Financial Inclusion of Vulnerable Sectors with a Gender Perspective: Risk Analysis Model with Artificial Intelligence Based on Complex Thinking

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Abstract

The objective is to present a proposal for a gender-sensitive risk analysis model using artificial intelligence (AI) within the framework of complex thinking, specifically for impoverished and vulnerable women. This international non-parametric study analyzed business and entrepreneurial activity in a sample of 2,787 women. The methodological design included data analysis, the postulation of a proposed model, and a validation method for the credit risk analysis model. There is a correlation between the level of schooling of impoverished and vulnerable women with the possibility of self-employment and selling a product or service. In the framework of complex thinking, the perception of innovative thinking is related to the level of education and innovative decision-making in professional projects. Women with a higher level of schooling tend to think about their professional projects systematically. Promoting complex thinking involves innovative educational practices to encourage critical, systemic, scientific, and innovative thinking in entrepreneurship and sustainable development. Integrating reasoning for complexity benefits women and contributes to economic and social growth in vulnerable regions. In contrast to other models, our credit risk analysis model uses AI and variables for gender, vulnerability, and complex thinking to detect patterns in women's behaviors and attitudes in the venture start-up process.

Keywords- Financial inclusion, vulnerability, women's entrepreneurship, model, artificial intelligence, complex thinking, educational innovation, higher education.

Introduction

Impoverished and vulnerable women who run microenterprises are underfinanced and excluded by formal financial institutions because they are considered to have zero capacity to save, run low-growth businesses, and lack the funds necessary to repay a loan. Most of the time, these women are in households where their members have inefficient savings strategies and lack accurate information about the products and services of formal financial institutions and how to access them (Lusardi, 2019; Zhang and Xiong, 2019; Lyons et al., 2020; Yang et al., 2022). Also, there is no supply of these products and services targeted to their circumstances and needs (Alberro et al., 2016; Cuesta-Gonzalez et al., 2021; Danquah et al., 2021; Ambarkhane et al., 2022). The products and services of conventional financial institutions have been designed for a population with a credit history, steady economic income, contingent family backup, and financial education, among others; that is, a population that can be granted credit with a low risk of default (Lotto, 2018; Shihadeh, 2018; Dar and Ahmed, 2020; Amari and Anis, 2021; Rahman et al., 2022). Since 2015, some actors with a much less traditional perspective than banking institutions have been redefining how to determine the creditworthiness of millions of underfinanced people using artificial intelligence (AI) with new algorithms capable of discovering behavioral patterns correlated with financial liability (Dheundje et al., 2020; Rodriguez, 2022; Zhou et al., 2022). So, a risk analysis model that uses AI and complexly connects the circumstances and needs of these women has the potential to offer a pathway to their financial inclusion.

Low-income people do not necessarily have higher credit risks than the banked population because they can transform the three basic types of available resources (physical capital, human capital, and social capital) into assets to improve their quality of life. Currently, AI and machine learning-based technologies have designed new ways to do credit scoring from customer characteristics (the complete profile of the borrower's current income level, employment opportunities, and potential ability to repay the loan) (Kumar et al., 2021; Kumar et al., 2021b); also, there are non-traditional combinations of various models and algorithms to design better options for credit scoring (Papouskova and Hajek, 2019; Xu et al., 2020; Liu et al., 2022). New models have improved the statistical performance of credit rating models, some incorporating alternative data sources such as calls made from cell phones, mobile device fingerprints, e-commerce, social networks, email, psychometric variables, and the integration of public and mobile geospatial data from satellites;

that is, non-financial variables (De Cnudde et al., 2019; Óskarsdóttir et al., 2019; Berg et al., 2020; Njuguna and Sowon, 2021; Simumba et al., 2022). The new credit risk models are based on alternative non-financial data, which allows millions of underfinanced people from poor and vulnerable segments of the population to access products and services from formal financial institutions to meet their needs.

This article proposes a comprehensive solution to promote access and permanence in the entrepreneurial ecosystem for women who run micro businesses and are in a situation of poverty and vulnerability in Mexico. The solution contemplates their financial inclusion for the granting of credit and the impact of a training model based on complex thinking in entrepreneurial competencies. Below, we address the strategy for their financial inclusion. We propose a gender-sensitive risk analysis model, specifically targeting impoverished and vulnerable women, using AI within the framework of complex thinking to achieve the financial inclusion of an under-financed population segment through formal financial institutions. Our proposal differs from others because the specialized literature on the subject (Kumar et al., 2021b; Akter et al., 2021) points to the need for new variables that integrate gender, poverty and vulnerability, and entrepreneurship to create specific products and services but do not contemplate complex thinking; although some models use AI and consider the clients' contextual complexity, they do not include the framework of complex thinking.

