# Gender Bias in Self-Perception of AI Knowledge, Impact, and Support among Higher Education Students: An Observational Study

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*Objectives.* This study investigates gender biases in AI perceptions among university students. It focuses on assessing self-perceptions regarding knowledge, impact, and support, with a specific emphasis on identifying any significant gender differences. The main hypotheses are focused on the existence of gender disparities in AI awareness, perceptions, and attitudes among higher education students.
*Participants.* The study involves 380 participants, enrolled in undergraduate courses across various academic disciplines. Participants are university students with diverse backgrounds in terms of age, academic majors, and prior exposure to AI technologies.
*Study Methods.* This research employs an observational study design. The sample size includes 380 participants. The study utilizes a structured questionnaire as the primary instrument for data collection. Outcome measures focus on variables such as perceived knowledge of AI, perceived impact of AI, and levels of support or apprehension towards AI technologies.
*Findings.* The findings reveal significant gender differences, with females exhibiting lower levels than their male counterparts in the level of perceived knowledge about AI ($p < 0.005$), exposure awareness ($p = 0.001$), perceived ability to apply AI ($p = 0.004$), sensitivity towards AI use of private data ($p = 0.004$), positive impact on society ($p = 0.002$), support for AI development ($p < 0.005$), and positive expectations towards AI ($p < 0.005$). Statistical analysis, including nonparametric tests, was used to validate these observations.
*Conclusions.* There are notable gender biases in the knowledge and perception of AI among university students. These biases have implications for the future development and adoption of AI technologies, suggesting a need for more gender-inclusive educational strategies in AI. The findings underscore the importance of addressing gender disparities in AI education to ensure equitable access and understanding of these technologies. It is important to integrate gender perspectives in AI curriculum and policy-making to mitigate potential biases and enhance inclusivity in the field of AI.

CCS Concepts: • **Computing methodologies** → **Artificial intelligence**; • **Social and professional topics** → **Gender**; **Computing literacy**;

Additional Key Words and Phrases: Artificial intelligence, gender bias, social implications, observational study, university students

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## 1 Introduction

AI is the ability of computer systems to mimic the functions of the human brain, such as learning and problem-solving. In recent years, thanks to huge advances in the development of deep artificial neural networks [14], these systems have moved out of academia and made their way into society, becoming an integral part of our daily lives: every Google search we do, every Amazon recommendation we receive, and every image filter we use on our mobile phone camera are supported by an AI system.

Given the tremendous impact that these technologies have and will have on our society, numerous government initiatives are emerging to support citizens' AI literacy. A prominent example is the European Commission's Digital Education Action Plan (2021–2027)[1] that establishes the enhancement of digital competencies and skills as one of its strategic priorities, proposing to "update the European Digital Competences Framework to include AI and data-related skills and support the development of AI learning resources for schools, vocational education and training (VET) organizations and other training providers."

In this context, it is essential to identify the main gaps and biases present among the population regarding these technologies, thus enabling a more effective strategy in the AI literacy process. These disparities and biases can vary based on several factors, including culture and gender. Instructors in higher education specializing in AI should be aware of these differences to foster educational equity. This concept entails that the educational system equips each student with the requisite resources to attain an acceptable level of performance [26].

Regrettably, there is a lack of empirical data that analyze the degree of variance in AI literacy based on cultural and gender factors, which would facilitate informed decision-making in customizing learning activities according to these variables. To address this, the present study aims to bridge this gap by investigating the gender variable as a potential determinant of differences in AI knowledge, perceived impact and support among Spanish university students. To achieve this objective, we designed an instrument that was administered to 380 students in higher education, enrolled in various degree programs. Subsequently, we analyzed the data to examine gender differences within this sample.

The identification of AI thoughts and concerns that should be reinforced or mitigated in the classrooms, and how they differ among genders, is important for both instructors and students. On the one hand, when instructors are aware of these misconceptions and gender differences, they are better prepared to design targeted educational actions that contribute to achieving AI educational equity and personalize the student's learning process. On the other hand, when students become aware of their knowledge gaps and perception biases, they can question them and get better prepared for a future where AI will, undoubtedly, play a major role.

The remainder of this article is structured as follows: Section 2 presents a narrative review of the literature that contextualizes this empirical research; Section 3 describes the conceptual model that guided this study; Section 4 describes the experimental design used in this work, including context, participants, instruments, variables, and hypotheses; Section 5 outlines the execution of the study;

[1] https://tinyurl.com/3kccsf8m.

Section 6 presents the main results; Section 7 analyzes and discusses the results and relates them to the findings of the related literature; finally, Section 9 provides conclusions and paths for future research.

## 2 Related Work

Among the studies addressing AI developments in recent years, those particularly relevant to our work are those examining the general public's perceptions and **Attitudes towards AI (ATAI)**.

A significant study in this category is the one developed by Holder et al. [16], which delved into the UK public's perceptions of AI. This study involved a survey to evaluate people's views on AI, its potential applications, the ways it might impact our lives, and the role legislation should play in its governance. Conducted with over 2,000 participants of diverse educational backgrounds and skill levels, its goal was to gather insights to aid technology companies in fostering trust in AI among the general population. The survey findings indicated general support for AI and its prospective advantages, yet they also highlighted substantial concerns about its possible adverse effects and the necessity for its responsible development and regulation.

Similarly, Zhang and Dafoe [33] explored the attitudes of the US population towards AI and its governance, surveying more than 2,000 adults. The study covered various aspects: workplace automation, opinions on international collaboration in AI development, public confidence in different entities managing AI, perceptions of the significance and expected impact of AI governance challenges, and historical and international trends in public opinion about AI. The survey revealed that most respondents (72%) anticipated AI to predominantly positively influence society in the future, noting potential benefits like enhanced efficiency and improved medical treatments. However, those with reservations pointed to issues like job displacement and the risk of AI becoming overly dominant.

Another significant research concerning ATAI is the study by Schepman and Rodway [28]. This research involved developing and validating a scale for general ATAI, recruiting 100 adult participants in the UK. Participants' attitudes were assessed using specific AI application examples from newspaper articles. The survey showed that people generally viewed AI applications dealing with large datasets positively (e.g., in fields like astronomy, law, and pharmacology) but were skeptical about its use in tasks requiring human judgment (such as medical treatment and psychological counselling). The findings indicated a mixed public opinion on AI.

The work by Budic [4] comprised a theoretical exploration of ethical dilemmas stemming from AI development and an empirical investigation into public ATAI. The study introduced a new scale to gauge public ATAI, focusing on 737 Serbian participants. Utilizing an online questionnaire, socio-demographic information, familiarity with AI, and attitudes towards its use were examined using a 5-point Likert scale. Factors such as age, education, profession, religiosity, and prior AI knowledge were assessed for their impact on attitudes. Findings revealed a split opinion among the Serbian public, with half expressing positive and the other half negative ATAI. Demographics and familiarity with AI significantly influenced attitudes, showing younger, highly educated, non-religious individuals, especially IT professionals, and those more acquainted with AI holding more favorable views. Concerns emerged regarding job displacement and AI-driven discrimination.

The study by Hick and Ziefle [15] employed a qualitative approach, with 30-minute interviews conducted with 25 participants over 2 months. The aim was to gauge public knowledge and expectations concerning AI. The interviews delved into participants' understanding of AI, their anticipated benefits and drawbacks, and their experiences with AI or AI-based technology. Two prominent themes emerged: a dystopian perspective and an overly optimistic view of AI's possibilities. Ultimately, this work underscored the necessity for accurate information, presentation, and educational initiatives to properly manage expectations and comprehend AI's actual capabilities.

Wu et al. [32] focused on medical AI, synthesizing public perceptions of its use and addressing concerns about credibility, responsibility, and ethics. The goal was to offer recommendations for the future management and utilization of AI in medical settings. A meta-synthesis of 12 qualitative studies was conducted. Three main themes emerged from the synthesis: the perceived advantages of medical AI, ethical and legal apprehensions, and the public's recommendations for AI in healthcare. Participants acknowledged the benefits and convenience of medical AI, but expressed concerns primarily centered around ethical and legal considerations.

To sum up, these previous studies suggest that the general public's perceptions and ATAI are mixed, influenced by factors such as age, education, profession, and culture, with positive attitudes towards certain applications and concerns about human judgment, workplace automation, and trust in AI development and regulation.

Equally relevant to the current research are studies that focus on the ethical implementation and use of AI globally, with a special emphasis on addressing gender equity. The **European Union (EU)** dictates that ethical AI use requires that technologies deployed in Europe must ensure adherence to the fundamental rights of EU citizens [1]. In particular, reliable AI should consider sex and gender equality as one of its ethical pillars [19]. Analyzing gender in science and technology helps identify the impact of certain practices on women's lives. Various reports from reputable organizations provide guidelines on incorporating gender equality into AI principles [9, 10, 31]. Such publications highlight the importance of investigating potential gender disparities in understanding and accepting AI as a critical area of research.

Conscious of this importance, the research community has published various studies where gender bias in AI perceptions and attitudes has been addressed in different contexts. The work by Pinto dos Santos et al. [24] presented a survey among undergraduate medical students at three major German universities. It was developed to assess their attitudes and concerns towards AI in radiology. Female students were 63.1% of the participants in the survey. The results showed that female respondents tended to be less confident both about the benefits of AI and about the impact of technology on radiology. They also seemed more fearful of these technologies and expressed less interest in AI being part of medical training. The authors concluded that there is a pressing need to include fundamental training on these topics for medical students, aiming to address and mitigate these gender disparities.

The study by Horowitz and Kahn [17] surveyed 690 U.S. local officials, key players in the adoption and regulation of AI, to gather their views on two potential AI applications: autonomous vehicles and autonomous surgery. Women comprised 33% of the respondents in this survey. The influence of gender was pronounced: female participants were significantly less supportive of both autonomous vehicles and autonomous surgery compared to their male counterparts. Also, women in the sample who rejected the use of autonomous surgery did it for issues related to control rather than societal consequences.

