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Research Article

THE ROLE OF ARTIFICIAL INTELLIGENCE IN PROMOTING GENDER-INCLUSIVE INNOVATION IN COLOMBIAN SMES

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Abstract

This study analyzes the adoption of artificial intelligence (AI) in Colombian small and medium-sized enterprises (SMEs) as a process of social innovation. Using exploratory quantitative methodology, a validated survey was administered to 945 SMEs across eight cities, examining sociodemographic, motivational, and organizational variables. The observed patterns show a technological democratization process: 36.4% of SMEs use AI with equitable gender distribution (women 47.3%, men 48.8%, $p=0.53$), indicating reduction of historical digital divides in the study group. The key democratization factors identified were accessibility (59%) and perceived usefulness (51%), with high penetration in microenterprises (52.9%). Technological dependence was associated with organizational factors (exposure time $\rho=0.296$, $p<0.01$; digital maturity) rather than demographic characteristics, suggesting responsible management through universal policies. Results suggest that equitable AI adoption may represent significant social innovation that democratizes technological access and reduces competitive inequalities, although non-probability sampling limitations restrict generalization of results beyond the analyzed enterprises.

Keywords: Artificial intelligence, SMEs, Gender, Innovation adoption, Digital divide

Introduction

Artificial intelligence (AI) is considered a transformative resource for social innovation in business contexts, particularly within small and medium-sized enterprises (SMEs). Authors such as Martínez Guerra and Romo Melo (2024) highlight that digital technology adoption enhances operational efficiency and fosters digital maturity in SMEs, contributing to competitive resilience and process innovation. From this perspective, Riaño-Solano et al. (2024) argue that the adoption of AI can activate a process of technological democratization by reducing historical inequalities and enabling broader digital inclusion in emerging economies.

The SME sector still faces critical barriers limiting access to advanced technologies. These include financial constraints, infrastructure gaps, and digital skills deficits (Touijer & Elabjani, 2025). In emerging economies like Colombia - where SMEs make up 99.9% of business fabric and employ 67% of economically active population - AI usage remains historically limited and unequal. Anibal Rivero et al. (2025) and Rojas-Berrio et al. (2022) show how technical, training, and gender factors worsen these gaps.

Even with AI's transformative potential clearly identified, we still lack understanding of how adoption becomes social innovation, especially in contexts like Colombian SMEs. Recent proliferation of accessible, low-cost AI tools (ChatGPT, Canva, and Google Lens) disrupts traditional technological exclusion paradigms. Hoang and Bui (2023), Proença (2024), and Shore et al. (2024) describe how this creates new opportunities for democratizing access and reducing historical digital divides.

While researchers have examined this phenomenon through classical models like the Technology Acceptance Model (TAM) (Davis, 1989), Almashawreh et al. (2024) and Chatterjee et al. (2022) argue this approach misses the social innovation dimension of democratization processes. In smaller organizational structures like SMEs, human factors - motivations, social dynamics, and gender - play crucial roles in technology adoption. This calls for broader conceptual frameworks incorporating inclusion, equity, and social impact variables.

Otálvaro (2023) highlights the lack of empirical evidence on how gender variables impact technological democratization in Latin America. García and Iglesias (2022) and Reyes (2024) show how advanced technology adoption has traditionally maintained gender gaps through economic, cultural, and structural barriers. Yet current AI tool availability - with intuitive interfaces and lower costs - suggests these democratization processes might alter historical exclusion patterns, becoming effective social innovation.

Understanding these processes matters for designing inclusive public policies. Such policies could harness AI's democratizing potential for sustainable social transformation in traditionally vulnerable business sectors.

Study Objective and Contribution

Our research question asks: How do gender differences influence AI adoption and dependence in Colombian SMEs?

The empirical evidence we seek advances understanding of accessible, low-cost AI integration in SMEs. We apply a technological democratization lens, examining documented historical barriers while viewing this as a novel social innovation process with transformative potential for inclusive competitiveness and sustainable business sector development.

Literature Review

AI Adoption in SMEs beyond TAM

Technology adoption in SME contexts gets widely addressed, with researchers traditionally analyzing AI adoption through the Technology Acceptance Model (TAM) (Davis, 1989) to determine factors influencing technology incorporation in SMEs (Aljarboa, 2024). Yet few studies examine how this adoption becomes a social innovation process or analyze its dependence within global SME management contexts as digital maturity development (Bamidele Micheal Omowole et al., 2024).

