




## Intersectional analysis of the barriers faced by university women accessing and using ai in the workplace



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### ABSTRACT

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The purpose of this study was to analyze the barriers faced by university women in accessing and using Artificial Intelligence (AI) in the workplace in Argentina, Chile, and Mexico from an intersectional perspective. We explored the complex interactions between gender, ethnicity, social class, and geographical location in shaping these barriers. The study's design and methodology followed an explanatory sequential mixed-methods approach. We collected data in the quantitative phase using an online survey on a sample of 812 university women working in three countries. In the qualitative phase, semi-structured interviews and focus groups were conducted with a subsample of participants. The findings revealed various barriers to accessing and using AI, such as lack of knowledge and skills, gender stereotypes, digital divides, and challenges in work-family balance. We also identified significant differences based on ethnicity and type of work. The qualitative analysis highlighted discrimination, lack of support, and mentoring, as well as the intersection of inequalities. The practical implications of this study underscore the importance of considering intersectionality when addressing the barriers faced by university women when interacting with AI. The findings have implications for the design of policies and programs that promote gender equity in AI and the workplace, taking into account the diversity of women's experiences.

**Contribution/ Originality:** This study uniquely explores the barriers faced by university women in accessing and using AI in the workplace from an intersectional perspective, considering the complex interactions between gender, ethnicity, social class, and geographical location in Argentina, Chile, and Mexico. The mixed-methods approach provides a comprehensive understanding of these barriers.

## 1. INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative and disruptive technologies of the 21st century, with a significant impact on various fields, including the workplace. Examining the barriers and challenges different population groups face in accessing and using AI, particularly from a gender perspective, becomes necessary as AI integrates into work practices and processes [1, 2].

In the Latin American context, the adoption of AI in the workplace has been gradual but growing, with countries such as Argentina, Chile, and Mexico at the forefront of this digital transformation [3, 4]. However,

despite the advances and opportunities offered by AI, gender gaps in access to and use of this technology remain a reality in the region [5, 6].

This study focuses on university women working in Argentina, Chile, and Mexico, exploring the barriers they face in accessing and using AI in their workplace from an intersectional perspective. These countries were chosen based on their leadership in the adoption of AI in the region, as well as the availability of data and the possibility of conducting a comparative analysis between different national contexts [7, 8].

Despite the growing interest and research on AI in the workplace, there is a scarcity of studies addressing the specific barriers and challenges faced by women, especially from an intersectional perspective that considers the interaction of multiple identities and inequalities [9, 10]. This study seeks to fill that knowledge gap by providing empirical evidence on the experiences and perceptions of university women working in relation to access to and use of AI.

Furthermore, this study's justification lies in its potential to inform policies and practices that promote gender equity in the field of AI and the workplace. This study, by identifying the specific barriers and challenges faced by women, can contribute to the development of strategies and programs that address these inequalities and foster the inclusion and empowerment of women in the AI era [11, 12].

#### Objectives and research questions

The main objective of this study is to analyze, from an intersectional perspective, the barriers faced by university women in accessing and using AI in the workplace in Argentina, Chile, and Mexico. The research questions guiding this study are as follows: (1) What are the main barriers faced by university women in accessing and using AI in their workplace? (2) How do different sociodemographic factors, such as ethnicity, social class, and geographic location, interact in shaping these barriers? (3) What strategies and recommendations can be derived from the results to promote gender equity in access to and use of AI in the workplace?

The theoretical framework of intersectionality, which acknowledges the interaction of multiple identities and inequalities in shaping people's experiences, and opportunities, forms the foundation of this study [13, 14]. From this perspective, the aim is to understand how gender intersects with other sociodemographic factors, such as ethnicity, social class, and geographic location, to shape the barriers faced by women in accessing and using AI in the workplace [15, 16].

Previous studies have highlighted gender disparities in access to and use of digital technologies, including AI. Studies conducted in different contexts have found that women face barriers such as lack of access to education and training in digital skills, gender stereotypes and biases in technology, and underrepresentation in AI-related fields [17-19].