In the study by Sindermann et al. [30], the researchers developed a measure for assessing individual differences in ATAI, which they validated through an online survey conducted in Germany (with 74.8% female participants), China (35.1% female participants), and UK (77.4% female participants). The findings showed that females generally scored lower on the ATAI Acceptance scale compared to males, while males scored lower on the ATAI Fear scale. Notably, these gender differences were significantly less pronounced in the Chinese sample, highlighting the influence of cultural factors on gender biases in ATAI.

Jang et al. [18] focused on examining differences in Korean students' ATAI ethics, based on gender and prior exposure to AI education. Their research involved undergraduate students who participated in a Massive Open Online Course offered by Korea University, with females constituting 56% of the study's participants. The study evaluated attitudes across five dimensions of AI ethics: fairness, transparency, non-maleficence, responsibility, and privacy. The findings revealed notable gender disparities in several of these dimensions. Specifically, female students demonstrated a heightened sensitivity compared to their male counterparts towards issues of fairness, privacy, and non-maleficence in AI ethics.

Colonna [7] studied how AI can be used in higher education and highlighted the importance of considering how it can affect diversity and inclusion. In particular, the article emphasized the need to address possible gender inequalities in the use of AI. It was also found that there was a higher participation of male students in the use of AI, suggesting the possible existence of gender inequalities in the use of AI in education.

Another related study by Fietta et al. [11] aimed to explore the coherence between implicit and explicit ATAI. The authors combined self-report measures and implicit association test and 829 participants' ATAI were examined. The study uncovered that while most participants expressed positivity towards AI, their implicit reactions indicated otherwise. Furthermore, findings highlighted gender disparities, with females exhibiting more negative attitudes than males across both explicit and implicit measures. Additionally, individuals working in AI displayed a predisposition towards a positive outlook on AI. This study shows the complexity of ATAI, revealing a discrepancy between expressed sentiments and underlying subconscious perceptions. It also underscored gender variations and professional influences on attitudes.

Also of particular interest to our work is the research conducted in Spain, due to the influence of the cultural context on gender disparities. While some studies focusing on gender bias in STEM have been identified in the Spanish context [5, 22, 23], there appears to be a research gap concerning the exploration of gender differences in AI perceptions and literacy among Spanish university students. To the best of our knowledge, only the study by Albarrán-Lozano et al. [2] addresses this issue. There, the authors analyzed the perceptions of Spanish citizens towards AI and the factors associated with them. Data from 6,308 individuals were used (48.6% male and 51.4% female). Although the gender gap was not the focus of that paper, the variable was included because the database was representative by gender. One of the main findings was that there was a gender gap with the attitude towards AI and robots.

Finally, Gilbert and Valls [13] detailed the establishment of a working group in Spain aimed at addressing and reducing the gender gap in AI. The article identifies the main barriers to women's participation in AI. The authors concluded that the working group was effective in raising awareness of the gender gap in AI and proposing measures to promote gender equality in the field.

## 3 Conceptual Model

Based on the dimensions and variables identified in related literature for assessing students' perceptions and ATAI, this section introduces the conceptual model informing the current research (see Figure 1). In this model, only gender was included as a potential factor influencing differences in AI perceptions and attitudes. Additionally, the age of the participants has been controlled to ensure consistency across all observations.

This model breaks down AI perceptions and attitudes into three dimensions: knowledge and awareness, perceived impact on everyday life (encompassing both positive and negative aspects, including employment, use of personal data, and societal change), and support for AI's future development. Each dimension is further subdivided into a set of variables, which have been identified in the related literature as can be seen in the *References* column of Table 1. The *Validated* column indicates whether the scale used has been validated in previous literature. Table 2 provides additional information about the population with which these scales were validated.

In addition, this model also includes three variables that, to the best of our knowledge, have not been studied in previous AI surveys: perceived ability to apply AI, need to learn AI for work, and

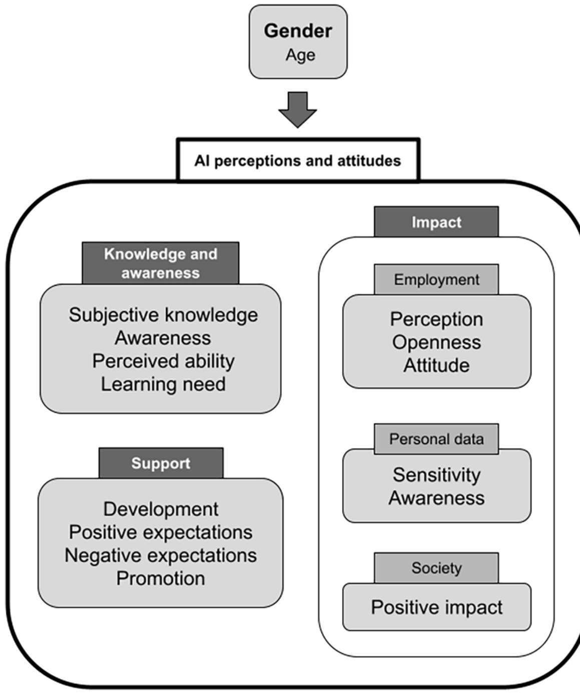


Fig. 1. Conceptual model: gender impact on the AI perceptions and attitude construct.

**Net Promoter Score (NPS)**. The first two have been included in order to get a broader picture of student's perceptions of the need to acquire AI knowledge and their ability to apply it in their future work. In addition, the NPS has been adapted to measure the willingness of students to promote AI among their peers [27]. It is a measure that has been subject to thorough psychometric evaluations [20] and, in other contexts, it provides a clear snapshot of user satisfaction and loyalty. We have adapted this model to the current context because we believe that the presence of word-of-mouth differences between genders, particularly in the social learning environments fostered by higher education institutions and modern learning methodologies, could contribute to exacerbating gender inequality.

## 4 Methodology

This is a cross-sectional study within the observational category. Observational studies are a kind of empirical study in which, unlike what happens with experiments or quasi-experiments, the independent variables (in our case, *gender*) cannot be manipulated and must instead be observed. Based on these observations, the researcher tries to draw some conclusions [3]. The main disadvantage of cross-sectional studies as compared to other types of empirical studies is that they do not permit to establish cause-effect relationships, since there is a lack of control over the confounding factors (that is, alternative explanations for the results of the study). However, in education they are very valuable to check assumptions and inform educational actions [6].

### 4.1 Objectives and Context Definition

The purpose of this study was to assess the differences in self-perceptions of AI knowledge, impact, and support depending on gender in the context of students attending Spanish higher education

Table 1. Conceptual Model: Variables Included in the Study, Description of Their Relation to Gender, Literature References Where They Have Been Previously Described and Measured, and Whether the Scale Was Validated in the Previous Literature or Not

| Variable | Description | References | Validated |
|---|---|---|---|
| | *Knowledge and awareness* | | |
| Level of knowledge about AI | This variable can reflect differences in educational exposure and access to resources, which may vary by gender due to sociocultural factors and potential biases in technology education. | [4, 15, 16] | No |
| Awareness of exposure to AI | This variable can vary based on the integration of technology in different environments. Gender may influence this perception, as access and familiarity with technology can differ across gender lines. | [15–17, 33] | No |
| Perceived ability to apply AI | This variable can be influenced by the educational context and previous experiences, varying among groups. Gender differences in confidence and experience with technology can shape this perception. | - | - |
| Need to learn AI for work | This variable can be influenced by industry and professional role. Gender disparities in certain industries and roles may affect motivation to acquire AI knowledge. | - | - |
| | *Impact* | | |
| Perception of impact of AI on professions | This variable can differ based on sector and personal experience. Gender may play a role, as different industries have varying gender distributions and ATAI. | [2, 16, 24] | No |
| Openness to the use of AI | This variable can be influenced by cultural, educational factors, and previous experiences, varying among different demographic groups. Gender can influence openness to AI, as societal norms and exposure to technology can differ by gender. | [2, 11, 16, 17, 24] | No |
| Attitude towards the impact of AI on employment | This variable can vary based on economic expectations and perceived job security among different groups. Gender can influence these attitudes, as economic opportunities and job security perceptions often vary by gender. | [2, 24, 30, 33] | Yes |
| *SUPD* | This variable can be influenced by personal experiences and awareness of privacy issues, varying among groups. Gender differences in privacy concerns and experiences can shape this sensitivity. | [15, 16, 28] | Yes |
| *AUPD* | This variable may depend on education level and exposure to privacy debates, differing among groups. Gender may influence this awareness, as educational opportunities and engagement in privacy issues can vary by gender. | [16, 28] | Yes |
| Positive impact in society | This variable can vary based on education level, cultural context, and personal experiences. Gender can shape these perceptions, as access to education and cultural norms can differ by gender. | [2, 11, 28, 30] | Yes |
| | *Support* | | |
| Support AI development | This variable can be influenced by economic, educational, and cultural factors, reflecting differences in the perception of AI's value. Gender disparities in economic and educational opportunities can influence this support. | [33] | No |
| Positive expectations towards AI | This variable can be influenced by exposure to optimistic information and positive experiences with technologies, varying among groups. Gender can influence these expectations, as access and attitudes towards technology can vary by gender. | [28, 33] | Yes |
| Negative expectations towards AI | This variable can be influenced by exposure to perceived risks, ethical debates, and negative personal experiences with technology, varying among groups. Gender may play a role, as experiences with and attitudes towards technology risks can differ by gender. | [28, 33] | Yes |
| NPS | This variable can reflect the willingness of different groups to recommend or advertise AI technologies. Gender can influence this score, as societal norms and personal experiences with technology can shape advocacy and promotion behaviors. | - | - |