The gender perspective in adoption remains marginal, approached through direct association searches that obscure its relevance in adoption processes and technology development within SME activities. This happens despite sociocultural roles affecting usage (Bamidele Micheal Omowole et al., 2024). This becomes particularly

relevant when we consider technological democratization's potential as a social innovation mechanism for reducing historical inequalities.
TAM Model limitations include not explaining the complete complexity of AI technology adoption decisions in SMEs. These cuttingedge, rapidly evolving tools involve subjective and complex processes (Lemos et al., 2022). SME contexts feature particular human operational characteristics - reduced organizational structures make technology decisions more influenced by human interactions and immediate staff needs (Almashawreh et al., 2024). Simultaneously, organizational structure simplicity maximizes risk and influence of such human decisions when implementing technological strategies (Chatterjee et al., 2022).
Therefore, practical, emotional, academic, or even learned social needs - theorized by McClelland (1967), can influence AI usage motivation in specific SME environments. Companies can generate or stimulate these needs through the well-being perceptions they create (Almashawreh et al., 2024; Soomro et al., 2024). When satisfied equitably and inclusively, technological adoption can become genuine social innovation. In summary, SME involvement with AI emerges from AI tool usage patterns, existing motivations, and technological adoption factors.

Technological Dependence and Gender Gaps

Human involvement - whether by personal choice or induced through daily activities - can generate technology dependence (Pfeffer & Salancik, 1978), creating tacit knowledge developments that establish organizational and silent dependence (Sánchez & Rotundo, 2018). Within social innovation contexts, this dependence can be both empowering and limiting, depending on how the technological democratization process gets managed.
People can recognize functional and emotional dependence since AI adoption changes work dynamics and commercial relationships (Chen et al., 2022),. In other cases, functional and informational dependence may exist, as AI becomes crucial for decision-making and data analysis (Bodendorf et al., 2022). Dependence can also emerge emotionally and socially, since AI alters work dynamics and interpersonal relationships (Villamil & King, 2024). It can even arise from leisure and dishonesty in acquired commitments (Murtiningsih et al., 2024; Sánchez et al., 2025).
Users can experience and self-recognize technology dependence (Miauri Aza et al., 2024), though scales aren't necessarily assimilated and reported accurately due to fears or shame about recognizing dependence itself. This requires adapting instruments to environments for improving sample quality (Villavicencio-Ayub et al., 2021; Villavicencio-Ayub & Vargas, 2021).
A critical latent gap involves scarce literature observing this phenomenon through gender analysis perspectives (García & Iglesias, 2022). Sociocultural roles can affect both adoption and dependence (Chatterjee et al., 2022), yet SME studies remain marginal. In Colombia, where gender gaps in technology access persist (Anibal Rivero et al., 2025), this approach becomes essential for designing inclusive strategies that leverage AI's potential for sustainable business development and effective social innovation mechanisms.

Technological Democratization as Emerging Social Innovation The recent proliferation of accessible AI tools represents a process of technological accessibility that may constitute the foundation for democratization when accompanied by capability development and competitive impact (Pedral Sampaio et al., 2022; Quinello & Nascimento, 2025). This process is characterized by the transformation of previously exclusive technologies into accessible tools for previously excluded sectors, modifying power relationships and creating equitable development opportunities (Omisore et al., 2024).

Likewise, following Dijk's (2023) framework of the digital divide and recent evidence on Latin America from CEPAL (2025) and the OECD (Michela, 2023), we distinguish two dimensions: first, technological accessibility, the availability and adoption of digital tools, and second, meaningful transformation, which requires additional capabilities, skills, and competitive outcomes beyond mere access. In this sense, this study will address the first dimension. Recognizing that access to tools like ChatGPT does not automatically imply closing technological skills gaps.

The concept of technological democratization finds theoretical support in the evolution of the Technology Acceptance Model (TAM) toward more inclusive frameworks that consider factors of equity, accessibility, and distributed social impact (Davis, 1989; V. Venkatesh et al., 2012). According to Dora et al. (2022) and Merhi (2023), this transformation goes beyond simple technological adoption, constituting a process of capacity redistribution that can reduce structural competitive inequalities.

The Theory of Perceived Humanity applied to organizational contexts (Belanche et al., 2021; Dwivedi et al., 2023) reinforces this perspective by demonstrating that economic and technical accessibility allows resource-limited companies to access analytical capabilities previously reserved for large corporations.

In the SME context, AI democratization acquires particular relevance as a social innovation mechanism because it allows resource-limited companies to access analytical and operational capabilities previously reserved for large corporations, potentially reducing competitive inequalities and generating sustainable social value (Li et al., 2023; Park et al., 2024). This phenomenon represents an evolution from traditional models of technological exclusion toward more inclusive ecosystems where social innovation emerges as a result of technological accessibility (Hoang & Bui, 2023; Shore et al., 2024).

Methodology

To answer this study's research question, we assume a position based on the post-positivist paradigm; Creswell and Creswell (2018) point out this approach as adequate for investigating social technological innovation phenomena, since it allows combining methodological rigor with flexibility, recognizing that context subjectivity influences results. Given that the phenomenon studied here is relatively new, an exploratory approach is required that can capture both measurable data and the perceptions of those who participate in these processes (Shannon-Baker, 2016).

