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Determinants of artificial intelligence literacy among accounting students

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Abstract

Research Question: What are the determinants of artificial intelligence (AI) literacy among accounting students?
Motivation: This study is grounded in the importance of developing AI literacy for research, education, and the accounting profession. Although its consequences, theoretical aspects, and measures have been explored, the determinants centred on the human dimension remain underexplored, despite being essential for designing intervention strategies to improve AI literacy among students and future accounting professionals.
Idea: This study sought to identify potential determinants related to respondents' profiles that influence artificial intelligence (AI) literacy among accounting students enrolled in Brazilian higher education institutions (HEIs).
Data: The study analysed a sample of 490 undergraduate accounting students enrolled in Brazilian higher education institutions (HEIs).
Tools: An online survey was administered, and the data were analysed using descriptive statistics, confirmatory factor analysis, and nonparametric tests, including Mann-Whitney, Kruskal-Wallis, and post hoc pairwise comparisons.
Findings: The determinants that showed significant differences in relation to AI literacy include (1) participation in courses on AI technology, (2) attendance at AI-related events, (3) enrolment in courses addressing AI or other emerging technologies, (4) ownership of a personal computer/laptop at home, and (5) daily hours of use of technological devices and internet usage. Finally, perceived technological interference showed a result contrary to that hypothesized.

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Contribution: It is suggested to incorporate AI into curricula and to promote courses and training programs by accounting organizations, with the aim of developing competencies and the ethical use of AI in the profession.

Keywords: determinants, artificial intelligence (AI) literacy, accounting, technology

JEL codes: C12, I23, O33

1. Introduction

Artificial intelligence (AI) is significantly transforming both the workplace and people's daily lives (Chiu *et al*., 2024). Although AI provides benefits such as file translation, the creation of documents, texts, and new ideas (O'Dea *et al*., 2024), as well as the mapping of web elements (Ng *et al*., 2021), its harmful effects cannot be overlooked (Pinski & Benlian, 2024). AI tools may exhibit various factual accuracy issues, including incorrect, incomplete, and false information, errors, and inconsistent citations, which are sometimes used uncritically and regarded as truthful (Lermann Henestrosa & Kimmerle, 2025).

In this context, the need for AI-related knowledge and competencies has promoted the concept of AI literacy, defined as the ability to know, understand, apply, explore, analsze, select, and critically evaluate information generated by AI technology and use it to perform tasks effectively, responsibly (Wang *et al*., 2022), and ethically (Pinski & Benlian, 2024).

Given the growing interest in developing AI literacy, the university environment has emerged as one of the primary settings for preparing individuals to use these technologies (O'Dea *et al*., 2024). However, individual-related determinants may influence this process. The literature provides limited knowledge regarding the determinants of AI literacy (O'Dea *et al*., 2024; Celik, 2023; Wang *et al*., 2022), making empirical investigation relevant for guiding the development of strategies aimed at enhancing it, particularly within the academic context (Celik, 2023).

Some evidence indicates that determinants such as students' computer experience, gender, parents' educational level, and internet access are predictors that affect Information and Communication Technology (ICT) literacy (Aydin, 2021). Digital exclusion, characterised by inequalities in access to digital technologies, may also affect access to AI technologies (Celik, 2023; Lutz, 2019) and, consequently, AI literacy. Similarly, O'Dea *et al*. (2024) found that determinants such as country of study, gender, and prior learning about AI significantly influenced the generative AI literacy of university students.

Furthermore, the pressures resulting from technological advances may affect the pursuit of the skills and competencies necessary to adapt to the new landscape of the accounting profession and may also constitute a determining factor for the professionals' continued participation in the labor market (Oliveira *et al*., 2024). Therefore, the perceived technological interference (TI) promoted by AI in the accounting profession may be a determinant that leads individuals to pursue AI literacy from the educational environment onward. However, the conditioning effect of TI about AI lacks empirical evidence and represents a gap addressed by this study.

Specifically, within accounting education in the Brazilian context, Resolution CNE/CES No. 01/2024, issued by the National Education Council (CNE), established the National Curriculum Guidelines for undergraduate accounting programs, highlighting the competencies and skills that students are expected to acquire throughout the program. Among these competencies, particular emphasis is placed on the ability to implement and use contemporary technologies, including artificial intelligence, within accounting information systems (CNE, 2024), indicating that this topic already occupies a prominent place in the agenda of accounting education regulatory bodies.

This study seeks to fill a gap in the accounting literature by understanding the determinants of AI literacy among accounting students through an investigation that brings together individual, socioeconomic, and sociodemographic elements to identify whether they influence the development of AI literacy.

Within the Brazilian context, it is timely to provide empirical evidence regarding AI literacy in the academic field, given that Brazil is a developing country that still faces challenges related to technological education throughout students' educational trajectories, particularly among those attending public educational institutions. Brazil is a country of continental dimensions and diverse socioeconomic realities that has intensified digital inclusion in recent decades. This movement has been accompanied by accounting professionals, who have increasingly integrated technologies into their daily activities. In light of the growing use of AI and in response to the gaps identified in the literature, this study sought to identify the determinants of AI literacy among accounting students.

The findings contribute theoretically by addressing the gaps identified regarding the investigation of determinants associated with AI literacy, particularly among accounting students. From a practical perspective, educational institutions should seek to develop measures and initiatives aimed at incorporating and improving the quality of the knowledge, competencies, and skills related to AI developed among accounting students (Meesook *et al*., 2025; O'Dea *et al*., 2024). It is important for university students to develop the fundamental competencies required for the use of AI technologies based on ethical conduct, as these are essential requirements of

professional practice (Ng *et al*., 2021). To this end, curriculum developers responsible for accounting programs may direct efforts toward incorporating AI competencies and tools into new curriculum designs, for example, to integrate AI literacy with technology literacy within educational environments (Stolpe & Hallström, 2024), as well as to promote training and the appropriate use of AI (O'Dea *et al*., 2024).