Table 2. Characteristics of the Population in Previous Literature Presenting Validated Scales (See Table 1): Bibliographic Reference (*Reference*), Population Size (*Size*), Percentage of Females (*F*) and Males (*M*), Age Range and Mean (*Age*), Geographical Distribution, and Educational Level

| Reference | Size | F (%) | M (%) | Age | Geographical Distribution | Educational Level |
|---|---|---|---|---|---|---|
| [2] | 6,308 | 51.4 | 48.6 | Adults | Spain | NA |
| [11] | 829 | 45.5 | 54.5 | 18–77<br>M = 34.9 | North America, Asia, South America, Europe, Australia, Africa | Mixed |
| [15] | 25 | 56 | 44 | 21–82<br>M = 43.7 | Germany | Mixed |
| [16] | 2,103 | NA | NA | 16–55+ | UK | NA |
| [24] | 263 | 63.1 | 35.7 | 19–58<br>M = 23.1 | Germany | Medical students |
| [28] | 99 | 50.5 | 49.5 | 20–64<br>M = 36.2 | UK | Mixed |
| [30] | 958 | 57.9 | 42.1 | M = 22.1 | Germany, China, UK | University students |
| [33] | 2,000 | 51 | 49 | 18–73+ | USA | Mixed |

Data not available are identified as *NA*.

institutions. The **Research Questions (RQ)** addressed in this study were designed to be answered using quantitative data. The questions were as follows:

- *RQ1*: How do perceived knowledge and awareness of AI vary among university students based on gender?
- *RQ2*: How does the perceived impact of AI vary among university students based on gender?
- *RQ3*: How does the support for AI vary among university students based on gender?

### 4.2 Empirical Study Design

In this study, data was gathered from two different universities, the University of Alicante and the Catholic University of Murcia, in different degrees from Engineering and Humanities. This sample of universities and degrees was selected for convenience reasons: there were fellow instructors in all these degrees who were willing to participate in the study. The study was planned for the first semester of the 2022/23 academic year.

*4.2.1 Variables.* To conduct the study, *gender* was defined as the independent variable. It is a categorical variable, inter-subject, with three possible values: *male*, *female*, and *non-binary*.

The set of dependent (measurable) variables, organized by RQ, was defined as follows:

- RQ1 (Knowledge and awareness):
  - *Subjective AI Knowledge (SKw)*: interval scale, from 0 to 4. The higher the score, the more knowledgeable the subjects perceive themselves.
  - *AI Awareness (Awar)*: ratio scale, ranging between 0 and 17, since the question contained 17 possible items. The higher the number, the higher the awareness of all the everyday applications that use AI.
  - *AI Perceived Ability (Abil)*: interval scale, ranging between 0 (students believe that they would lack the ability to apply AI in their work) and 4 (students think that they would be good at applying AI in their work).

  - *Perceived AI Learning Need (LearnNeed)*: interval scale, ranging between 0 (students think that they do not need to learn AI to succeed in their future profession) and 4 (students believe that they will need to learn AI to succeed in their future profession).
- RQ2 (Impact):
  - *Perception of Impact of AI on Professions (EmployImpact)*: ratio scale, from 0 (minimum impact on any of the listed professions) to 104 (26 professions with a maximum impact of 4 points).
  - *Openness to AI (Openness)*: ratio scale, ranging between 0 (the subject does not want any of the listed tasks to be executed by an AI) and 22 (the subject is open to all the 22 listed tasks to be executed by an AI). The higher the number, the higher the openness towards AI use.
  - *Attitude Towards the Impact of AI on Employment (EmployAtt)*: interval scale, from 0 (it will destroy many more jobs than create) to 4 (it will create many more jobs than destroy). The higher the score, the more positive the attitude.
  - *Sensitivity Towards AI Use of Private Data (SUPD)*: nominal scale with *Yes* (the subject agrees to this use) and *No* (the subject is against this use) as possible values.
  - *Awareness About AI Use of Private Data (AUPD)*: nominal scale with *Yes* (the subject is aware of this use) and *No* (the subject is not aware) as possible values.
  - *Positive impact in society (PI)*: nominal scale with *Yes* and *No* as possible values.
- RQ3 (Support):
  - *AI Development Support (Support)*: interval scale ranging from 0 (strong opposition) to 4 (strong advocacy).
  - *Expectations Positive (E-P)*: ratio scale ranging from 0 to 40 (10 motivators with a maximum value of 4 points each). Higher scores mean more positive attitudes, i.e., higher expectations regarding the use of AI.
  - *Expectations Negative (E-N)*: ratio scale ranging from 0 to 52 (13 concerns with a maximum value of 4 points each). Higher scores mean more positive attitudes, i.e., lower concerns regarding AI.
  - *NPS*: a ratio scale ranging between −100 (all detractors) and 100 (all promoters). It identifies the willingness to promote AI among peers.

*4.2.2 Hypotheses.* Drawing upon the literature review presented in Section 2, and guided by the RQs and variables discussed previously, we defined the alternative hypotheses as follows:

- $H1.1_A$: the *SKw* score differs among students depending on gender.
- $H1.2_A$: the *Awar* score differs among students depending on gender.
- $H1.3_A$: the *Abil* score differs among students depending on gender.
- $H1.4_A$: the *LearnNeed* score differs among students depending on gender.
- $H2.1.1_A$: the *EmployImpact* score differs among students depending on gender.
- $H2.1.2_A$: the *Openness* score differs among students depending on gender.
- $H2.1.3_A$: the *EmployAtt* score differs among students depending on gender.
- $H2.2.1_A$: the *SUPD* score differs among students depending on gender.
- $H2.2.2_A$: the *AUPD* score differs among students depending on gender.
- $H2.3_A$: the *PI* score differs among students depending on gender.
- $H3.1_A$: the *Support* score differs among students depending on gender.
- $H3.2_A$: the *E-P* score differs among students depending on gender.
- $H3.3_A$: the *E-N* score differs among students depending on gender.
- $H3.4_A$: the *NPS* score differs among students depending on gender.

The corresponding null hypotheses simply assert that there are no statistically significant gender-based differences for each variable of interest. Each hypothesis is linked to one of the variables detailed in Table 1. The initial two digits of each hypothesis correspond to the components of the conceptual model (1: Knowledge and awareness, 2: Impact, and 3: Support) and, when applicable, their subcomponents (2.1: Employment, 2.2: Personal data, and 2.3: Society). The final digit denotes the sequence number of the hypothesis within that component or subcomponent.

*4.2.3 Measuring Instruments.* In the absence of global standardized assessment tools for the "AI perception and attitudes" construct defined in Section 3 and to address the need for an instrument adaptable to university students with varying levels of AI knowledge, a new questionnaire was developed, incorporating quantitative components measured with Likert and nominal scales.

Its design was inspired by the various proposals outlined in the literature review, utilizing validated scales for all the conceptual model constructs for which one was available (see Table 1). The questionnaire's structure was organized into three sections:

— *Informed Consent Form*: participants were informed about the study's objectives and their consent was sought for the use of their data in an anonymized and aggregated manner.
— *Demographic Information*: this section included questions about age, gender, degree program, course, and self-assessed computer literacy level.
— *Questions Related to Variables*: This section included one question for each variable defined in Section 4.2.1 (see Table 3).

The survey created was implemented online using the Qualtrics[2] platform, which allowed for easy dissemination among students. The survey was designed to be anonymous to allow students to freely express themselves. All answers were set to mandatory.[3]

## 5 Execution of the Study

Before initiating the main study, a pilot study was conducted with two students to evaluate the questionnaire's comprehensibility and usability. In response to their feedback, and considering the obligatory nature of the questions, a "Don't know" option was added to several of them.

The survey was ultimately conducted between November and December 2022. Owing to the workload of the students, the questionnaire was administered online. Out of the 452 targeted students, 380 agreed to participate in the study. However, not all the subjects filled in all the questions. For this reason, a slightly different number of subjects (as reflected in the degrees of freedom of the statistical tests carried out) has been used for each analysis.

After the study, five students who had declined to participate in the study and five students who had not answered all the questions were asked about their reasons. All of them blamed the workload and the lack of a tangible benefit in exchange for their participation. Neither of these reasons was related to their particular AI perception, so we consider that the drop-off rate does not pose a severe risk to the analysis results.

The average values of all the dependent variables were automatically computed using the Qualtrics platform. The mean time to fill in the questionnaire was 15 minutes.

## 6 Results

To analyze the data, the SPSS Statistics v. 26 software package was used. The bachelor's degrees that participated in the study were primary education, business administration and management, psychology, robotic engineering, computer science, and biomedical engineering.

[2] https://www.qualtrics.com/.
[3] The complete questionnaire, in Spanish and English, is available at the following link: https://bit.ly/aiknowatt.

