Artificial Intelligence: Exploring Self-Efficacy in Business Students. The Case of Chile

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Summary

The study of artificial intelligence (AI) in educational processes has generated growing interest in the academic community. In this context, innovations are being developed in public and private organizations that have installed the need for professionals who demonstrate AI-related competencies. This work aims to analyze the self-efficacy of AI according to the sociodemographic characteristics of business students in Chile. The methodology used is exploratory in nature. Exploratory factor analysis was applied and significant differences were examined. The results show differences according to sex, occupation, family income and territory. In relation to these findings, it is suggested to include AI tools in educational innovations related to the training of business students. Finally, the implementation of new approaches that contribute to the implementation of innovations that facilitate the installation of AI competencies in students of Higher Education Institutions in Chile is recommended.

Keywords: Artificial intelligence, business students, higher education, innovation, professional skills.

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1. Introduction

The new challenges of globalization have demonstrated the relevance of technological development and artificial intelligence (AI) in private companies and public institutions around the world (Bai et al., 2024; Qin et al., 2024). This encourages innovation in different organizations and various industrial sectors (Dub et al., 2023; Zare y Persaud, 2024). This includes adjustments, transformations and adaptations in higher education institutions (HEIs) as a result of the new complexities of the new era of knowledge (Kang, 2023; Hafezi et al., 2024). Innovation is critical for organizations to create and sustain sustainable advantages (Chen et al., 2024). The above contributes to success and survival in complex and global environments (Abrar-ul-haq, 2025). In this context, innovation can contribute to the definition of a strategy that must be valuable, rare and difficult to imitate (Agazu y Kero, 2024). Such innovations can be applied in public and private organizations and educational institutions (Casper y West, 2024)

The study on AI, in educational contexts, includes perspectives such as: assessment/validation, prediction, AI assistance, intelligent tutoring system and student learning management (Crompton y Burke, 2023). All of which create opportunities and challenges in higher education that involves faculty and students (Jafari y Keykha, 2024), which includes personalized learning paths, greater accessibility, economic efficiency and a boost in the performance of the participants (George y Wooden, 2023).

Now, in relation to this research, self-efficacy is the perception that people have regarding the use of AI technologies/products (Wang y Chuang, 2024). The study of self-efficacy is transcendental to design strategies that contribute to acceptance and adoption of different digital technologies (Bennet et al., 2024; FakhrHosseini et al., 2024). In this sense, sometimes the use of AI can be impacted by sociodemographic characteristics of users, affecting individual competencies linked to the understanding and use of AI. (Kozak y Fel, 2024).

Likewise, HEIs have the mission of training competent professionals in accordance with the needs of the local environment and the challenges of hyper-connected population (Severino-González et al., 2022). The above should motivate innovation in educational models, policies and strategies that include, for example: critical thinking, global citizenship and AI (Campo et al., 2023; Monzó-Martínez et al., 2024; Tan et al., 2024), which leads to the installation of teaching methodologies that must incorporate the challenges of a modern society, which is complex, dynamic, uncertain and changing (Caspari-Sadeghi, 2023; Quy et al., 2023).

The study of AI in HEIs is transcendental due to the potential they have in learning through the creation of content, provision of dynamic classrooms and disruptive spaces (López-Chila et al., 2023). In this sense, this research considers business students from the Maule region, because this group of the population has proven to be culturally sensitive to the new challenges facing society (Mumtaz et al.,

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2024). In relation to methodology, this research considers the decisions and methodologies used by Oliva-Albornoz et al. (2024) and Sarmiento-Peralta et al. (2024) for the determination of differences in educational actors that can be used for the design of innovations based on teaching strategies.

According to the above, the research question is: What are the sociodemographic characteristics associated with the self-efficacy of artificial intelligence in business students of Higher Education Institutions in Chile? The main objective of this study is to analyze the self-efficacy of AI based on the sociodemographic characteristics of students.
The text is structured as follows. In the introduction there is the problematization that seeks to raise the relevance of the study. Then, in the literature review, contextual and conceptual aspects are detailed in relation to the objective of the study. In the research methodology, the design, scale of measurement and the description of the fieldwork are included. In results, the results are deepened through the application of analysis strategies. On the other hand, in discussion, the findings of this work are compared with proposals from previous publications. Finally, the conclusions, reflections, limitations and future lines of research are presented.