Literature review

Vulnerable women in the framework of complex thinking

The members of poor and vulnerable households have always engaged in financial activities but not through formal financial institutions; instead, they use non-formal mechanisms to meet their economic needs. Some of the monetary savings and credit mechanisms of low-income households are tandas or pyramids, savings banks, cash savings in their homes, speculation, the purchase of material goods for animal husbandry or vehicles, and loans from borrowers with very high interest rates; however, these strategies present a risk to people's assets (Carswell et al., 2021; Malik et al., 2021; Reboul et al., 2021; Cull et al., 2022). Households with a greater scarcity of economic resources more frequently resort to non-monetary flow through reciprocity relationships to pay and accumulate debts, the most common being food production and care for children, the elderly, or the sick (Islam and Alam, 2018; Griffiths, 2019; Ma et al., 2020). Women in emerging countries play an essential role in these households; they bear much responsibility for diversifying savings and credit mechanisms in informal financial institutions and making decisions regarding non-cash economic flows to safeguard their family's welfare.

Another strategy women use to contribute to the family income is to start a micro business despite their challenges, difficulties, and disadvantages compared to men in entrepreneurial ventures. Women play a crucial role in entrepreneurship development, economic growth, and poverty alleviation (Agarwal et al., 2020; Sallah and Caesar, 2020; Nguyen et al., 2021; Nguyen, 2022; Sallah and Caesar, 2022). In Latin America, women running a micro business are 27% less likely than men to receive a bank loan, and most establish their businesses with capital provided by their spouses (Dini and Stumpo, 2020). Ecuador is one of the most entrepreneurial countries in Latin America, leading the region's rate of female entrepreneurship by necessity (Delgado et al., 2020). In Mexico, 99.5% of the ventures run by women entrepreneurs in Mexico are micro businesses, of which 78.4% are informal; 83.9% of the employed personnel are women, and only 13 out of every 100 establishments obtained credit (INEGI, 2019). In the country, 29.1 million women live in poverty, and 47.7% are economically active (CONEVAL, 2021). Mexican women decide to undertake ventures to support family needs. They state that they earn less money being salaried workers, resort to external sources of financing before risking their own, and most of the time, they do not have a plan but are motivated by expectations or beliefs about the cost-benefits they can obtain (Pérez-Paredes et al., 2021). Statistics show that in Latin America, most women entrepreneurs in Mexico run small-scale, primarily informal businesses. Women-led businesses generally hire women, and the number of women obtaining credit is few.

However, these are only some factors to be considered in a complex analysis of women's poverty and vulnerability when they decide to start or sustain their businesses. The complex thinking framework contemplates expanding the capacity for higher-order skills, such as critical, systemic, scientific, and innovative thinking (Baena-Rojas et al., 2022; Ramírez-Montoya et al., 2022; Vázquez-Parra et al., 2022), that lead to more entrepreneurship (Cruz-Sandoval et al., 2022) and positively impact sustainable development (Sanabria-Z et a., 2022). Some authors have systematized empirical evidence in emerging countries to generate maps of the complex relationships and magnitudes of the main dimensions affecting the development of women-led entrepreneurship: work-life balance, entrepreneurial learning, role models, competencies, support from non-profit organizations, social identity, family, culture, friends, entrepreneurial experience, education and training, government support, and support from financial institutions. These must be considered with multiple factors such as determination, independence, market knowledge, opportunity identification, risk, networks, entrepreneurial resilience, freedom, ability to provide employment, recognition, ability to learn from experiences, personal growth, innovation, experiential learning, digital skills, social skills, and financial skills (Agarwal et al., 2021; Agarwal et al., 2022; Rahman et al., 2022; Rastogi et al., 2022). In addition, a complex thinking approach must also incorporate the particular context of these women and, in this sense, explore other variables such as asymmetrical power relations, exclusion, oppression, and subordination that complicate equal access to entrepreneurship; also, the quality of life and violence they suffer within their homes and communities due to their gender (Huis et al., 2020; Mahato and Vardhan, 2021; Hillesland et al., 2022; Navarro-Mantas et al., 2022). Poor and vulnerable women entrepreneurs are trapped in a vicious cycle: they cannot obtain the formal credit they need because their businesses have low growth due to a lack of the necessary funds.