Table 3. Questionnaire Variables and Items

| RQ | Var | #I | Question |
|---|---|---|---|
| RQ1 | Skw | 1 | Rate your level of knowledge about AI [0...4] |
| | Awar | 1 | In your opinion, which of the following applications/technologies use AI? (17 technologies, all using AI) [0...17] |
| | Abil | 1 | I believe that I would be good at applying AI in my job [0...4] |
| | Learn-Need | 1 | I think I need to learn AI to be able to do my future job properly [0...4] |
| RQ2 | Employ-Impact | 1 | In your opinion, to what degree will these professions be affected by AI? (26 professions) [0...104] |
| | Openness | 1 | Would you allow AI to do these tasks? (22 tasks) [0...22] |
| | Employ-Att | 1 | In general, I believe that the AI... [0: destroy many more than create ... 4: create many more than destroy] |
| | SUPD | 1 | Would you be okay with AI using your personal data and information about your personal life to perform tasks for you? [No, Yes] |
| | AUPD | 1 | Do you think AI uses our personal data (age, gender, online shopping habits, ...) to perform its tasks? [No, Yes] |
| | PI | 1 | Do you think AI will have a positive or negative effect on society? [Positive, Negative] |
| RQ3 | Support | 1 | How much do you support or oppose AI development? [0: strongly object. 4: very supportive] |
| | E-P | 1 | Indicate your degree of agreement with the following statements (10 positive statements) [0...40] |
| | E-N | 1 | Indicate your degree of agreement with the following statements (13 negative statements, reversed) [0...52] |
| | NPS | 1 | How likely are you to recommend the use of AI to a friend or family member? [0...10] |

Table 4. Subjects Distribution by Degree and Gender

| Degree | #Females | #Males |
|---|---|---|
| Primary education | 92 | 32 |
| Business administration and management | 20 | 18 |
| Psychology | 23 | 21 |
| computer science | 19 | 36 |
| Robotics | 19 | 37 |
| Biomedical engineering | 41 | 22 |
| Total | 214 | 166 |

Table 4 shows the distribution of the 380 subjects who finally participated in the study according to gender and degree in which they were enrolled.

As can be seen in Table 4, the final sample included 214 females (56.32%) and 166 males (43.68%). Regarding gender, the experimental design had originally considered three categories: *Female*, *Male*, and *Non-binary* (see Section 4.2.1). However, owing to all the subjects categorizing themselves as either male or female, all the analyses have been carried out with these two categories.

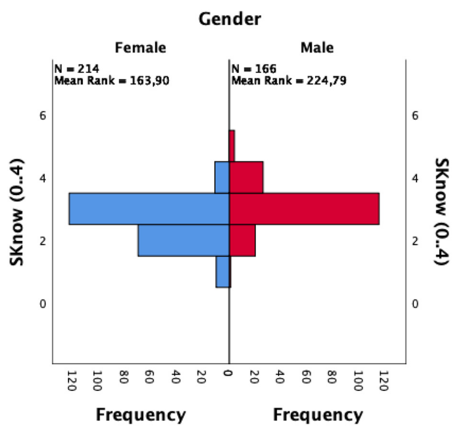


Fig. 2. Subjective AI knowledge (*Skw*).

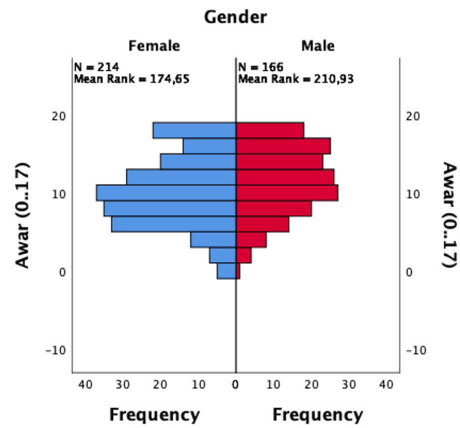


Fig. 3. AI awareness (*Awar*).

The remainder of this section presents the results obtained for each of the RQs (see Section 4.1) and the corresponding hypotheses (see Section 4.2.2).

For the hypotheses that involved nominal variables (H2.2.1, H2.2.2 and H2.3, and individual comparisons in H2.1.2), the Fisher's exact test, also known as the Chi-square test for homogeneity, was applied. This test is used to determine if a difference exists between the binomial proportions of two independent groups on a dichotomous dependent variable. Our study design for the affected hypotheses complies with the main assumptions: we have one independent variable (gender) and independent variables that are all measured at the dichotomous level (i.e., they both have two categorical, independent groups: females/males and yes/no, respectively). Also, observations are independent and we have a sufficient number of observations.

For the remaining hypotheses, we have applied the nonparametric Mann-Whitney U test. The reason is that the variable scores for each level of gender were not normally distributed for any of the interval and ratio variables included in the study, as assessed by Shapiro-Wilk's test ($p < 0.05$). Our study design to test these hypotheses also complies with the three main assumptions of the Mann-Whitney U test: (i) we have a continuous dependent variable; (ii) our independent variable (gender) is categorical with two groups (male and female); and (iii) we have independence of observations. The interpretation of the test results depends on whether the variable being analyzed complies or not with the fourth assumption, that is, whether the distribution of scores for males and females have the same shape. When the shapes were considered fairly similar (assessed through visual inspection of the population pyramid chart), the interpretation of significant differences was attributed to differences in medians, while when the shape was deemed dissimilar, the interpretation of significant differences was attributed to differences in mean ranks.

### 6.1 RQ1 (Knowledge and Awareness)

To address the first RQ, gender differences in *SKw*, *Awar*, *Abil*, and *LearnNeed* were analyzed using a Mann-Whitney U test. The value distributions for males and females are depicted in Figures 2–5. These figures offer a clear comparative overview of the distributions for each variable by gender.

With regard to the hypothesis defined, in $H1.1_A$ the distributions of *SKw* scores for males and females were similar, as assessed by visual inspection of the population pyramid chart. The median *SKw* score was statistically significantly different between males and females, $U = 23,454.5$, $z = 6.23$, $p < 0.005$.

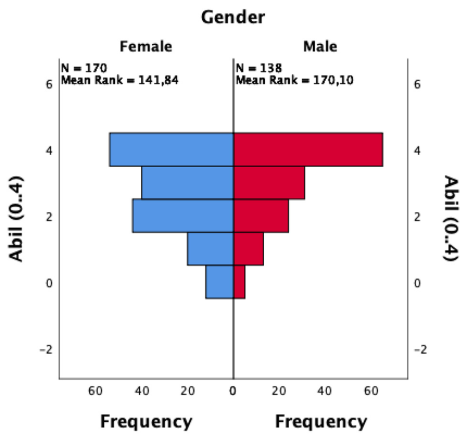


Fig. 4. AI perceived ability (*Abil*).

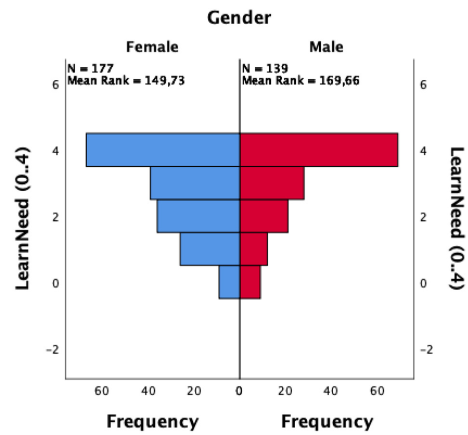


Fig. 5. AI learning need (*LearnNeed*).

Table 5. RQ1 Variables: Mean, Median, SD, and Mann-Whitmann's U Results (U)

| Variable (#f, #m) | Females Mean (Median) | SD | Males Mean (Median) | SD | U | p |
|---|---|---|---|---|---|---|
| *SKw* (214, 166) | 2.63 (3) | 0.66 | 3.07 (3) | 0.63 | −6.60 | $< 0.001^{**}$ |
| *Awar* (214, 166) | 9.53 (9) | 4.42 | 10.98 (11) | 4.21 | −3.20 | $0.001^{**}$ |
| *Abil* (170, 138) | 2.61 (3) | 1.24 | 3.00 (3) | 1.17 | −2.80 | $0.004^{**}$ |
| *LearnNeed* (177, 139) | 2.73 (3) | 1.25 | 2.98 (3) | 1.26 | −1.76 | $0.043^{*}$ |

#f and #m represent the number of females and males that responded to each question. An asterisk (*) denotes a significance level of 0.05, whereas a double asterisk (**) indicates a significance level of 0.01.

In H1.$2_A$ the distributions of *Awar* scores for males and females were similar, as assessed by visual inspection. The median *Awar* score was statistically significantly different between males and females, $U = 21,153.5, z = 3.20, \text{p} = 0.001$.

In H1.$3_A$ the distributions of the *Abil* scores for males and females were similar, as assessed by visual inspection. The median *Abil* score was statistically significantly different between males and females, $U = 13,883, z = 2.89, \text{p} = 0.004$.

Finally, in H1.$4_A$ the distributions of the *LearnNeed* scores for males and females were similar, as assessed by visual inspection. The median *LearnNeed* score was statistically significantly different between males and females, $U = 13,853, z = 2.205, \text{p} = 0.043$.

Table 5 presents the mean, median, SD, and the U Test results. These values show that men perceive themselves as significantly more knowledgeable and capable than females regarding AI. Also, they perceive a greater learning need and show a higher awareness of the prevalence of AI in their daily activities.

To further understand the everyday applications where students are more likely to identify the AI component (variable *Awar*), Table 6 shows the list of applications included in the questionnaire, ranked by the number of votes from highest to lowest. According to this table, virtual assistants (e.g., Siri, Google Assistant and Amazon Alexa) are the systems where the use of AI is most clearly perceived, followed by self-driving cars and drones. At the bottom of the table it is notable that Google translator and Facebook photo tagger are less commonly perceived as AI-driven tools.

Table 6. Applications, Ranked from Highest to Lowest, Based on the Number of Respondents Who Felt They Are Driven by AI

| Application | % Yes | % No | % Don't Know |
|---|---|---|---|
| Virtual assistants (e.g., Siri, Google, Alexa) | 89.97 | 5.01 | 5.01 |
| Autonomous cars | 87.07 | 6.60 | 6.33 |
| Autonomous drones | 78.36 | 12.40 | 9.23 |
| Mobile voice recognizer | 74.93 | 14.25 | 10.82 |
| Netflix movie recommender | 64.64 | 23.22 | 12.14 |
| Industrial robots used in factories | 59.10 | 31.13 | 9.76 |
| Personalized advertisements | 58.84 | 25.86 | 15.30 |
| Tablet handwriting recognition | 58.84 | 22.43 | 18.73 |
| Automatic classification of photos and videos | 54.62 | 26.65 | 18.73 |
| Prediction of a patient's risk of heart attack | 53.30 | 23.48 | 23.22 |
| Automatic analysis of product reviews | 52.51 | 22.16 | 25.33 |
| Enemy characters in a video game | 50.40 | 34.56 | 15.04 |
| Plagiarism detection | 49.87 | 31.13 | 19.00 |
| Google search engine | 49.34 | 31.93 | 18.73 |
| Filters to block spam | 47.49 | 31.40 | 21.11 |
| Google translator | 43.54 | 39.31 | 17.15 |
| Facebook automatic photo tagger | 43.01 | 33.51 | 23.48 |

## 6.2 RQ2 (Impact)

The students' perceived impact of AI was divided into three subcomponents: the impact of AI on employment, impact on data privacy, and impact on society as a whole. The following sections describe each one in more detail.

