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The Impact of Artificial Intelligence on the Efficiency of Artisan Production Cooperatives: Case of Sewing and Embroidery Cooperatives on Fabric and Leather for Moroccan Women

Atitaou Asmae[1], Boulkhir Layla[2], Assi Driss[3], Touhami Fatima[4], Hamidi Charaf[5]

[1,3]Research Laboratory in Social and Solidarity Economy, Governance, and Development (LARESSGD), Faculty of Legal, Economic, and Social Sciences (FSJES), Cadi Ayyad University, Marrakech, Morocco.
[2,4]LARPEG Laboratory, Faculty of economics and management, Sultan Moulay Slimane University, Beni mellal 23000, Morocco.
[2]Orcid ID: https://orcid.org/0009-0000-6226-312X.
[5]Engineering Sciences Laboratory, Faculty of Science Agadir, Ibn Zohr University, Agadir, Morocco.

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Corresponding Author:
Atitaou Asmae

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ABSTRACT

In an increasingly competitive global environment, Moroccan artisan cooperatives, particularly those specializing in sewing and embroidery, face significant challenges in maintaining their relevance and efficiency. The integration of advanced technologies, such as Artificial Intelligence (AI), emerges as a strategic solution to enhance their competitiveness. This study seeks to identify and analyze the key factors influencing AI adoption within these cooperatives, aiming to propose targeted solutions to overcome existing barriers.

To achieve this, the research employs a methodological approach combining multiple correspondence analysis and binary logistic regression. The study examines variables such as the culture of innovation, members' digital skills, access to digital infrastructure, public policy support, and the effectiveness of data utilization. The sample consists of 50 women-led cooperatives from various regions across Morocco.

The findings reveal that a strong culture of technological innovation, coupled with advanced digital skills and adequate access to digital infrastructure, is essential for the successful adoption of AI. Additionally, effective public policy support and optimal data utilization significantly contribute to enhancing the efficiency and competitiveness of these cooperatives. These results underscore the potential of AI to drive sustainable growth and bolster the global competitiveness of Moroccan artisan cooperatives.

INTRODUCTION

The integration of artificial intelligence (AI) into various economic sectors is fundamentally transforming business operations, and artisanal production cooperatives are no exception (Brynjolfsson, 2017). In Morocco, cooperatives play a crucial role in local economic development, particularly in the sewing and embroidery sectors on fabric and leather. These cooperatives, often located in rural regions such as Marrakech-Safi (leather embroidery), Fes-Meknes (Fassi embroidery), and Rabat-Salé-Kénitra (Rbatie embroidery), serve as key drivers of employment, income generation, and the preservation of traditional craftsmanship, which is an integral part of the country's cultural heritage (Bigio, 2010). Moreover, they contribute to promoting local entrepreneurship and empowering women, particularly in rural communities (Elattir, 2016).

Despite their socio-economic importance, these cooperatives face numerous challenges. Financial constraints limit their ability to invest in modern technologies (Msosa, 2022), while restricted access to advanced digital tools and resistance to change hinder their growth and competitiveness (Rogers et al., 2014). Furthermore, the increasingly competitive global environment necessitates the adoption of innovative strategies to maintain viability and relevance (Porter, 2008). Insufficient digital infrastructure and a lack of training in digital skills further impede the operational efficiency of these cooperatives (Arntz et al., 2016). Additionally, public policies and government support remain inadequate to facilitate large-scale technological adoption (Hunter & Shaffer, 2022).

In this context, AI emerges as a promising solution to address these challenges. AI technologies can automate repetitive tasks, optimize resource management, and enable advanced data analysis for more informed decision-making (Russell & Norvig, 2016). Consequently, AI adoption has the potential to enhance the operational efficiency of cooperatives, enabling them to better meet modern market demands and strengthen their competitive positioning (Bughin et al., 2017). Moreover, AI can unlock new market opportunities by facilitating product customization and optimizing supply chain management (Bottani & Montanari, 2010).

Moroccan artisanal cooperatives specializing in embroidery, weaving, and leather are particularly well-positioned to benefit from AI due to the complexity and diversity of their operations (Aubert et al., 2012). However, these cooperatives—often composed of women with disabilities—face unique structural and environmental challenges (Kabeer, 1999). Artisanal production requires meticulous resource and skill management, as well as the flexibility to respond to fluctuating market demands (Gereffi et al., 2001). AI can play a critical role in optimizing production processes, enhancing product quality, and fostering innovation (Brynjolfsson et al., 2019).