In the Latin American context, research has pointed out the persistence of gender gaps in access to and use of digital technologies, including AI. For example, a study conducted by ECLAC [5] found that women in the region have less access to the internet and digital devices, and face barriers such as a lack of digital skills and gender discrimination in the technological workplace [5].

In addition, studies have highlighted the importance of considering intersectionality when examining the barriers faced by women in accessing and using technology. For example, research has found that women from ethnic minorities and lower social classes face greater challenges in accessing education and opportunities in AI-related fields [20, 21].

Regarding the specific barriers faced by women in accessing and using AI in the workplace, studies have identified factors such as the lack of female representation and role models in the AI field, discrimination and gender bias in hiring and promotion processes, and the gender pay gap in AI-related jobs [22-24].

Research has also highlighted the impact of gender stereotypes and biases on the development and use of AI in the workplace. For example, studies have found that AI algorithms used in recruitment and selection processes can perpetuate gender biases, discriminating against women [25, 26].

Furthermore, research has pointed out the importance of organizational policies and practices in promoting gender equity in access to and use of AI in the workplace. Studies have highlighted the need to implement diversity and inclusion policies, mentoring programs and support networks for women, and gender bias training for AI development teams [27, 28].

However, despite the growing attention to gender gaps in AI and the workplace, there is still a scarcity of studies addressing this issue from an intersectional perspective in the Latin American context. This study seeks to contribute to filling that knowledge gap by providing empirical evidence on the barriers faced by university women in accessing and using AI in their workplaces in Argentina, Chile, and Mexico.

This study's relevance lies in its ability to inform policies and practices that promote gender equity in the field of AI and the workplace in Latin America. By identifying the specific barriers faced by women and considering the intersectionality of their experiences, this study can contribute to the development of strategies and programs that address these inequalities and foster the inclusion and empowerment of women in the AI era.

Moreover, this study aligns with the United Nations Sustainable Development Goals (SDGs), particularly SDG 5, which seeks to achieve gender equality and empower all women and girls. By addressing the barriers faced by women in accessing and using AI in the workplace, this study contributes to global efforts to reduce gender gaps and promote equal opportunities in the digital age [29].

To achieve the proposed objectives, this study employed a mixed-methods sequential explanatory approach, combining quantitative and qualitative methods. An online survey collected data in the quantitative phase from a sample of 812 university women working in Argentina, Chile, and Mexico. In the qualitative phase, semi-structured interviews and focus groups were conducted with a subsample of the participants to delve into their experiences and perceptions.

The organization of this article is as follows: the introduction section presents the contextualization of the topic, the justification of the study, the objectives and research questions, the theoretical framework, and the background. Next, we described the employed methodology, which includes the research design, sample, instruments, and data analysis procedures. In the results section, the quantitative and qualitative findings are presented, organized according to the research objectives and questions. In the discussion and conclusion, we interpret the results based on the theoretical framework and background, discuss the practical and theoretical implications, and recommendations and future lines of research paths.

This study has important theoretical and practical contributions. At a theoretical level, this study expands the understanding of the barriers faced by women in accessing and using AI in the workplace from an intersectional perspective, providing empirical evidence from the Latin American context. Furthermore, this study contributes to the development of the theoretical framework of intersectionality, demonstrating its usefulness for examining gender inequalities in the field of AI and the workplace.

At a practical level, the results of this study can inform the development of policies and programs aimed at promoting gender equity in access to and use of AI in the workplace in Latin America. This study provide a solid foundation for the design of interventions and strategies that address these inequalities and foster women's inclusion and empowerment in the AI era by identifying the specific barriers, they face and considering the intersectionality of their experiences.

## 2. METHODOLOGY

The present study employed a mixed-methods approach, combining quantitative and qualitative methods, to obtain a comprehensive understanding of the barriers faced by university women in accessing and using Artificial Intelligence (AI) in the workplace. Data collection was carried out over a period of 6 months, from January to June 2023.

The quantitative component of the study was based on data collection through an online survey, which underwent a rigorous validation and reliability process. 7 experts in the fields of AI and gender performed content validation, resulting in an average content validity index (CVI) of 0.92, indicating excellent validity. We conducted a pilot test with 75 working university women, and calculated the Cronbach's alpha coefficient for the scales used, obtaining values between 0.85 and 0.93, indicating high reliability.

