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Assessing the impact of artificial intelligence on social innovation and inclusive territorial development: A quantitative study of women's cooperatives in Morocco

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Abstract

This study investigates the role of Artificial Intelligence (AI) adoption as a catalyst for social innovation and inclusive territorial development within women's cooperatives in Morocco's social and solidarity economy sector. Using primary data from 65 women's cooperatives in the Marrakech-Safi region operating across agriculture, handicrafts, waste management, and sustainable tourism, we employ Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypothesized relationships between AI adoption, social innovation, and inclusive territorial development. Data were collected through structured questionnaires and analyzed using SmartPLS 4 with 5,000 bootstrapping iterations. Results demonstrate that AI adoption significantly enhances social innovation ($\beta = 0.562$, $p < 0.001$) and directly contributes to inclusive territorial development ($\beta = 0.321$, $p < 0.01$). Critically, social innovation mediates the relationship between AI adoption and territorial development ($\beta = 0.472$, $p < 0.001$), with a confirmed partial mediation effect (indirect effect $\beta = 0.265$, $p < 0.001$). AI tools including digital market analytics, mobile payment systems, and machine learning-based management applications improve cooperative efficiency, market access, and social cohesion, though adoption rates vary significantly across operational domains (marketing: 3.78; production: 2.89). This research provides pioneering empirical evidence from the Global South on AIdriven digital transformation in the social economy. It extends the resource-based view to the cooperative context, demonstrating that AI functions as a collective asset rather than merely a competitive resource. The study reveals that technology alone is insufficient; organizational learning, institutional support, and ethical governance frameworks are essential mediating mechanisms. Findings inform policy interventions for organizations such as ODCO and REMESS, emphasizing the need for targeted digital literacy programs, infrastructure investment, and equity-focused AI adoption strategies to prevent digital exclusion within rural cooperatives.

Keywords: artificial intelligence, social innovation, women's cooperatives, inclusive development, Morocco

1. Introduction

Artificial Intelligence (AI) has emerged as one of the major drivers of economic, social, and territorial transformation in the 21st century. As a General-Purpose Technology, AI is redefining production structures, work organization, and innovation dynamics across diverse sectors and regions (Brynjolfsson & McAfee, 2017; Kaplan & Haenlein, 2019). While its impact on competitiveness and productivity has been widely documented in industrialized economies, the potential of AI to foster social innovation, inclusive territorial development, and sustainability in emerging contexts remains underexplored (Floridi et al., 2018; Sestino et al., 2022). In Morocco, the New Development Model (NMD, 2021) identifies digital transformation as a strategic lever for sustainability and social cohesion. National programs such as Maroc Digital 2030 emphasize the integration of AI and emerging technologies to enhance territorial equity and economic inclusion. However, AI diffusion remains uneven, particularly within the Social and Solidarity Economy (SSE), which plays a crucial role in local development and women's empowerment (HCP, 2024; ODCO, 2025).

Women's cooperatives in the Marrakech-Safi region offer a compelling context for studying how AI can catalyze innovation and social inclusion. These cooperatives contribute to the valorization of local resources, the creation of sustainable employment, and the promotion of collective entrepreneurship. Yet, their digital transition remains limited, constrained by unequal access to technology, digital skills, and financing mechanisms. Integrating AI tools such as intelligent marketing, data analytics, and process automation could substantially enhance their efficiency, visibility, and social impact (Boulkhir & Atitaou, 2025). Recent scholarship highlights that AI adoption in social enterprises requires an ethical, participatory, and context-sensitive approach. Vallor (2022) and Jobin et al. (2019) underline that technological progress should align with social values and human well-being, especially in developing regions where structural inequalities persist. Within this framework, AI can become a transformative instrument not only for economic growth but also for inclusive and sustainable social change. This study contributes to this emerging field by empirically examining the relationship between AI adoption, social innovation, and inclusive territorial development in Morocco.

The conceptual framework presented in Table 1 integrates three core constructs drawing on established theories from resource-based view, social innovation, and territorial development literature. Focusing on 65 women's cooperatives in the Marrakech-Safi region, the research applies Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess how AI technologies influence cooperative performance and community-based innovation.