2. Literature review

AI has installed new dynamics in HEIs, generating ethical, social and educational implications (Al-Zahran y Alasmari, 2024). To a large extent, AI has focused on adaptive systems innovation and the personalization of learning. (Bond et al., 2024), which brings benefits such as challenges in the various academic environments and involves various actors within HEIs (Pisica et al., 2023). In this context, the inclusion of AI-based technologies has contributed to the renewal and improvement of teaching and learning processes (Chiu, et al., 2023).
However, innovation management seeks to improve performance through increased competitiveness (Farida & Setiawan, 2024). This is due to the implications that innovation has on the growth and development of economies around the globe. (Mara et al., 2024). In this sense, HEIs have implemented teaching strategies that seek to install skills related to creativity, critical thinking and collaboration skills in coherence with AI (Marougkas et al., 2023).

Digital transformation and technological innovation have motivated the development of curricular adjustments for the implementation of AI competencies in response to the challenges of the Industry 4.0 (Cannavacciuolo et al., 2023; Deroncele-Acosta et al., 2023). All of which generates tensions and opportunities for the development of professional competencies traditionally developed by HEIs. (Stumbrienė et al., 2024).

Innovations in teaching strategies seek to install professional competencies that include aspects related to TRIZ innovative problem-solving theory and social cognitive career theory. (Wu & Fernando, 2024). In relation to this research, innovation has connections with AI due to the need for comprehensive professionals, capable of mobilizing knowledge for the creative resolution of complex situations in diverse scenarios (Zhan et al., 2024).

The use of AI in teaching processes has motivated its study to determine the ethical implications in academic environments (Burton et al., 2017). This has established the need for policy innovations and the development of regulations to ensure ethics in the use of AI tools. (Vera, 2023). In this sense, the study of AI and higher education has raised several dilemmas that include aspects of daily life, interactions, thoughts and emotions. (Mouta et al., 2024).

The study on business students' views on AI has shown the importance they attach to the various challenges facing society. (Mumtaz et al., 2024). In this context, differences in the understanding of Slovenian business and economics students according to their socio-demographic characteristics have been identified. (Tominc y Rožman, 2023). In this context, according to Sova et al. (2024), increased awareness and access to AI tools have contributed to the experiences and academic outcomes of economics students in Romania. All of which highlights the importance of the study on the opinions of business students in Chile.

The AI study considers the analysis of self-efficacy which includes the perception about the experience in the use of AI technologies/products. (Wang y Chuang, 2024). These studies are fundamental for the design of innovations that can contribute to the acceptance and adoption of technologies in different organizational processes (Bennet et al., 2024; FakhrHosseini et al., 2024). These experiences can be modified, altered, or adjusted according to the sociodemographic characteristics of the users (Kozak y Fel, 2024).

HEIs have undergone several transformations that have led to the incorporation of different innovations aimed at improving organizational and teaching processes. (López-Chila et al., 2023). In this context, this study seeks to analyze a group of business students from the Maule region. This group of the population has demonstrated a greater sensitivity and acceptance of the local and global challenges facing society. (Mumtaz et al., 2024).

However, the examination of statistical differences has proven useful for the development of organizational and educational innovations involving various university stakeholders. (Oliva-Albornoz et al., 2024; Sarmiento-Peralta et al., 2024). All of which contributes to the determination of integral strategies, contextualized and coherent with the needs of specific population groups. (Rababah et al., 2021; Blell et al., 2023).

In relation to the above, the following hypotheses are put forward:
(H_0): Null hypothesis: There are no statistically significant differences in AI self-efficacy among business students according to their sociodemographic characteristics.

(H_1): Alternative hypothesis: There are statistically significant differences in AI self-efficacy among business students according to their sociodemographic characteristics.

3. Methodology

3.1 Study Design

The study design is exploratory, which considers the application of a self-administered online survey, distributed by email and social networks to university students in the Maule region. (Chile). In this sense, we intend to develop an initial analysis of the opinions of students enrolled in different business careers, such as Chartered Accountant, Certified Public Accountant and Auditor and Business Management.