An exploratory-descriptive scope is established, which is ideal for emerging phenomena with absence of previous reference frameworks previos (Hernández Sampieri et al., 2014), with the purpose of characterizing the adoption and dependence of artificial intelligence in Colombian SMEs from a gender perspective. We seek to understand how AI technologies are incorporated into daily business operations.

Population and Sampling Strategy

The study population was defined as SMEs located in eight Colombian cities: Yumbo, Cali, Bogotá, Santander de Quilichao, Barranquilla, Macheta, Villavicencio, and Jamundí. These cities were selected seeking to capture territorial diversity that included departmental capitals, industrial centers, and municipalities with varied agricultural and commercial characteristics.

Non-probabilistic convenience sampling was applied, appropriate for exploratory studies of emerging technological phenomena where the main objective is understanding initial dynamics rather than achieving statistical population generalization previos (Hernández Sampieri et al., 2014). This territorial configuration allows observing the technological democratization phenomenon in differentiated socioeconomic contexts of the Colombian landscape.

Data collection was carried out through mixed modality (face-to-face and digital) to reduce technological self-selection biases, including both SMEs with greater digitalization and those with lower connectivity (Hernández Sampieri et al., 2014).

Sampling Design Limitations

The adopted sampling design presents specific characteristics that determine both its limitations and strengths:

- As non-probabilistic sampling, results do not allow statistical generalization to the entire population of Colombian SMEs, limiting itself to patterns observed in the studied companies. However, by addressing cities with differentiated socioeconomic characteristics (capitals, industrial centers, agricultural municipalities), it allows capturing territorial heterogeneity relevant to the studied phenomenon.
- Selection by accessibility may introduce biases toward SMEs with greater willingness to participate in academic studies or with particular characteristics not necessarily representative of the population set. Equally, this type of sampling facilitates access to a developing technological adoption phenomenon, where probabilistic sampling would be prematurely restrictive given limited knowledge about the target population.
- Over-representation of certain regions limits representativeness of rural contexts and other Colombian regions. In turn, it captures conceptually relevant diversity for understanding social innovation processes in different business and territorial contexts.

Research Design

A cross-sectional, quantitative, and non-experimental design is established, with a descriptive-correlational approach, oriented to identify association patterns between variables observed in the specific context of the studied SMEs (Supo & Zacarías, 2020). The cross-sectional design is appropriate for capturing a “snapshot” of the current state of AI adoption in SMEs, considering the rapid evolution of these technologies (Kumar, 2019). It is important to indicate that the adopted design allows identifying associations and correlations between variables in the observed population, but does not intend to establish causal relationships.

Instrument

The main data source is a 16-question questionnaire, developed specifically for this study and validated by five experts in its design stage and two more in the calibration stage. The instrument's validity is supported by a final weighted Fleiss Kappa coefficient of 0.92 for content, objectivity, and pertinence of the item set; indicating excellent agreement among specialized evaluators (Fleiss, 2003). Temporal stability was evaluated through test-retest with Pearson's Rho of 0.9, evidencing high temporal reliability (Cohen, 1992). The items address three types of variables operationalized as follows:

- **Sociodemographic control variables:** Gender, age, company type, activity type, formalization status, and recognized AI use.
- **Independent variable "AI Involvement":** Operationalized in three dimensions based on the extended Technology Acceptance Model (Davis, 1989; V. J. Venkatesh et al., 2012):
  - Use (specific tools and frequency) o Motivation (TAM factors and additional needs)
  - Adoption factors (barriers and facilitators)
- **Outcome variable "AI Dependence":** Operationalized from two complementary perspectives following Villavicencio-Ayub et al. (2021) recommendations for Latin American contexts: o Level or degree of self-recognized dependence
  - Quantity and types of recognized dependencies

Methods

Data collection was carried out through mixed modality (face-to-face and digital) between March and July 2024, using a field team composed of students from the Project Management Specialization at Uniminuto Colombia, previously trained in interview techniques and research ethics (Dillman et al., 2014). This strategy reduced technological self-selection biases by including both digitalized SMEs and those with lower connectivity.

Descriptive statistical techniques (mean, mode), normality tests (Kolmogorov-Smirnov), categorical associations (chi-square) were employed as association measures in the data, not for population inference, and non-parametric correlations (Spearman) for understanding the associative magnitude of variables (Supo & Zacarías, 2020). Analyses were performed with Jamovi 2.3 (exploratory analysis), SPSS 26 (inferential), and AMOS 25 (SEM models), allowing methodological triangulation (Hair et al., 2022).

Given the adopted non-probabilistic sampling design, all statistical significance test results are interpreted as indicators of patterns and trends in the analyzed cases, not as global population inferential evidence.