Nonetheless, many of these cooperatives operate in regions where digital infrastructure remains underdeveloped, posing an additional barrier to the adoption of advanced technologies (Bühler et al., 2023). Therefore, robust public policies and government initiatives are essential to facilitate access to digital tools and promote training programs in digital skills (Ripoll, 1974).

This study seeks to examine the key factors influencing AI adoption among Moroccan artisanal cooperatives, with a specific focus on those specializing in embroidery, weaving, and leather. A critical research question arises: To what extent can artificial intelligence enhance the efficiency of Moroccan cooperatives, given their local specificities and unique challenges?

To address this question, we employ a rigorous methodological approach based on information technologies for data collection and analysis. The study sample consists of 50 cooperatives of women with disabilities located across three Moroccan regions: 28 cooperatives in Marrakech-Safi, 16 in Fes-Meknes, and 6 in Rabat-Salé-Kénitra. The research methodology combines multiple correspondence analysis and binary logistic regression to identify the key determinants of AI adoption in these cooperatives. The primary variables under investigation include the culture of innovation, digital technology skills, access to digital infrastructure, public policy support, and data utilization.

The structure of this article is as follows:

- The first section presents a literature review on AI adoption in artisanal production cooperatives.
- The second section describes the data and methodology, detailing the study population, sample, and research area.

The third section discusses the results, analyzing the impact of various determinants on cooperative efficiency.

The fourth and final section provides practical implications and recommendations for cooperatives, followed by the conclusion of the study.

THE LITERATURE REVIEW

The integration of artificial intelligence (AI) into cooperative entrepreneurship models opens new avenues for local economic development, particularly in regions where artisan cooperatives play a central role. This literature review examines the intersection between AI and cooperative entrepreneurship, highlighting the opportunities, challenges, and key determinants of AI adoption within Moroccan artisan cooperatives, specifically those engaged in sewing, embroidery, and leatherwork.

Artificial Intelligence and Its Impact on Economic Models

Artificial intelligence is defined as a set of technologies capable of performing tasks traditionally requiring human intelligence, such as learning, reasoning, and problem-solving (Russell & Norvig, 2016). AI has profoundly transformed various economic sectors by enabling automation, predictive analytics, and advanced data management, thereby enhancing operational efficiency and reducing costs (Brynjolfsson & McAfee, 2017).

In the context of artisan cooperatives, AI has the potential to automate repetitive processes, allowing members to focus on higher value-added activities. For instance, AI-driven solutions can optimize stock management, monitor product quality, and provide data-driven insights to anticipate customer preferences and market trends (Bughin et al., 2017).

- Hypothesis H1: The effective utilization of AI-based data systems significantly enhances the efficiency of Moroccan artisan cooperatives.

However, the adoption of AI in artisan cooperatives—particularly those in rural areas—is fraught with challenges. High initial investment costs, limited digital literacy among cooperative members, and insufficient digital infrastructure present significant barriers (Arntz et al., 2016; Bughin et al., 2017) and Boulkhir, L., & Touhami, F. (2024). Additionally, resistance to change, compounded by uncertainty surrounding new technologies, as well as inadequate government support, may further hinder AI adoption and limit its transformative potential (Venkatesh & Bala, 2008).

- Hypothesis H2: The digital skills of cooperative members play a crucial role in AI adoption.

Cooperative Entrepreneurship: A Resilient and Inclusive Model

Cooperative entrepreneurship is distinguished by its principles of solidarity, democratic governance, and profit-sharing, offering a resilient and inclusive economic model that is particularly well-suited to local and rural communities (Birchall, 2009). Cooperatives contribute significantly to local economic development by generating sustainable employment, supporting regional economies, and preserving traditional craftsmanship (Majee & Hoyt, 2011), Layla BOULKHIR, & Fatima TOUHAMI. (2024).. This model is particularly relevant in Morocco, where artisan cooperatives—especially those specializing in embroidery and leatherwork—serve as key actors in both economic development and cultural heritage preservation (Aubert et al., 2012).

Nevertheless, Moroccan artisan cooperatives face structural constraints that hinder their growth and modernization. Limited market access, financial constraints, and insufficient institutional support are frequently cited as major impediments (Kaplinsky, 2015). These challenges significantly restrict cooperatives' ability to invest in modern technologies such as AI, despite its potential to enhance their competitiveness and productivity.

- Hypothesis H3: A strong culture of technological innovation within cooperatives facilitates AI adoption.