*6.2.1 Employment.* Concerning the perceived impact (either positive or negative) of AI on employment, a list of 26 different professions [16] from all sorts of fields was provided. Table 7 shows the selected set of jobs together with the percentage of students that think that they will be (a) highly affected (score 3 or 4) or (b) lowly affected (score 0 or 1) by AI. Also, the median and mean perceived impact and the SD of AI on each job are shown for males and females. Higher scores indicate a greater perceived impact of AI on that job.

The five professions that were considered by the students to be most affected were: Robotics Engineering (81.2%), Computer Engineering (79.5%), advertising/marketing (68.5%), factory workers (64.8%), and professional translation (66.3%). Conversely, the professions deemed least affected included: journalist/writer (56.8%), creative professions (53.8%), infant/primary school teachers (51.9%), elderly or disabled care (49.1%), and chef/kitchen staff (47.1%).

For all the subjects that filled in all the *EmployImpact* scale items, the global score was calculated to try to refute H2.1.1. This score consisted of the sum of their ratings for all the jobs. A Mann-Whitney U test was run to determine if there were differences in *EmployImpact* score between males and females. Distributions of the *EmployImpact* scores for males and females were similar, as determined through visual inspection of the population pyramid chart (see Figure 6). Median *EmployImpact* score was not statistically significantly different between males and females, $U = 6,773.5$, $z = -0.22$, $p = 0.826$.

Then, to measure the openness of the students towards AI use for work-related tasks, students were asked whether they would allow the AI to carry out 22 different tasks, instead of a person. Table 8 shows the 22 selected tasks, together with the number of females (#f)/males (#m) that answered the question, the percentage of females/males that would allow the task to be carried out by an AI, and whether the differences are significant as tested by the Chi-square test of homogeneity.

Table 7. EmployImpact Variable: Selection of Jobs and Percentage of Students That Think That They Will Be (a) Highly Affected (Score 3 or 4) or (b) Lowly Affected (0 or 1) by AI

| Task (#f, #m) | % High | % Low | Females Mean (Median) | SD | Males Mean (Median) | SD |
|---|---|---|---|---|---|---|
| Robotics engineering (184, 145) | 81.2 | 11.6 | 3.18 (4) | 1.25 | 3.41 (4) | 1.08 |
| Computer engineering (182, 145)* | 79.5 | 11.9 | 3.12 (4) | 1.24 | 3.39 (4) | 1.08 |
| Advertising/marketing (184, 143) | 68.5 | 13.5 | 2.92 (3) | 1.09 | 2.87 (3) | 1.27 |
| Professional translation (183, 143) | 66.3 | 14.7 | 2.82 (3) | 1.16 | 2.90 (3) | 1.21 |
| Worker (factory) (177, 141) | 64.8 | 16.7 | 2.87 (3) | 1.26 | 2.83 (3) | 1.26 |
| Accounting (176, 143) | 57.1 | 15.4 | 2.64 (3) | 1.06 | 2.63 (3) | 1.14 |
| Medicine/veterinary medicine (181, 144) | 56.6 | 24.9 | 2.43 (3) | 1.26 | 2.74 (3) | 1.26 |
| Business administration (179, 138) | 54.6 | 20.2 | 2.45 (3) | 1.16 | 2.64 (3) | 1.17 |
| Architecture (176, 140) | 53.2 | 20.6 | 2.47 (3) | 1.20 | 2.53 (3) | 1.13 |
| Physics/chemistry (177, 140) | 51.4 | 22.1 | 2.34 (2) | 1.17 | 2.58 (3) | 1.21 |
| Driver/transporter (179, 145)* | 49.4 | 23.8 | 2.30 (2) | 1.30 | 2.59 (3) | 1.23 |
| Nursing (184, 140) | 48.1 | 28.4 | 2.23 (2) | 1.19 | 2.39 (3) | 1.21 |
| Delivery (173, 143) | 47.2 | 29.4 | 2.30 (2) | 1.35 | 2.32 (2) | 1.30 |
| Biology (175, 140) | 42.2 | 25.1 | 2.22 (2) | 1.14 | 2.39 (2) | 1.19 |
| Tourism professionals (178, 142) | 40.9 | 25.0 | 2.26 (2) | 1.08 | 2.18 (2) | 1.16 |
| Sociology (164, 139) | 39.3 | 31.4 | 2.05 (2) | 1.19 | 2.28 (2) | 1.32 |
| Language teaching (177, 142)* | 39.2 | 28.5 | 2.37 (2) | 1.16 | 2.02 (2) | 1.14 |
| Cleaner (174, 140) | 38.2 | 44.6 | 1.87 (2) | 1.45 | 1.98 (2) | 1.47 |
| Shop assistant (177, 137) | 37.3 | 35.0 | 2.12 (2) | 1.23 | 2.00 (2) | 1.27 |
| Public relations (174, 134) * | 34.4 | 40.6 | 2.11 (2) | 1.20 | 1.69 (2) | 1.28 |
| Archaeology (169, 136) | 32.5 | 42.6 | 1.82 (2) | 1.22 | 1.89 (2) | 1.36 |
| Creative professions (179, 139) | 26.1 | 53.8 | 1.59 (1) | 1.34 | 1.53 (1) | 1.38 |
| Care of elderly and/or handicapped people (174, 142)* | 25.9 | 49.1 | 1.48 (1) | 1.23 | 1.90 (2) | 1.27 |
| Journalist/writer (175, 142) | 23.3 | 56.8 | 1.57 (1) | 1.26 | 1.42 (1) | 1.24 |
| Chef/kitchen staff (174, 138) | 22.4 | 47.1 | 1.60 (1.5) | 1.15 | 1.66 (2) | 1.17 |
| Infant/primary school teachers (179, 141)* | 20.3 | 51.9 | 1.68 (2) | 1.12 | 1.40 (1) | 1.11 |
| Total (sum) | | | 43.64 (44) | 15.69 | 42.97 (44) | 16.03 |

Higher values imply a higher perceived impact of AI on the job. An asterisk (*) denotes a significance level of 0.05.

According to these results, females were in general less inclined to let AI perform any of the selected tasks, with a lower rate of "Yes" answers to 16 out of the 22 tasks. The application of a Chi-square to the individual tasks showed that the differences between females and males were significant ($p < 0.05$) for two tasks: "Carry out domestic chores" and "Be an actor in a movie," while they were very significant ($p < 0.01$) for five more: "Paint a picture," "Provide emotional support," "Provide sexual services," "Write novels," and "Perform surgical interventions." In all these tasks, females showed a significantly lower openness towards using AI than males.

For all the subjects that filled in all the openness scale items, a global openness score was computed to try to refute $H2.1.2_A$. This score represented the total number of tasks each participant was comfortable having performed by an AI. A Mann-Whitney U test was run to determine if there were differences in the global openness score between males and females. Distributions of the openness scores for males and females were similar, as assessed by visual inspection (see Figure 7). The median openness score was not statistically significantly different between males and females, $U = 3,377.5, z = 1.667$, $p = 0.096$.

Finally, the general attitude towards the impact of AI on the creation/destruction of employment was measured through the *EmployAtt* scale, ranging from 0 (it will destroy many more jobs than

Table 8. Openness to AI Use: Selection of Tasks and % of Students That Would Allow an AI to Carry Out Each Task