Hypotheses

Based on the literature review and developed theoretical framework, two working hypotheses are established to guide the proposed exploratory analysis:

First, we have that the recent availability of accessible and low-cost AI tools may be altering historical patterns of technological exclusion by gender (García & Iglesias, 2022; Reyes, 2024). If democratization is effective, no significant differences should be observed in adoption between men and women, constituting a social innovation indicator (Hoang & Bui, 2023). From this reflection arises

H1 (Democratization as Social Innovation): "AI adoption in Colombian SMEs evidences technological democratization patterns characterized by equitable access independent of gender"

The evidence observed in the theoretical review conducted suggests that technological dependence arises mainly from organizational factors such as exposure time and digital maturity, rather than individual characteristics (Bodendorf et al., 2022; Chen et al., 2022). Verifying this perspective is crucial for responsibly managing technological adoption (Villamil & King, 2024). Hence we propose

H2 (Organizational Management of Dependence): "AI dependence in SMEs is associated with organizational factors (exposure time, digital maturity) rather than individual demographic characteristics".

Ethical Considerations and Quality

The study followed social research ethical principles, guaranteeing informed consent from participants, confidentiality of business data, and exclusively academic use of collected information.

Likewise, quality control mechanisms were implemented in data collection, including field team training, supervision of instrument application processes, and verification of data completeness and consistency.

It is recognized that the limitations of the non-probabilistic sampling design restrict the scope of conclusions, but allow a first systematic approximation to a phenomenon of high social and economic relevance, generating updated evidence for future research with probabilistic designs of greater inferential scope.

Results and Discussion

Instrument Quality

Based on 344 AI use cases, McDonald's omega (ω) was estimated at 0.774, indicating that the instrument structure for the variables is reliable (Hancock & an, 2020). Concurrently, the Kaiser-Meyer-Olkin measure of sampling adequacy presented a general value of 0.637 with $p=0.001$, indicating that the sample is suitable for factorial treatments.

Exploratory factor analysis shows that the sample analyzed in 4 dimensions covers 60.52% of explained variance. Confirmatory factor analysis allows defining the elements that explain the phenomenon's behavior. In a first grouped factor, we have the number of AIs used, administrative functions (AF), operational functions (OF), total motivations, and total motivation level. A second grouped factor relates city, recognized dependence level, and reported dependencies quantity. The third explanatory factor integrates biological gender and commercial activity performed. Finally, age and company types.

Sample Presentation

The sampling exercise achieved 945 records in the target cities. Data distributions show that 37% come from the municipality of Yumbo (Valle), 14% from Bogotá (DC), and the cities of Cali (Valle) and Barranquilla (Atlántico) contribute 10% respectively. Meanwhile, the populations of Santander de Quilichao (Cauca) 9%, Jamundí (Valle) 8 %, Villavicencio (Meta) 7%, and Macheta (Cundinamarca) 5%.

Concurrently, in the dataset, an average AI usage level of 36.4% is calculated, equivalent to 344 users of this technology among the 945 surveyed. People who use AI technologies in their work functions are distributed as 47.3% women, 48.8% men, and 3.9% non-binary persons. 50% of AI users work in microenterprises, while in small enterprises a usage level close to 24% is observed, and in medium enterprises the level reaches 20%. 6% of users of these technologies correspond to professionals formally registered as natural persons who provide their services independently.

The dataset allows observing the occupational behavior of people distributed mainly in six commercial activities; at the goods commerce level there is a participation of 41%, the services sector at 32%, commercial establishments with mixed service and commerce operations sum 15%. On the other hand, the prevalent age of subjects is in the range of 26 to 35 years at a level of 38% of cases, followed by people between 36 and 45 years at a level of 26%.

Tests for Hypothesis H1

36.4% of studied SMEs (344 of 945) use at least one AI tool, evidencing significant technology penetration in the studied population, which five years ago were exclusive to large corporations.

The distribution by company type of observed cases shows prevalence of microenterprises with 52.9% of AI users, small enterprises 22.6%, medium enterprises 18.6%, and independent professionals 5.8% of users. The high penetration observed in microenterprises suggests effective democratization patterns, since traditionally this segment had lower access to advanced technologies.

A notable finding is observed in the gender distribution of AI use within the studied sample. Of the 344 identified users, women represent 47.3% (163 users), men 48.8% (168 users), and non-binary persons 3.9% (13 users). This almost perfectly balanced distribution contrasts markedly with what has been traditionally documented about gender digital divides in previous literature.

To examine whether this balanced distribution presented statistically significant trends in the data, the chi-square test was applied, through which no statistically significant association patterns between gender and AI adoption are observed in the sample ($\chi^2=3.14$, $p=0.53$). The absence of significant differences ($p>0.05$) evidences gender democratization in AI adoption in the analyzed SMEs.