On the other hand, the qualitative component used semi-structured interviews and 8 focus groups, each consisting of 6-8 participants. The interviews had an average duration of 60 minutes, while the focus groups lasted approximately 90 minutes. We reached data saturation after conducting 25 interviews and 6 focus groups.

The mixed methodology allowed for addressing the intersections between different sociodemographic factors, such as gender, ethnicity, social class, and geographic location, as well as their influence on the barriers faced by university women in accessing and using AI in the workplace. Data on these variables were collected through the survey and explored in depth during the interviews and focus groups.

The research design was sequentially explanatory, starting with the quantitative phase and followed by the qualitative phase. The survey results influenced participant selection and the development of interview and discussion guides for the qualitative phase. Finally, an integration of the quantitative and qualitative data was carried out to obtain a more complete understanding of the barriers studied.

The study used a sequential, explanatory research design. In the first phase, we collected data from 812 working university women, selected through proportional stratified sampling. The sample was distributed as follows: 351 participants were from UNQ, 288 from ULS, and 173 from UM. We calculated the sample size with a 95% confidence level, a 3% margin of error, and an expected response rate of 75% (Table 1).

**Table 1.** Sample of female students who work by country.

University	Total women	Working university students	Sample of working university students
UNQ	13.250	3.975	351
ULS	3.825	1.148	288
UM	1.040	312	173
Total	18.115	5.435	812

The second phase involved conducting semi-structured interviews were conducted with 25 participants, and conducting 8 focus groups with a total of 56 participants. Purposive sampling, based on survey results, selected participants for the qualitative phase, aiming for diverse representation in terms of age, ethnicity, socioeconomic level, area of study, and type of work.

The research design also incorporated an intersectional approach, considering the interaction of different sociodemographic factors in the barriers faced by university women. Data were collected on variables such as age (mean = 22.5 years, SD = 3.2), ethnicity (45% white, 30% mestizo, 20% Afro-descendant, 5% indigenous), socioeconomic level (25% low, 60% medium, 15% high), area of study (40% STEM, 35% social sciences, 25% humanities), and type of work (55% full-time, 45% part-time).

We collected participant's responses through an online survey during the 8-week quantitative phase. We conducted the qualitative phase over 12-weeks, conducting interviews and focus groups concurrently until we reached data saturation.

In addition, a comprehensive literature review was conducted on the topic, consulting academic databases such as Scopus, Web of Science, and Google Scholar. We identified a total of 85 relevant articles and analyzed them to contextualize the study findings and compare them with previous research.

The online survey consisted of 45 questions, including 5-point Likert scales (from "strongly disagree" to "strongly agree"), multiple-choice questions, and open-ended questions. The survey addressed aspects such as the

level of knowledge and familiarity with AI, the frequency of use of AI-based tools at work, perceived barriers to accessing and effectively using AI, and perceptions of the impact of AI on job opportunities and professional development for women.

The survey was developed by a team of 3 expert researchers in the field of AI and gender and reviewed by 2 additional researchers to ensure its clarity and relevance. A pilot test was conducted with 75 working university women to assess the understanding of the items and response time. We hosted the final survey on the Survey Monkey platform and made it available for 8 weeks.

For the qualitative phase, semi-structured interview guides and discussion guides for focus groups were developed. The guides included 12 main questions and several follow-up questions, addressing topics such as personal experiences with the use of AI at work, barriers faced, strategies used to overcome these barriers, and perceptions of the impact of AI on gender equality in the workplace.

The interviews and focus groups were conducted by 2 researchers trained in qualitative research techniques who followed standardized protocols to ensure consistency and quality of the data collected. The sessions were audio and video recorded and subsequently transcribed verbatim using NVivo 12 software.

Additionally, we used qualitative data analysis tools like NVivo 12 and Atlas.ti 8, were used to facilitate coding, categorization, and thematic analysis of the interview and focus group transcripts. These tools allowed for organizing and systematizing the qualitative data, identifying patterns and emerging themes, and making comparisons between different groups of participants.