Financial inclusion of female entrepreneurs

In countries like Mexico, financial inclusivity is low, and low-income people are most affected. Households with lower incomes are more exposed to losing their savings for developing their productive activities, so they require services from formal financial institutions and public policies to implement financial education programs (Woodruff, 2006; McKenzie and Woodruff, 2014; Osei-Mensah et al., 2018). Several studies have been conducted evidencing the inability of the formal financial sector to serve this segment of the population globally (Matin et al., 2002; UN Women, 2016; Shahe-Emran et al., 2021; Bashir and Danlami, 2022). Traditional financial institutions typically exclude women in vulnerable situations (with low income and schooling level) for credit granting because they lack such a specialized service, coupled with scoring based mainly on their credit history and economic solvency (Xiao et al., 2016; Mukid et al., 2018; Xiao et al., 2020; Gopinath et al., 2021). A credit designed for the poor and vulnerable population, specifically for women running a business, could cushion their risk of losing their savings. If the design incorporates financial education and other features that address their needs and suit their financial behavior, it increases the economic impact on their households.

Most poor and vulnerable people distrust formal financial institutions and, at the same time, are unaware of the products and services they offer and their risks and advantages. The use of formal credit has a positive impact on households in poverty (income-poor households as defined by the welfare line, multidimensional and extremely multidimensional poor) because it increases household purchasing power and improves aspects related to housing, education, and food (Annim, 2018; Cintina, 2019; Islam and Pakrashi, 2020; Mora-Rivera et al., 2020). The problem is that little is known about the needs of poor households and how they make their decisions (Banerjee et al., 2018; Banerjee and Duflo, 2020; Buera et al., 2020; Sinha and Piedra, 2021). Thus, the financial inclusion of women in poverty depends on the creation of specialized services, which in turn requires properly refined information based on an adequate segmentation of the population (Jaafar and Alwazni, 2019; Datta and Sahu, 2021; Sahu et al., 2021; Okesina, 2022). The provision of financial services impacts the status of complex conditions in the heterogeneous context of poverty, and formal financial services enable and help to overcome women's deprivation and disadvantages (CIESAS and UIA, 2006; Alberro et al., 2016; Malik et al., 2021; Pal and Gupta, 2022).

One way to contribute to women's financial inclusion is through innovation in financial institution services. Using AI in credit risk analysis can reduce and mitigate gender bias by incorporating appropriate data governance. Traditional credit scoring systems lack gender perspective, but new models bring the benefits of algorithmic fairness to mitigate bias (Andreeva and Matuszyk, 2019; Corrales-Barquero et al., 2021; Mishra et al., 2021; Aristei and Gallo, 2022; Perez, 2022). When using AI, it is essential to consider the most relevant ethical references or guidelines for developing algorithms and models and have an internal committee expert in ethical principles to ensure that the development, deployment, and use of AI do not affect users' fundamental rights and their underlying values. An ethics implementation plan should specify all future steps to ensure documentation of the work performed, transparent procedures, and auditable data access. An ethics compliance architecture must be built into the development infrastructure with feasible organizational structures and procedures for the technology. The evolving socio-technical environment must be monitored in case any adaptations need to be made in the AI systems (UNESCO, 2020; European Commission, 2021; Hauer, 2022; Hentzen, 2022). Discussions of gender biases in AI credit risk analysis for the poor and vulnerable population are very recent. More research is needed focusing on the role of ethics in AI in specialized financial services contexts for women entrepreneurs.

Credit risk analysis models with artificial intelligence

The problem formal financial institutions face is determining the creditworthiness of people with low incomes. However, they are often unaware that this population resorts to informal financial institutions to acquire services that have interest rates that exceed the average of the formal market, such as pawnshops that operate irregularly and charge more than 250% annual interest on pawned objects and only offer 40% of the value of the pledge (Medina-Vidal, 2018; Mpofu and Sibindi, 2022; Shihadeh, 2022). Generally, low-income people make intensive use of tandas, demonstrating their ability to save (Nguyen and Canh, 2021); then, formal financial institutions could create savings instruments that allow these people to contribute fixed and regular installments during short and medium terms. Credit scoring models seek to identify the risk or non-risk outcome from a dependent variable against an indeterminate set of socioeconomic variables that constitute the independent variables. There are several general models (parametric, non-parametric, and semi-parametric) (Rodríguez-Guevara et al., 2017). Conventional decision-making models must be updated with applicant data, while new models work from another logic.