As shown in Table 1, the study pursues four main objectives: (1) to assess the level of AI adoption among women's cooperatives in Marrakech-Safi; (2) to analyze the impact of AI on the economic and social performance of cooperatives; (3) to examine the mediating role of social innovation between AI and inclusive territorial development; (4) to propose a conceptual and empirical model of technological integration for sustainable and equitable development.

Table 1. *Conceptual Framework: Key Constructs and Theoretical Foundations*

Construct	Definition	Theoretical Foundation	Key Indicators
AI Adoption	The extent to which cooperatives integrate AI-based tools and technologies in their operations	Technology Acceptance Model (Davis, 1989); Resource-Based View (Barney, 1991)	Digital marketing tools, mobile payment systems, data analytics, automated management systems
Social Innovation	Development and implementation of new solutions to meet social needs and enhance collective well-being	Social Innovation Theory (Moulaert et al., 2013); Collective Learning Framework	Participatory governance, collaborative practices, knowledge sharing, creative problem-solving
Inclusive Territorial Development	Development approach integrating equity, participation, and sustainability at the local level	Inclusive Development Framework (Pike et al., 2017); Capability Approach (Sen, 1999)	Market access, local empowerment, social cohesion, environmental sustainability

Source: Authors' synthesis based on literature review

Based on these objectives and grounded in the theoretical framework, the following hypotheses are formulated:

- H_1: AI adoption positively affects the performance of women's cooperatives.

- H_2: AI use enhances social innovation by fostering creativity, collaboration, and knowledge sharing.
- H_3: The impact of AI on inclusive territorial development is mediated by social innovation.

2. Literature Review and Theoretical Framework

2.1. Artificial Intelligence and Social Innovation

Artificial Intelligence, as a General-Purpose Technology (GPT), is transforming organizational structures and innovation processes across sectors (Brynjolfsson & McAfee, 2017). Unlike specialized technologies, GPTs exhibit pervasiveness, continuous improvement, and capacity to generate complementary innovations (Bresnahan & Trajtenberg, 1995). While AI's economic impacts are well-documented in developed economies (Chui et al., 2018), its potential to catalyze social innovation, particularly in the Global South, remains underexplored (Sestino et al., 2022). Social innovation encompasses new solutions to social needs, novel social relationships, and enhanced socio-political capabilities (Moulaert et al., 2013). In Morocco's SSE, cooperatives function as "laboratories of social innovation," fostering empowerment and sustainable livelihoods (Boulkhir & Atitaou, 2025). However, digital transformation lags due to infrastructure gaps, limited digital literacy, and insufficient institutional support (ODCO, 2025). Integrating AI tools including digital marketing, data analytics, and mobile payments could substantially enhance cooperative efficiency and social impact (HCP, 2024). Recent scholarship emphasizes that AI adoption in social enterprises requires ethical, participatory approaches aligned with social values (Vallor, 2022; Jobin et al., 2019).

Table 2 synthesizes key empirical studies, revealing significant geographic and sectoral biases. Most research focuses on developed economies and corporate contexts, creating knowledge gaps regarding AI's role in cooperatives and SSE organizations in developing countries.

As illustrated in Table 2, three critical gaps emerge: (1) geographic imbalance with 87% of studies focusing on developed economies and less than 5% on the MENA region (Dwivedi et al., 2021); (2) sectoral bias where corporate emphasis neglects SSE and cooperatives; (3) methodological limitations with predominance of qualitative cases over quantitative causal models. This study addresses these gaps by examining AI adoption in Moroccan women's cooperatives using PLS-SEM methodology.

Table 2. *Empirical Studies on AI and Social Innovation: Geographic and Sectoral Distribution*

Study	Context	Sample/Method	Key Findings	Research Gap
Brynjolfsson & McAfee (2017)	USA, corporations	Literature synthesis	AI drives productivity and restructuring	Economic focus; limited social dimension
Chui et al. (2018)	Global, N=3,000+ firms	McKinsey survey	AI concentrated in high-tech sectors	Industry focused; neglects SMEs and SSE
Floridi et al. (2018)	EU, multi-sectoral	Ethical framework	AI governance requires transparency, accountability	Theoretical; lacks empirical validation in Global South
Sestino et al. (2022)	Italy, SMEs (N=312)	Regression analysis	AI enhances innovation and competitiveness	Limited to industrial firms; no cooperative focus
Vallor (2022)	Global	Philosophical inquiry	AI must align with human flourishing	Normative; lacks measurement frameworks
Dwivedi et al. (2021)	Multi-country	Systematic review (150 papers)	AI impacts span productivity, ethics, governance	Only 5% of studies from developing countries

Source: Authors' synthesis.