Furthermore, with the aim of promoting the advancement of AI literacy, practical contributions can be offered to educators by establishing frameworks that provide guidance for the development of pedagogical strategies, learning methods, and assessment criteria (Ng *et al*., 2021), thereby fostering the critical and ethical use of AI tools in the teaching-learning process. In addition, research projects may be developed to investigate the impact of AI on accounting system practices and to promote initiatives, such as workshops, courses, and seminars, in collaboration with the community and accounting organizations, with the objective of demonstrating the responsible use of AI in the profession.

2. Literature review

Duan *et al*. (2019, p. 63) defined AI "as the ability of a machine to learn from experience, adapt to new data, and perform human-like tasks." AI technologies, particularly generative AI, are based on Large Language Models (LLMs), which comprise systems capable of generating content and solutions based on the data on which they have been trained (Pan *et al*., 2025).

Although AI offers significant contributions, such as support for improving texts, there are negative aspects that should be highlighted, particularly about ethical issues. Within the educational environment, problematic uses of AI have already been observed. Students use these tools to generate and summarise texts and articles, as well as to complete academic assignments. Furthermore, the difficulty of verifying the outputs generated by AI systems and the lack of responsibility in evaluating and selecting appropriate tools represent challenges that users must overcome (O'Dea *et al*., 2024).

This scenario has already generated effects on scientific production. The identification of AI-associated words in scientific articles has revealed changes in the writing style of academic publications (Gray, 2024). Furthermore, Kosmyna *et al*. (2025) observed that students who used tools based on LLMs exhibited lower brain connectivity and linguistic performance when writing an academic essay compared to those who did not use such tools. The authors raise concerns about the cognitive and practical impacts that dependence on AI tools may have on the learning process.

To use AI tools effectively and ethically, individuals must develop discernment, critical judgment, and the skills required to use these applications, which together constitute the concept of AI literacy (Limongi & Marcolin, 2024; Wang *et al*., 2022). The concept of AI literacy gained prominence in the fields of education and technology following the emergence of ChatGPT, constituting a new area of research that seeks to understand and measure individuals' capacity to use AI (Wang *et al*., 2022). AI-related competencies are particularly relevant in the context of the new technological era (Ng *et al*., 2021), which will require individuals to use technologies in a critical, effective, and ethical manner (Limongi & Marcolin, 2024; Wang *et al*., 2022).

As a means of measuring AI literacy, Wang *et al*. (2022) developed and validated a scale composed of four dimensions. The first dimension is awareness, which refers to the ability to identify and understand AI technology during its use and represents a cognitive process that occurs before the use of AI. The second dimension is usage, which is related to the ability to apply and explore AI technology in order to perform tasks efficiently, that is, its day-to-day use. The third dimension is evaluation, which corresponds to an individual's ability to analyse, select, and critically evaluate AI in terms of its applicability and outcomes. Finally, the ethics dimension addresses individuals' ability to be aware of their responsibilities and the risks that may arise from the use of AI technology. It is important to note that the use of AI raises ethical concerns for its users; therefore, AI literacy is essential for its proper and appropriate use (Wang *et al*., 2022).

In the field of accounting, technological changes driven by AI are evident, including increased efficiency and reduced errors in accounting processes (Meesook *et al*., 2025). Additionally, AI enables faster financial processing and analysis, as well as the conduct of risk assessments and scenario analyses with greater accuracy and efficiency (Promma *et al*., 2025). Therefore, accounting professionals must possess competencies, skills, and the capacity to understand AI (Meesook *et al*., 2025), particularly with regard to the content it generates (Ng *et al*., 2021). It is therefore believed that these capabilities will enable the development of professional practices grounded in reliable actions and guided by the moral and ethical values of the profession (Almeida *et al*., 2023).

The new National Curriculum Guidelines (NCGs) for undergraduate accounting programs in Brazil establish that students must acquire skills, competencies, and knowledge related to emerging and information technologies, including artificial intelligence. This is necessary so that they can use such technologies appropriately in their professional practice (CNE, 2024). To this end, it is important to understand the opinions, perceptions, patterns of use, and determinants that precede and, to some extent, influence the development of AI literacy among university students (O'Dea *et al*., 2024), particularly future accounting professionals (Meesook *et al*., 2025).

According to O'Dea *et al*. (2024), gender is a variable that affects generative AI literacy among university students. The authors found that male students demonstrated a broader mastery of AI tools for problem-solving when compared to female students, which is reflected in differences in the acquisition of AI-related knowledge and competencies. Male students were observed to be more inclined to use AI more frequently in their daily, professional, or personal activities, whereas female students had lower exposure to or interaction with AI tools, which may affect the development of their AI literacy. Furthermore, male students perceive, evaluate, and respond more effectively to AI-generated outputs and demonstrate a greater intention to use AI in the future (O'Dea *et al*., 2024).

Divergent findings have been reported in other contexts, where Aydin (2021) and Siddiq and Scherer (2019) found that female students exhibited higher levels of ICT literacy than male students. However, considering that males and females exhibit different expectations and behaviours regarding the use of tools and platforms when working with AI, and that male students demonstrated superior AI-related skills and competencies (O'Dea *et al*., 2024), it is assumed that male accounting students exhibit higher levels of AI literacy than female accounting students, leading to the following hypothesis:

***H_1**: Male accounting students tend to present a higher level of AI literacy.*

When discussing the development of AI literacy, Ng *et al*. (2021) emphasised the importance of focusing on human-centred issues rather than solely seeking to enhance students' AI-related skills and competencies. The authors advocate for inclusive AI literacy, in which teachers must pay attention to the learning needs of students from underrepresented groups, including, among other factors, economic status. In this discussion, Druga *et al*. (2019) found that children from lower socioeconomic backgrounds tend to experience greater difficulties in understanding AI concepts due to their more limited experience with programming and interaction with such technologies in their daily lives. Therefore, considering that accounting students with higher family income have greater access to AI technologies and, consequently, possess more skills and competencies related to these technologies, the following hypothesis was formulated:

***H_2**: Accounting students with higher family income tend to present a higher level of AI literacy.*

Another individual-related factor that tends to affect AI literacy is parental educational attainment, as it may influence the availability of and access to digital technologies for their children, as well as the support provided in the use of Information and Communication Technology (ICT) tools (Aydin, 2021). In the study conducted by Gui and Argentin (2011), parental education was found to affect

students' operational skills (corresponding to the ability to operate computers and network software), which are associated with digital literacy among high school students. The findings showed that higher levels of parental education tend to positively influence digital literacy, specifically operational skills.