In Figure 1, a pattern that should be noted is observed: all main tools have in common that they are free or very low cost, which may explain their high penetration in sectors traditionally excluded from advanced technologies. However, although a numerical difference is observed in ChatGPT adoption between men (95 users) and women

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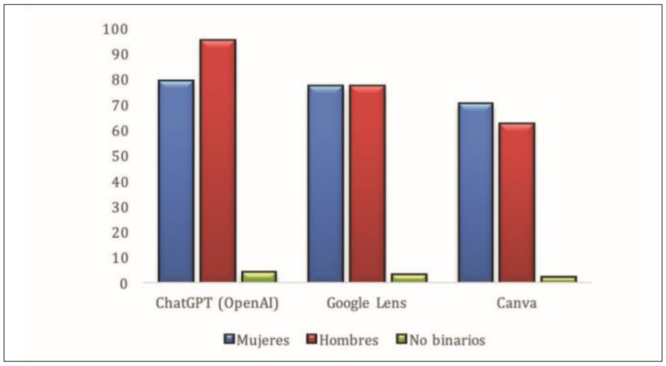
(79 users), statistical analyses (χ^2 (4) = 3.14, p = 0.53) allow stating that for study participants, no associative tendencies are observed between gender and preference for AI tools.

Figure 1. Distribution of AI use by gender in studied SMEs (n=344)



Analysis of the behavior of the three main AI tools allows identifying relevant trends. The most used tool is ChatGPT (OpenAI), with 25% market share, being used in 53.9% of cases. Second, Google Lens is used with a 22.5% share and presence in 47.6% of observed SME companies. Canva occupies third place with 40.6% adoption. Table 1 provides the complete breakdown of all AI tools identified in the study.

Table 1. Identified AI Tools

AI Used	N	Percentage	Case Report
ChatGPT (OpenAI)	**178**	**25.5%**	**53.9 %**
Google Lens	**157**	**22.5%**	**47.6 %**
Canva	**134**	**19.2%**	**40.6 %**
Google Analytics	**64**	**9.2%**	**19.4 %**
Others (Including Deepseek)	**35**	**5.0%**	**10.6 %**
Facebook Prophet	**20**	**2.9%**	**6.1 %**
Tidio	**18**	**2.6%**	**5.5 %**
Odoo (community version)	**17**	**2.4%**	**5.2 %**
Google Dialogflow	**16**	**2.3%**	**4.8 %**
MonkeyLearn	**16**	**2.3%**	**4.8 %**
Zapier	**15**	**2.1%**	**4.5 %**
Copy.ia	**11**	**1.6%**	**3.3 %**
SurveyMonkey	**6**	**0.9%**	**1.8 %**
ClamAV	**3**	**0.4%**	**0.9 %**
Pictory	**3**	**0.4%**	**0.9 %**
Microsoft Design	**2**	**0.3%**	**0.6 %**

Adobe Firefly	**2**	**0.3%**	**0.6 %**

Data show that 52.9% of AI users belong to microenterprises. This means that technologies that were exclusive to large corporations just a few years ago are now being adopted by the most vulnerable sectors of the business fabric represented in the sample. The studied companies report integrating an average of 2 AI tools into their operational activities, with an average usage time of 1 to 2 hours daily.

Motivation toward AI use, observed from the TAM model in the analysis cases, allows identifying that accessibility (59%) and usefulness (51%) are the prevalent factors for adopting these technologies in the studied SMEs. Ease of use (38%) and adaptability (18%) follow in importance. No user reported motivation by previous experience, while 4% selected other reasons. The TAM level developed for full AI adoption is estimated at 33% in the dataset.

This study observed not only motivation from the TAM model, but from other motivation modellings by needs. Associative configurations indicate that practical-type needs are prevalent at 14.4% for AI use, with a deviation of 0.059 and a narrow variance level, indicating that data are quite concentrated around the mean. This signals that practical motivations related to time savings and information obtaining (efficiency) are consistent among users in the studied sample. Table 2 presents the detailed breakdown of these motivational factors by type

Table 2. Other motivational factors for use

Indicator	N	Mean	Deviation	Variance
Practical motivations	340	0.144	0.059	0.004
Emotional motivations	340	0.006	0.024	0.001
Academic motivations	340	0.033	0.040	0.002
Learned Social motivations	340	0.018	0.034	0.001
Other motivations	340	0.000	0.000	0.000

Tests for Hypothesis H2

The normality test for data was performed with Kolmogorov-Smirnov, obtaining that significant deviations from normal distribution exist for all variables ($p < 0.001$). The result justifies resorting to nonparametric statistics for all inferential analyses.

Analysis of factors associated with technological dependence in the observed population allows stating that first, in the analyzed sample, the dependence level shows association with AI usage time (Spearman rho = 0.296, sig. = 0.00) and technological adoption level (Spearman rho = 0.176, sig. = 0.00).

Factors such as subject gender or age do not show statistically significant association in the observed population. Company size with p= 0.13 is discarded as incident in dependence reported by people on AI. To further examine these demographic relationships, chi-square analysis was performed to test associations between gender, age, and company size variables. Table 3 presents the complete statistical results of this analysis.