Machine learning (ML) is an AI technique that teaches computers to learn from experience. Its algorithms use computational methods to learn information directly from data without relying on a predetermined equation as a model. During the last few years, machine learning techniques have been widely used in credit risk analysis. Assef and Steiner (2020) identified in the specialized literature approximately 93 techniques based on machine learning that outperformed 36 different techniques using statistics. They identified that most authors specifically favored techniques employing Artificial Neural Networks (ANN) and support vector machines (SVM). Authors who favored machine learning methods used rule-based algorithms, particularly Decision Trees (DT) and k-Nearest Neighbors (KNN). The most common boosting techniques were Bagging and AdaBoost (Chornous and Nikolskyi, 2018; Ala'raj et al., 2022; Jutasompakorn et al., 2022). The main advantage of these models is that the algorithms adaptively improve their performance as the number of samples available for learning increases. Still, it is vital to correctly validate the model, not only in terms of precision or accuracy but also in terms of possible biases that would lead to increased inequalities or discrimination.

Regarding selecting features that can improve the predictor models' performance, some techniques can facilitate the visualization and understanding of the estimated parameters and avoid overfitting problems. Some of the approaches recommended in the literature are Feature Ranking, which serves to establish a ranking of the features based on information gain independent of the classifier algorithm, and Wrapper Subset Eval, to select a subset of features that results in better evaluation performance, depending on the classifier algorithm (Fenerich et al., 2020). Notably, some features may be irrelevant and generate poor classification results and higher complexity, so selecting and removing them is necessary. Tripathi et al. (2021) used the BAT binary optimization technique with a new fitness function. Arora and Kaur (2020) considered the Bolasso-enabled Random Forest (BS-RF) algorithm more effective, and Fejza et al. (2022) concluded that the Balanced Random Forest (BRF) method is suitable for clients in developing countries, where there is usually more informality in the economy. Other alternative models combine the socio-demographic aspects of customer characteristics using data from mobile network operators, data stored in cell phones, e-commerce data, social network data, and others, depending on customer segmentation. This fact constitutes an open issue for integration into a comprehensive model to gain more knowledge and hidden insights that transactional data does not necessarily reflect.

Research Methodology

This research uses a non-parametric method analyzing a secondary source of information from an international study in Mexico since 2001 (its most recent edition was in 2019) to demonstrate the importance of developing a risk analysis model that uses artificial intelligence and considers complex thinking for the financial inclusion of impoverished and vulnerable Mexican women running a micro business. The research questions were:

R1. How do women's poverty, vulnerability, and the possibility of self-employment and product or service sales relate to their level of schooling and the decisions they make or do not make?

R2. How do women's poverty and vulnerability and the possibility of self-employment and product or service sales relate to their level of schooling and innovative thinking?

Although the concepts of micro business, self-employment, or entrepreneurial activity could be conceived as distinct, this article treats them as interchangeable elements that speak of categories that represent entrepreneurship. This perspective is broader and more heterogeneous, especially considering the call for "entrepreneurial diversity," which allows focusing on the insights relevant to the phenomenon of entrepreneurship (Welter et al., 2017).

The Global Entrepreneurship Monitor (GEM) is one of the broadest and most comprehensive research on the phenomenon of entrepreneurship (Thebaud, 2015) and provides detailed information on the motivations and attitudes of entrepreneurial activity in several economies, including Mexico (GEM, 2022). This database has been widely used in research on business and entrepreneurial activity.

To show the situation of women in poverty regarding factors that may affect their financial inclusion, we analyzed data from the GEM 2019 study corresponding to the Adult Population Survey (APS) sample for 2019. Women with an average annual family income of fewer than 42,000 pesos (approximately $2,000 USD) were selected from the total sample. This sample comprised an economically active population between 16 and 24 years old (GEM, 2022). Although this study does not explicitly measure the construct of financial inclusion, it is very relevant to observe attitudes, behaviors, and actions around creating enterprises or micro businesses.

Sample description: 2,787 women from APS Mexico, and 671 were classified with lower 33% (income below 42,000 pesos per year). Some data varied based on responses not provided by participants. Table 1 describes the variables selected in this analysis.

Insert Table 1 about here

Results and Discussion

Analysis of the context, activity, and perceptions of women regarding microbusinesses and entrepreneurial activity

Table 2 shows the variables corresponding to the socioeconomic environment of women living in poverty in Mexico. It is worth noting that some women were below the extreme poverty line regarding annual family income. Most of them also had an educational level below secondary or primary school.

Insert Table 2 about here

As for the analysis of differences per educational level, Figure 1 describes the perception of the women in the sample regarding their ability to start a business.

Insert Figure 1 about here

Differences were found in the proportion of educational level achieved that influences the perception of one's capacity to start a business among women in poverty in the sample analyzed (X2 = 36.465, $p < 0.05$). Proportionally, women with a higher educational level considered that they had a greater capacity.