3.2 Sample

The participants are 266 university business students in the Maule region (Chile), which constitute a convenience sample due to the design of the study and the accessibility of the students. 46.6% of the sample were men, while 53.4% were women. Regarding age, 80.8% were between 18 and 23 years old. 69.5% of students were exclusively dedicated to their studies, while 30.5% combined studies and work. The majority of the students were in their first to third year of their studies (27.8%, 19.9%, and 31.2%, respectively). 57.5% lived in households with 4 to 6 members, 39.9% in households with 1 to 3 members, and 2.6% in households with more than 7 members. 38.3% of participants reported household income of less than CLP$500,000 (approximately US$500), 36.5% reported income between CLP$500,001 and CLP$1,000,000, 18.1% between CLP$1,000,001 and CLP$2,000,000, and 7.1% reported revenues above CLP$2,000,000. Finally, 59.4% of the participants resided in urban areas, while 40.6% came from rural areas (see Table 1).

Table 1: Sociodemographic characteristics of the participants

Demographic variable	Answer Option	Percentage
Gender	Man	46.6%
	Woman	53.4%
Age	18 to 20	45.5%
	21 to 23	35.3%
	24 to 26	7.5%
	27 or more	11.7%
Occupation	Just study	69.5%
	Study and work	30.5%
Career Year	First year	27.8%
	Second year	19.9%
	Third year	31.2%
	Fourth year	11.3%
	Fifth year	9.8%
Family group	1 to 3 members	39.9%
	4 to 6 members	57.5%
	7 or more members	2.6%
Family income level (monthly)	Less than CLP$500.000	38.3%
	CLP$500,001 - CLP$1,000,000	36.5%
	CLP$1,000,001 - CLP$2,000,000	18.1%
	Above CLP$2,000,001	7.1%
Territory (origin)	Urban	59.4%
	Rural	40.6%

3.3 Instrument

An instrument organized in three sections was applied: 1. Filter questions, to verify the inclusion criteria of the participants, 2. Sociodemographic profile: it consists of questions about the demographic characteristics of the participants and 3. AI self-efficacy scale: in this section there is a scale composed of 22 items distributed in four dimensions: assistance, anthropomorphic interaction, comfort with AI, and technological skills (Wang y Chuang, 2024). In relation to the response, a 6-point Likert scale is used, where 1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, and 6 = Strongly agree.

Table 2: AI Self-Efficacy Scale

Dimensions	Items	Variables
Attendance	V1	Some AI technologies/products make learning easier.
	V2	I find that AI technologies/products are helpful for learning.
	V3	AI technologies/products are good aids to learning.
	V4	Using AI technologies/products makes learning more interesting.
	V5	I'm confident in my ability to learn simple programming of AI technologies/products if I were provided the necessary training.
	V6	AI technologies/products help me to save a lot of time.
	V7	I find it easy to get AI technologies/products to do what I want it to do.
Anthropomorphic interaction	V8	I think the interactive process of AI technologies/products is very vivid, just like chatting with a real person.
	V9	I think the way that AI technologies/products express content when interacting is unique, just like a real person.
	V10	I think there is no difference between the dialogue method of AI technologies/products compared with the dialogue with real people.
	V11	I think the tone of AI technologies/products when interacting is the same as that of real people.
	V12	I feel that the way of expression of AI technologies/products in the interactive text is the same as that of real people.
Comfort with AI	V13	When interacting with AI technologies/products, I feel very calm.
	V14	When interacting with AI technologies/products, I find it easy.
	V15	When interacting with AI technologies/products, I feel comfortable in my heart.
	V16	When interacting with AI technologies/products, I feel very peaceful.
	V17	When interacting with AI technologies/products, I feel very relaxed.
	V18	I can happily interact with AI technologies/products smoothly
Technological skills	V19	When using AI technologies/products, I am not worried that I might press the wrong button and cause risks.
	V20	When using AI technologies/products I am not worried that I might press the wrong button and damage it.
	V21	When using an AI technology/product, there is nothing that I do not know why.
	V22	AI technologies/products jargon does not baffle me.

Source: Wang y Chuang, 2024.

This research uses the measurement scale designed by Wang and Chuang (2024), which presents an excellent global fit. Then in Bai (2024), in the analysis of the opinions of employees in the service sector in China, a reduction of variables is presented, showing at all times through the indicators that the adjustments are reliable and acceptable. On the other hand, in this research an AFE is applied and the internal consistency coefficients are analyzed, demonstrating at all times that the indicators are satisfactory and reliable.

