the management and utilization of Gen-AI tools among diverse user groups. By acknowledging and addressing the unique needs and preferences of different demographic segments, HEIs can foster a more inclusive and effective adoption of Gen-AI tools. This, in turn, can lead to improved teaching and learning outcomes, as well as greater overall satisfaction with technology integration in educational settings.

In conclusion, this research underscores the necessity of incorporating gender and age as critical moderating variables in studies of technology adoption. By doing so, it offers valuable insights for educators, policymakers, and researchers aiming to promote the effective and equitable use of Gen-AI tools in higher education.

Keywords: Artificial Intelligence; Technology Acceptance Model; Perceived Usefulness; Perceived Ease of Use; Subjective Norm; Higher Education Institutions

1. INTRODUCTION

Problem Statement

Generative Artificial Intelligence (Gen-AI) tools have revolutionized the field of artificial intelligence by enabling the creation of new content – such as text, images, and videos – based on learned patterns from existing data. Tools like ChatGPT (OpenAI), DeepSeek (China), Gemini (Google), and Microsoft Copilot are transforming various industries by offering innovative solutions and enhancing productivity.

Before November 2022, AI's role in daily life was often understated, integrated into smart devices as background tools. The launch of ChatGPT marked a pivotal shift, making AI a

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prominent and accessible resource. This transformation has had a particularly significant impact on education, where Gen-AI tools offer personalized learning, instant access to information, and new ways to engage students. However, their adoption also raises concerns, emphasizing the need for thoughtful and balanced implementation [1].

Gen-AI tools can generate human-like text conversations, enabling students to complete high-quality tasks such as writing a word essay, solving math problems, and composing music. Moreover, Gen-AI extends beyond student support, assisting in research tasks by generating and compiling knowledge, summarizing large amounts of text information, analysing data, and drafting manuscripts [2].

In the ever-changing landscape of higher education institutions (HEI), it is essential for educators to stay updated with new technological integrations, which has become crucial. As AI tools gain prominence as a means of transforming this landscape [3], understanding the motivations and intentions of teachers in their adoption becomes vital in navigating the challenges posed by the rapidly evolving educational paradigm [4]. The swift pace of technological change presents educators with both opportunities and challenges as they strive to harness the potential of AI tools to optimize teaching, learning, and administrative processes. However, the complexity and diversity of Gen-AI tools require teachers to navigate new terrain, necessitating a deep understanding of their motivations and intentions in adopting these technologies. The significance of this problem lies in its implications for educational innovation, digital literacy, and the broader development of society and the state.

Analysis of Recent Studies and Publications

While existing research has provided valuable insights into the main determinants of Gen-AI tool usage by HEI teachers, each study contributes a distinct perspective that, when examined critically, reveals both conceptual strengths and important gaps. Bhaskar et al. [5] focused on perceived trust and risk in the use of ChatGPT, emphasizing psychological barriers that may hinder adoption. However, their study did not account for how these perceptions might vary across demographic groups such as age or gender. Guan et al. [6] explored pre-service teachers' capabilities and identity development in AI-integrated education, highlighting the importance of internal dispositions. Yet, their findings are limited to early-career educators and do not address how these factors evolve across different age cohorts.

Habib [7] added depth by analysing the emotional and cognitive dimensions of educators' attitudes and intentions, reinforcing the idea that adoption is a multidimensional process. Nevertheless, the study did not explore whether these dimensions are experienced differently by men and women or by younger versus older teachers. Lu et al. [8] proposed an integrated model combining individual and contextual variables, offering a more holistic framework. However, their model treats the teaching population as homogeneous, overlooking the potential moderating effects of demographic characteristics.

This lack of differentiation is a recurring limitation. Many researchers implicitly assume that the population under study is homogeneous, leading to generalized conclusions about the relationships among antecedents of Gen-AI adoption. In reality, individuals differ significantly in their behavioural intentions and perceptions of technology, particularly in the diverse context of higher education.

Recent literature has also emphasized that age and gender influence how individuals perceive and use online technologies, though findings remain inconsistent and context-dependent. For example, Enam et al. [9] examined older adults' perceptions of LLM-based chatbots and found that digital familiarity, trust, and perceived usefulness were key factors shaping adoption. These insights suggest that age-related differences in cognitive and emotional responses to AI tools may significantly affect usage intentions. In contrast, Assaker [10] found

that both age and gender influenced the adoption of user-generated content in the travel sector, but the effects varied depending on the credibility of the content and the technological context. These studies underscore the need to move beyond generalizations and examine how demographic variables interact with psychological and contextual factors in shaping technology adoption.