Quantitative data were analyzed using SPSS software version 26. We performed descriptive analyses, including means, standard deviations, frequencies, and percentages, to characterize the sample and gain an overview of the participants' perceptions and experiences. Normality tests (Kolmogorov-Smirnov and Shapiro-Wilk) were applied, and non-parametric tests were used due to the non-normal distribution of the data.

Mann-Whitney U tests were conducted to compare perceived barriers and the use of AI between different groups, such as age ( $\leq 25$  years vs.  $> 25$  years), ethnicity (white vs. non-white), socioeconomic level (low/medium vs. high), area of study (STEM vs. non-STEM), and type of work (full-time vs. part-time). We also performed Spearman's correlation analyses to examine the relationships between variables of interest, including the level of AI knowledge and the frequency of use of AI-based tools. A significance level of  $p < 0.05$  was considered.

We followed an inductive thematic coding process for the qualitative analysis. Two researchers independently coded 20% of the data (5 interviews and 2 focus groups) and discussed discrepancies until reaching a 90% agreement (kappa index = 0.85). Then, the rest of the data was coded. Five main themes and 15 sub-themes were identified, which were reviewed and refined by the research team. We conducted participant verification with 5 interviewees and 2 focus groups to confirm the interpretation of the findings, achieving 95% agreement.

The integration of quantitative and qualitative data was carried out through a concurrent triangulation strategy. We compared and contrasted the results from both phases to identify convergences and divergences. Visualization techniques, such as matrices and diagrams, were used to facilitate integration and presentation of the findings. The study's results section presented both quantitative and qualitative results in an integrated manner.

Finally, a global interpretation of the findings was performed, considering the theoretical and practical implications of the study. We discussed the strengths and limitations of the methodology, as well as possible directions for future research in the area of barriers faced by university women in accessing and using AI in the workplace.

### 3. RESULTS

The final sample of the study consisted of 812 working university women, selected through proportional stratified sampling from three universities: UNQ ( $n = 351, 43.2\%$ ), ULS ( $n = 288, 35.5\%$ ), and UM ( $n = 173, 21.3\%$ ). The mean age of the participants was 22.5 years ( $SD = 3.2, range = 18-35$ ).

Regarding ethnicity, 45% (n = 365) of the participants identified as white, 30% (n = 244) as mestizo, 20% (n = 162) as Afro-descendant, and 5% (n = 41) as indigenous. Chi-square analysis showed a significant association between ethnicity and university ( $\chi^2(6) = 24.56, p < 0.001$ ), with a higher proportion of white women in UNQ and a higher proportion of Afro-descendant and indigenous women in ULS and UM.

25% (n = 203) of the participants belonged to a low socioeconomic level, 60% (n = 487) to a medium level, and 15% (n = 122) to a high level. A significant relationship was found between socioeconomic level and area of study ( $\chi^2(4) = 18.32, p < 0.01$ ), with a higher proportion of women from high socioeconomic levels in STEM careers and a higher proportion of women from low socioeconomic levels in humanities.

Regarding the area of study, 40% (n = 325) of the participants were pursuing STEM careers, 35% (n = 284) social sciences, and 25% (n = 203) humanities. The type of work also varied, with 55% (n = 447) of the women working full-time and 45% (n = 365) part-time.

As shown in Table 2, the level of knowledge and familiarity with AI among the participants was moderate, with a mean of 3.2 (SD = 1.1) on a scale of 1 to 5. Significant differences were found according to the area of study ( $F(2, 809) = 28.45, p < 0.001, \eta^2 = 0.07$ ), with higher knowledge in women from STEM careers (M = 3.6, SD = 1.0) compared to those from social sciences (M = 3.1, SD = 1.1) and humanities (M = 2.8, SD = 1.1).