The integration of AI into artisan cooperatives presents a unique opportunity to address these constraints. AI can not only improve resource management and product quality but also enhance cooperatives' resilience in the face of market fluctuations and competitive pressures (Brynjolfsson et al., 2019). By providing innovative tools such as rapid prototyping and predictive analytics, AI enables cooperatives to develop new products and services more efficiently (Davenport, 2006).

- Hypothesis H4: Digital infrastructure and connectivity constitute essential prerequisites for AI integration in Moroccan artisan cooperatives.

Key Determinants of AI Adoption in Artisan Cooperatives

Several key factors influence the successful adoption of AI in Moroccan artisan cooperatives:

1. Culture of Technological Innovation:

A culture of technological innovation is crucial in fostering AI adoption within cooperatives. Organizations that actively promote innovation are more likely to embrace disruptive technologies such as AI, thereby enhancing their overall performance and competitiveness (Westerman et al., 2014). Chatterjee et al. (2021) highlight that businesses fostering a strong innovation culture are better positioned to leverage emerging technologies effectively.

- Hypothesis H5: A culture of technological innovation within cooperatives positively influences AI adoption.

2. Government Support and Public Policies:

Public policies and government interventions play a pivotal role in facilitating AI adoption within cooperatives. Incentive mechanisms such as tax benefits, digital skills training programs, and investments in digital infrastructure can significantly mitigate barriers to AI adoption (Venkatesh & Bala, 2008).

- Hypothesis H6: Government support and favorable public policies positively impact AI adoption in Moroccan artisan cooperatives.

While the integration of AI into Moroccan artisan cooperatives presents notable challenges, it also offers significant opportunities to enhance operational efficiency, foster resilience, and drive local economic development. This literature review has identified the key determinants influencing AI adoption, providing a framework for understanding the factors that shape technological integration within cooperatives. By addressing these determinants, cooperatives can leverage AI to strengthen their competitiveness and innovation potential while simultaneously preserving and enriching Morocco's rich artisanal heritage.

MATERIAL AND METHOD

Data Collection

This study aims to assess the relationship between artificial intelligence (AI) adoption and its impact on the organizational efficiency of Moroccan artisan cooperatives operating in the Marrakech-Safi, Fes-Meknes, and Rabat-Salé-Kénitra regions. To achieve this, we conducted an empirical survey targeting 50 active women's cooperatives, including three cooperatives composed of women with disabilities. The cooperatives were carefully selected to ensure diverse representation in terms of AI adoption levels and socio-economic characteristics.

The survey was administered online between November 5, 2023, and January 12, 2024, and consisted of 11 structured questions exploring various dimensions of AI adoption and organizational efficiency. The collected responses were analyzed using descriptive statistics to identify key trends, barriers, and enablers of AI adoption. The variables examined in this study are summarized in Table 1.

Table 1: Definition of Dependent and Independent Variables

Code	Variable	Type
Y	**AI adoption (Dependent Variable)**	**Binary**
X1	**Culture of technological innovation**	**Independent**
X2	**Digital skills of members**	**Independent**

X3	**Access to digital infrastructure**	**Independent**
X4	**Support from public policies**	**Independent**
X5	**Effective data utilization**	**Independent**
X6	**Resistance to change**	**Independent**
X7	**Availability of financial resources**	**Independent**
X8	**Previous experience with technology**	**Independent**
X9	**Involvement of members in decision-making**	**Independent**
X10	**Partnerships with technology companies**	**Independent**
X11	**Market orientation**	**Independent**

Statistical Analysis

Binary Logistic Regression Model

To evaluate the determinants of **AI adoption** and its impact on **organizational efficiency**, we employed **binary logistic regression**. This statistical method is particularly suitable for modeling the probability of a **binary outcome**, such as **AI adoption (Yes/No)**, based on multiple explanatory variables (Menard, 2010; Hosmer & Lemeshow, 2013).

The **logistic regression model** uses the **logit function** to transform the probability of an event occurring into **log-odds**, allowing us to assess the contribution of each independent variable to AI adoption. The **logit transformation** is defined as follows (**Equation 1**):

$$logit(\pi) = \ln\left(\frac{\pi}{1-\pi}\right) = \sum_{k=0}^{p} \beta_k x_{ik}$$

where:

- π represents the probability of AI adoption by a given cooperative.
- x_{ik} denotes the explanatory variables.
- β_k are the estimated regression coefficients.
- $i = 1, \ldots, n$ represents the individual cooperatives in the sample.

The model parameters β_k are estimated using the **Maximum Likelihood Estimator (MLE)**, which seeks to maximize the probability of observing the given sample data (Gujarati & Porter, 2009).