| Task (#f, #m) | Total | | Females | | Males | | Chi-Square | p |
|---|---|---|---|---|---|---|---|---|
| | %Yes | %No | %Yes | %No | % Yes | % No | | |
| Simultaneously translate conversations in different languages (179, 140) | 90.6 | 9.4 | 90.5 | 9.5 | 90.7 | 9.3 | 0.004 | 0.949 |
| Agricultural support (planting, harvesting, weeding...) (168, 135) | 75.9 | 24.1 | 72.6 | 27.4 | 80 | 20 | 2.23 | 0.135 |
| Analyze patient data to develop new drugs (170, 139) | 79.3 | 20.7 | 75.3 | 24.7 | 84.2 | 15.8 | 3.67 | 0.055 |
| Detect copies in tests (175, 139) | 83.1 | 16.9 | 86.3 | 13.7 | 79.1 | 20.9 | 2.82 | 0.093 |
| Composing music (175, 127) | 39.7 | 60.3 | 37.7 | 62.3 | 42.5 | 57.5 | 0.71 | 0.4 |
| Paint a picture (168, 129) | 32.3 | 67.7 | 25 | 75 | 41.9 | 58.1 | 9.48 | 0.002** |
| Predicting the risk of recidivism when deciding the release of an inmate (161, 130) | 45.4 | 54.6 | 42.2 | 57.8 | 49.2 | 50.8 | 1.42 | 0.233 |
| Driving/piloting (cars, buses, trains, planes, trucks) (158, 121) | 63.1 | 36.9 | 58.2 | 41.8 | 69.4 | 30.6 | 3.69 | 0.055 |
| Delivering parcels or letters (169, 134) | 71.3 | 28.7 | 69.2 | 30.8 | 73.9 | 26.1 | 0.79 | 0.374 |
| Select teams and develop tactics in soccer (155, 129) | 52.5 | 47.5 | 54.8 | 45.2 | 49.6 | 50.4 | 0.77 | 0.38 |
| Act as a censor for material uploaded to social networks (166, 135) | 71.4 | 28.6 | 74.1 | 25.9 | 68.1 | 31.9 | 1.29 | 0.256 |
| Telephone answering systems (176, 137) | 67.7 | 32.3 | 67 | 33 | 68.6 | 31.4 | 0.09 | 0.769 |
| Emotional support for sick and dependent people (172, 132) | 31.6 | 68.4 | 23.3 | 76.7 | 42.4 | 57.6 | 12.7 | <0.001** |
| Domestic chores (172, 142) | 85 | 15 | 80.8 | 19.2 | 90.1 | 9.9 | 5.32 | 0.021* |
| Sexual services (162, 122) | 26.4 | 73.6 | 17.3 | 82.7 | 38.5 | 61.5 | 16.16 | <0.001** |
| Writing novels (173, 130) | 22.4 | 77.6 | 15 | 85 | 32.3 | 67.7 | 12.73 | <0.001** |
| Facial recognition to fine pedestrians who commit infractions (178, 131) | 77.3 | 22.7 | 79.8 | 20.2 | 74 | 26 | 1.41 | 0.234 |
| Being an actor/actress in a movie (161, 131) | 25.7 | 74.3 | 19.9 | 80.1 | 32.8 | 67.2 | 6.34 | 0.012* |
| Performing surgical interventions (152, 131) | 58 | 42 | 50.7 | 49.3 | 66.4 | 33.6 | 7.17 | 0.007** |
| Making stock market investments (150, 132) | 53.2 | 46.8 | 55.3 | 44.7 | 50.8 | 49.2 | 0.59 | 0.442 |
| Identifying suicidal attitudes from messages on social networks (169, 136) | 81 | 19 | 81.1 | 18.9 | 80.9 | 19.1 | 0.002 | 0.968 |
| Manage the hiring of personnel in a company (158, 133) | 39.5 | 60.5 | 35.4 | 64.6 | 44.4 | 55.6 | 2.40 | 0.121 |

An asterisk (*) denotes a significance level of 0.05, whereas a double asterisk (**) indicates a significance level of 0.01.

create) to 4 (it will create many more jobs than destroy). The higher the score, the more positive the attitude.

Again, a Mann-Whitney U test was run to determine if there were differences in *EmployAtt* scores between males and females. Distributions of the *EmployAtt* scores for males and females were similar, as assessed by visual inspection (see Figure 8). Median *EmployAtt* score was statistically significantly different between males and females, $U = 12,002.5, z = -2.014, \text{p} = 0.044$. These numbers show that both females and males tend to think that AI will create more jobs than it will

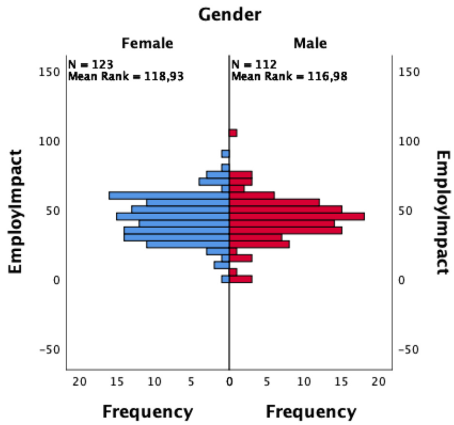


Fig. 6. Impact of AI on professions (*EmployImpact*).

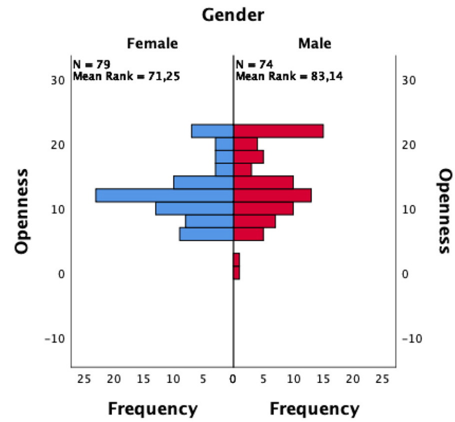


Fig. 7. Openness to AI (*Openness*).

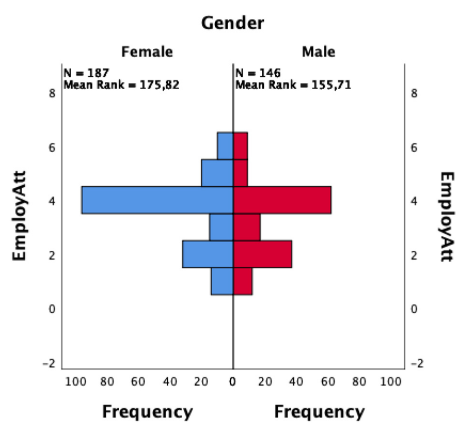


Fig. 8. Attitude AI on employment (*EmployAtt*).

Table 9. Sensitivity (*SUPD*) and Awareness (*AUPD*) About AI Use of Personal Data

| | | Females | | | Males | | |
|---|---|---|---|---|---|---|---|
| Variable | N (#f, #m) | Yes (%) | No (%) | Don't Know (%) | Yes (%) | No (%) | Don't Know (%) |
| *SUPD* | 360 (194, 166) | 43 (22.2) | 81 (41.7) | 70 (36.1) | 62 (37.35) | 62 (37.35) | 42 (25.3) |
| *AUPD* | 360 (194, 166) | 171 (88.1) | 5 (1.6) | 18 (9.3) | 159 (95.8) | 2 (1.2) | 5 (3) |

destroy, with a slight but significantly more positive attitude of females than males regarding the impact of AI on employment.

*6.2.2 Personal Data.* Concerning the awareness and sensitivity of students with respect to the use of personal data by AI (hypotheses $H2.2.1_A$ and $H2.2.2_A$), two variables with their corresponding scales, *SUPD* and *AUPD*, were defined. The descriptive statistics for these two variables are presented in Table 9.

In the first one, "sensitivity" or degree of agreement of the subjects concerning this use (*SUPD*), 43 females (22.2%) agreed that the AI used their personal data to carry out their tasks, while 62 males

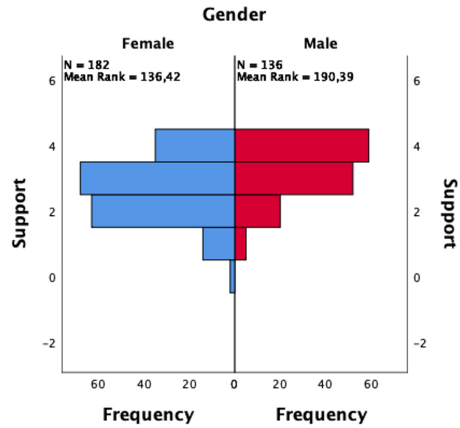


Fig. 9. AI development support (*Support*).

(37.35%) expressed the same opinion, a difference in proportions of 0.15. The running of a Chi-square test shows that this difference was statistically very significant, $Chi\text{-}square(2) = 10.850$, $p = 0.004$.

Regarding *AUPD*, it was measured through the question "Do you think AI uses our personal data to perform its tasks?"; 360 students answered this question (194 females and 166 males); 171 females (88.1%) were aware of the use of their personal data, compared to 159 (95.8%) males, a difference in proportions of 0.08. The running of a Chi-square test shows that this difference was statistically significant, $Chi\text{-}square(2) = 6.934$, $p = 0.031$.

*6.2.3 Society.* Another aspect deemed important in this study is the perceived impact of AI on society ($H2.3_A$). To this end the variable *PI* was defined, consisting of a nominal scale with "Yes" and "No" as possible values.

A total of 326 students answered this question (185 females and 141 males). Of these, 62.6% (54.6% of females and 73% of males) believed that AI would have a positive impact on society. Conversely, 10.1% (13.5% of females and 5.7% of males) anticipated a negative effect from AI. To test whether this difference in proportions of 0.18 is significant, a Chi-square test was run. The results show that this difference was highly statistically significant, $Chi\text{-}square(2) = 12.516$, $p = 0.002$.

### 6.3 RQ3 (Support)

The last RQ was related to the support and expectations of students regarding AI development.

*6.3.1 AI Development Support.* The variable *Support* consisted of an interval scale ranging from 0 (strong opposition) to 4 (strong advocacy). It is associated with the question "How much do you support or oppose the development of AI?". A Mann-Whitney U test was run to determine if there were differences in *Support* scores between males and females. Distributions of the *Support* scores for males and females were similar, as assessed by visual inspection (see Figure 9). Median *Support* score was statistically significantly different between males and females, with males showing higher support towards the development of AI, $U = 16,710.5$, $z = 5.51$, $p < 0.001$.