Despite these contributions, there remains a notable gap in research specifically addressing how gender and age moderate the adoption of Gen-AI tools by HEI teachers [11]. This gap is particularly relevant given the increasing integration of AI in educational settings and the diversity of the teaching workforce. Addressing this issue, Hidayat-ur-Rehman and Ibrahim [12] employed a mixed-methods approach to explore educators' motivations and concerns, offering a more nuanced understanding of adoption dynamics. Shen and Guo [13] added a cultural lens by analysing Chinese EFL teachers' emotional responses to Gen-AI, while Strzelecki et al. [14] examined institutional and social influences on AI acceptance in academia.

Together, these studies provide a valuable foundation but also highlight the need for further research that explicitly incorporates demographic moderators. This study responds to that need by investigating how gender and age influence the relationships between key determinants—such as perceived usefulness, ease of use, attitude, and subjective norms—and the intention to adopt Gen-AI tools in higher education.

Research Goal

Given this context, the purpose of this article is to examine how gender and age moderate the relationships between perceived usefulness, perceived ease of use, attitude, and subjective norms in influencing HEI teachers' intention to adopt and use Gen-AI tools. The study contributes to the theoretical development of the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) by integrating demographic moderators. It also offers practical insights for HEI administrators and policymakers to tailor strategies that support diverse user groups in adopting Gen-AI technologies effectively. Accordingly, this study aims to explore the moderating role of gender and age in the adoption of Gen-AI tools by HEI teachers, within the framework of TAM and TPB

2. THE THEORETICAL BACKGROUNDS

To analyse the adoption of Gen-AI tools in university teaching, it is crucial to consider established theories of technology adoption. In our study, we will utilize the C-TAM-TPB model [15] to examine the primary factors influencing HEI teachers' intention to use Gen-AI tools in their teaching activities. This hybrid model combines the Technology Acceptance Model (TAM) by Davis [16] and the Theory of Planned Behaviour (TPB) by Fisbein & Ajzen [17], aiming to seamlessly integrate normative or social aspects and perceived behavioural control into the TAM.

The proposed model, illustrated in Figure 1, posits that a teacher's decision to use Gen-AI tools in their teaching is a rational process influenced by both personal and social variables. Personal variables include attitude, perceived usefulness, and self-efficacy. Attitude reflects the teacher's beliefs about the potential positive or negative outcomes of using these tools in their teaching. Perceived usefulness pertains to the perceived benefits that this technology can bring to the teacher's work. Self-efficacy relates to the teacher's confidence in their ability to use Gen-AI tools in their teaching activities and can be assessed through the perceived ease of use of this technology. On the other hand, the social variable is evaluated through subjective norms, which refer to the teacher's perception of their environment's opinion regarding the appropriateness of using these tools in the university setting.

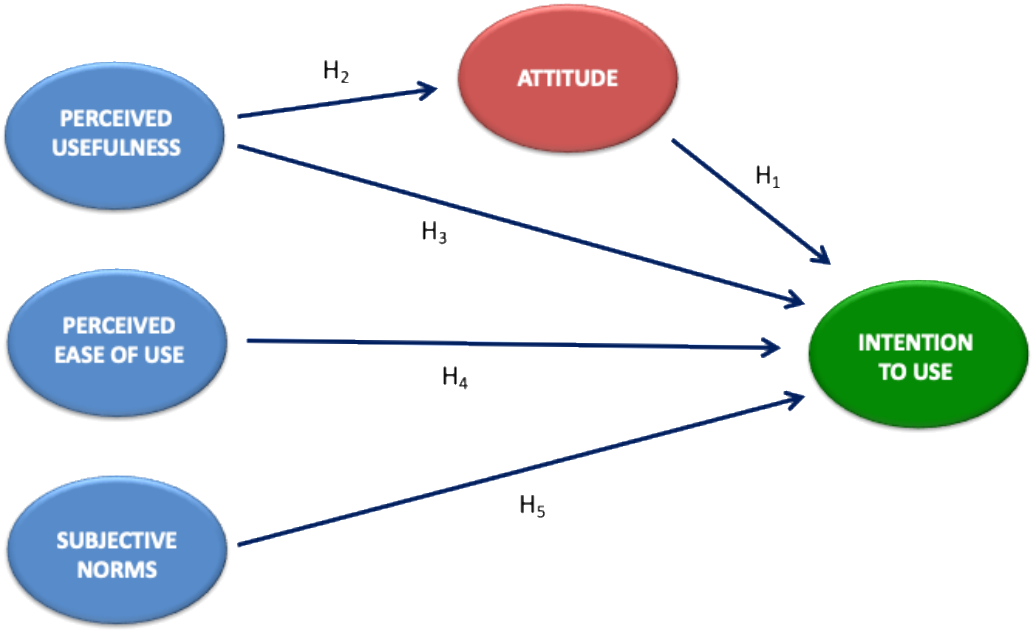

Figure 1.- Proposed model

Effects of attitude

The attitude of users towards a new technology plays a crucial role in their intention to adopt it. A positive attitude can significantly increase users' willingness to try and use the technology, as it is associated with greater openness to change and a favourable perception of potential benefits. For instance, users who believe that a technology will enhance their efficiency or make their work easier are more inclined to adopt it. Additionally, a positive attitude can reduce resistance to change, as users feel more comfortable and confident in their ability to learn and use the new technology [5]. In summary, attitude directly influences the intention to use by shaping users' perceptions and expectations about the technology, which can determine its success or failure in adoption.