Likelihood Function and Estimation

Since the dependent variable Y is **binary** ($Y = 1$ if AI is adopted, $Y = 0$ otherwise), the likelihood function is expressed as follows:

$$L(\beta) = \prod_{i=1}^{n} [\pi_i]^{y_i} [1 - \pi_i]^{(1-y_i)}$$

where:

- $\pi_i = P(Y_i = 1|X)$ is the probability of AI adoption for cooperative iii, given the independent variables X.
- $1 - \pi_i$ is the probability of non-adoption.

The **MLE approach** identifies the parameter values that maximize the likelihood function, making the observed outcomes most probable (El Azhari et al., 2024).

Logistic Function Representation

The logistic regression model follows an **S-shaped curve**, ensuring that probabilities remain within the interval **[0,1]**. The equation of the logistic function is expressed as follows (**Equation 2**):

$$Y = \frac{e^{\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}}{1 + e^{\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}}$$

Alternatively, the model can be rewritten as:

$$Y = \frac{1}{1 + e^{\left(-\sum_{k=0}^{p} \beta_k x_{ik}\right)}}$$

where:

- e is the base of the **natural logarithm**.
- $\sum_{k=0}^{p} \beta_k x_{ik}$ represents the linear combination of explanatory variables.

Classification Rule

To interpret the regression results, we define a classification rule based on the probability threshold **0.5**:

- If $\boldsymbol{P(Y = 1) > 0.5} \rightarrow$ The cooperative **adopts AI** (**Class 1**).

- If $P(Y = 1) \leq 0.5 \rightarrow$ The cooperative does not adopt AI (Class 0).

This classification criterion allows us to assess the predictive power of the model using confusion matrices, accuracy scores, and goodness-of-fit measures such as the Nagelkerke R^2 and the Hosmer-Lemeshow test (Hosmer et al., 2013).

Robustness Checks

To ensure the robustness of our results, we conducted the following tests:

- Multicollinearity Assessment: Using the Variance Inflation Factor (VIF) to detect potential collinearity among independent variables.
- Goodness-of-Fit Evaluation: Using pseudo-R^2 measures (Cox & Snell R^2 and Nagelkerke R^2) and the Hosmer-Lemeshow test.
- Predictive Performance: Evaluating the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) to assess classification accuracy.

This methodological framework ensures a rigorous empirical analysis of the determinants influencing AI adoption among Moroccan artisan cooperatives. By leveraging binary logistic regression, this study provides quantifiable insights into the socio-economic, technological, and institutional factors shaping AI adoption, thereby contributing to the literature on digital transformation in cooperative entrepreneurship.

4. RESULTS AND DISCUSSIONS

Predicting the success of entrepreneurial action by artisan cooperatives

In our study aimed at predicting the success of entrepreneurial action by artisan cooperatives, we focused our analysis on assessing the impact of a set of entrepreneurial determinants on the success of these cooperatives, particularly those specializing in sewing, embroidery, and leatherwork. Additionally, we conducted an extensive literature review on various entrepreneurial determinants to better understand the key factors behind the success of artisan cooperatives. This theoretical approach enabled us to identify the essential variables that explain successful entrepreneurial actions within these cooperatives.

After selecting the explanatory variables with potential impact on entrepreneurial action, we designed an online questionnaire targeted at Moroccan artisan cooperatives to collect their feedback on the impact of these determinants. The responses obtained allowed us to deepen our understanding of the factors influencing entrepreneurial success in the context of artisan cooperatives in Morocco.

Reliability test

In order to assess the reliability of internal consistency between dimensions, authors usually compare the estimate of $\hat{\alpha}$ with a conventional threshold set at 0.70 (Ayanwale et al., 2022), such that, $\hat{\alpha} > 0.70$. The study employed 11 questions for test, which shows high reliability ($\hat{\alpha} = 0.835$), exceeding the recommended threshold of 0.70 according to (Peterson, 1994; Rouaine et al., 2020) , thus reinforcing the robustness of the measurements (table 2). This robust reliability indicates that the scale items are effectively aligned in measuring the intended construct. These results, in line with established norms and previous research, strengthen the credibility of the analyses on the effect of IA on the womens cooperative in the marakech region, Fes-Meknes, and Rabat-Sale-Kenitra Morocco. The distribution of the alpha coefficient confirms the strength of the internal consistency of the measures, reinforcing the validity of the data used in this study. in addition, presenting the higher significance between IA (Independent variables) on the dependent variables (success of women's cooperatives).