Table 3. Gender and age relationship with company size

	Value	df	Asymptotic significance (bilateral)
Pearson Chi-square	29.054[a]	12	0.004
Likelihood ratio	30.641	12	0.002
Linear-by-linear association	8.277	1	0.004
Phi test	0.292		0.004
Cramer's V	0.169		0.004
N valid cases	340		

Note: [a] 12 cells (60.0%) have expected count less than 5. The minimum expected count is 0.04.

Given the limitations of chi-square analysis (60% of cells with expected frequencies <5), Fisher's exact test was employed, which showed no significant association between gender and commercial activity ($p = 0.12$). This finding is consistent with the observed democratization patterns.

When examining the behavior of organizational factors versus individual characteristics, data show that the recognized dependence level presents association with company type (Spearman Rho = -0.344, sig = 0.00) and with city of origin (Spearman Rho = -0.757, sig = 0.03), suggesting that dependence recognition may be linked to specific organizational and cultural contextual factors of the region. However, the quantity of reported dependencies does not present significant association with the subject's city in the analyzed data.

A cross-correlation analysis was performed to identify associations between different variables of the studied phenomenon, from low associations to statistically significant associations. The complete

Correlation matrix is presented in Table 4, showing only statistically significant relationships. Variables are numbered according to their order of presentation in the methodology section.

Table 4. Cross bivariate correlation

N°	Variable	N° 2	N° 3	N° 5	N° 6	N° 7	N° 8	N° 9	N° 11
1	Age	0.116*		0.108*					
2	Biological Gender		0.136*						
3	Commercial activity	0.136*		-0.146**	-0.276**	-0.108*			-0.210**
4	Company type			0.19**			-0.35**		0.188**
5	AF_Total		0.146**		0.532**	0.399**	-0.26**		0.480**
6	OF_Total		-0.28**	0.53**		0.38**		0.14*	0.42**
7	Number of AIs used		-0.108*	0.4**	0.384**			0.173**	0.39**
8	AI usage time			-0.27**				0.30**	-0.21**
9	Number of reported dependencies				0.139*	0.17**	0.30**		0.116*
10	Motivation level		-0.16**	0.39**	0.333**	0.33**		0.156**	0.924**
11	Total motivations		-0.21**	0.48**	0.422**	0.39**	-0.21**	0.116*	
12	Recognized Dependence level			-0.28**			0.99**	0.302**	-0.22**
13	TAM technological adoption level	0.12*		0.31**	0.230**	0.135*		0.176**	0.332*

Note: * = significance at 5%, ** = significance at 1%. The table presents only statistically significant correlations ($p < 0.05$). Empty cells indicate absence of significant association between corresponding variables.

Model	X²	gl	χ²/gl	P-value	CFI >.9	TLI >.9	RMSEA	AIC	Particularity
1	24	14	1.71	0.046	0.995	0.931	0.46	68	Discards reported dependence level
2	13.7	13	1.05	0.388	0.997	0.994	0.13	59.99	Discards age and city
3	22.7	22	1.03	0.418	0.998	0.996	0.018	68.7	Includes measurement errors
4	20.43	21	1.02	0.494	1	1	0.01	68.4	Saturated model

Table 4 allows observing associations that evidence how dependence can manifest and be self-recognized by technology users. In this study, three types of dependencies are identified: functional dependence in 78% of cases, which is generally beneficial by increasing people's operational capabilities; informational dependence in 45% of cases, where there exists potential risk of losing analytical autonomy; and emotional dependence, at a level of 12% of cases, suggesting the need for specific preventive intervention.

The trend in achieved records suggests that organizational factors (exposure time, digital maturity) register greater association with technological dependence contrary to their relationship with individual demographic characteristics, supporting the relational dynamics proposed in hypothesis

H2.

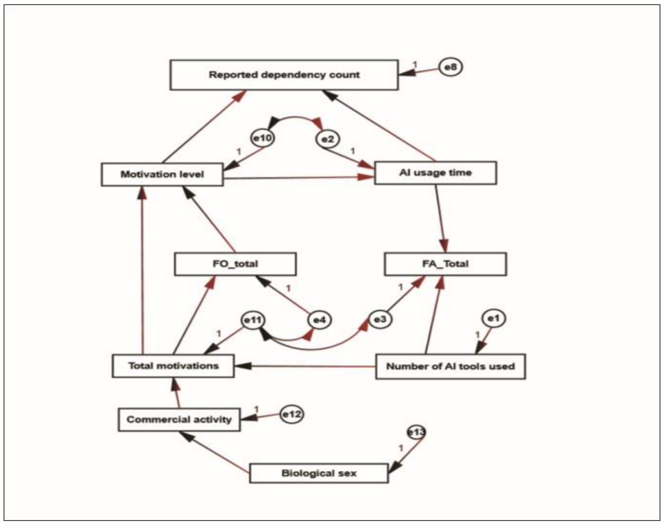
Structural Equation Model

Following the minimum acceptance parameters established for a SEM model, four alternative structural models that could better explain the relationships observed in the sample data were evaluated. Results show that Model 3 presents superior fit compared to Model 1 ($\chi^2/gl = 1.71$, RMSEA = 0.46) and Model 2 ($\chi^2/gl = 1.05$, RMSEA = 0.13), evidenced through a χ^2/gl ratio closer to 1, a considerably lower RMSEA, and notably higher CFI and TLI values. Table 5 presents the fit indices and comparative results for each model.