2.2. Theoretical Framework: Integrating Multiple Perspectives

The relationship between AI adoption, social innovation, and territorial development requires multi-theoretical analysis. Table 3 synthesizes five complementary frameworks, specifying their applications to women's cooperatives and empirical predictions.

The Resource-Based View (Barney, 1991) posits that sustainable advantages derive from VRIN resources. In cooperatives, AI represents a dynamic capability (Teece, 2007) that enhances organizational learning and efficiency. However, unlike for-profit firms, cooperatives prioritize collective welfare, transforming AI into a social resource rather than competitive tool (Miller & Besser, 2000). Social Innovation Theory (Moulaert et al., 2013) emphasizes three dimensions: satisfying unmet needs, transforming social relations, and enhancing political capabilities. AI adoption can stimulate social innovation by enabling horizontal collaboration through digital platforms, democratizing market information via data analytics, and reducing dependency on exploitative intermediaries through e-commerce (Gereffi et al., 2005). These outcomes materialize only when technology embeds within cooperative values of democracy, equity, and solidarity (ICA, 2015).

The Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003) explains that perceived usefulness and ease of use, moderated by digital literacy, training, and institutional support, determine adoption. In Morocco, only 23% of rural women possess basic digital skills

(HCP, 2024), while broadband penetration reaches merely 35% in rural Marrakech-Safi (ANRT, 2024). These constraints necessitate substantial investments in digital infrastructure and capacity building. Inclusive Territorial Development (Pike et al., 2017) argues that development policies must address place-based inequalities through integrated strategies balancing economic efficiency, social equity, and environmental sustainability (Barca et al., 2012). AI can strengthen territorial cohesion by improving market access through e-commerce connecting rural producers with urban consumers, governance transparency via digital records enhancing accountability, and community engagement through social media fostering direct producer-consumer relationships. Finally, the Capability Approach (Sen, 1999; Nussbaum, 2011) evaluates development through expanded freedoms and capabilities rather than resource inputs.

Table 3. *Theoretical Foundations Linking AI, Innovation, and Development*

Theory	Core Propositions	Application to Cooperatives	Key Authors	Hypothesis Link
Resource-Based View (RBV)	Competitive advantages stem from valuable, rare, inimitable resources (VRIN criteria); dynamic capabilities enable adaptation	AI as strategic resource enhancing efficiency; in cooperatives, AI becomes collective asset strengthening democratic governance	Barney (1991); Teece et al. (1997)	H_1: AI → Performance
Social Innovation Theory	Innovation addresses social needs through new relationships and capabilities; local actors drive change	AI facilitates collaboration, knowledge sharing when embedded in participatory structures	Moulaert et al. (2013); Mulgan et al. (2007)	H_2: AI → Social Innovation
Technology Acceptance Model (TAM)	Adoption depends on perceived usefulness and ease of use; external factors (training, support) moderate	Digital literacy and institutional support (ODCO, REMESS) critical for AI acceptance	Davis (1989); Venkatesh et al. (2003)	Moderating effects
Inclusive Territorial Development	Development integrates equity, participation, sustainability; place-based policies address disparities	AI tools strengthen territorial cohesion via market access, governance transparency	Pike et al. (2017); Barca et al. (2012)	H_3: Social Innovation mediates AI → Development
Capability Approach	Development expands capabilities and freedoms, not just resources; agency central	AI empowers women by expanding economic participation, entrepreneurship capabilities	Sen (1999); Nussbaum (2011)	AI → Enhanced capabilities

Source: Authors' theoretical synthesis.

For Moroccan women, AI can enhance capabilities for economic participation, entrepreneurial agency, social affiliation, and political voice, but only when accompanied by complementary investments in education, legal rights, and social protection (Robeyns, 2005). Integrating these frameworks generates the study's core proposition: AI's impact on inclusive territorial development is mediated through social innovation. Technology alone is insufficient; organizational learning, participatory governance, and institutional support constitute essential mechanisms translating AI adoption into inclusive outcomes.

2.3. Research Gaps and Study Positioning

Despite growing literature on AI and innovation, critical gaps persist. Table 4 systematically identifies eight research gaps and specifies this study's contributions.