3.4 Procedure

The information was collected through a Google Forms instrument. This link was distributed between July and September 2024 by email and through social networks. At all times, it was pointed out that participation was voluntary, confidential and not financially remunerated. In addition, it was assured that participation would not affect the integrity of the students. Once the data were obtained, they were exported to a Microsoft Excel spreadsheet and subsequently transferred to SPSS v18 software for analysis.

3.5 Data Analysis

Exploratory Factor Analysis (EFA) is a multivariate statistical method whose purpose is to identify a factor structure underlying a large data set. (Pérez and Medrano, 2010; Lloret-Segura et al., 2014). In this sense, the EFA used in this research included the principal component extraction method and the Varimax rotation. Subsequently, descriptive statistics and measures of central tendency were calculated. The internal consistency of the dimensions was evaluated using Cronbach's Alpha coefficient. The Shapiro-Wilk and Kolmogorov-Smirnov tests were used to evaluate the normality of the data. Finally, in relation to the hypotheses of this study, significant differences were determined according to the dimensions of the AI self-efficacy scale in relation to the sociodemographic characteristics of the participants.

4. Results

This section presents the main findings of the research. A factor analysis is exhibited. Then, the descriptive statistics and internal consistency coefficient are analyzed. Finally, statistical differences are examined according to the sociodemographic characteristics of the research subjects according to AI self-efficacy opinions.

4.1 Exploratory factorial analysis

To verify an adequate matrix analysis, an exploratory factor analysis (EFA) was developed, for which the Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests were applied. In relation to the KMO, the result obtained is 0.913 and in relation to Bartlett's test of sphericity, the values are Chi-square= 4606.55; $p< 0.000$. Principal component extraction is applied and the Varimax method with Kaiser normalization is considered. All of which ensures that there is sufficient validity to continue with the analysis (Lloret-Segura et al., 2014). The scale is reduced to 21 items, due to the elimination of item v14. Finally, the total variability of the data is explained by 73.9%.

Table 3: Rotated components matrix of AI self-efficacy

Item	Dimensions			
	Attendance	Anthropomorphic interaction	Comfort with AI	Technological skills
v3	0.871			
v1	0.868			
v2	0.864			
v6	0.826			
v4	0.787			
v5	0.740			
v7	0.692			
v11		0.873		
v12		0.836		
v9		0.796		
v10		0.746		
v8		0.743		
v16			0.853	
v17			0.844	
v15			0.826	
v13			0.614	
v18			0.605	
v19				0.847
v20				0.838
v22				0.760
v21				0.741
Variance explained (%)	25.860	17.639	16.364	14.092

4.2 Descriptive statistics

Table 4 shows the means, medians, standard deviation (SD) and Cronbach's Alpha of each dimension. In relation to the Assistance dimension, it is identified that the highest value is found in v7 due to the importance given to the ease of getting AI technologies to do what is requested of them (mean= 2.25; median= 2; SD= 1.053). On the other hand, in relation to the dimension Anthropomorphic Interaction, the highest rating is identified in v11 as a result of the opinion held about the AI interacting with a real person (mean=3.5; median= 4; SD= 1.176). Regarding the AI Comfort dimension, the highest value is found in v16 due to the importance given to the feeling of peace during the use of an AI technology (mean= 2.93; median= 3; SD= 1.034). Finally, in the Technological Skills dimension, the highest value it identifies in v21 because people value most that AI has answers for everything they need to ask (mean= 3.11; median= 3; SD= 1.086).

Table 4: Descriptive statistics according to AI self-efficacy dimension

Dimensions	Item	Mean	Median	SD	Cronbach's Alpha
Attendance	V3	2.03	2	0.971	0.935
	V1	1.88	2	1.012	
	V2	1.99	2	1.024	
	V6	1.89	2	1.393	
	V4	2.21	2	1.063	
	V5	2.13	2	1.053	
	V7	2.25	2	1.077	
Anthropomorphic interaction	V11	3.5	4	1.176	0.891
	V12	3.46	4	1.163	
	V9	3.23	3	1.112	
	V10	3.32	3	1.208	
	V8	3.07	3	1.075	
Comfort with AI	V16	2.93	3	1.034	0.921
	V17	2.78	3	1.034	
	V15	2.92	3	1.045	
	V13	2.56	3	1.034	
	V18	2.24	2	1.077	
Tech skills	V19	3.00	3	1.232	0.867
	V20	2.98	3	1.236	
	V22	2.81	3	1.080	
	V21	3.11	3	1.086	

Finally, regarding reliability, Cronbach's alpha coefficient was calculated for each dimension. The values are as follows: Attendance is 0.935, Anthropomorphic Interaction is 0.891, AI Comfort is 0.921, and Technological Skills is 0.867. Therefore, all values are adequate and satisfactory.