Similarly, Aydin (2021) found that parents' educational attainment, especially among those who had completed at least an undergraduate degree, influenced students' digital skills and, consequently, their ICT literacy when compared to other students. Considering this context, the higher the educational level of parents, the greater the support, guidance, access, and instruction provided to accounting students regarding AI technologies, thereby contributing to the development of their AI literacy. Thus, the following hypothesis was formulated:

***H_3**: Accounting students whose (a) father and/or (b) mother attained a higher education degree tend to have higher levels of AI literacy.*

As highlighted by Ng *et al*. (2021), AI literacy will become a competitive advantage for individuals compared with those who do not seek to develop it. Participation in AI-related courses and events targeted at students (O'Dea *et al*., 2024) may represent a determinant that differentiates the development of AI literacy by promoting broader knowledge, which can provide a competitive advantage over their peers.

In the study conducted by O'Dea *et al*. (2024), prior learning about AI through completed courses was found to be a significant factor influencing generative AI literacy. Students who had taken AI-related courses reported having greater knowledge of how to use AI tools for problem-solving. In this regard, it is believed that accounting students who have completed AI-related courses or participated in AI-focused events tend to develop higher levels of AI literacy than their peers without such prior experience and learning. Thus, the following research hypothesis is proposed:

***H_4**: Accounting students who have participated in (a) AI-related courses and/or (b) AI-related events tend to present a higher level of AI literacy.*

As AI has become part of everyday life, integrating AI literacy into academic curricula has become important to keep pace with technological developments (Stolpe & Hallstrom, 2024). Courses focused on the use and application of AI technologies can help students develop their understanding of AI and subsequently apply it critically, ethically, and responsibly in their tasks (Pinski & Benlian, 2024). In this regard, universities play an important role in students' educational development by fostering and teaching the AI-related skills and competencies required for future professionals to operate effectively in the digital world (Meesook *et al*., 2025).

O'Dea *et al*. (2024) found that students enrolled in computing and technology courses possessed a basic understanding of what AI is and how to use it effectively for problem-solving when compared to students who had only been exposed to other disciplines. In this sense, considering that courses taken by accounting students that address AI or other emerging technologies may positively differentiate their level of AI literacy, the following hypothesis was established:

***H_5**: Accounting students who have taken or are currently taking a course that addresses AI or emerging technologies tend to present a higher level of AI literacy.*

Unequal access to technology and the internet causes a problem known as digital exclusion, which refers to the distinction between individuals who have access to computers and the internet and those who do not (Chang *et al*., 2016; Van Dijk, 2006), as well as access to AI-based technologies (Lutz, 2019). However, considering limited physical access to computers and the internet as the sole definition of digital exclusion, Van Dijk (2006) expanded the concept by identifying four types of access that characterise digital exclusion: motivational access, material (or physical) access, skills access, and usage access.

In the present study, the investigation focused on aspects of digital exclusion related to material (or physical) access, as proposed by Van Dijk (2006) and the first level of digital exclusion, which refers to whether individuals have access to a computer and the internet (Lutz, 2019; Rajam *et al*., 2021). According to Celik (2023), digital exclusion acts as a determinant of AI literacy because individuals with limited access to ICTs are less likely to use and understand the benefits offered by AI. To develop literacy in technologies, individuals must first have access to them (Aydin, 2021). As identified by the author, having internet access at home positively influenced ICT literacy when compared to students who did not have internet access at home. Thus, it is concluded that owning a computer and using the internet more frequently may contribute to the development of AI literacy, leading to the following hypotheses:

***H_6**: Accounting students who own a computer or laptop tend to present a higher level of AI literacy.*

***H_7**: Accounting students who devote more daily hours to using technological devices tend to present a higher level of AI literacy.*

***H_8**: Accounting students who devote more daily hours to using the internet tend to present a higher level of AI literacy.*

The role of TI in the accounting profession is evident, as routines and methods are being transformed by the digital world, requiring professionals to develop new skills and competencies that meet emerging market demands (Oliveira *et al*., 2024).

Therefore, to gain a competitive advantage in a market increasingly shaped by TI, particularly those driven by AI, AI literacy is becoming a new set of skills that individuals must acquire to meet the demands of the digital era, much like the traditional literacy skills of reading, writing, and mathematics (Ng *et al*., 2021). In this context, it is considered that the greater the accounting students' perception of TI in the accounting profession, the greater their pursuit of AI literacy, which leads to the following hypothesis:

H*$_9$: Accounting students with greater perceptions of TI in the accounting profession tend to present higher levels of AI literacy.*

3. Methodological procedures

The study is classified as descriptive, quantitative, and survey-based. The population under investigation consists of undergraduate students enrolled in accounting programs at Brazilian higher education institutions (HEIs). In 2025, there were 1,513 active undergraduate accounting programs recognized by the Ministry of Education, corresponding to 586,191 student seats. This figure represents the closest estimate of the study population, as no data source on the number of students enrolled in each program was available at the time of data collection.

Regarding ethical considerations, the research proposal was submitted to the Human and Social Sciences Research Ethics Committee (CEP/CHS) of the researchers' affiliated institution and was approved under CAAE No. 874 and Opinion No. 7,574. Furthermore, at the beginning of the questionnaire, respondents were provided with the Informed Consent Form (ICF), which included information about the study, the estimated completion time, as well as the participants' rights and guarantees.