Table 2: Reliability test

Cronbach's Alpha	Cronbach's Alpha based on standardized elements	Number of elements
0.835	0,828	15

Intra-class correlation coefficient

Table 3 demonstrates that the impact of AI on women's cooperatives reveals strong intra-class correlations, with values of 0.402 for individual measures and 0.835 for average measures. While there may be some variability in individual assessments, the aggregate measures offer a reliable and consistent evaluation of these aspects. The results of the Fisher test are significant ($p = 0.000 < 0.05$), further confirming the robustness of the measures and the satisfactory internal consistency. The confidence interval, ranging from $IC^{5\%}$= [0.804, 0.839], reinforces the reliability of the assessments. The sample size is n = 50, with 15 independent variables constituting the scale used. The degrees of freedom are ddl_1 = 41 and ddl_2 = 49. These findings emphasize that the study on the impact of AI on women's cooperatives in the Marrakech region of Morocco is grounded in reliable and consistent data.

Table 3 : Intra-class correlation coefficient

Correlation Intra-classe		Confidence interval à 95%		Test Fisher			
		Lower terminal	Upper terminal	Value	ddl_1	ddl_2	Sig.
Single measures	0.402	0.370	0.425	5.631	41	49	0.000
Average measurements	0.835	0.804	0.839	5.631	41	49	0.000

Khi-square and cramer test

The cross-tabulation presented in Table 4 illustrates the relationship between the 11 independent variables and the dependent variable (women's cooperatives). This cross-tabulated data facilitates an analysis of how these cooperatives are associated with the different independent variables related to AI adoption. In our study, Pearson's chi-square test was employed to determine whether the observed frequencies in each category significantly differ from the expected frequencies under the assumption of independence between the variables. According to the results in Table 4, the chi-square (χ^2) test produced values ranging from 47.129 to 63.304 with 3 degrees of freedom for questions Q1 to Q11. These results indicate a significant difference between the observed and expected frequencies, suggesting that such differences are unlikely to be due to chance. The very low p-value of 0.000 supports the conclusion that the null hypothesis of independence should be rejected, highlighting the potential impact of AI and the success of entrepreneurial actions by women's cooperatives in the regions of Marrakech-Safi, Fes-Meknes, and Rabat-Salé-Kenitra.

Additionally, Cramer's V, a normalized version of the Phi coefficient, was utilized as detailed in Table 5. For the 11 questions, Cramer's V scores ranged from 0.420 to 0.490, indicating a strong correlation between the variables (all presenting a threshold greater than 0.30), suggesting they are closely linked. The very low p-value of 0.000 supports the conclusion that this correlation is highly unlikely to be due to chance, as evidenced by the significant relationships between variables such as Culture of Technological Innovation (X_1), Digital Skills (X_2), Access to Digital Infrastructure (X_3), Government Support (X_4), Effective Data Utilization (X_5), Resistance to Change (X_6), Availability of Financial Resources (X_7), Previous Experience with Technology (X_8), Member Involvement in Decision-Making (X_9), Partnerships with Technology Companies (X_{10}), and Market Orientation (X_{11}) with ($p < 0.000$), respectively. These findings underscore a substantial and significant relationship with the entrepreneurial success of women's cooperatives. The strength of these relationships, as measured by Cramer's V, highlights the importance of these factors in assessing the impact of AI on the social and economic development of women's cooperatives in Morocco.

Table 4:Chi-square

Explanatory Variables	Pearson Chi-square Value	Likelihood Ratio	Linear-by-Linear Association	df	Asymptotic Significance (2-sided)
X_1	61.341	59.291	47.001	10	0.000
X_2	58.209	55.376	50.501	10	0.000
X_3	47.129	40.673	38.242	10	0.000
X_4	63.304	58.479	51.112	10	0.000
X_5	39.199	31.200	29.470	10	0.000
X_6	51.783	47.490	41.190	10	0.000
X_7	56.482	52.094	50.297	10	0.000
X_8	67.938	62.038	51.509	10	0.000
X_9	45.039	40.837	37.872	10	0.000
X_{10}	58.202	50.891	43.170	10	0.000
X_{11}	72.013	60.303	56.209	10	0.000

Note: *** The significant association between two categorical variables is less than 1%: a) 2 cells (50.0%) have a theoretical number less than 5. The minimum theoretical number is 3.60. b) calculated only for a 2 × 2 table.