Prior studies have demonstrated the impact of attitude on the intention to use Gen-AI tools among various groups, including general users [18], students [19], [20] and HEI teachers [5], [8]. Based on these findings, we propose the following hypothesis.

H_1.- Attitude towards Gen-AI tools has a positive influence on the intention to use them.

Effects of perceived usefulness

Perceived usefulness refers to the user's belief that utilizing a particular system will enhance their job performance within an organizational setting [21]. In online contexts, perceived usefulness indicates that employing a specific technology can help an individual achieve specific outcomes.

Some studies have shown that perceived usefulness exerts a dual influence on the intention to use Gen-AI tools in the university [8], [22]. The first effect is indirect, where perceived usefulness shapes the user's attitude towards the technology. A positive attitude, in turn, enhances the likelihood of adopting the technology. The second effect is direct, where perceived usefulness directly impacts the intention to use Gen-AI tools, independent of the user's attitude.

This dual influence underscores the importance of perceived usefulness in technology adoption. When users recognize the practical benefits and improvements in performance that Gen-AI tools offer, they are more inclined to integrate these tools into their academic and professional routines. This is particularly relevant in educational settings, where teachers seek tools that can enhance learning outcomes and teaching efficiency.

Therefore, we propose the following hypotheses:

H_2.- Perceived usefulness has a positive influence on the attitude towards using Gen-AI tools.

H_3.- Perceived usefulness has a positive influence on the intention to use Gen-AI tools.

Effects of perceived ease of use

According to TAM, perceived ease of use is a critical factor that affects users' acceptance and adoption of new technologies. When users find a technology easy to use, they are more likely to use it. For instance, if teachers perceive a new technology tool as user-friendly and straightforward, they are more likely to integrate these tools into their teaching practices. This ease of use reduces the learning curve, and the effort required to utilize the technology, making it more appealing and accessible.

In the context of Gen-AI tools, the significance of this relationship is heightened due to the advanced nature of these technologies, which may appear complex or daunting to those not well-versed in AI. Perceived ease of use is shaped by beliefs regarding the learning process, the time investment required, and the overall user-friendliness of the technology.

Both [5] and [8] have emphasized that the perception of ease of use is a crucial factor for teachers in adopting and utilizing AI-based technologies. Consequently, we propose the following hypothesis:

H_4.- Perceived ease of use has a positive influence on the intention to use Gen-AI tools.

Effects of subjective norms

Subjective norms are the beliefs an individual holds about the expectations of others and their inclination to conform to these expectations [16], [17]. They reflect the extent to which a person perceives the opinions of significant others regarding the use of an information system or technology [23]. Subjective norms establish a social framework that encourages teachers to adopt Gen-AI tools. This adoption is influenced not only by personal or professional motivations but also by the desire to meet the expectations and norms prevalent in their work environment.

Research has consistently shown that subjective norms significantly influence the intention to use Gen-AI tools, both in studies focusing on teachers [5], [22], as well as in studies with students [19] and in mixed research [20]. Therefore, we propose the following research hypotheses:

H_5.- Subjective norm has a positive influence on the intention to use Gen-AI tools.

Gender as a moderating variable

Gender differences in behaviour can be understood through both social psychology and gender role studies. Social psychology suggests that men tend to be more pragmatic, task-oriented, and focused on results compared to women [24]. Gender role literature indicates that men exhibit traits associated with masculinity, such as higher confidence, adventurousness, and

a greater propensity for risk-taking, whereas women are more inclined towards routine tasks, exhibit higher risk aversion and are more likely to make emotional decisions [25], [26], [27].

In the context of technology acceptance and usage, based on social psychology and gender role theories, it is anticipated that the relationship between perceived usefulness and usage intention will be stronger for male users, who prioritize task efficiency, and the benefits derived from using Gen-AI tools. Conversely, perceived ease of use (PEOU) is expected to be more influential for female users, who value the ease of use of Gen-AI tools, given their more risk-averse nature.