**Table 2.** Level of knowledge and familiarity with AI according to field of study.

Field of study	Mean	SD	95% CI
STEM	3.6	1.0	[3.5, 3.7]
Social sciences	3.1	1.1	[3.0, 3.2]
Humanities	2.8	1.1	[2.7, 2.9]

The frequency of using AI-based tools at work was also moderate, with a mean of 2.8 (SD = 1.2) on a scale of 1 to 5. Women who worked full-time reported a higher frequency of use (M = 3.1, SD = 1.2) compared to those who worked part-time (M = 2.5, SD = 1.1), with this difference being statistically significant ( $t(810) = 6.78, p < 0.001, d = 0.48$ ).

On a scale of 1 to 5, the perceived barriers to accessing and effectively using AI had a mean of 3.6 (SD = 0.9), indicating a relatively high perception of obstacles. Significant differences were found according to ethnicity ( $F(3, 808) = 5.21, p < 0.01, \eta^2 = 0.02$ ), with higher perceived barriers by Afro-descendant (M = 3.9, SD = 0.8) and indigenous (M = 3.8, SD = 0.9) women compared to white (M = 3.5, SD = 0.9) and mestizo (M = 3.6, SD = 0.9) women (Table 3).

**Table 3.** Perceived barriers to access and use of AI by ethnicity.

Ethnicity	Mean	SD
White	3.5	0.9
Mestizo	3.6	0.9
Afro-descendant	3.9	0.8
Indigenous	3.8	0.9

Perceptions about the impact of AI on job opportunities and professional development for women were mixed, with a mean of 3.1 (SD = 1.0) on a scale of 1 to 5. Sociodemographic variables did not show any significant differences ( $p > 0.05$ ). Spearman's correlation analysis revealed a positive and significant relationship between the level of AI knowledge and the frequency of use of AI-based tools ( $r_s = 0.45, p < 0.001$ ). A negative and significant relationship was also found between perceived barriers and the frequency of use of AI-based tools ( $r_s = -0.38, p < 0.001$ ). Table 4 shows, a multiple regression analysis was performed to predict the frequency of using AI-based tools based on the level of knowledge, perceived barriers, and sociodemographic variables. The model was significant ( $F(8, 803) = 32.56, p < 0.001$ ) and explained 24% of the variance (adjusted  $R^2 = 0.24$ ). The significant



predictor variables were the level of knowledge ( $\beta = 0.38$ ,  $p < 0.001$ ), perceived barriers ( $\beta = -0.25$ ,  $p < 0.001$ ), and type of work ( $\beta = 0.14$ ,  $p < 0.001$ ).

**Table 4.** Multiple regression analysis to predict the frequency of use of AI-based tools.

Predictor variable	B	SE B	$\beta$	t	p
Level of knowledge	0.42	0.04	0.38	10.82	<0.001
Perceived barriers	-0.35	0.05	-0.25	-7.29	<0.001
Type of work	0.37	0.08	0.14	4.48	<0.001

The interviews and focus groups thematic analysis identified five main themes related to the barriers faced by university women in accessing and using AI in the workplace: (a) gender stereotypes and biases in AI, (b) knowledge and skills gaps, (c) structural and organizational barriers, (d) challenges in work-family balance, and (e) intersectionality and additional barriers.

Within the theme "Gender stereotypes and biases in AI," participants highlighted the perception of AI as a masculine field ( $n = 20$ , 80%), the lack of female representation in AI development ( $n = 18$ , 72%), and gender biases in AI algorithms and systems ( $n = 15$ , 60%).

In the theme "Knowledge and skills gaps," women mentioned the lack of early exposure to AI and programming ( $n = 22$ , 88%), limited access to education and training in AI ( $n = 19$ , 76%), and difficulties in staying up to date in a constantly changing field ( $n = 17$ , 68%).

"Structural and organizational barriers" included the lack of support and mentoring in the workplace ( $n = 21$ , 84%), discrimination and unequal treatment in hiring and promotion processes ( $n = 18$ , 72%), and the masculine and non-inclusive organizational culture ( $n = 16$ , 64%).

Regarding "Challenges in Work-Family Balance," participants highlighted the double burden of paid and unpaid work ( $n = 23$ , 92%), the lack of work-family balance policies and practices in companies ( $n = 20$ , 80%), and the impact of family responsibilities on professional development ( $n = 19$ , 76%). Finally, in the theme "Intersectionality and additional barriers," women mentioned experiences of multiple discrimination based on ethnicity, social class, and other factors ( $n = 14$ , 56%), linguistic and cultural barriers for women from minority groups ( $n = 12$ , 48%), and the lack of support networks and social capital for women from disadvantaged backgrounds ( $n = 10$ , 40%).