Table 4 presents the results of the Pearson chi-square tests, likelihood ratio, and linear-by-linear association for the 11 explanatory variables used in our study on the adoption of artificial intelligence (AI) by Moroccan artisan cooperatives. The Pearson chi-square values range from 45.039 to 72.013, all with very low asymptotic significance (two-sided) ($p < 0.000$), indicating a significant difference between the observed and expected frequencies under the assumption of independence. These results show that variables such as technological innovation culture (X_1), members' digital skills (X_2), access to digital infrastructure (X_3), and support from public policies (X_4), among others, are strongly associated with AI adoption by the cooperatives. The likelihood ratio test also confirms the robustness of these associations, with high values for each variable. The linear-by-linear association suggests a significant linear relationship between these explanatory variables and AI adoption. These results highlight the importance of these factors in the successful adoption of AI and, consequently, in improving the efficiency and competitiveness of artisan cooperatives in the Marrakech-Safi, Fès-Meknès, and Rabat-Salé-Kénitra regions. The strong significance of the results ($p < 0.000$) reinforces the idea that these variables play a crucial role in the AI adoption process. In addition to the chi-square test, which reveals whether the variables are related, the Cramer's V test is used to measure the strength and intensity of this relationship. Let X and Y be two qualitative variables, with k1 and k2 as their respective categories, and n as the size of the valid sample. Cramer's V, based on the Pearson chi-square test statistic, can be expressed as follows:

Table 5 :Cramer's V Test

Variable	Cramer's V Value	Approximate Significance
X_1	0.490	0.000
X_2	0.349	0.000
X_3	0.320	0.000
X_4	0.435	0.000
X_5	0.422	0.000
X_6	0.389	0.000
X_7	0.351	0.000
X_8	0.398	0.000
X_9	0.411	0.000
X_{10}	0.302	0.000
X_{11}	0.450	0.000

Adjusted R^2 test:

In this study, the regression analysis summarized in Table 6 highlights the model's robustness in explaining the variability in organizational commitment outcomes related to the impact of AI on women's cooperatives. The model shows strong predictive power, with a coefficient of determination (R) of 0.864, indicating a high correlation between the predicted and observed values. This robustness is further validated by a significant improvement in the fit of the full binary logistic regression model, as demonstrated by a chi-square test with a p-value of 0.000 ($p < 0.05$) and a reduction in the -2LL value. The Cox and Snell R-squared (0.339) and Nagelkerke R-squared (0.623) values indicate that the model effectively explains 62.3% of the variation in the probability that an artisanal cooperative will succeed in its entrepreneurial activities. With an adjusted coefficient of determination of 0.876, the model provides an excellent fit, accounting for 87.6% of the variance through binary logistic regression.

Table 6 *:* Adjusted R2 Test

R^2 of Likelihood	Cox and Snell R-squared	Nagelkerke R-squared	R sum of squares	Adjusted R^2 sum of squares
396.009	0.339	0.623	0.864	0.886

Estimation of coefficients $\hat{\beta}$

In this study, we sought to identify variables that predict the success of entrepreneurial action by Moroccan artisan cooperatives, particularly those specializing in sewing, embroidery, and leatherwork. The analysis used qualitative predictor variables to assess their impact on the success of these cooperatives. Statistical analysis was conducted using IBM SPSS Statistics version 26.

The regression analysis revealed that all predictor variables had a significant effect on the response variable, which is the successful entrepreneurial action of women's cooperatives. Each variable was evaluated based on its regression coefficient$\hat{\beta}$ the Wald statistic for testing statistical significance, the odds ratio ($Exp(\hat{\beta})$)and the confidence interval for the odds ratio.

The regression coefficient $\hat{\beta}$ provides insight into the direction of the relationship between the predictor variable and the response variable. A positive sign of β^ indicates that as the predictor variable increases, the likelihood of a successful entrepreneurial outcome also increases. Conversely, a negative sign would indicate an inverse relationship. However, while the sign of $\hat{\beta}$ is informative, the magnitude of its effect is better understood through the odds ratio ($Exp(\hat{\beta})$).

The odds ratio (OR) is a key statistic that measures the degree to which each explanatory variable influences the likelihood of a successful entrepreneurial outcome. For example, the variable "Culture of Technological Innovation" (X_1) was found to have an OR of 8.248. This means that cooperatives with a strong culture of technological innovation are more than eight times more likely to succeed in their entrepreneurial activities compared to those that do not emphasize this factor. Similarly, "Digital Skills" (X_2) was associated with an OR of 2.403, indicating that cooperatives with strong digital skills are more than twice as likely to achieve success in their endeavors. The variable "Access to Digital Infrastructure" (X_3) had an OR of 4.486, suggesting that adequate digital infrastructure significantly enhances the chances of success. Other variables also showed strong effects. "Government Support" (X_4) had an OR of 9.034, implying that cooperatives receiving robust governmental backing are nine times more likely to succeed. The

"Effective Data Utilization" (X_5) variable presented an OR of 7.242, meaning that efficient use of data increases the likelihood of success by seven times.