However, previous studies on the moderating effect of gender on technology adoption and behavioural intention in various online contexts have yielded mixed results across different applications and sometimes even within the same applications. Some studies found no significant gender differences in the relationships between perceived usefulness, ease of use, and use intentions [28], [29], [30]. However, other studies found that perceived usefulness had a stronger impact on behavioural intention for males, while ease of use was more influential for females [10], [31], [32], [33]. These findings highlight the complex and context-dependent nature of gender's moderating role in technology adoption, suggesting the need for further research in the context of Gen-AI tools adoption and usage.

In this study, we hypothesize that gender will moderate the relationships between perceived ease of use, perceive usefulness, attitude, subjective norms and use intention, Therefore, we propose the following general hypothesis, which will be further examined and tested in the context of Gen-AI tools adoption:

> *H_6: The influence of determinants (PU, PEOU, ATT and SN) on the intention to use Gen-AI tools is moderated by gender.*

Age as a moderating variable

Age differences in customer behaviour can be explained by self-efficacy, aging processes, and accumulated life experiences. Older adults often feel they are too old to learn new technologies, whereas younger adults are more inclined to embrace new technologies, driven by efficiency and performance [10], [34]. Older adults, due to their extensive experience, tend to rely more on their own beliefs and are less likely to seek additional information during decision-making and adoption processes [35].

However, the results of previous studies on the moderating effect of age in the context of technology adoption tend to be mixed and contextual. For instance, in the realm of online learning, Tarhini et al. [33] found that perceived usefulness has a stronger relationship with the intention to adopt e-learning technologies among younger students, whereas perceived ease of use has a stronger relationship with e-learning technology adoption among older students. Conversely, in the context of online and mobile shopping, Liébana-Cabanillas et al. [36] argued that trust, expertise, and usefulness have a stronger influence on purchase intention for younger adults compared to older ones, while ease of use equally influences both younger and older adults. On the other hand, Tan & Ooi [28] found that age does not moderate the relationships between usefulness, ease of use, and trustworthiness with behavioural intention in online shopping.

Therefore, we expect the relationship between perceived usefulness and attitude with usage intention to be stronger for younger adults, who are more result-oriented but less experienced. Conversely, the relationship between perceived ease of use, subjective norms and usage intention is expected to be stronger for older adults, who may find it more challenging to learn new technologies and thus place greater value on the ease of use of Gen-AI tools.

H_7: The influence of determinants (PU, PEOU, ATT and SN) on the intention to use Gen-AI tools is moderated by age.

3. RESEARCH METHODS

The study targeted the teaching staff from the 82 Spanish universities. Due to the lack of a comprehensive list of active academic staff, the sampling frame was created using information from the universities' websites, encompassing 1,030 university centres and 2,998 university departments. The questionnaire was distributed via email. A total of 896 valid responses were collected (see Table 1).

Drawing from previous research, the intention variable was measured with 7 items, the attitude variable with 5 items, the perceived usefulness variable with 7 items, the perceived ease of use variable with 5 items and the social norm variable with 5 items.

Table 1

Technical data sheet

Universe	Teaching and research staff of the 82 Spanish universities (115,332 people)
Geographical scope	Spain
Data Collection Method	Online survey
Sample size	896 questionnaires received
Sampling error	For a confidence level of 95% and p=q, the error for the entire sample is ± 3.27%
Fieldwork	October 2024

When comparing our sample with official statistics [37], we find it representative in terms of seniority, gender, and research field. The sample consists of 57% men, with 82% having a permanent affiliation with their university. The distribution across research fields is as follows: 40% in the social sciences, 21% in technical fields, 16% in biomedical fields, 12% in scientific fields, and 10% in the humanities.

For data analysis, we employed the partial least squares (PLS) regression technique [38]. This method was chosen for several reasons: it accommodates complex models with multiple latent variables and relationships, is robust against non-normal data distributions, and performs well with smaller sample sizes. PLS is particularly suitable for studies with a predictive focus, such as usage intention, and for exploratory research in emerging areas like the adoption of Gen-AI, where theoretical models are still evolving. It also effectively handles both formative and reflective variables and allows for the simultaneous modelling of personal and contextual factors.

All constructs were measured using Likert scales (1-5) based on established literature. Most constructs were treated as reflective, except for the usage intention construct, which was considered formative [39], [40].

The model estimation was conducted using SmartPLS 4.0, and the significance of the parameters was determined through a bootstrap resampling procedure with 5,000 subsamples, each the same size as the original sample.

4. THE RESULTS AND DISCUSSION

The evaluation of the relationship model considered the individual reliability of the items and the discriminant validity of the constructs [41]. For assessing the reliability of each item, factor loadings were utilized as the benchmark, with a common threshold being a value greater than 0.707 [42]. After refining the scales, it is evident from Table 2 that all items have loadings exceeding this reference value.