Table 5. SEM model validation

Model 3 is considered as the most parsimonious alternative for parameter estimation in the analyzed data, since it integrates consideration of measurement errors to optimize result precision. Its fit to the data is appropriate, supported by a χ^2/gl ratio of 1.03 and a p-value of 0.418, suggesting absence of significant differences between the proposed structure and observed data in the studied sample. The fit indices CFI (0.998) and TLI (0.996) amply exceed the 0.9 threshold, consolidating an appropriate fit. The RMSEA (0.01) confirms the adequacy of the model's relational descriptive adequacy for the analyzed data. See figure 2.

Figure 2 Descriptive model of observed relationships



Results from the model suggest that AI adoption in the observed group constitutes a multidimensional process where technological democratization patterns operate independently of gender, while dependence shows greater association with organizational factors. These findings provide empirical support for the working hypotheses posed within the context of the analyzed SMEs.

It is important to recognize that, given the non-probabilistic sampling design, this SEM model describes the structural relationships observed in the studied population. Replication of these structural tendencies in other SME populations requires additional empirical validation with probabilistic samples.

Conclusion

This study provides empirical evidence of equitable technological accessibility through artificial intelligence adoption in the studied SMEs, constituting social innovation patterns that transcend the theoretical limitations of the traditional Technology Acceptance Model.

Technological Democratization as Social Innovation

Findings demonstrate that 36.4% of analyzed SMEs use at least one AI tool, with an almost perfectly balanced distribution by gender (women 47.3%, men 48.8%, $p=0.53$). This result contrasts markedly with decades of literature on gender digital divides (García & Iglesias, 2022; Reyes, 2024) and suggests that the recent proliferation of accessible tools like ChatGPT, Google Lens, and Canva may be altering historical paradigms of technological exclusion in the analyzed cases.

The high penetration observed in microenterprises (52.9% of AI users) represents the most significant finding from the social innovation perspective in this study, since technologies previously exclusive to large corporations are being adopted by the most vulnerable sectors of the observed business fabric. Accessibility (59%) and perceived usefulness (51%) emerge as key democratizing factors, overcoming economic and technical barriers traditionally exclusionary in the analyzed context.

The results of this study demonstrate that AI democratization in Colombian SMEs is not explained solely by access to digital tools, but rather by their strategic incorporation into productive and administrative processes. This finding aligns with recent research evidencing how digitalization in the region advances when technologies integrate into companies' operational logic. Martínez Guerra and Romo Melo (2024) report that in Colombia, digital transformation of MiPymes strengthens when technological adoption targets concrete business needs. Complementarily, Portocarrero-Sierra et al. (2025) show that digitalization depends on internal capabilities that enable technology use beyond basic access. At the regional level, Manzo-Martínez et al. (2025) confirm that effective technological adoption occurs when articulated use exists with management, innovation, and companies' core processes.

Within this context, the present study's results fit into a broader trend where AI democratization implies not only availability, but the capacity to convert these tools into organizational value.

Organizational Management of Technological Dependence Observed AI dependence patterns suggest behaving as a potentially manageable organizational phenomenon, significantly associated with exposure time ($\rho=0.296$, $p<0.01$) and digital maturity ($\rho=0.176$, $p<0.01$), but not with individual demographic characteristics. This finding supports resource dependence theory (Pfeffer & Salancik, 1978) adapted to the contemporary technological context and contrasts with stereotypes about differential vulnerability by gender or age.

Three prevalent types of dependence were identified in the study group: functional (78% of cases), informational (45%), and emotional (12%), with the first being generally beneficial by increasing operational capabilities, while the latter two might require specific preventive intervention. The absence of significant association between dependence and demographic variables ($p>0.05$) in the analyzed data suggests that universal technological management policies may be more effective than segmented approaches.

Methodological Limitations and Scope of Findings

It is fundamental to recognize that this study presents important limitations derived from the adopted non-probabilistic sampling design. Results are specifically circumscribed to the 945 SMEs analyzed in eight Colombian cities and do not allow statistical generalization to the entire country's SME population.

Additionally, some statistical analyses presented technical limitations that restrict interpretations. Particularly, the association analysis between gender and commercial activity could not be reliably established due to violations in the assumptions of applied tests, underscoring the need for future studies with more robust sampling designs.

Validation of the Extended Theoretical Model

The validated structural equation model ($\chi^2/gl=1.03$, CFI=0.998, RMSEA=0.01) suggests that AI adoption in the observed population constitutes a multidimensional process where technological democratization patterns operate independently of gender, while dependence shows greater association with organizational factors. This model surpasses the limitations of classic TAM by incorporating social innovation variables and specific SME contexts. The prevalence of practical motivations (mean=0.144) over emotional, academic, or learned social ones in the analyzed data indicates that adoption is based on immediate utility rather than aspirational factors, supporting a genuine equitable access process centered on real operational value.