**Table 5.** Themes and subthemes identified in the thematic analysis.

Theme	Sub theme	n	%
Gender stereotypes and biases in AI	Perception of AI as a masculine field	20	80%
	Lack of female representation in AI development	18	72%
	Gender biases in AI algorithms and systems	15	60%
Knowledge and skill gaps	Lack of early exposure to AI and programming	22	88%
	Limited access to AI education and training	19	76%
	Difficulties in staying updated in a constantly changing field	17	68%
Structural and organizational barriers	Lack of support and mentoring in the workplace	21	84%
	Discrimination and unequal treatment in hiring and promotion processes	18	72%
	Masculine and non-inclusive organizational culture	16	64%
Challenges in work-family balance	Double burden of paid and unpaid work	23	92%
	Lack of work-family balance policies and practices in companies	20	80%
	Impact of family responsibilities on professional development	19	76%
Intersectionality and additional barriers	Experiences of multiple discrimination based on ethnicity, social class, and other factors	14	56%
	Linguistic and cultural barriers for women from minority groups	12	48%
	Lack of support networks and social capital for women from disadvantaged backgrounds	10	40%

The integration of quantitative and qualitative results allowed for a more comprehensive understanding of the barriers faced by university women in accessing and using AI in the workplace. Quantitative data provided an overview of participants' perceptions and experiences, while qualitative data delved into the specific experiences and challenges faced.

Quantitative and qualitative results converged in several aspects. For example, the differences found in perceived barriers according to ethnicity in the quantitative analyses were reflected in the themes and sub-themes identified in the qualitative analysis, such as gender stereotypes and biases in AI, and the additional barriers faced by women from minority groups.

Furthermore, the negative relationship between perceived barriers and the frequency of use of AI-based tools found in the correlation analyses aligned with the challenges and obstacles identified in the qualitative themes, such as knowledge and skills gaps, and structural and organizational barriers.

Table 6 presents, in summary that the results of this mixed-methods study provide empirical evidence on the diverse barriers faced by university women in accessing and using AI in the workplace, highlighting the importance of considering the intersectionality of factors such as gender, ethnicity, social class, and others in shaping these barriers. These findings have implications for the developing policies and programs that promote gender equity in the field of AI.

Table 6. Summary of the main quantitative and qualitative results.

Quantitative results	Qualitative results
<ul style="list-style-type: none"> <li>Significant differences in the level of knowledge of AI according to the field of study</li> </ul>	<ul style="list-style-type: none"> <li>Identification of five main themes related to barriers: gender stereotypes and biases, knowledge and skill gaps, structural and organizational barriers, challenges in work-family balance, and intersectionality and additional barriers</li> </ul>
<ul style="list-style-type: none"> <li>Higher frequency of use of AI-based tools in women working full-time</li> </ul>	<ul style="list-style-type: none"> <li>In-depth exploration of the specific experiences and challenges faced by female university students in accessing and using AI in the workplace</li> </ul>
<ul style="list-style-type: none"> <li>Significant differences in perceived barriers according to ethnicity, with higher barriers in Afro-descendant and indigenous women</li> </ul>	<ul style="list-style-type: none"> <li>Convergence with quantitative results regarding differences in perceived barriers according to ethnicity and the negative relationship between barriers and frequency of use of AI-based tools</li> </ul>
<ul style="list-style-type: none"> <li>Positive and significant relationship between the level of knowledge of AI and the frequency of use of AI-based tools</li> </ul>	<ul style="list-style-type: none"> <li>Identification of specific subthemes within each main theme, providing a more detailed understanding of the barriers and challenges faced by female university students in the field of AI</li> </ul>
<ul style="list-style-type: none"> <li>Negative and significant relationship between perceived barriers and the frequency of use of AI-based tools</li> </ul>	<ul style="list-style-type: none"> <li>Emergence of intersectionality as a key factor in shaping the experiences and barriers of female university students in accessing and using AI in the workplace</li> </ul>

Table 5 presents a summary of the main quantitative and qualitative results of the study, aiming to highlight the most relevant findings and show the integration of both methodological approaches.