Table 2

Measurement Model Evaluation

Constructs	Factor loading	Cronbach Alpha	Composite Reliability	AVE
PERCEIVED USEFULNESS		**0.924**	**0.926**	**0.687**
PU1: Gen-AI tools improve my efficiency in preparing classes and teaching materials.	0.869			
PU2: Gen-AI tools facilitate the creation of more innovative content.	0.821			
PU3: Gen-AI tools help personalize teaching according to students' needs.	0.839			
PU4: Gen-AI tools improve my productivity in teaching.	0.886			
PU5: Gen-AI tools will contribute to achieving better learning outcomes.	0.820			
PU6: Using Gen-AI tools will reduce the time spent on repetitive tasks.	0.734			
PU7: Using Gen-AI tools will help me adapt more quickly to technological changes in education.	0.826			
PERCEIVED EASE OF USE		**0.882**	**0.884**	**0.681**
PEOU1: Learning to use Gen-AI tools is easy for me.	0.823			
PEOU2: I believe I can solve technical problems that arise using Gen-AI tools.	0.767			
PEOU3: I have the necessary skills to integrate Gen-AI tools into my teaching.	0.840			
PEOU4: Gen-AI tools are intuitive and easy to use.	0.826			
PEOU5: The time I need to invest in learning to use Gen-AI tools is reasonable.	0.825			
ATTITUDE		**0.893**	**0.902**	**0.703**
ATTITUDE1: In the future, a large part of teaching activities will rely on AI tools.	0.735			
ATTITUDE2: There are many varied possibilities for applying AI tools in university teaching.	0.793			
ATTITUDE3: I have a positive opinion about the use of AI applications in university teaching.	0.908			
ATTITUDE4: Using AI applications in teaching is a good idea.	0.914			
ATTITUDE5: AI tools make teaching more interesting.	0.828			
SUBJECTIVE NORMS		**0.786**	**0.786**	**0.701**
NORM2: The people I admire use AI tools.	0.793			

NORM3: My students consider it important that their teachers use AI tools.	0.868
NORM5: My students consider it important that we facilitate AI tools use.	0.849

The Cronbach's alpha values for each construct range from 0.786 to 0.924, demonstrating good reliability among the indicators. The composite reliability of all constructs surpasses the reference threshold of 0.7 [43] and the average variance extracted (AVE) values exceed 0.5 (confirming the convergent validity of the model according Fornell & Larcker [44].

To assess discriminant validity, it was ensured that no item had higher loadings on constructs other than the one it was intended to measure [45]. A construct is considered to have discriminant validity if its AVE is greater than the square of its correlations with other constructs [44]. According to this criterion, all constructs in the model exhibit discriminant validity, allowing us to proceed with the evaluation of the structural model.

For formative constructs, traditional measures of reliability and convergent validity are not applicable. Instead, it is essential to ensure that there is no collinearity among the indicators [46]. The variance inflation factor (VIF) values for both the external and structural models are all below the reference threshold, ranging from 1.587 to 3.49. Following a scale refinement process, which involved removing a single indicator with non-significant weight, Table 3 demonstrates the reliability of the formative construct "intention to use."

Table 3

Formative constructs validity

Construct	Weights	t value (bootstrap)	VIF
INTENTION TO USE			
INTENTION1: In the future, AI tools will become an essential part of my teaching practices.	0.182	0.000	2.414
INTENTION3: I am likely to recommend the use of AI tools to other teachers.	0.359	0.000	3.322
INTENTION4: If I have access to an AI tool, I will use it to automate repetitive tasks in my teaching work.	0.124	0.001	2.020
INTENTION5: I will integrate AI tools into my teaching methods, if conditions allow.	0.280	0.000	3.493
INTENTION6: I am willing to learn more about AI tools to integrate them into my teaching.	0.117	0.000	2.287
INTENTION7: I am willing to pay for a subscription to AI tools.	0.108	0.000	1.586

Figure 2 presents the results of our structural model estimation. The arrows depict causal relationships, and the numbers adjacent to each arrow represent the standardized coefficients. Additionally, the product of these standardized coefficients and the correlation coefficients between the two constructs is expressed as a percentage in parentheses [47].