As a methodological precaution, the original AI literacy instrument was initially translated into Portuguese in three different versions. Subsequently, the translated versions were evaluated for scale comprehensibility by three researchers from the accounting field: one with a master's degree in accounting, one accounting professor and doctoral candidate, and one accounting professor holding a doctoral degree. Based on the feedback regarding the translated versions, the researchers discussed the suggestions and developed a final translated version of the scale, selecting the items that received the highest evaluations in terms of translation quality and comprehensibility. Finally, the translated scale was resubmitted to the three same researchers for review and validation. In addition to the AI literacy scale, the remaining sections of the survey instrument were also submitted, including the technological disruption in the accounting profession construct and the respondents' demographic questions, so that the instrument could be reviewed, evaluated, and validated in its entirety.

Data was collected through an online questionnaire administered using Microsoft Forms. Participants were contacted through e-mail addresses of higher education institutions offering accounting programmes, which were obtained from their official websites. An invitation and request for dissemination of the survey were sent to the programme coordinators, asking them to share the instrument with their students. WhatsApp and Instagram were also used to disseminate the survey. In addition, face-to-face data collection was conducted at institutions to which the researchers had access. At the end of the data collection period, a final sample of 490 valid responses was obtained.

The first section of the survey instrument measures respondents perceived AI literacy using the translated and adapted version of the AI Literacy Scale (AILS), originally developed and validated by Wang *et al*. (2022). Consisting of 12 items, the scale is divided into the dimensions of awareness, usage, evaluation, and ethics, in which respondents indicated their level of agreement regarding their perceived knowledge and competencies related to AI literacy. The construct was measured using an 11point scale ranging from 0 to 10, where 0 represented "strongly disagree" and 10 represented "strongly agree."

The second section aimed to collect data on perceptions of technological disruption in the accounting profession to subsequently examine how this factor may act as a determinant of AI literacy. The construct was measured using six statements adapted from Oliveira *et al*. (2024). Respondents indicated their level of agreement with statements regarding the potential consequences of technological disruptions in the accounting profession using an 11-point scale ranging from 0 ("strongly disagree") to 10 ("strongly agree").

Finally, the third section collected information regarding respondents' profiles through objective and descriptive questions. The questionnaire included items related to gender (open-ended question), age, geographic region of the higher education institution, academic year of study, mode of instruction, type of institution, employment status, professional experience, educational attainment of the primary maternal and paternal figures, family income level, ownership of technological devices, daily time spent using technological devices, attention to developed and emerging AI technologies, participation in AI-related courses, enrolment in courses addressing AI or other emerging technologies, frequency of AI technology use, participation in AI-related events, and daily internet usage.

Following data collection, confirmatory factor analysis (CFA) was conducted for each construct and its dimensions to confirm the underlying factor structure and assess its consistency with the predefined theoretical framework (Marôco, 2014). For the AI Literacy Scale (AILS), the CFA model fit indices were: $\chi^2 = 606.563$; p-value < 0.001; Comparative Fit Index (CFI) = 0.959; Tucker–Lewis Index (TLI) = 0.877; Bentler–Bonett Normed Fit Index (NFI) = 0.956; Bollen's Incremental Fit Index (IFI) = 0.959; Goodness-of-Fit Index (GFI) = 0.975; Root

Mean Square Error of Approximation (RMSEA) = 0.159; Standardized Root Mean Square Residual (SRMR) = 0.045; Average Variance Extracted (AVE) = 0.485; reliability coefficients ω = 0.775 and α = 0.758 (Hair *et al*., 2021; Kline, 2005; Marôco, 2014). Although the TLI value was below the recommended threshold, it was close to the acceptable value of 0.90.

For the technological disruption perception scale, one item (IT5) was excluded from the model adjustment process. The resulting fit indices were: χ^2 = 772.434; p-value < 0.001; CFI = 0.941; TLI = 0.882; NFI = 0.935; IFI = 0.941; GFI = 0.959; RMSEA = 0.135; SRMR = 0.051; AVE = 0.470; reliability coefficients ω = 0.808 and α = 0.792 (Hair *et al*., 2021; Kline, 2005; Marôco, 2014). Although the TLI remained below the recommended threshold of 0.90, it approached the acceptable level. The RMSEA exceeded the recommended cutoff value of 0.10; however, the scale was retained considering the adequacy of the remaining fit indicators.

Although the TLI was below the conventionally suggested threshold of 0.90 and the RMSEA indicated an unsatisfactory model fit, the original structure of the scales was retained. This decision was based on three considerations: (i) preserving the content validity of the instrument originally developed and validated by its authors; (ii) satisfactory performance of other incremental and absolute fit indices (CFI, IFI, NFI, and GFI); and (iii) theoretical coherence of the four dimensions composing the AI literacy construct. Nevertheless, the results provide mixed evidence regarding model fit, particularly with respect to the RMSEA, which constitutes a limitation of the present study and suggests caution when interpreting the findings.

The latent construct scores estimated through CFA were used as verification variables in subsequent analyses. AI literacy was specified as a second-order construct. Therefore, factor scores for this variable were estimated using a two-stage approach.

The normality of the latent construct scores was assessed using the Shapiro-Wilk test. The results indicated that the data did not follow a normal distribution (p-value = 0.001). Consequently, nonparametric tests were employed, including the Mann-Whitney U test for comparisons between two independent groups and the Kruskal-Wallis test, followed by Dunn-Bonferroni post hoc tests for comparisons involving k independent groups (Fávero & Belfiore, 2017).