On the other hand, Figure 2 shows the perception of planned long-term decisions, giving indications of a basic conception of systemic thinking.

Insert Figure 2 about here

Differences were also found in the proportion of educational level achieved that influences the perception that each decision is part of a long-term professional plan among women in poverty in the sample analyzed (X2 = 79.358, $p < 0.05$). Proportionally, women with a higher educational level considered that each decision they made was part of a long-term professional plan.

Finally, Figure 3 presents an approach to innovative thinking, together with what the women in the selected sample perceive that others see in them.

Insert Figure 3 about here

Regarding the analysis of the educational level achieved that influences the perception that other people think that the respondent is highly innovative among impoverished women in the analyzed sample (X2 = 47.588, $p < 0.05$), women with a higher educational level felt, to a greater degree, that other people thought they were innovative.

Proposal of a risk analysis model based on complex thinking and artificial intelligence

Based on the analyses, we propose a model that considers the variables of gender, financial inclusion, AI, and complex thinking. Figure 4 is based on complex thinking for the financial inclusion of impoverished and vulnerable Mexican women in charge of a micro business (in the description, include reference to a success case in another area or discipline).

Insert Figure 4 about here

To design an inclusive risk analysis model with a gender perspective appropriate for the particular context of women in situations of poverty and vulnerability, we considered, on the one hand, gender variables and, on the other, financial inclusion variables as 20 characteristics. We took as a reference the German Credit dataset, which includes 20 characteristics necessary to determine the credit score of a conventional loan client. We adapted it to the context of potential female entrepreneurial clients excluded from formal financial institutions due to their difficulty saving and repaying loans. Table 3 below presents the description of the characteristics present in the dataset.

Insert Table 3 about here

Discussion

Credit risk analysis models that use AI based on complex thinking can detect the creditworthiness of women who earn low incomes from their micro businesses and patterns in their behaviors and attitudes while creating them. GEM data in Mexico suggest that there is a correlation between the level of schooling of impoverished and vulnerable women and the possibility of self-employment and selling a product or service (as shown in Figure 1); women with a higher level of education consider that they have a greater capacity to do so. In emerging countries, there is a gender gap in formal financial inclusion. As women's educational level increases, they are more likely to become credit subjects, given that formal institutions contemplate in their conventional risk analysis that educational level influences the level of income (Lotto, 2018). Women's educational level influences a pattern in their behaviors and attitudes to become self-employed or engage in selling some product or service.

Women's decision-making shows they have a structured plan to reach a professional goal. GEM data in Mexico suggest that women with a higher level of schooling tend to think about their professional projects systematically (as shown in Figure 2). According to Nguyen and Canh (2021), a context of poverty, vulnerability, and high educational lag impacts how an individual gathers, processes, and evaluates information to make decisions in their professional projects. For example, these influence the cognitive financial decisions of individuals more likely to finance their ventures through their own resources rather than external financing. Systemic thinking is a characteristic to consider in credit risk analysis. It is related to a higher level of schooling, which formal financial institutions consider when assessing the probability of non-payment of loans.

The perception of innovative thinking by other people is related to the women's level of education and innovative decision-making in their professional projects. GEM data in Mexico suggest that women with higher levels of education are considered to be perceived as highly innovative (as shown in Figure 3). Entrepreneurial innovation determines the introduction of new products, improvement of current products, or change in the production process and is associated with knowledge transfer (Nguyen, 2022). There is a relationship between systems thinking and innovative thinking; from the perspective of complex thinking, women who make strategic decisions and are highly innovative have a higher probability of repaying the loans they apply for in formal financial institutions.

Conclusion

This article focused on the financial risk analysis of vulnerable populations based on an international study where variables of gender, vulnerability, and complex thinking were analyzed. Two questions were posed in the study: How do women's poverty, vulnerability, and the possibility of self-employment and product or service sales relate to their level of schooling and the decisions they make or do not make? And how do women's poverty and vulnerability and the possibility of self-employment and product or service sales relate to their level of schooling and innovative thinking? The findings show that (a) there is a correlation between the level of schooling of women in situations of poverty and vulnerability with the possibility of self-employment and selling a product or service, (b) in the framework of complex thinking, the perception of innovative thinking is related to the level of education and innovative decision-making in professional projects, (c) women with a higher level of schooling tend to think about their professional projects systematically.