Regarding the quantitative results, the table highlights the significant differences found in the level of AI knowledge according to the area of study, the higher frequency of use of AI-based tools in women working full-time, and the significant differences in perceived barriers according to ethnicity, with higher barriers in Afro-descendant and indigenous women. Additionally, the table mentions the relationships between the level of AI knowledge, perceived barriers, and the frequency of use of AI-based tools.



On the other hand, the qualitative results presented in the table include the identification of five main themes related to the barriers faced by university women in accessing and using AI in the workplace, as well as the in-depth exploration of the specific experiences and challenges faced by these women. The table also highlights the convergence between quantitative and qualitative results regarding differences in perceived barriers according to ethnicity and the negative relationship between barriers and the frequency of use of AI-based tools. Furthermore, the table mentions specific sub-themes within each main theme, offering a more detailed understanding of the barriers and challenges. Lastly, the emergence of intersectionality as a key factor in shaping the experiences and barriers of university women in the field of AI is highlighted.

#### 4. DISCUSSION AND CONCLUSION

The results of this mixed-methods study explored the barriers faced by university women in accessing and using Artificial Intelligence (AI) in the workplace from an intersectional perspective. The findings highlight the complex interaction of individual, social, and structural factors that shape these barriers and emphasize the importance of considering intersectionality when addressing gender equity in the field of AI.

One of the main findings of this study is that the area of the study has a significant influence on university women's level of knowledge and familiarity with AI. Participants in STEM careers showed higher knowledge compared to those in the social sciences and humanities. These results are consistent with previous research that has identified a gender gap in education and skills related to AI [30, 31]. This gap can be attributed to factors such as the lack of early exposure to AI and programming, as well as gender stereotypes and biases that discourage women from pursuing careers in technological fields [32].

Furthermore, the type of work found significant differences in the frequency of use of AI based tools, with full-time working women adopting them more frequently than part-time workers. These findings suggest that access to and exposure to AI in the workplace can be influenced by the nature and conditions of employment [33]. Women working part-time may face greater challenges in acquiring AI skills and experience due to time and resource constraints.

A key aspect of this study examined the perceived barriers to accessing and effectively using AI from an intersectional perspective. The results revealed significant differences according to ethnicity, with higher perceived barriers among Afro-descendant and indigenous women compared to white and mestizo women. These findings highlight the importance of considering the intersection of multiple identities and inequalities when addressing barriers in the field of AI [9, 34]. Women from minority ethnic groups may face additional challenges due to discrimination, stereotypes, and gaps in access to educational opportunities and resources [35, 36].

Correlation analysis revealed a positive and significant relationship between the level of AI knowledge and the frequency of use of AI-based tools, as well as a negative relationship between perceived barriers and the frequency of use. These results suggest that knowledge and familiarity with AI can promote its adoption, while perceived barriers can hinder its effective use. Previous studies have supported these relationships by highlighting the importance of education and training in AI to foster its adoption and overcome barriers [36, 37].

The thematic analysis of the qualitative data provided a deeper understanding of the specific experiences and challenges faced by university women in accessing and using AI in the workplace. The theme of gender stereotypes and biases in AI was prominent, with participants highlighting the perception of AI as a masculine field and the lack of female representation in its development. These findings coincide with previous research that has identified gender stereotypes and biases as significant barriers for women in technological fields [38, 39].

Knowledge and skills gaps also emerged as a key theme, with participants mentioning the lack of early exposure to AI and programming, limited access to education and training, and difficulties in staying up-to-date in a constantly changing field. These findings highlight the need to address gender gaps in AI education and training by providing accessible and inclusive opportunities for women to acquire the necessary skills [40, 41].

The participants also identified structural and organizational barriers, such as the lack of support and mentoring in the workplace, discrimination and unequal treatment in hiring and promotion processes, and the masculine and non-inclusive organizational culture. These findings are consistent with previous studies that have highlighted the systemic barriers faced by women in male-dominated fields, including AI [42-44].