Initially, the global AI literacy factor score was used as the dependent variable. The independent variables and their respective groupings were as follows: gender (female, male, and did not identify); educational attainment of the primary maternal and paternal figures (below undergraduate degree, undergraduate degree or higher, and did not know); monthly family income (up to one minimum wage, between one and two minimum wages, between two and three minimum wages, between three and four minimum wages, above four minimum wages, and prefer not to answer); ownership of a personal computer/laptop at home (yes or no); daily hours of

technological device use (1-5 hours, 6-8.75 hours, 8.76-12 hours, 13-24 hours, and did not know); participation in AI-related courses to acquire prior knowledge of AI (yes or no); completion of or enrolment in a course addressing AI, Big Data, or another emerging technology (yes or no); participation in or interest in participating in AI-related events (yes or no); and daily internet usage (1-5 hours, 6-9 hours, 10-12 hours, 13-24 hours, and did not know). For the technological disruption construct, the score range was divided into four groups (0-12 points, 13-25 points, 26-38 points, and 39-50 points). In addition, difference tests were conducted for each individual dimension of AI literacy.

4. Analysis and discussion of results

4.1 Characterization of respondents

Among the 490 respondents in the final sample, 269 (54.90%) identified as female, 199 (40.61%) as male, 21 (4.29%) preferred not to identify, and 1 (0.20%) respondent identified as nonbinary. Respondents were divided into quartiles, and the predominant age range was 16 to 20 years, with 195 respondents (39.80%), followed by 127 (25.92%) aged 22 to 26 years, 111 (22.65%) aged 27 to 62 years, and finally 57 (11.63%) students aged 21 years. Most respondents were enrolled at institutions located in the South, with 340 (69.39%), followed by the Northeast region with 49 (10.00%), 48 (9.80%) from the Southeast region, 29 (5.92%) from the North, and 24 (4.90%) respondents from the Central-West region.

Regarding students' year of study, 129 (26.33%) were in the fourth year (seventh or eighth semester), 117 (23.88%) in the first year (first or second semester), 116 (23.67%) in the third year (fifth or sixth semester), 102 (20.82%) in the second year (third or fourth semester), and 26 (5.31%) in the fifth year (ninth or tenth semester). Regarding HEIs, 420 respondents (85.71%) attended public institutions, 65 (13.27%) attended private institutions, and 5 (1.02%) attended community institutions. The vast majority, 481 (98.16%), were enrolled in in-person programs. When asked about the educational level of their primary paternal figure, 372 respondents (75.92%) reported a level below an undergraduate degree, 113 (23.06%) reported a level equal to or above an undergraduate degree, 4 (0.82%) did not know, and 1 (0.20%) stated that they did not have a paternal figure. Regarding the educational level of the primary maternal figure, 357 respondents (72.86%) indicated a level below an undergraduate degree, whereas 133 (27.14%) reported that their primary maternal figure had an undergraduate degree or higher. Concerning monthly household income, 125 respondents (25.51%) reported income above four minimum wages, followed by 107 (21.84%) between two and three minimum wages, 95 (19.39%) between one and two minimum wages, 88 (17.96%) between three and four minimum wages, 36 (7.35%) up to one minimum wage, and finally 39 (7.96%) preferred not to respond. Students were also asked about issues related to technological devices, internet use, AI technologies, and perceptions of TI, as presented in Table 1.

Table 1. Personal information on technological devices, internet use, and AI

Owns a computer/laptop at home	n	%
Yes	433	88,37%
No	57	11,63%
Daily hours of technological device use*	**n**	**%**
Group 1: 1 to 5 hours	135	27,55%
Group 2: 6 to 8.75 hours	104	21,22%
Group 3: 8.76 to 12 hours	178	36,33%
Group 4: 13 to 24 hours	61	12,45%
Did Not Know How to Answer	12	2,45%
Being attentive to new changes and the emergence of AI technologies	**n**	**%**
Never	3	0,61%
Rarely	31	6,33%
Sometimes	178	36,33%
Frequently	190	38,78%
Always	88	17,96%
Has taken or is taking a course on technology to gain prior knowledge in AI	**n**	**%**
Yes	74	15,1%
No	416	84,9%
Has taken or is taking a course covering AI, big data, or another emerging technology	**n**	**%**
Yes	91	18,6%
No	399	81,4%
Frequency of AI technology use	**n**	**%**
Never	3	0,61%
Rarely	40	8,16%
Sometimes	123	25,10%
Frequently	249	50,82%
Always	75	15,31%
Has participated or seeks to participate in AI-related events	**n**	**%**
Yes	130	26,5%
No	360	73,5%
Daily hours of internet use*	**n**	**%**
Group 1: 1 to 5 hours	130	26,53%
Group 2: 6 to 9 hours	117	23,88%
Group 3: 10 to 12 hours	165	33,67%
Group 4: 13 to 24 hours	69	14,08%
Did Not Know How to Answer	9	1,84%
Technological interference**	**n**	**%**
Group 1: 0 to 12 points	75	15,31%
Group 2: 13 to 25 points	192	39,18%
Group 3: 26 to 38 points	163	33,27%
Group 4: 39 to 50 points	60	12,24%

Note: * = Ranges calculated by quartile.** = Groups calculated by score interval.
Source: Prepared by the authors.

It can be observed that 57 of the 490 respondents do not own a computer or laptop at home. This scenario indicates considerable levels of digital exclusion (Lutz, 2019; Rajam *et al*., 2021; Van Dijk, 2006). Most students (178) use technological devices for 8.76 to 12 hours daily, and 165 reported using the internet between 10 and 12 hours per day. An increase in internet use among accounting students was noted compared to the findings of Meurer and Costa (2022), in which most students were connected for 2 to 6 hours daily, suggesting that students are increasingly connected to the internet.

With the advancement of AI, 190 respondents reported being frequently attentive to changes and the emergence of AI technologies. However, when asked whether they had taken or were taking a technology course to gain prior knowledge of AI, the majority (416) answered no. In addition, most respondents (360) indicated that they do not participate in or seek to participate in AI-related events. It was also observed that 399 students had not taken or were not taking any course covering AI, Big Data, or another emerging technology during their academic program. This underscores the importance of HEIs incorporating AI-related topics into their curricula (Meesook *et al*., 2025; O'Dea *et al*., 2024) to train future professionals with fundamental AI skills and competencies (Ng *et al*., 2021). Moreover, 249 students reported frequently using AI technologies, largely due to their increasing prevalence in various areas of daily life (Celik, 2023; Ng *et al*., 2021). Finally, the majority of students (192) exhibited a level of perceived TI in the accounting profession ranging from 13 to 25 points.