These findings were vital to support a proposal for a gender-sensitive risk analysis model, specifically targeting impoverished and vulnerable women, using AI within the framework of complex thinking to achieve financial inclusion of an under-financed population segment through formal financial institutions. The method of validity for the model is also provided. Practical implications include the possibility of promoting complex thinking with instances of educational innovation that encourage critical, systemic, scientific, and innovative thinking linked to entrepreneurship and sustainable development. Similarly, integrating reasoning for complexity into educational models can benefit women and contribute to vulnerable regions' economic and social growth.

The limitations of the study lie in the fact that it analyzed quantitative source data in a specific population; although it comprised a considerable sample, it would be valuable to expand it with qualitative instruments that allow for an in-depth analysis of the framework of reasoning for complexity in its dimensions of critical, scientific, systemic, and innovative thinking. In future studies, it would be of great value to apply mixed methods to extend the depth and integrate populations from different regions for comparative analysis. This study is an invitation to continue expanding social and economic growth possibilities, especially among vulnerable populations.

List of abbreviations

AI- artificial intelligence

ANN- Artificial Neural Networks

APS- Adult Population Survey

BS-RF- Bolasso-enabled Random Forest algorithm

BRF- Balanced Random Forest method

CONEVAL- El Consejo Nacional de Evaluacion de la Politica de Desarrollo Social (National Council for the Evaluation of Social Development Policy). In Mexico.

DT- Decision Trees

GEM- The Global Entrepreneurship Monitor

INEGI- Instituto Nacional de Estadística, Geografía e Informática (National Institute of Statistics, Geography and Informatics). In Mexico.

KNN- k-Nearest Neighbors

ML- Machine learning

SVM- support vector machines

BAT- binary optimization technique

Availability of data and materials

This publication is based on data obtained for the Global Entrepreneurship Monitor Mexico study. Patricia E. Galicia-Alonso (co-author in this paper) is one of the Regional leaders of the Global Entrepreneurship Monitor Mexico. The datasets generated and/or analysed during the current study are not publicly available due a 5-year safeguard but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

PEAG analyzed the women sample from the GEM 2019 study corresponding to the Adult Population Survey (APS). MGM proposed the artificial intelligence model and algorithm. AMV was a major contributor in writing the manuscript. All authors read and approved the final manuscript.

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Tables

Table 1.

Variables selected for analysis

Variable	**Description**	**Measurement**
UNEDUC	Attained education harmonized by UN categories	In categories ranging from elementary or first stage education to bachelor's degree or equivalent
HHINC	Annual income ranges including all respondents' household members	Six ranges of annual household income in Mexican Pesos
HHSIZE	Number of household members, including the respondent	Number
Phone line	Availability of landline and/or cell phone use	Dichotomous (Yes/No)
AGE9	Age range of respondents	In five categories from 18 to 64 years old
BSTART	Are you, alone or with others, currently trying to start a new business, including any self-employment or selling any goods or services to others	7-point likert scale (1 in total disagreement to 7 in total agreement)
SUSKILL	You personally have the knowledge, skill and experience required to start a new business	7-point likert scale (1 in total disagreement to 7 in total agreement)

VISIONSL	Every decision you make is part of your long-term career plan	7-point likert scale (1 in total disagreement to 7 in total agreement)
CREATIL	Other people think you are highly innovative	7-point likert scale (1 in total disagreement to 7 in total agreement)

Source: GEM APS Mexico, 2019-2020.

Table 2.

Variables of the sample of women living in poverty in Mexico

Selected sample variable	**Results and indicators**
Education (UNEDUC)	46.8% with educational levels lower than high school or basic education. Only 17 women have a higher education.
Annual income ranges (HHINC)[1]	72% with an income between $18,000 and $42,000 pesos per year, placing them below the poverty line (CONAPRED, 2022).
Number of household members (HHSIZE)	64% with a maximum of 4 permanent household members.
Availability of telephone line use (Telephone line)	79% of women with access to landline and/or cell phone use.
Age range (AGE9)	45% young people under 35 years old, 16% between 55 and 64 years old.
Attempting to start a business alone or jointly with others, including self-employment or sale of goods or services (BSTART).	21% of the women in the sample are trying to start a business.

Source: GEM APS Mexico, 2019-2020.

[1] Value calculated on CONAPRED 2022 poverty lines, for urban sectors in Mexico. In addition, in relative terms, in the second quarter of 2022, the income of employed men is approximately 1.3 times higher than that of women. (https://www.coneval.org.mx/Medicion/Paginas/ITLP-IS_pobreza_laboral.aspx#:~:text=32.3%25%2C%20respectivamente.-,Ingreso%20laboral%20real%20per%20c%C3%A1pita,un%20aumento%20de%20%2430.66%20pesos)

Table 3.