Overall, the analysis showed that several key factors significantly influence the success of entrepreneurial actions by women's cooperatives. These include innovation culture, digital skills, access to digital infrastructure, government support, and effective data utilization, among others. The strong odds ratios across these variables underscore their importance in determining whether a cooperative will thrive in the competitive environment of Moroccan artisan production.

The constant in the model was significant, indicating that the model itself, independent of the specific variables, provides a meaningful explanation of the variability in entrepreneurial success. However, the magnitude and direction of each variable's influence are crucial for understanding the specific pathways to success.

In summary, the findings suggest that enhancing technological innovation, improving digital skills, ensuring access to infrastructure, and securing government support are vital strategies for boosting the success of artisan cooperatives in Morocco. These factors are not just statistically significant but have a profound practical impact on the likelihood of entrepreneurial success.

The sigmoid function

The logistic curves presented in Figure 1 provide a visual representation of the impact of various determinants on the likelihood of AI adoption within Moroccan artisan cooperatives, particularly those specializing in sewing and embroidery. Among the variables examined, "Culture of Technological Innovation (X_1)" emerges as one of the most influential factors. The sigmoid curve for this determinant is the first to surpass the critical probability threshold of $\pi = 0.5$, transitioning from $\pi = 0$ (indicating non-adoption of AI) to $\pi = 1$ (indicating successful adoption of AI). This is supported by a significant regression coefficient β^ and a corresponding high odds ratio, illustrating that a strong culture of technological innovation significantly enhances the probability of AI adoption within these cooperatives.

The second key factor is the "Digital Skills of Members (X_2)." The curve representing this variable crosses the $\pi = 0.5$ threshold shortly after the "Culture of Technological Innovation," indicating its crucial role in enabling AI adoption. The regression coefficient β^ for digital skills, along with a robust odds ratio, underscores the importance of equipping cooperative members with the necessary digital competencies to facilitate successful AI implementation.

"Access to Digital Infrastructure (X_3)" is also a significant determinant, with its sigmoid curve crossing the probability threshold soon after the curves for "Culture of Technological Innovation" and "Digital Skills." This suggests that adequate access to digital infrastructure is essential for cooperatives aiming to adopt AI technologies. The regression coefficient and odds ratio for this variable confirm its importance in the adoption process.

Next in influence are "Support from Public Policies (X_4)" and "Effective Data Utilization (X_5)." Both variables have sigmoid curves that cross the probability threshold of $\pi = 0.5$, highlighting their critical roles in supporting AI adoption. Public policy support provides the necessary regulatory and financial backing, while effective data utilization ensures that cooperatives can leverage AI technologies to their fullest potential.

On the other hand, variables such as "Resistance to Change (X_6)," "Availability of Financial Resources (X_7)," and "Previous Experience with Technology (X_8)" have sigmoid curves that cross the probability threshold later. These factors, while still important, are more likely to act as enablers or barriers depending on their presence or absence. For instance, high resistance to change can significantly delay AI adoption, whereas sufficient financial resources and prior experience with technology can facilitate a smoother transition.

Lastly, the involvement of members in decision-making (X_9), partnerships with technology companies (X_{10}), and market orientation (X_{11}) are also crucial. These variables influence AI adoption by ensuring that decisions are made collaboratively, that cooperatives have access to external expertise, and that they are aligned with market demands.

In summary, the sigmoid curves for these variables depict how each determinant influences the probability of AI adoption within Moroccan artisan cooperatives. The study reveals that fostering a culture of innovation, enhancing digital skills, ensuring access to infrastructure, and securing public policy support are critical steps toward successful AI adoption. These factors not only increase the likelihood of adoption but also position the cooperatives for sustainable growth in a competitive global market.