4.3 Inferential Analysis

The examination of statistical differences considered the nonparametric Mann-Whitney U and Kruskal-Wallis tests due to the non-normal distribution of the data according to the Kolmogorov-Smirnov and Shapiro-Wilk tests. In this context, statistical differences are found in sex, occupation, family income and territory. Now, in relation to the design of this study, it is deepened according to the sociodemographic profile in accordance with the AI self-efficacy views of university students.

Table 5 shows statistical differences according to gender, occupation and family income level. In this context, in relation to sex, statistical differences are found in items V1 (p-value=0.007), V2 (p-value=0.002), V3 (p-value=0.000) and V6 (p-value=0.000) because men and women value the usefulness of AI in the development of learning differently. On the other hand, according to occupation, significant differences are found in items V3 (p-value=0.010), V4 (p-value=0.039) and V5 (p-value=0.031) as a result of the different recognition given by students who study and work with respect to those who only study AI in correspondence with the technologies that positively help learning. Finally, with respect to family income level, only one exclusive difference was found in V3 (p-value=0.041) because students, depending on their level of family income, have different opinions about how positive the use of AI can be for learning.

Table 5: Statistically significant differences by Attendance dimension

Items	Gender	Age	Occupation	Career Year	Household Members	Family Income Level	Territory
V1	0.007	0.770	0.309	0.264	0.728	0.073	0.401
V2	0.002***	0.197	0.107	0.171	0.407	0.108	0.225
V3	0.000***	0.483	0.010**	0.051	0.756	0.041	0.627
V4	0.082	0.645	0.039**	0.541	0.819	0.374	0.151
V5	0.238	0.839	0.031**	0.174	0.848	0.079	0.473
V6	0.000***	0.485	0.676	0.824	0.415	0.407	0.302
V7	0.119	0.560	0.817	0.573	0.350	0.153	0.227

*Note: *=p<0.10; ** = p<0.05; *** = p<0.01.*

Table 6 shows statistical differences according to the Anthropomorphic Interaction dimension in relation to occupation. In this sense, differences are found in items V10 (p-value=0.045) and V11 (p-value=0.009). The aforementioned, due to the fact that students who only study with respect to those students who study and work have different opinions regarding the method of AI dialogue compared to dialogue with real people and the tone of AI technologies/products when interacting is the same as that of real people.

Table 6: Statistically significant differences according to dimension Anthropomorphic Interaction

Items	Gender	Age	Occupation	Career Year	Household Members	Family Income Level	Territory
V8	0.330	0.612	0.629	0.514	0.551	0.399	0.149
V9	0.954	0.226	0.124	0.467	0.637	0.391	0.860
V10	0.900	0.307	0.045**	0.355	0.229	0.984	0.961
V11	0.065	0.245	0.009***	0.625	0.910	0.564	0.493
V12	0.081	0.445	0.050	0.306	0.780	0.564	0.791

*Note: *=p<0.10; ** = p<0.05; *** = p<0.01.*

Table 7 shows statistical differences according to the Comfort with AI dimension in gender and territory. In this context, according to gender in all items and according to territory in items V17 and V18. With respect to gender, both men and women have different opinions regarding the tranquility, comfort, peace and sense of relaxation during the interaction with the AI. On the other hand, in the territory variable, differences are found in items V17 (p-value=0.038) and V18 (p-value=0.022), due to the fact that the origin of the students (urban/rural) derives in the feeling of relaxation during the interaction with the AI and, at the same time, product of interaction without problem with the AI.