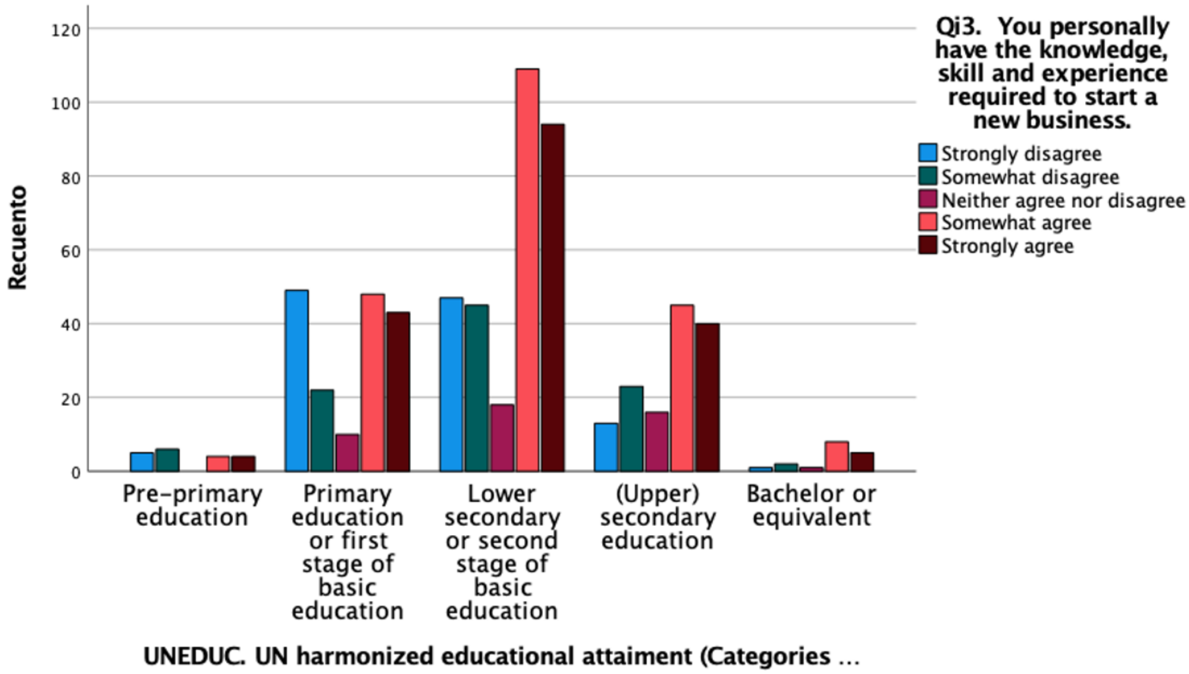
Women's characteristics for the credit risk analysis model

Feature	Description	Feature	Description
A1	Amount of credit	A11	Savings culture (strategies)
A2	Duration in months	A12	Marital status
A3	Age in years	A13	Children/dependents
A4	Gender	A14	Credit history in informal institutions
A5	Schooling	A15	Government support
A6	Purpose	A16	Support networks
A7	Entrepreneurship experience in months or years	A17	Email
A8	Entrepreneurship characteristics	A18	Phone number
A9	Entrepreneurship knowledge	A19	Current residence since
A10	Complex Mindset (systemic and innovative thinking)	A20	Other payment terms

Figures

Figure 1.