*6.3.2 Positive Expectations.* Regarding the impact of gender on positive expectations, Table 10 presents a detailed analysis of the individual scale items, where each item is regarded as a potential "motivator" for the use of AI. A Mann-Whitney U test was applied to each individual item to analyze gender differences. All motivators except two ("I am impressed by what AI can do" and "Some

Table 10. AI Positive Expectations (Motivators)

| Motivator (#f, #m) | Females Median (Mean) | Males Median (Mean) | p |
|---|---|---|---|
| There are many beneficial applications of AI (183, 136) | 4 (3.33) | 4 (3.61) | 0.001** |
| I'm impressed by what AI can do (183, 136) | 4 (3.4) | 4 (3.55) | 0.058 |
| AI excites and motivates me (183, 136) | 2 (2.31) | 3 (2.90) | <0.001** |
| AI can have a positive effect on people's welfare (183, 136) | 3 (2.80) | 3 (3.20) | <0.001** |
| AI can bring new economic opportunities to our country (183, 136) | 3 (2.84) | 3 (3.07) | 0.05* |
| AI systems can perform better than humans (183, 136) | 2 (1.87) | 2 (2.60) | <0.001** |
| The majority of society can benefit from an AI-filled future (183, 136) | 2 (2.27) | 3 (2.69) | <0.001** |
| I am interested in using AI systems in my daily life (183, 136) | 2 (2.35) | 3 (2.89) | <0.001** |
| An AI system would be better than a human employee in many routine jobs (183, 136) | 2 (1.85) | 3 (2.65) | <0.001** |
| Some complex decisions are best left to an AI system (183, 136) | 1 (1.37) | 1 (1.67) | 0.107 |

From 0 (totally disagree) to 4 (totally agree). Higher scores imply higher expectations. An asterisk (*) denotes a significance level of 0.05, whereas a double asterisk (**) indicates a significance level of 0.01.

complex decisions are best left to AI systems") showed significant gender differences, with males feeling more optimistic towards AI possibilities than their female counterparts.

For all the subjects that filled in all the *E-P* scale items, the global score (0…40) was calculated, which consisted of the sum of the individual scores (0…4) for the 10 scale items, regarding positive expectations towards AI. A Mann-Whitney U test was run to determine if there were differences in global *E-P* scores between males and females. Distributions of the *E-P* scores for males and females were similar, as assessed by visual inspection (see Figure 10). The median for the *E-P* score was statistically significantly different between males (median = 27) and females (median = 23), with males holding more positive beliefs regarding the development of AI, $U = 21,576.5$, $z = 3.602$, $p < 0.001$.

*6.3.3 Negative Expectations.* Regarding AI negative expectations (variable *E-N*), which reflect students' concerns regarding the use of AI, Table 11 shows the mean and median for males and females regarding each individual concern. A Mann-Whitney U test was applied to each individual item to analyze gender differences. In this table it can be seen how five out of the thirteen tested concerns showed gender differences, namely "AI can take control of people," "People like me will suffer if AI is used more and more," "AI should be used only for matters which are not important," "AI scares me," and "AI is a fad." For all these items, males expressed significantly lower concerns than females.

Again, for all the subjects that filled in all the *E-N* scale items, the global E-N score (0…52) was calculated, which consisted of the sum of the individual scores (0…4) for the 13 scale items. A Mann-Whitney U test was run to determine if there were differences in the global *E-N* scores between males and females. Distributions of these scores for males and females were similar, as assessed by visual inspection (see Figure 11). The median for the *E-N* score was not statistically significantly different between males and females, with males expressing slightly lower concerns regarding the development of AI, $U = 18,388$, $z = 0.591$, $p = 0.554$.

Table 11. AI Concerns

| Concern (#f, #m) | Females Median (Mean) | Males Median (Mean) | p |
|---|---|---|---|
| AI systems should not make life and death decisions (183, 136) | 0 (0.58) | 0 (0.71) | 0.357 |
| AI is used to spy on people (183, 136) | 2 (1.95) | 2 (1.93) | 0.917 |
| AI is limited in its abilities (183, 136) | 2 (1.83) | 2 (1.73) | 0.527 |
| AI can take control of people (183, 136) | 2 (2.19) | 3 (2.51) | 0.026* |
| I think AI is dangerous (183, 136) | 3 (2.05) | 3 (2.15) | 0.630 |
| Organizations use AI unethically (183, 136) | 2 (1.80) | 2 (1.67) | 0.241 |
| I think AI systems make a lot of mistakes (183, 136) | 2 (2.11) | 2 (2.21) | 0.316 |
| Companies use AI only for their own benefit (183, 136) | 2 (1.62) | 2 (1.63) | 0.979 |
| People like me will suffer if AI is used more and more (183, 136) | 2 (2.42) | 3 (2.82) | 0.001** |
| AI should be used only for matters that are not of importance (183, 136) | 2 (2.26) | 3 (2.57) | 0.014* |
| I have an instinctive aversion to AI (183, 136) | 2 (2.54) | 3 (2.72) | 0.132 |
| AI scares me (182, 136) | 2 (2.41) | 3 (2.75) | 0.01** |
| AI is a fad (180, 135) | 4 (3.30) | 4 (3.61) | 0.001** |

From 0 (totally agree) to 4 (totally disagree). Higher scores imply lower concerns regarding AI. An asterisk (*) denotes a significance level of 0.05, whereas a double asterisk (**) indicates a significance level of 0.01.

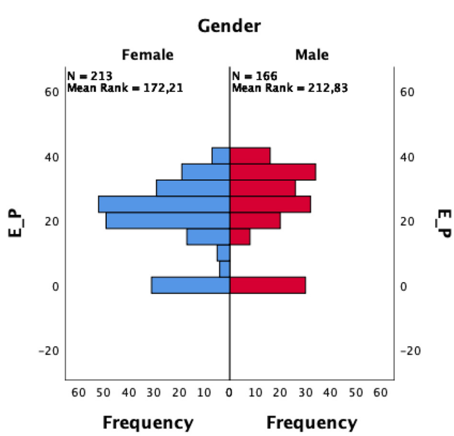


Fig. 10. Expectations positive (*E-P*).

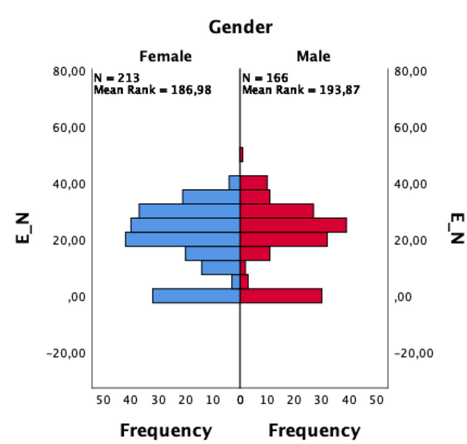


Fig. 11. Expectations negative (*E-N*).

*6.3.4 NPS.* Finally, the AI development support included the *NPS*, a scale commonly used in user satisfaction surveys regarding a particular product or service. This metric measures the level of customer loyalty and growth potential towards a particular business or, in this case, a particular technology such as AI. This variable is associated to the question "What is the likelihood that you would recommend the use of AI to a friend or family member?".

The *NPS* is calculated as the percentage of promoters (people scoring 9 or 10) minus the percentage of detractors (people scoring 6 or less). Although the threshold values for "good" *NPS* scores greatly depend on the industries and the values of competitors, generally speaking, an *NPS* between 0 and 30 is considered medium and an *NPS* over 70 is considered excellent [25].

Table 12. *NPS* Distribution

| | #Promoters (%) | #Neutral (%) | #Detractors (%) | Score |
|---|---|---|---|---|
| Females (179) | 17 (9.5) | 96 (53.6) | 66 (36.9) | −27.4 |
| Males (129) | 35 (27.1) | 65 (50.4) | 29 (22.5) | 4.6 |
| Total (308) | 52 (16.9) | 161 (52.27) | 95 (30.84) | −13.94 |

Table 12 shows the global number of promoters, neutrals, and detractors, both in aggregated form and disaggregated by gender.

The analysis of the *NPS* segregated by gender reveals that a mere 17 out of 179 females (9.5%) are classified as AI promoters. In contrast, the proportion of male promoters is significantly higher, with 35 out of 129 (27.1%). Regarding the detractors, 66 out of 179 females (36.9%) are categorized as such, compared to only 29 out of 129 males (22.5%). Consequently, the *NPS* for females stands at −27.4, indicating a low level, whereas for males, it registers at 4.6, signifying a medium level [25]. The primary insight here extends beyond the NPS scores themselves, highlighting the stark contrast in attitudes: males are notably more enthusiastic proponents of AI and are more inclined to recommend its adoption to their peers.

## 7 Discussion

Table 13 summarizes the results of the hypothesis testing. The results of this study offer valuable insights into the perceptions and ATAI within the framework of Spanish higher education institutions. Regarding knowledge and awareness (RQ1), we observed significant gender differences in all the variables studied: level of knowledge about AI ($H1.1_A$), exposure awareness to AI ($H1.2_A$), perceived ability to apply AI ($H1.3_A$), and need to learn AI for work ($H1.4_A$). Moreover, our analysis highlights the importance of increasing AI literacy among university students. Despite a general awareness of AI, many students fail to recognize its application in everyday technologies. This lack of awareness, as noted in studies like [16, 33], suggests a gap in education that university instructors should address. Incorporating AI-related content into various curricula, not limited to technical fields, could enhance students' understanding and preparedness for a future where AI plays a significant role.

The impact on employment, personal data and society (RQ2) shows mixed results. While the perception of the impact of AI on professions ($H2.1.1_A$), and the openness to the use of AI ($H2.1.2_A$) show no statistically significant differences between genders, there are significant differences in the case of attitudes towards the impact of AI on employment ($H2.1.3_A$), where females have a significantly more positive attitude than males. Female representation in certain industries might influence this perception. In sectors historically less represented by women, such as technology or engineering, females might hold a more positive view of AI's job-creating potential as they see opportunities for increased inclusion and diversification.

Furthermore, our findings on the perceived impact of AI on various professions provide valuable insights for educational strategies. Students' views on AI's influence on different jobs, ranging from high-tech roles to creative professions, underscore the need for a nuanced approach to AI education. Instructors should emphasize the diverse applications of AI, moving beyond the common focus on automation and job displacement. This approach aligns with insights by Moravec [21], who pointed out the varied capabilities of AI in different tasks.

There are also significant differences in *SUPD* by AI ($H2.2.1_A$) and in *AUPD* ($H2.2.2_A$). The analysis indicated that males were more aware of AI's use of personal data and exhibited less sensitivity towards its utilization.