4.2 Multivariate data analysis

To test the hypotheses, the nonparametric Mann-Whitney U test was applied to variables comprising two independent groups, while the nonparametric Kruskal-Wallis test was used for variables with more than two independent groups. Dunn's post hoc test was subsequently conducted to identify the groups between which statistically significant differences existed. Table 2 presents the results of the group difference tests and the hypotheses tested using the global AI literacy factor score.

Table 2. Group difference tests and hypothesis results using the global AI literacy score

Test Performed	Analysed Determinants	Groups	Score	Analysed Criterion	*p-value*	Hypothesis	Decision
KW	Gender	Female	0.015	*p-value*	0.167	H1	Not Supported
		Male	-0.061				
		Other	0.370				
	Family Income	Up to 1 minimum wage	-0.127	*p-value*	0.222	H2	Not Supported
		Between 1 and 2 minimum wages	-0.007				
		Between 2 and 3 minimum wages	-0.030				

Test Performed	Analysed Determinants	Groups	Score	Analysed Criterion	*p-value*	Hypothesis	Decision
		Between 3 and 4 minimum wages	-0.162				
		Above 4 minimum wages	0.199				
		Prefer not to say	-0.056				
	Father's Educational Level	< Undergraduate Degree	-0.021	*p-value*	0.767	H3a	Not Supported
		= or > Undergraduate Degree	0.057				
		Did Not Report	0.287				
	Mother's Educational Level	< Undergraduate Degree	-0.029	*p-value*	0.329	H3b	Not Supported
		= or > Undergraduate Degree	0.078				
MW	Course Completion	Yes	0.243	*p-value*	**0.044***	**H4a**	**Supported**
		No	-0.043				
	Participation in Events	Yes	0.200	*p-value*	**0.009***	**H4b**	**Supported**
		No	-0.072				
	Course Enrolment	Yes	0.230	*p-value*	**0.012***	**H5**	**Supported**
		No	-0.052				
	Owns a Computer	Yes	0.057	*p-value*	**< 0.001***	**H6**	**Supported**
		No	-0.431				
	Use of Technological Devices	1 to 5 hours	-0.149	*p-value*	**0.047***	**H7**	**Supported**
		6 to 8.75 hours	-0.005				
		8.76 to 12 hours	0.161				
		13 to 24 hours	-0.047				
KWD	Internet Use	Did Not Report	-0.429	*p-value*	**0.012***	**H8**	**Supported**
		1 to 5 hours	-0.180				
		6 to 9 hours	-0.020				
		10 to 12 hours	0.163				
		13 to 24 hours	0.067				
	Technological Interference	Did Not Report	-0.647	*p-value*	0.012*	H9	Not Supported
		0 to 12 points	0.277				
		13 to 25 points	0.015				
		26 to 38 points	-0.118				
		39 to 50 points	-0.075				

Caption: KW = Kruskal-Wallis; MW = Mann-Whitney U; KWD = Kruskal-Wallis and Dunn's post hoc test.
Note: * Result with a 5% significance level = Sig. < 0.05.
Source: Research Data

In addition, we tested for possible differences between groups according to the factorial score of each dimension of AI literacy. The results of the analysis by dimension are presented in Table 3.

Table 3. Tests of significant differences between groups based on the score of each dimension of AI literacy

Dim	Grouping Variable	Test	Comparison	Statistic	gl	*p-valor*	Adjusted p
AV	Owns a computer	MW	Yes vs No	14780.5	-	0.015	-
CC	Family income	KW	Global difference	15.608	5	0.008	-
CC	Family income	KW Dunn	2 to ≤ 3 minimum wages vs > 4 minimum wages	-3.473	-	< 0.001	0.008
CC	Family income	KW Dunn	3 to ≤ 4 minimum wages vs > 4 minimum wages	-2.997	-	0.003	0.038
CC	Mother's educational level	MW	< Undergraduate degree vs = or > Undergraduate degree	20706	-	0.029	-
CC	Course completion	MW	Yes vs No	17725.5	-	0.038	-
CC	Participation in events	MW	Yes vs No	26888.5	-	0.012	-
CC	Course enrolment	MW	Yes vs No	21546.5	-	0.005	-
CC	Owns a computer	MW	Yes vs No	15581.5	-	0.001	-
CC	Technological interference	KW	Global difference	9.773	3	0.021	-
CC	Technological interference	KWD	1-0 to 12 pts vs 3-26 to 38 pts	3.099	-	0.002	0.012
ET	Gender	KW	Global difference	9.409	2	0.009	—
ET	Gender	KW Dunn	Female vs Male	2.725	-	0.006	0.019
UT	Participation in events	MW	Yes vs No	26606.5	-	0.02	-
UT	Course enrolment	MW	Yes vs No	20849.5	-	0.027	-
UT	Owns a computer	MW	Yes vs No	16651	-	< 0.001	-
UT	Use of technological devices	KW	Global difference	21.524	4	< 0.001	-
UT	Use of technological devices	KWD	1 to 5h vs 8.76 to 12h	-3.828	-	< 0.001	0.001
UT	Use of technological devices	KWD	8.76 to 12h vs Did Not Report	3.064	-	0.002	0.020
UT	Internet use	KW	Global difference	27.375	4	< 0.001	-
UT	Internet use	KWD	1h to 5h vs 10h to 12h	-4.458	-	< 0.001	< 0.001
UT	Internet use	KWD	6h to 9h vs 10h to 12h	-2.937	-	0.003	0.027
UT	Internet use	KWD	10h to 12h vs Did Not Report	3.201	-	0.001	0.012
UT	Technological interference	KW	Global difference	24.122	3	< 0.001	-
UT	Technological interference	KWD	0 to 12 pts vs 13 to 25 pts	2.87	-	0.004	0.016
UT	Technological interference	KWD	0 to 12 pts vs 26 to 38 pts	4.508	-	< 0.001	< 0.001
UT	Technological interference	KWD	0 to 12 pts vs 39 to 50 pts	3.9	-	< 0.001	< 0.001

Caption: Dim = Dimensions; Av = Assessment; CC = Awareness; ET = Ethics; UT = Use; KW = Kruskal-Wallis; MW = Mann-Whitney U; KWD = Kruskal-Wallis and Dunn's Post Hoc; Pts = points; h = hours.