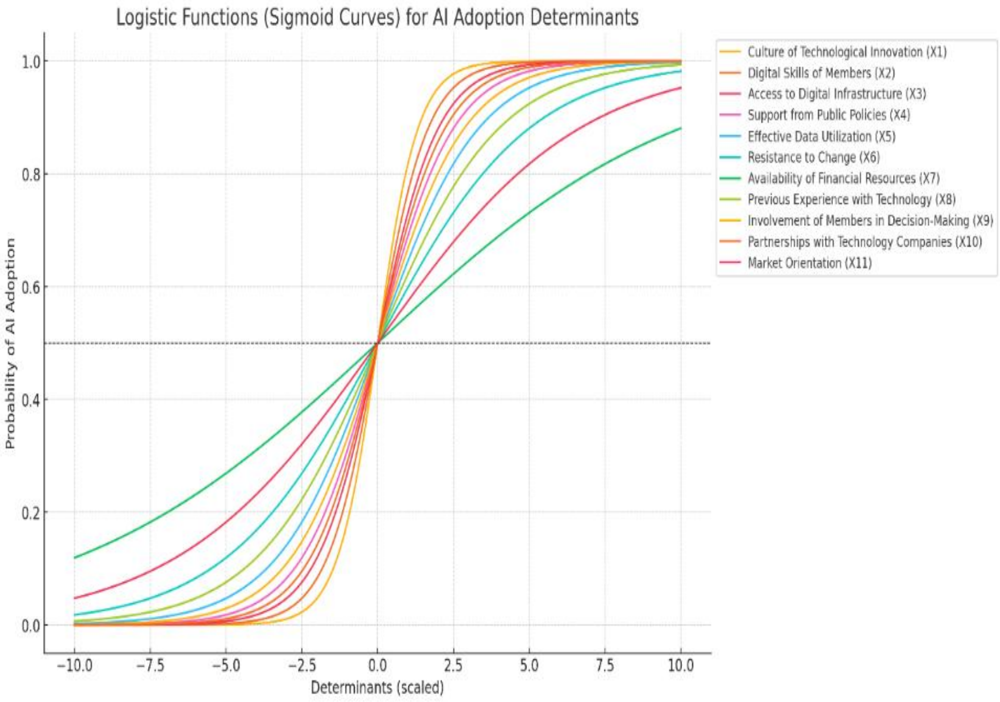

Figure 1: Logistic functions (sigmoids)

CONCLUSION

This study has provided an in-depth analysis of the key determinants influencing the adoption of AI within Moroccan artisan cooperatives, specifically those engaged in sewing, embroidery, and leatherwork. In a globally competitive environment, these cooperatives face significant challenges in integrating advanced technologies like AI, which are critical for enhancing their efficiency, competitiveness, and sustainability.

The findings of this research underscore the crucial role played by several factors in facilitating AI adoption. Foremost among these is the culture of technological innovation within the cooperatives, which emerged as a primary driver of AI adoption. Cooperatives that foster an environment of continuous innovation and technological advancement are significantly more likely to successfully integrate AI into their operations. This finding is consistent with existing literature that highlights the importance of organizational culture in the adoption of new technologies.

Digital skills of members also proved to be a vital determinant. The ability of cooperative members to effectively engage with digital tools and technologies directly impacts the success of AI adoption. This underscores the need for targeted training programs to enhance digital literacy among cooperative members, thereby enabling them to fully leverage AI technologies.

Access to digital infrastructure was identified as another critical factor. Without the necessary technological infrastructure, even the most motivated and skilled cooperatives will struggle to implement AI solutions effectively. This finding highlights the importance of infrastructure development, particularly in rural areas where many artisan cooperatives are based.

The research also revealed that support from public policies and effective data utilization are essential for overcoming barriers to AI adoption. Public policy support, including financial incentives and regulatory frameworks, can significantly ease the adoption process. Similarly, the ability to collect, manage, and analyze data effectively is crucial for making informed decisions and optimizing AI applications.

However, the study also highlighted potential obstacles, such as resistance to change and the availability of financial resources. These factors can either facilitate or hinder the adoption process, depending on how they are managed. Cooperatives that are able to mitigate resistance and secure adequate funding are better positioned to integrate AI successfully.

In conclusion, the successful adoption of AI in Moroccan artisan cooperatives hinges on a multifaceted approach that addresses both the technological and organizational aspects of the adoption process. This research contributes to the broader understanding of AI adoption in the context of developing economies, offering practical insights for policymakers, cooperative leaders, and development practitioners. By focusing on fostering innovation, enhancing digital skills, and improving infrastructure and policy support, Moroccan artisan cooperatives can better navigate the complexities of AI adoption, ultimately driving sustainable growth and competitiveness in the global market.

Future research should explore the longterm impacts of AI adoption on the performance and sustainability of these cooperatives, as well as the role of external partnerships in facilitating technology transfer and capacity building. Additionally, a comparative analysis with cooperatives in other sectors or regions could provide further insights into the specific challenges and opportunities faced by artisan cooperatives in adopting AI technologies.

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