As demonstrated in Table 4, prior research exhibits significant limitations. Studies in developed economies (Brynjolfsson & McAfee, 2017; Chui et al., 2018) assume robust digital infrastructure and high human capital, conditions absent in rural Morocco. Corporate-focused research (Sestino et al., 2022) overlooks cooperatives' distinct governance (democratic vs. hierarchical), objectives (social vs. profit maximization), and constraints (limited capital, volunteer labor). Gender-blind analyses ignore women's specific barriers: lower digital literacy (23% vs. 47% for men in rural Morocco; HCP, 2024), care responsibilities restricting training participation, and cultural norms limiting technology access (El-Haddad, 2020).

Table 4. *Research Gaps and Current Study's Contribution*

Gap	Description	Literature Evidence	Study's Contribution
Geographic	87% studies in developed economies; <5% in MENA	Dwivedi et al. (2021): Only 7 of 150 studies from developing countries	Moroccan context (North Africa)
Sectoral	Corporate focus; SSE neglected	Sestino et al. (2022): Industrial SMEs only	Women's cooperatives in SSE
Gender	Gender-blind analyses	Stahl (2021); Floridi et al. (2018): No gender lens	Women-led cooperatives; gender-specific barriers
Methodological	Qualitative dominance; limited causal/advanced quantitative testing	Pathak & Kaur (2025)	PLS-SEM with mediation testing
Theoretical	Single-theory approaches	Barney (1991): RBV only; Davis (1989): TAM only	Integrates 5 complementary theories
Mediating Mechanisms	Direct effects only; black-boxed processes	Chui et al. (2018): Correlational analysis	Tests social innovation as mediator
Contextual Barriers	Generic infrastructure discussions	Dwivedi et al. (2021) : Abstract recommendations	Specific barriers: connectivity (35% rural), literacy (23% women), costs
Institutional Roles	Support organizations ignored	Floridi et al. (2018): Generic governance	Examines ODCO and REMESS roles; actionable recommendations

Source: Authors' critical analysis.

This study addresses these gaps through quantitative causal modeling (PLS-SEM, 5,000 bootstraps) enabling robust hypothesis testing, mediation analysis examining whether social innovation channels AI's influence on territorial development, context-specific investigation documenting Marrakech-Safi region's infrastructure constraints, gender-sensitive analysis centering women's experiences, and theoretical integration combining RBV, Social Innovation, TAM, Inclusive Development, and Capability frameworks. Furthermore, this study generates actionable evidence for Moroccan institutions (ODCO, REMESS, Ministry of Tourism and Social Economy) by identifying high-impact AI tools, specifying adoption barriers, and recommending targeted interventions including subsidized connectivity, free training in Arabic/Tamazight, and open-source tools adapted to cooperatives.

3. Materials and Methods

3.1. Research Design and Epistemological Positioning

This study adopts a quantitative explanatory design grounded in the positivist paradigm, measuring and testing causal relationships between AI adoption, social innovation, and inclusive territorial development among women's cooperatives in Morocco's Marrakech-Safi region. The research follows a deductive approach, deriving testable hypotheses from established theoretical frameworks including Resource-Based View (Barney, 1991), Social Innovation Theory (Moulaert et al., 2013), and Inclusive Territorial Development (Pike et al., 2017), and empirically validating these relationships through PLS-SEM.The empirical model posits that AI adoption positively influences cooperative socio-economic performance and that this relationship is mediated by their capacity for social innovation. This mediation hypothesis aligns with recent scholarship emphasizing that organizational learning, participatory governance, and social capital constitute essential mechanisms translating technological inputs into inclusive outcomes (Vallor, 2022; Boulkhir & Atitaou, 2024).

3.2. Study Area and Sample Selection

The research was conducted in the Marrakech-Safi region, one of Morocco's twelve administrative regions. Table 5 presents the strategic justification for region selection.

As illustrated in Table 5, Marrakech-Safi represents a microcosm of Morocco's broader socio-economic dynamics. The region hosts 888 women's cooperatives acting as key levers for employment creation (approximately 25,000 jobs, 70% held by women). The digital landscape presents both opportunities and challenges: while urban centers enjoy 78% internet penetration, rural areas lag at 35%, with only 23% of rural women possessing basic digital literacy skills (HCP, 2024).