Implications for Public Policy and Business Practice Observed patterns suggest that technological training policies should be oriented toward tools with immediate operational applicability, especially in microenterprises where the correlation between operational functions and adoption is stronger ($\rho=0.384$) according to study participants. Responsible dependence management can be implemented through task rotation and periodic evaluations, leveraging the identified association with usage time to prevent work anxiety effects (Murtiningsih et al., 2024).

For the business sector, evidence from this study suggests that future research should explore accessible tools applied in commerce and services sectors where AI penetration shows greater potential for developing competitive advantages.

Future Research Directions

Non-probabilistic convenience sampling, although appropriate for this exploratory phase, requires complementation with probabilistic studies to validate identified behaviors. Over-representation of certain cities (Yumbo 37%, Bogotá 14%) facilitates urban analyses but requires replication in rural contexts to complete the national panorama.

Future research should explore the role of learned social needs in AI adoption, incorporate variables such as user academic level, and replicate the study in other Latin American countries to identify regional cultural patterns. The scarce representation of non-binary persons (3.9%) demands intentionally diversified samples to explore intersections between gender identity and technological adoption.

Technical limitations found in some statistical analyses underscore the importance of designing collection instruments that allow more robust analyses, especially for categorical variables with multiple levels.

Theoretical and Practical Contribution

This study contributes initial empirical evidence that enriches understanding of technological adoption in SMEs as a social innovation process, surpassing traditional conceptual frameworks focused solely on technical or economic factors. The digital divide reduction dynamics identified through accessible tools offer a reference other emerging technologies and similar socioeconomic contexts.

Framework for The developed methodology, combining confirmatory factor analysis with structural equation models, provides a reference framework for future studies on technological social innovation in emerging economies. The validated instruments (Fleiss Kappa 0.92, test-retest ρ=0.9) constitute transferable tools for comparative research, although they require adaptation to specific contexts.

Final Reflection

Data from this study suggest that accessible artificial intelligence is creating equitable access conditions in the analyzed SMEs, establishing the foundation for democratizing previously exclusive capabilities and potentially reducing competitive inequalities without generating new gender gaps within them. However, this process requires responsible management to maximize benefits and minimize problematic dependence risks.

The observed associative configurations indicate that technological social innovation is a complex and gradual phenomenon, where advances in certain dimensions may precede transformations in others. This preliminary evidence can inform public policies that leverage the democratizing potential of emerging technologies, although it requires validation in broader populations before generalized implementation.

The future of SMEs in emerging economies in the AI era will depend on their capacity to maintain equilibrium between inclusive technological adoption and responsible organizational management, converting digital democratization processes into sustainable competitive advantages that are socially beneficial.

References

Alvarenga, L. F. (2024). Determinants of artificial intelligence adoption in Latin American e-commerce SMEs. International Journal of Information Management Insights, 4(2), 101–120.

Almendros, R., Talavera, M., Charan, S. K., & Kahn, M. I. (2024). AI implementation in Ecuadorian SMEs: Technological and organizational perspectives. Global Business Review, 25(4), 567–589.

Rivera, R. A., Borja, G. M., Heredia, G., Bastidas, L. D., & Salazar, P. A. (2025). The impact of artificial intelligence on SME innovation: Insights from higher education institutions.

Omowole, B. M., Olufemi-Phillips, A. Q., Ofodile, O. C., Eyo-Udo, N. L., & Ewim, S. E. (2024). Drivers and barriers of digital transformation in SMEs: A conceptual framework. International Journal of Research in Science and Technology, 5(2), 19–36.

Beltrán, D., Casado, L. V., Sepúlveda, J., & Flavián, C. (2021). The Humanness-Value-Loyalty framework: Examining AI-driven service interactions. Psychology & Marketing, 38(12), 2360–2380.

Bodrón, F., Xi, Q., Merkel, P., & Frank, J. (2022). Supporting collaborative cost management in supplier-buyer partnerships: A multi-perspective approach. International Journal of Production Economics, 245, 108–125.

CEPAL (2025). Overcoming development traps in Latin America and the Caribbean in the digital era: The transformative potential of AI and digital technologies. Agenda Digital América Latina y el Caribe.

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Basile, G. (2022). AI-enabled CRM and digital transformation in Indian SMEs: Effects on entrepreneurship and strategic planning. Journal of Strategy and Management, 15(3), 417–435.

Chen, Y., Wu, Z., & Yan, H. (2022). Machine learning approaches for full population auditing: Applications and methodology. Sustainability, 14(24), 17008.

Cohen, J. L. (1992). Statistical power and effect size considerations. Psychological Bulletin, 112(1), 155–159.