Table 7: Statistically significant differences according to Comfort with AI dimension

Items	Gender	Age	Occupation	Career Year	Household Members	Family Income Level	Territory
V13	0.001***	0.205	0.252	0.387	0.880	0.429	0.169
V15	0.000***	0.929	0.132	0.573	0.675	0.613	0.900
V16	0.000***	0.926	0.318	0.619	0.852	0.332	0.376
V17	0.001***	0.674	0.179	0.653	0.761	0.369	0.038**
V18	0.000***	0.448	0.867	0.187	0.201	0.377	0.022**

*Note: *=p<0.10; ** = p<0.05; *** = p<0.01.*

In Table 8, statistical differences can be observed according to the Technological Skills dimension in gender, occupation and territory. In relation to gender, both men and women have different opinions regarding the fear of pressing a button that could cause risks and harm in the use of AI. On the other hand, according to occupation, statistical differences are found in item V20 (p-value=0.035) as students have different opinions regarding the concern about pressing the wrong button when using AI. Finally, according to territory exclusive statistical differences in found in V19 (p-value=0.018) due to the fact that students residing in rural areas with respect to urban areas have different opinions in relation to the concern during the use of AI in pressing a wrong button that could cause risks.

Table 8: Statistically significant differences according to Technological Skills dimension

Items	Gender	Age	Occupation	Career Year	Household Members	Family Income Level	Territory
V19	0.008**	0.063	0.130	0.242	0.790	0.056	0.018**
V20	0.001**	0.593	0.035**	0.373	0.891	0.154	0.131
V21	0.027**	0.294	0.181	0.298	0.288	0.383	0.644
V22	0.000***	0.471	0.074	0.748	0.235	0.091	0.411

*Note: *=p<0.10; ** = p<0.05; *** = p<0.01.*

5. Discussion

The results indicate that self-efficacy in the use of artificial intelligence (AI) in business students varies significantly with their sociodemographic characteristics, in particular with gender, occupation, family income, and territory of origin. These findings suggest that access, familiarity, and confidence in AI do not behave homogeneously within the population studied, which has important implications for higher education and professional training for students in business-related careers. The aforementioned is relevant for the development of innovations in private companies and transcendental for the integral formation of HEIs, due to the implications it has on the professional practice in coherence with the challenges faced by AI.

Gender shows significant differences in several aspects. In this sense, with respect to the dimension of Assistance and Comfort with AI, men consider AI as a supportive resource, while women are more cautious or insecure about this aspect, especially in relation to trust and practical usefulness. Significant differences in Technological Skills evidence a gap in the self-assessment of technological capabilities, which could be linked to numerous sociocultural factors or previous experiences.

These results indicate the need to generate differentiating training strategies to reduce the gender gap in the adoption of AI.

In relation to gender, significant differences were identified in the dimensions of assistance, comfort and interaction with AI, suggesting that men more readily perceive the usefulness of AI and feel more comfortable using it, while women show a more cautious attitude. This could be related to sociocultural factors and previous experiences with technology (Wang and Chuang, 2024).

The results also show significant differences according to sociodemographic variables in occupation and income level. This is because students have different perceptions about the constructs of Anthropomorphic Interactions and Technological Skills. Similarly, household income levels also affect the perception of AI Assistance, which could be linked to the availability of technological resources. This finding could indicate that digital inclusion policies should take into account certain economic and labor aspects that ensure a fair implementation of Artificial Intelligence.

Both occupation and family income level have also been found to influence self-efficacy in the use of AI. Students who combine studies with some paid work activity show a higher perception of usefulness and interaction with AI compared to those who only study. This suggests that exposure to technology in work contexts favors its acceptance and use. Likewise, students from lower income families present differences in the perception of the usefulness of AI, which could be linked to limitations in access to devices and digital training.

The significant differences found with respect to the students' area of origin (urban and rural) could indicate possible inequities in access to and familiarity with Artificial Intelligence. In this context, students coming from urban areas may have a greater technological impact, while those coming from rural areas may face greater challenges in terms of access and infrastructure. These findings underscore the relevance of implementing programs that help reduce technological inequalities between students in rural and urban areas, thus preventing digital exclusion.