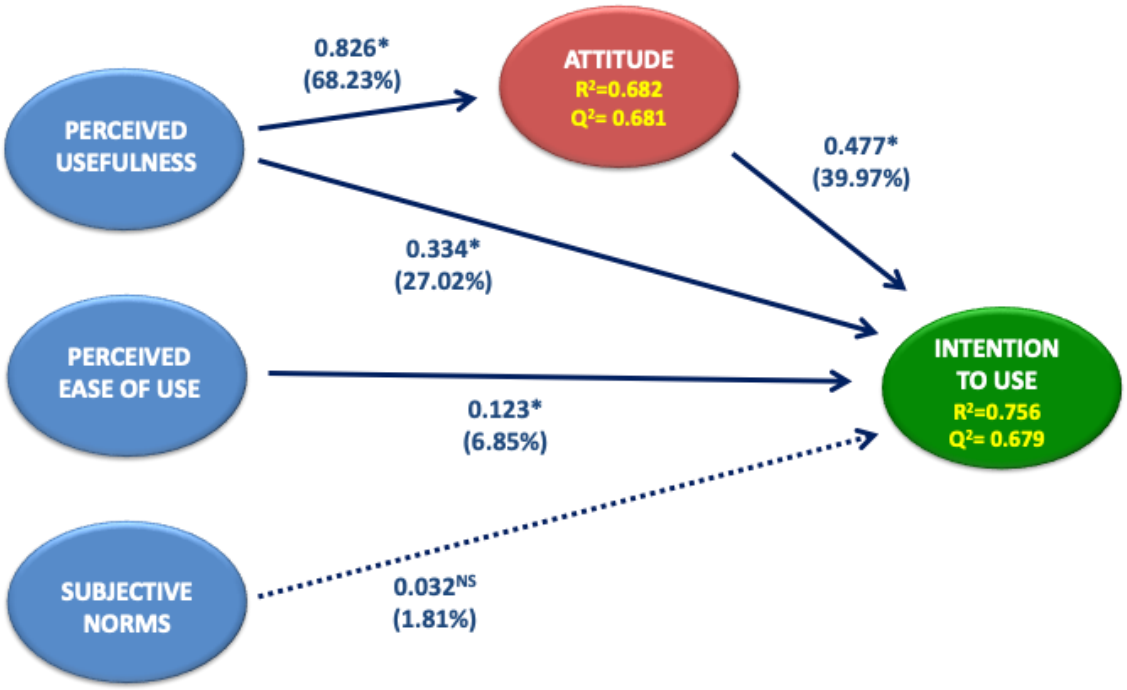

Figure 2.- Structural model

(*) Significant relationship at the 99% level

Perceived usefulness significantly influences the intention to use Gen-AI tools. It explains 68.23% of the variance in attitude, which in turn accounts for near 40% of the variance in the intention to use these tools. Additionally, perceived usefulness directly explains 27% of the variance in the intention to use Gen-AI tools. This indicates that perceived usefulness not only has a strong direct impact on the intention to use but also an indirect effect through its influence on attitude.

In contrast, perceived ease of use (6.85%) has minimal impact. And subjective norms do not significantly influence the intention to use Gen-AI tools among university faculty at the 99% confidence level.

The figure indicates that all Q^2 values from the Stone-Geiser test are greater than zero, demonstrating predictive relevance. The model exhibits strong predictive power (R^2), explaining 75.6% of the variance in the intention to use construct and 68.1% of the variance in attitude. The goodness of fit, measured by the standardized root mean square residual (SRMR), is 0.048, indicating that our model fits the empirical data well [48].

Results of the multigroup analysis

The previously analysed data represent the outcomes of a global model, where no specific criteria were applied to categorize them, if the shared variance spans the entire sample. Multigroup analysis is a technique used to determine if there are statistically significant differences between various data groups for the same model [49].

In this study, two variables were identified as potential moderators of the established relationships: gender and age. These moderating effects are formally stated in Hypothesis H6 (gender) and Hypothesis H7 (age). Each variable was divided into two groups to standardize the samples and facilitate comparison. Table 4 presents the groups formed, their divisions, respective sample sizes, and the frequency of each group relative to the total sample.

Table 4

Moderating variables considered

Division	Gender		Age (years)	
	Male	Female	<40	>50
Population	494	378	56	630
Frequency	56,7%	43,3%	8,2%	91,8%
Total	872		686	

According to Table 4, all groups meet the criteria for a satisfactory sample size, with each group having more than 20 observations [49]. The groups were created using SmartPLS 4 software as described in the table, and the new models were tested to verify the results. In this regard, after validating all models for each group of each moderator variable, the results of the tests conducted are presented below.

The first moderator variable analysed was gender, with respondents divided into male and female groups. According to Hair et al. [49], heterogeneity is present when the reporting groups show significant differences ($p < .05$) in their model relationships. As shown in Table 5, both groups exhibit homogeneity in all structural relationships, as the multigroup analysis table does not show any statistically significant p-values at the < .05 level. Therefore, it can be concluded that gender does not moderate the relationships between the factors in the proposed model for this study, indicating that there are no differences between men and women regarding their behavioural intention to use Gen-AI tools.