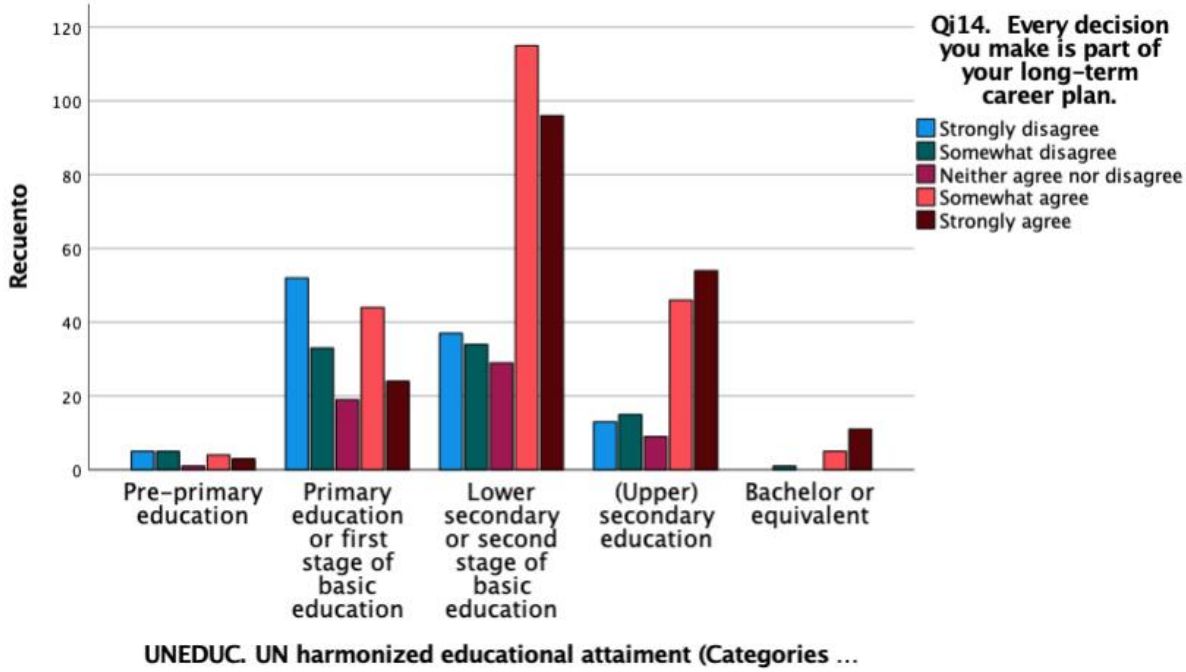
Have the knowledge, skills and experience required to start a business.



Source: GEM APS Mexico, 2019-2020.

Figure 2.

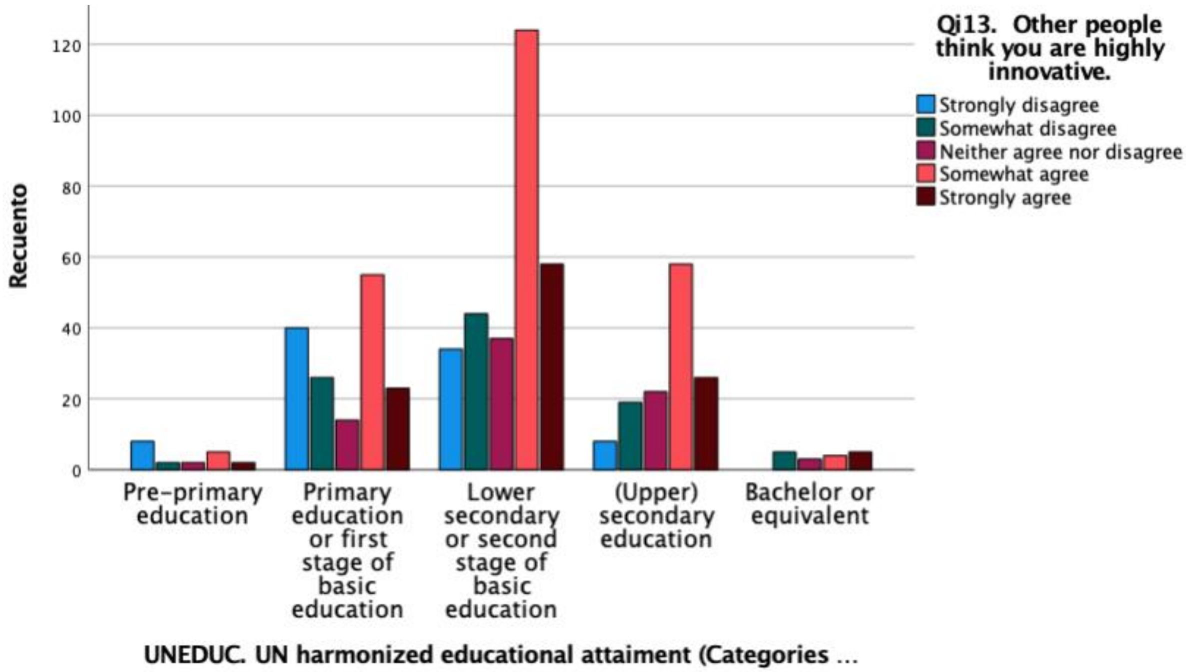
Every decision you make is part of a long-term professional plan (systems thinking).



Source: GEM APS Mexico, 2019-2020.

Figure 3.

Considers that other people think she is highly innovative.



Source: GEM APS Mexico, 2019-2020.

Figure 4.

Risk analysis model using artificial intelligence.