Challenges in work-family balance emerged as another important theme, with participants highlighting the double burden of paid and unpaid work, the lack of work-family balance policies and practices in companies, and the impact of family responsibilities on professional development. These findings coincide with previous research that has identified work-life balance challenges as a significant barrier for women in technological fields [45, 46].

The theme of intersectionality and the additional barriers faced by women from minority groups and disadvantaged backgrounds were highlighted by the participants. Experiences of multiple forms of discrimination, linguistic and cultural barriers, and the lack of support networks and social capital were mentioned as additional challenges. These findings highlight the importance of adopting an intersectional approach when addressing barriers in the field of AI, recognizing the diversity of women's experiences and inequalities [47, 48].

The integration of quantitative and qualitative results allowed for a more comprehensive understanding of the barriers faced by university women in accessing and using AI in the workplace. Quantitative data provided an overview of participants' perceptions and experiences, while qualitative data delved into the specific experiences and challenges faced. Previous studies on gender equity in technological fields have highlighted this integration of methods as a strength [49, 50].

The results of this study have important implications for higher education, organizations, and public policies. At the higher education level, it is critical to promote the participation and retention of women in AI-related careers by addressing gender gaps in education and providing training and mentoring opportunities [51, 52]. Universities can play a key role in reducing gender stereotypes and biases, fostering an inclusive environment, and providing diverse role models [53, 54].

At the organizational level, it is essential for companies to adopt policies and practices that promote gender equity and address the structural and cultural barriers faced by women in the field of AI [55, 56]. This may include implementing mentoring programs and support networks, promoting diversity and inclusion in hiring and promotion processes, and adopting flexible work-family balance policies [57, 58].

At the public policy level, it is necessary to develop strategies and programs that address the intersectional barriers faced by women in accessing and using AI. This may include initiatives to promote AI education and training for women from diverse backgrounds and communities, as well as policies that address socioeconomic inequalities and digital divides [59, 60]. Furthermore, it is crucial to foster collaboration between government, industry, and academia to address the challenges of gender equity in the field of AI in a comprehensive manner [61, 62].

One limitation of this study is that it focused on university women from three specific universities, which may limit the generalization of the results to other contexts. Future research could expand the scope of the study, including a more diverse sample of women from different regions and types of institutions. Furthermore, it would be beneficial to conduct longitudinal studies to examine how the barriers and experiences of women in the field of AI change over time and in response to specific interventions and policies.

Another direction for future research is to explore in greater depth the intersections between gender and other identities and inequalities, such as race, ethnicity, sexual orientation, disability, and social class. Understanding how these identities and inequalities intersect and shape women's experiences in the field of AI is essential for developing more inclusive and equitable approaches [63, 64].

Moreover, it would be valuable to examine the impact of the barriers and challenges identified in this study on women's long-term professional outcomes and trajectories in the field of AI. Future research could explore how

these barriers influence the retention, advancement, and success of women in AI-related roles, as well as their well-being and job satisfaction [65, 66].

It would also be fascinating to conduct comparative studies between different countries and cultural contexts to identify similarities and differences in the barriers faced by women in the field of AI. This could provide valuable insights into strategies and best practices for addressing gender equity in different environments and systems [67, 68].

In conclusion, this mixed-methods study provides empirical evidence on the intersectional barriers faced by university women in accessing and using AI in the workplace. The results highlight the importance of considering the interaction of multiple individual, social, and structural factors when addressing gender equity in the field of AI. It is crucial for educational institutions, organizations, and policymakers to adopt comprehensive and evidence-based approaches to promote inclusion and equal opportunities for women in this rapidly evolving field.

The study's findings have significant implications for advancing gender equity in AI and building a more inclusive and diverse future in this field. We can fully utilize this transformative technology and distribute its benefits equitably in society by addressing the identified barriers and promoting women's participation and leadership in AI. This study provides a solid foundation for future research and actions that drive change towards a more inclusive and equitable AI.

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**Transparency:** The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.

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