Table 5

Multigroup analysis of moderator variable gender

Hypothesis	Structural relationships	Difference (male-female)	p-values
H1	ATT → INT	0.153	0.362
H2	PU → ATT	0.045	0.092
H3	PU → INT	-0.075	0.629
H4	PEOU → INT	-0.027	0.645
H5	SN → INT	-0.067	0.356

Note: ATT = Attitude; PU = Perceived utility; PEOU= Perceived ease of use; SN = Social norms; INT = Intention of use.

Table 6 displays the results of the multigroup analysis for the specified age levels. According to the data presented, it can be observed that the variable age moderates the relationships established by all hypotheses in the proposed model [49].

Table 6

Multigroup analysis of moderator variable age

Hypothesis	Structural relationships	Difference (younger-older)	p-values
H1	ATT → INT	2.354	0.000
H2	PU → ATT	0.085	0.009
H3	PU → INT	-2.429	0.000
H4	PEOU → INT	0.123	0.000
H5	SN → INT	0.022	0.000

Note: ATT = Attitude; PU = Perceived utility; PEOU= Perceived ease of use; SN = Social norms; INT = Intention of use.

The main differences are observed in the relationship between perceived usefulness, attitude, and intention to use. Among younger teachers, attitude has a greater total impact on the intention to use, suggesting that their disposition and positive perception towards these tools play a crucial role in their decision to use them. On the other hand, for older teachers, perceived usefulness is the determining factor when choosing to use these tools. This indicates that older teachers value the functionality and practical benefits they can obtain from Gen-AI tools more highly. In contrast, for younger teachers, perceived usefulness is not a determining factor; in fact, it could be said that their decision to use these tools is more influenced by their attitude and less by perceived usefulness.

4. CONCLUSIONS AND PROSPECTS FOR FURTHER RESEARCH

The study makes a substantial contribution to the literature by examining how various factors such as perceived usefulness, perceived ease of use, social norms, and attitudes shape teachers' intention of using Gen-AI tools in teaching and academic settings. The findings shed light on technology acceptance theories, particularly regarding AI integration in education, and confirm that effort and performance expectations are key drivers of teachers' attitudes. These results align with established theories such as the Technology Acceptance Model (TAM) and its extensions, which underscore the importance of perceived ease of use and perceived usefulness in technology adoption. The research also underscores the necessity of refining theoretical models to better capture the complexities of AI integration in educational contexts, in line with advancements in technology acceptance theories.

The significant impact of perceived usefulness on the intention to use Gen-AI tools suggests that users are more likely to adopt these tools if they find them beneficial. This highlights the importance of demonstrating the practical advantages and effectiveness of Gen-AI tools to potential users. Since perceived usefulness also influences intention indirectly through attitude, it is crucial to foster positive attitudes towards these tools. This can be achieved through user education, showcasing success stories, and providing hands-on experiences.

HEI must establish learning objectives for all students and staff to develop their skills and stay up to date with new Gen-AI tools. These institutions should create a knowledge management repository to capture all implicit and tacit knowledge, including information related to market demands, employee needs, and educational requirements. The technical resources available to all staff and students at these institutions are essential for achieving high levels of AI adaptation, thereby enhancing their readiness for future challenges or changes. By taking these actions, higher education institutions can improve their educational capacity and meet market demands. Consequently, faculty members can benefit from collaboration, automated grading, and intelligent systems supported by AI. The integration of AI will significantly enhance our ability to increase digital literacy and skill sets.

The minimal influence of perceived ease of use indicates that while ease of use is important, it is not the primary driver for the adoption of Gen-AI tools. This suggests that users might be willing to invest time and effort in learning to use these tools if they perceive them as highly useful. This research result can also be justified by the fact that AI tools are, in their essence, born to be accessible and simple for any user, i.e. as a technology that does not really require technical knowledge.

The lack of significant influence from subjective norms implies that peer pressure or societal expectations do not strongly affect university faculty's intention to use Gen-AI tools. This suggests that individual perceptions of usefulness and personal attitudes are more critical factors in their decision-making process.

The absence of significant differences between male and female groups suggests that gender does not play a role in moderating the relationships in the model. This implies that strategies to promote the use of Gen-AI tools can be gender neutral.

The significant differences between younger and older groups indicate that age is an important factor in moderating the relationships. This suggests that tailored approaches may be necessary to address the specific needs and preferences of different age groups. For example, younger users might be more receptive to innovative features, while older users might prioritize ease of use and support.

Overall, these findings emphasize the importance of perceived usefulness in driving the adoption of Gen-AI tools and suggest that targeted strategies considering age differences can enhance their acceptance and usage. For instance, younger faculty might adapt more quickly to Gen-AI tools due to their higher digital literacy, while older faculty might require additional training and support to achieve the same level of comfort and proficiency.