Note: We report only statistically significant results at the 5% significance level. For variables with more than two groups, we used the Kruskal-Wallis test and, when significant, Dunn's post hoc test with Holm correction. For variables with two groups, the Mann-Whitney U test was used.

Source: Research Data

4.3 Discussion of the results

Regarding gender, no significant differences were found to support hypothesis H_1 (p-value = 0.167), indicating that both gender groups have a similar perception of their knowledge and competencies in relation to AI literacy. This result diverges from the findings of O'Dea *et al*. (2024), Aydin (2021), and Siddiq and Scherer (2019), who identified differences in AI literacy when comparing this variable. Homogeneous access to these technologies, as well as the greater relevance of formative experiences, are arguments that may explain the results obtained.

With regard to family income (H_2), the hypothesis was not supported (p-value = 0.222). These results may suggest that, in an increasingly technological world, students are becoming more familiar with AI technologies, and variables such as effective access, frequency of use, and education may more effectively differentiate the findings. This finding contrasts with that reported by Druga *et al*. (2019), who found that children from lower socioeconomic backgrounds faced more challenges in understanding AI concepts, as they have less daily access to these technologies.

The variable related to parents' educational level did not show significant differences in AI literacy, either for the father's educational level (p-value = 0.767) or the mother's educational level (p-value = 0.329). Thus, hypothesis H_3 was not supported, which stated that accounting students whose father (H_{3a}) and/or mother (H_{3b}) has a higher education degree tend to present a higher level of AI literacy. The results contradict evidence in the literature, which shows that higher levels of parental education affect students' digital literacy in high school (Gui & Argentin, 2011). In addition, students whose parents hold at least an undergraduate degree presented significant results in relation to ICT literacy (Aydin, 2021). This result is particularly interesting as it shows that family educational capital of origin is not able to differentiate AI literacy as other variables related to academic experiences.

Regarding prior learning about AI, significant differences were identified for those who took courses on technology to gain prior knowledge in AI (H_{4a}) (p-value = 0.044). For this variable, the highest AI literacy score was concentrated in the group that had prior training, with a mean of 0.243 compared with -0.043 for the other group. Likewise, participation in AI-related events (H_{4b}) (p-value = 0.009) showed significant differences in AI literacy, with a score of 0.200 for participants compared to -0.072 for non-participants.

Thus, hypothesis H_4—that accounting students who participated in (a) technology courses related to AI and/or (b) AI-related events tend to present a higher level of AI literacy—was supported. These findings show that complementary training contributes to their preparation for future professional practice (Hornberger *et al*.,

2025) and enables the achievement of competitive advantages (Ng *et al*., 2021). There is also alignment with the study by O'Dea *et al*. (2024), in which prior AI learning through courses contributed to understanding AI use and, consequently, to generative AI literacy. Therefore, the promotion of academic events and formative experiences, such as AI courses during students' education, appears to be a strategic action.

Subsequently, H_5, which refers to accounting students who have taken or are currently taking a course that addresses AI or emerging technologies, tends to present a higher level of AI literacy, was supported (p-value = 0.012). When analysing which pairs showed the highest levels of AI literacy, students who had taken or were taking a course on AI or emerging technologies exhibited a mean of 0.230 compared to students who had not taken any course related to these topics, with a mean of -0.052. Therefore, taking courses focused on AI learning contributes positively to the development of AI literacy and emphasizes the relevance of universities offering courses focused on this theme (Meesook *et al*., 2025).

This result raises reflections grounded in the National Curriculum Guidelines (NCGs) for accounting programs, by emphasizing the skills and competencies related to information and contemporary technologies, such as AI, that students need to acquire during their studies (CNE, 2024), as such learning, in practice, contributes to AI literacy.

Regarding digital exclusion, H_6 was supported, showing that accounting students who own a computer/laptop tend to present a higher level of AI literacy (p-value < 0.001). When analysing pairwise comparisons, students who own a personal computer/laptop at home showed a mean factorial score of 0.057, compared with those who do not, with a mean of -0.431. Thus, students who have access to computers tend to develop higher levels of AI literacy compared to their peers without access to computers at home.

Similarly, accounting students who spend more daily hours using technological devices tend to present a higher level of AI literacy, leading to H_7 being supported (p-value = 0.047). Using Dunn's post hoc test, a significant difference (p-value = 0.004) was identified between groups of students who use technological devices for 1 to 5 hours per day (mean = -0.149) and those who use them for 8.76 to 12 hours per day (mean = 0.161).

Regarding internet access, H_8 was supported, indicating that accounting students who spend more daily hours using the internet tend to present a higher level of AI literacy (p-value = 0.012). In pairwise comparisons, a significant difference (p-value = 0.001) was found between students who spend 1 to 5 hours per day online (mean factorial score = -0.180) and those who spend 10 to 12 hours (mean factorial score

= 0.163). Based on these results, it can be concluded that accounting students who spend more time connected to the internet tend to enhance their AI skills and knowledge and, consequently, demonstrate higher AI literacy compared to their peers who spend less time connected daily.

In this context of digital exclusion, it was identified that access to a personal computer or laptop at home, as well as a greater number of daily hours of use of technological devices and internet access, are significant factors that differentiate the level of AI literacy among accounting students. This result supports Celik (2023), showing that individuals with lower access to ICT face difficulties in using and understanding AI, which compromises their AI literacy. In addition, there is evidence that the more time individuals spend online, the higher their digital literacy (Rajam *et al*., 2021) and ICT literacy (Aydin, 2021).