Table 13. Results of Hypothesis Testing

| RQ | Variable (Hypothesis) | Test | Significance | Interpretation |
|---|---|---|---|---|
| R1 | Level of knowledge about AI (H1.1) | Mann-Whitney | $p < 0.005$ | The medians of the two groups are not equal. Males are significantly more knowledgeable. |
| | Exposure awareness to AI (H1.2) | Mann-Whitney | $p = 0.001$ | The medians of the two groups are not equal. Males are significantly more aware of their exposure to AI. |
| | Perceived ability to apply AI (H1.3) | Mann-Whitney | $p = 0.004$ | The medians of the two groups are not equal. Males feel significantly more able to apply AI in their work. |
| | Need to learn AI for work (H1.4) | Mann-Whitney | $p = 0.043$ | The medians of the two groups are not equal. Males express a significantly higher need to learn AI for their future. |
| R2 | Perception of impact of AI on professions (H2.1.1) | Mann-Whitney | $p = 0.826$ | The distribution of scores for the two groups are equal. |
| | Openness to the use of AI (H2.1.2) | Mann-Whitney | $p = 0.096$ | The distribution of scores for the two groups are equal. |
| | Attitude towards the impact of AI on employment (H2.1.3) | Mann-Whitney | $p = 0.044$ | The medians of the two groups are not equal. Females tend to be more optimistic about the impact of AI in creating new job opportunities. |
| | *AUPD* (H2.2.2) | Chi-square | $p = 0.031$ | Statistically significant difference between the two independent binomial proportions. Males are significantly more aware of the potential use of personal data by the AI. |
| | *SUPD* (H2.2.1) | Chi-square | $p = 0.004$ | Statistically significant difference between the two independent binomial proportions. Males are considerably more inclined to allow AI to utilize their personal data for executing tasks. |
| | Positive impact on society (H2.3) | Chi-square | $p = 0.002$ | Statistically significant difference between the two independent binomial proportions. Males are significantly more optimistic about the potential positive impact of AI on society. |
| R3 | Support for AI development (H3.1) | Mann-Whitney | $p < 0.005$ | The medians of the two groups are not equal. Males express significantly greater support for the development of AI. |
| | Positive expectations towards AI (H3.2) | Mann-Whitney | $p < 0.005$ | The medians of the two groups are not equal. Males express significantly higher expectations towards AI. |
| | Negative expectations towards AI (H3.3) | Mann-Whitney | $p = 0.554$ | The distribution of scores for the two groups are equal. |
| | NPS (H3.4) | - | - | Men show a greater inclination to advocate for AI among their peers. |

This observation supports the hypothesis that females may perceive themselves as more vulnerable to privacy breaches or misuse of personal data. Concerns about data security and potential exploitation might lead to heightened sensitivity towards AI's handling of their private information, which in turn may hamper its adoption. These data also raise important ethical considerations. The apprehensions about AI's use in handling personal data, as well as concerns about its ethical application, reflect broader societal issues. These findings resonate with the work in [10] and [9], emphasizing the need for ethical AI education. University instructors have a unique opportunity to integrate discussions on AI ethics within their courses, preparing students to navigate and shape the future ethical landscape of AI.

The positive impact of AI on society ($H2.3_A$) also shows significant differences, since males anticipated a more positive effect from AI. Females might exhibit lower trust due to various reasons, such as a lack of transparency in AI algorithms, past experiences of bias or discrimination, or media reports highlighting data breaches or privacy violations. These results are in line with female concerns on privacy issues mentioned above, as this lack of trust can influence their reluctance to share their data with AI.

In the last RQ (RQ3), there are significant differences concerning the support for AI development ($H3.1_A$) and positive expectations towards AI ($H3.2_A$). Males show higher support for the development of AI and feel more optimistic about AI possibilities than their female counterparts. The revelation that female students are less enthusiastic about AI can be influenced by the gender gap in STEM fields, as discussed by Calvo-Iglesias et al. [5]. The underrepresentation of women in these areas might contribute to a lack of exposure to and confidence in AI-related technologies, which in turn affects their attitudes. This is a critical insight for university instructors, who can play a significant role in bridging this gap by creating more inclusive and supportive learning environments. Interestingly, there are no statistical differences concerning negative expectations towards AI ($H3.3_A$). Despite this, males exhibited marginally lower concerns about the development of AI, aligning with the trends observed in the previously mentioned variables.

In conclusion, these results highlight the extension of the gender gap identified in **Information and Communication Technologies (ICT)** into the realm of AI. For instance, Gebhardt et al. [12] highlighted gender differences in self-efficacy: male students reported higher confidence in their advanced ICT skills despite exhibiting lower performance in computer and information literacy assessments, whereas female students demonstrated stronger competencies but lower confidence in their abilities. In a similar vein, Siddiq and Scherer [29] investigated gender disparities in ICT literacy using data from 23 empirical studies. Their findings indicated that although men generally perceived their ICT literacy to be higher than that of women, performance-based assessments consistently showed that female students outperformed their male counterparts in ICT literacy. Moreover, the study found that this gender difference was more pronounced in primary school but diminished in secondary school, suggesting that early educational interventions may influence gender disparities in ICT skills.

These findings underscore the role of gender-related perceptions in shaping students' engagement and success in digital environments, highlighting the need for targeted interventions to bridge the confidence gap and promote equitable ICT education. Given the profound impact of AI on current and future employment landscapes, its rapid advancement could exacerbate existing gender disparities in the workforce. Therefore, instructors in higher education institutions must recognize this issue and implement proactive measures to mitigate this risk.

Several specific actions can be taken in the classrooms to help bridge the gender gap in AI. The most crucial step, as highlighted earlier, is to ensure that all the students receive thorough and current AI training. This includes workshops or seminars focused on developing essential skills in AI and technology, such as coding, data analysis, and critical thinking. These workshops should be designed to be inclusive and supportive for students of all genders, ensuring equal participation and accessibility. Furthermore, it's important to integrate AI and technology examples and case studies that resonate with the challenges and interests of female students. Hosting female guest speakers and implementing AI mentorship programs can serve as inspirational role models for female students.

Equally important is the application of teaching methods that recognize and cater to gender differences in learning. This may involve collaborative projects, hands-on experiences, and discussion-based learning that foster active engagement from all students. Additionally, it's vital to raise awareness among instructors and students about unconscious bias and its impact in the classroom and the wider technology field. Engaging in discussions and training on this topic can contribute to a more equitable learning environment. Lastly, continuous feedback from students is essential, not just regarding the course content, but also the inclusivity of the course materials and teaching methods. Such feedback is instrumental in ensuring that educational approaches are truly inclusive and effective.

## 8 Limitations of the Study

According to Cook et al. [8], the threats to the validity of this type of study can be classified into four categories: internal, external, construct, and conclusion. This classification is employed to discuss the main threats to the validity of this study, as shown below.

Threats to internal validity are concerned with the possibility of hidden factors that may provide alternative explanations for the result. All the students agreed to participate in the study, and it was confirmed that those absences that occurred on the day of the peer assessment (experimental mortality) were not owing to the experiment itself. The sample included a balanced number of males and females. The questionnaire was designed based on a conceptual framework, and some of the scales were validated in previous literature. The whole design was carefully explained and tested through the use of a pilot study. However, the study relied on single-item scales for certain constructs, which may limit the robustness and granularity of the measurements. This approach might not fully capture the complexity of the constructs under study, posing a risk to internal validity. Future research could address this by employing multi-item scales to enhance the reliability and depth of the data.

Threats to external validity are concerned with the generalization of the results. The main threat to the external validity is that the student sample included in the study is a limited representation of the population of Spanish higher education students, which limits the generalizability of the findings to other cultural or educational settings. Unfortunately, this risk was unavoidable, since we needed the collaboration of fellow instructors to reach the intended audience. This contextual specificity suggests that further investigations are necessary to explore gender differences in AI literacy and attitudes across diverse countries, cultures, and educational systems.

Threats to construct validity are related to the relationship between theory and observation. Both the conceptual framework that sustains this work and all the hypotheses were constructed on the basis of previous related literature. Additionally, the hypotheses were not discussed beforehand to reduce bias in their interpretation. Nevertheless, the study's heavy reliance on subjective perceptions and self-reported measures introduces a risk to construct validity. While these perceptions are valuable for understanding individual attitudes, they might not fully align with objective measures of AI literacy or competence. Future studies could incorporate objective assessments or triangulate data from multiple sources to mitigate this limitation.

Finally, threats to conclusion validity refer to the relationship between the treatment and the outcome. All the statistical analyses have been preceded by tests that verified that the assumptions of the statistical procedure were not violated, and nonparametric tests, such as the Mann-Whitney U test, have been applied whenever the assumptions were violated, in order to augment the robustness of the results.

## 9 Conclusions and Future Work

This study adds to the expanding body of research on ATAI within the Spanish context, highlighting a noticeable gender gap. Instructors at higher education institutions have a critical role in shaping these attitudes and preventing them from evolving into future obstacles for female students. By addressing gender disparities, enhancing AI literacy, and emphasizing ethical considerations, educators can profoundly impact the way future professionals perceive and engage with AI.

The key contributions of this article are threefold:

- Development of a conceptual model encompassing the main variables identified in relevant literature for measuring attitudes and perceptions towards AI.
- A gender-focused analysis of AI attitudes and perceptions within the Spanish context, addressing the scarcity of empirical data in this country.
- An in-depth discussion of the potential implications of these findings, accompanied by a series of guidelines for higher education instructors aimed at preventing the expansion of the gender gap in AI.

It's noteworthy that this study was conducted just prior to the widespread emergence of AI generative tools such as ChatGPT. For future research, it is planned to replicate the study in the same context with the goal of comparing results and determining how these popular generative AI tools are influencing the variables examined in our research. Additionally, it is planned to extend this study to include other universities and academic programs.

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