According to the findings, the origin (urban or rural) of the students impacts the perception of AI, especially in terms of comfort and technological skills. Students coming from urban areas show greater confidence in using AI, while those coming from rural areas present more difficulties and greater fear of making mistakes. These results may reflect possible access and digital literacy gaps that should be considered in the implementation of inclusive educational policies.
Now, according to Wang & Chang (2024) the development of innovations in AI applications has been listed as a critical issue for academics, educators and practitioners to understand, due to the risk in educational contexts. In this sense, some research has placed emphasis on the experiences and confidence that students have in the use of AI (Kelly et al., 2022). In this context, it is suggested that gender is a determining variable in the use of AI in teaching, with female teachers having greater knowledge and applying it in the majority of cases (Alissa & Hamadneh, 2023). Which can negatively affect students' productivity and decision-making ability (Ahmad et al., 2023). Finally, the findings of this research reinforce the need to build differentiated educational strategies to address the gaps in access and training in AI-based tools. It is recommended that HEIs design specific training programs, considering the socio-demographic profile of students, thus ensuring that AI education is accessible, equitable and contextualized, promoting initiatives that reduce technological inequalities among students.

5.1 Implications for innovation in university teaching

The findings present different challenges and opportunities: university professors and educational managers should consider sociodemographic characteristics for the design of educational experiences that include AI. It is also recommended that curricula, training and workshops be adjusted to incorporate technological innovations in coherence with the access and infrastructure needs of students. All of which must include the underlying implications of AI self-efficacy in relation to gender, occupation and place of origin. Finally, public policies related to university education should focus on reducing inequalities in access, knowledge and the use of new technologies such as AI.

5.2 Social implications

The results of this study have important social implications, particularly in a context where AI is expected to play a relevant role in daily, university and work life. In this context, we consider it necessary to establish public policies and programs that promote access to equal participation in the digital environment, such as seminars, short training programs, workshops and specialized training to reduce and avoid possible gender barriers associated with this group.

Due to the different opinions in relation to the sociodemographic characteristics of students, it may be essential to create programs with content on ethics in the use of artificial intelligence. In short, the results of this research could contribute to the increase of self-efficacy in the use of AI tools, for which it is essential to ensure that the design of technological systems is inclusive, ethical and transparent.

5.3 Future lines of research

In relation to the findings of this work, it is important to further explore the implications that cultural, educational and psychological factors may have on the perception of self-efficacy in the use of AI. The aforementioned, due to the aspects that characterize a culture, define the educational systems and constitute the experiences of people in society.

The development of longitudinal studies is necessary for the analysis of the evolution of the gaps in relation to the implementation of possible educational innovation strategies that could increase AI self-efficacy.

6. Conclusions

AI has motivated the development of business and academic innovations due to the particularities of today's complex, volatile, dynamic and uncertain society. In this sense, the development of professional AI competencies and innovation are fundamental in the professional practice of business degrees. This is because they are the professionals who, due to the nature of their functions, will make use of technologies, management of various types of intelligence and application of social skills for the success of the companies.

AI is a disruptive tool that can contribute to the performance of HEI students and generate improvements in their academic performance. In this sense, it is necessary to include in the implementation the opinions of students according to their sociodemographic characteristics, which should include AI self-efficacy capabilities. In this context, AI provides the mechanisms to facilitate its use and application in various fields of the different disciplines of knowledge.

Self-efficacy in the use of AI is essential to establish strategies that allow business students of HEIs in Chile to develop their technological skills and use AI in a safe, reliable and comfortable way. The aforementioned, both for university development and personal-group work, which is consistent with the different perceptions of the study group.

In relation to the object of this study, the design of teaching strategies that include the sociodemographic characteristics of university students is necessary due to the implications it has on AI self-efficacy. In this sense, the findings of this study can be used for the preparation of self-efficacy strategies, especially when considering business students from HEIs in Chile.

However, it is pertinent to develop spaces where students can use the AI tool that contribute to the normalization of its use. At the same time, it is necessary to provide mechanisms and resources that contribute to the installation of AI competencies. All of which is a product of the nature of the application of AI and the way in which students approach the subject of using the tool in their academic work.

Self-efficacy is presented as a tool for the design of educational strategies in business schools of HEIs in Chile. As AI technology and tools continue to advance it becomes essential to implement policies that enable all sectors of society to make efficient use of AI. Finally, with respect to the limitations of the study, it is necessary to expand the number of participants, design a sampling plan that includes the representativeness of the opinions and the diversification of analysis strategies for a better understanding of the study phenomenon.

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