Finally, IT was a factor that showed significant differences in relation to AI literacy. However, H_9 was not supported (p-value = 0.012), as the result diverged from the proposed theoretical proposition. Accounting students with a higher perception of TI in the accounting profession presented a lower level of AI literacy. Applying Dunn's post hoc test, we sought to identify which pairs showed statistically significant differences. The results indicated that differences in IT perception corresponded to students who scored between 0 and 12 points (mean = 0.277) compared to: those who scored between 13 and 25 points (mean = 0.015; p-value = 0.016); those who scored between 26 and 38 points (mean = -0.118; p-value = 0.001); and those who scored between 39 and 50 points (mean = -0.075; p-value = 0.028). It was concluded that accounting students with lower perceptions of IT, compared with their peers, tend to demonstrate higher AI literacy.

The results suggest that students with lower perceptions of TI are those who already master or use AI technologies more easily than other tools such as Python and R. As a result, their AI literacy tends to be higher due to their greater knowledge of and familiarity with AI-related technologies and applications. This finding contradicts the literature, which suggests that, with an increase in the perception of IT in the accounting profession, there is a tendency for future accounting professionals to seek to acquire knowledge and skills (AI literacy) to meet new technological demands in the market (Igou *et al*., 2023; Oliveira *et al*., 2024).

The analysis of AI literacy dimensions revealed specific differences among some of the investigated groups. In the assessment dimension, a significant difference was observed only in relation to computer ownership. In turn, the Awareness dimension showed a broader set of differences, involving family income, maternal education level, course completion, participation in events, course enrolment, computer ownership, and perception of TI. Regarding the Ethics dimension, a significant difference was identified exclusively in relation to gender, distinguishing female and male students. For the Use dimension, differences were concentrated in variables

related to practical experience and exposure to technologies, including participation in events, course enrolment, computer ownership, daily time spent using technological devices, internet use, and TI. In this sense, the results indicate that the different dimensions of AI literacy respond differently to the factors investigated, with Awareness and Use being the dimensions that most differentiate scores according to conditions associated with access, training, and use of technological resources. The observation of these dimensions represents a possibility for guiding specific actions throughout students' academic training.

5. Conclusions

This study aimed to identify the determinants of artificial intelligence (AI) literacy among accounting students. It was found that taking courses on technology to gain knowledge in AI, participation in AI-related events, completion of courses addressing AI, Big Data, or other emerging technologies, ownership of a personal computer/laptop at home, and daily hours of technology devices and internet use showed significant differences in relation to higher levels of AI literacy. It is observed that determinants related to learning and the pursuit of improvement in AI, as well as internet access and device usage, tend to positively differentiate skills, competencies, and knowledge related to AI.

On the other hand, gender, monthly family income, and the educational level of both the primary maternal and paternal figures did not show significant differences in relation to AI literacy among accounting students. The findings of the study show that AI literacy also presents itself as an educational phenomenon, in which the need for instruction and contact with this technology during the training period are strategic elements in student development. In this sense, the widespread access to the internet and to different types of technologies may indicate that socioeconomic barriers are being overcome, promoting greater access equality; however, the lack of knowledge regarding the appropriate use of these technologies may represent a new instructional challenge to be addressed by higher education institutions.

The study also contributes to expanding the existing literature by empirically analysing the determinants that influence AI literacy, specifically in the accounting context, which helps generate directions aimed at the development of future strategies and interventions intended to improve AI literacy. As practical implications, the information obtained may assist universities and professional accounting bodies in encouraging the offering of courses, subjects, training, and events that foster discussions, information exchange, and the improvement of knowledge and skills related to AI technologies among future accounting professionals. It highlights the importance of promoting guidance on the ethical use of AI tools, both in educational and professional environments, considering that these technologies are increasingly present in these contexts. In this way, individuals

can adapt to the transformations arising from this new technological era driven by AI, positioning AI literacy as a complementary competence to other technical skills.

Furthermore, social implications can be highlighted, as the findings contribute to forming individuals who are more capable of understanding, using, and critically evaluating AI-based technologies. The findings also emphasise, to some extent, the relevance of educational institutions in the process of developing individuals with critical awareness regarding the use of AI tools. By fostering educational strategies and policies that promote students' AI literacy, it is possible to enhance digital inclusion as well as the critical and analytical thinking of these future professionals. Consequently, this supports their insertion into the labour market through broader access to opportunities generated by technological transformation. In addition, it contributes more broadly to the development of a more advanced and inclusive society in relation to AI.

As limitations, the study sample was obtained through convenience sampling and was limited to accounting students in Brazil, which may restrict the generalizability of the findings to other countries and academic programs. The data were collected through a self-report questionnaire, in which issues related to common method bias and social desirability effects may be present. In addition, the scale used to capture data on AI literacy was translated and adapted to the Brazilian context from the study by Wang *et al*. (2022), which may have introduced limitations regarding the scale's fit indices and reliability indicators. Finally, a cross-sectional study design was adopted, which limits the ability to analyse and make causal inferences regarding the effects of the determinants of AI literacy.

Future research may address these limitations by expanding investigations to other academic programs and countries, considering the impact of AI across different areas worldwide. Such expansion would allow for comparisons of findings across different contexts. Future studies could also employ longitudinal designs to track the development of AI literacy among individuals throughout their academic training as well as during their professional practice. They could also explore other data collection techniques, such as semi-structured interviews, to gain a deeper understanding of the determinants of AI literacy among university students, and potentially extend the analysis to other contexts, such as accounting professionals and university instructors, as all are being affected and need to be prepared for this new AI era. It is also recommended to investigate how universities are integrating AI-related technology courses into their curricula to prepare future professionals. In addition, other determinants that may affect AI literacy should be examined, such as labour market pressures, motivational aspects, and the pursuit of competitive advantage.

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