HEIs should consider implementing age-specific training programs that address the unique needs and learning styles of different age groups. This could involve more hands-on workshops and personalized support for older users, while younger users might benefit from advanced features and integration of Gen-AI tools into their existing workflows.

Overall, by acknowledging the age-related differences in the adoption and use of Gen-AI tools, HEIs can enhance the overall effectiveness of their AI integration efforts, ensuring that all members of the institution can benefit from these advanced technologies.

This study has several limitations, the foremost being the use of the intention of use construct as the dependent variable. Despite the high variance observed in this construct, it is crucial to note that behavioural intention does not necessarily equate to the actual use of technology by the respondents. In certain contexts, behavioural intentions do not always translate into actual usage. Second, it relied solely on quantitative data to examine the relationships among various factors. Future research should incorporate qualitative data collected from HEI teachers to gain deeper insights into their perspectives and underlying motivations. Third, this study focused on teachers' perceptions of the use of generative AI (Gen-AI) in education. While Gen-AI holds great potential in this field, it also poses certain challenges, such as the risk of the technology being misused for improper purposes. Finally, it is crucial to note that the study's participants are from a single country (Spain), highlighting the need for further research to understand Gen-AI acceptance in diverse educational settings.

This study enhances our understanding of the factors influencing faculty engagement with Gen-AI tools in HEI. By pinpointing the drivers and obstacles that shape faculty attitudes and behaviours towards Gen-AI, the findings offer valuable insights for educational policymakers, administrators, and practitioners aiming to leverage AI technologies in teaching and learning environments.

The research emphasizes the importance of continuous dialogue and collaboration among faculty, administrators and technologists to address the ethical, pedagogical, and practical challenges associated with Gen-AI tools adoption in HEI. Promoting interdisciplinary collaboration and fostering a culture of ethical reflection can help universities harness the transformative potential of Gen-AI while mitigating potential risks and challenges.

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ВПЛИВ СТАТІ ТА ВІКУ ВИКЛАДАЧІВ НА ВИКОРИСТАННЯ ІНСТРУМЕНТІВ ГЕНЕРАТИВНОГО ШТУЧНОГО ІНТЕЛЕКТУ В ЗАКЛАДІ ВИЩОЇ ОСВІТИ

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Анотація. Хоча існуючі дослідження визначили ключові детермінанти використання інструментів генеративного штучного інтелекту (Gen-AI) викладачами закладів вищої освіти (ЗВО), вплив індивідуальних характеристик, таких як стать і вік, залишається недостатньо вивченим. Багато досліджень припускають однорідну популяцію, тим самим ігноруючи різноманітні поведінкові наміри та сприйняття технологій окремими людьми, особливо в контексті вищої освіти.

Це дослідження спрямоване на усунення цієї критичної прогалини шляхом вивчення того, як стать і вік впливають на взаємозв'язок між сприйняттям корисності, простотою використання, ставленням і суб'єктивними нормами на наміри викладачів ВНЗ впроваджувати інструменти Gen-AI. Інтегруючи ці моделюючі фактори в рамках Моделі Прийняття Технологій (МПТ) та Теорії Запланованої Поведінки (ТЗП), це дослідження пропонує детальне розуміння диференційованого впливу гендеру та віку на впровадження технологій.

Результати цього дослідження роблять значний внесок у літературу з Gen-AI, автори підкреслюють важливість врахування індивідуальних відмінностей у демографічних характеристиках при дослідженні поведінки, пов'язаної з впровадженням технологій. Зокрема дослідження показало, що стать і вік не тільки впливають на прямі детермінанти використання інструментів ШІ, але й пом'якшують силу та напрямок цих зв'язків. Наприклад, молоді викладачі можуть сприймати інструменти Gen-AI як більш корисні та прості у використанні порівняно зі своїми старшими колегами.

Дослідження надає викладачам ЗВО практичні рекомендації щодо покращення управління та використання інструментів Gen-AI серед різних груп користувачів. Визнаючи та враховуючи унікальні потреби та вподобання різних демографічних сегментів, ЗВО можуть сприяти інклюзивному та більш ефективному впровадженню інструментів Gen-AI. Це, своєю чергою, може призвести до покращення результатів викладання та навчання, а також до більшого загального задоволення від інтеграції технологій в освітні заклади.
Як висновок: це дослідження підкреслює необхідність врахування статі та віку як критично важливих моделюючих змінних у дослідженнях впровадження технологій. Отже, воно пропонує цінну інформацію для освітян, політиків і дослідників, які прагнуть сприяти ефективному і рівноцінному використанню інструментів Gen-AI у вищій освіті.

Ключові слова: штучний інтелект; Модель Сприйняття Технологій; сприйнята корисність; сприйнята простота використання; суб’єктивна норма; заклади вищої освіти

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