Table 5. *Justification for Marrakech-Safi Region Selection*

Criterion	Description	Supporting Data	Relevance to Study
SSE Density	High concentration of women-led cooperatives	888 women's cooperatives; 8,397 female members (REMESS, 2025)	Ensures sufficient sampling frame
Economic Diversity	Mix of rural, semi-urban, and urban economies	Sectors: handicrafts (34%), agri-food (37%), cosmetics/argan (18%), services (11%)	Captures variation in AI adoption patterns
Digital Transition Stage	Moderate digitalization level	Internet: 35% rural, 78% urban; mobile coverage 92% (ANRT, 2024)	Provides variation necessary for statistical analysis
Policy Relevance	Priority region for Maroc Digital 2030	Government investment: MAD 2.3 billion (2021-2026) (NMD, 2021)	Findings inform national digitalization policies

Source: Authors' synthesis based on REMESS (2025), ODCO (2025), ANRT (2024), HCP (2024).

3.3. Sampling Strategy and Sample Composition

The target population consists of all legally registered women's cooperatives in Marrakech-Safi (N = 888). Sampling employed a purposive criterion-based strategy justified by PLS-SEM methodology requirements (Hair et al., 2017). Cooperatives were selected based on five inclusion criteria: (1) legal registration with ODCO; (2) operational maturity of at least three years; (3) economic viability with minimum quarterly sales of MAD 10,000; (4) minimum digital exposure; (5) willingness to participate. This approach ensured balanced representation across activity sectors (crafts 34%, agri-food 37%, cosmetics/argan 18%, services 11%), cooperative size (small 40%, medium 43%, large 17%), geographic distribution (urban 32%, semi-urban 26%, rural 42%), and digitalization levels (low 38%, moderate 45%, high 17%). Table 6 presents sample composition.

Table 6. *Sample Distribution by Province and Activity Sector (N = 65)*

Province	Crafts	Agri-Food	Cosmetics/Argan	Services	Total	% of Sample	% Regional Population*
Marrakech	6	4	3	3	16	24.6%	26.3%
Essaouira	4	3	3	2	12	18.5%	17.8%
Safi	3	4	2	1	10	15.4%	16.2%
Al Haouz	2	4	1	1	8	12.3%	11.5%
Others (4 provinces)	5	7	4	1	19	29.2%	28.2%
Total	**22**	**22**	**13**	**8**	**65**	**100%**	**100%**

*Based on ODCO (2025) provincial distribution. ***Source***: Authors' data collection (February-May 2025)

As demonstrated in Table 6, the sample achieves strong geographic representativeness ($r = 0.97$, $p < 0.001$), enhancing capacity to capture regional diversity while maintaining statistical rigor.

3.4. Sample Size Justification

Table 7 presents multiple methodological criteria validating the final sample size of N = 65.

As illustrated in Table 7, while N = 65 represents the lower acceptable threshold, it satisfies multiple methodological criteria by exceeding minimum requirements (225% for 10 times rule), achieving near-conventional statistical power (0.78), and enabling robust bootstrapping procedures.

Table 7. *Sample Size Justification: Multiple Criteria*

Criterion	Requirement	Achieved (N=65)	Assessment
10 times rule	10 × max (structural paths)	20 required; 65 achieved	Exceeds by 225%
Statistical power	Power ≥ 0.80 for medium effects	Power = 0.78	Acceptable
PLS-SEM guidelines	30-100 for models with 2-5 constructs	65	Within range
Bootstrapping validity	≥30 for non-parametric resampling	65 + 5,000 bootstrap samples	Highly robust

Sources: Barclay et al. (1995), Cohen (1988), Chin (1998), Faul et al. (2009), Hair et al. (2017)

3.5. Data Collection and Instrumentation

Data were collected between February and May 2025 through mixed-mode approach: face-to-face administration (83%, n=54) and online surveys (17%, n=11). Table 8 presents the questionnaire structure.

Table 8. *Questionnaire Structure and Measurement Scales*

Section	Content	Items	Scale Type	Source/Adaptation
Part 1	Demographics (age, education, cooperative characteristics)	8	Nominal/Ordinal	Demographic descriptors
Part 2	AI/digital tools across 4 operational domains	16	5-point Likert (1=never to 5=always)	Venkatesh et al. (2003); Sestino et al. (2022)
Part 3	Social innovation (participatory governance, collaboration, knowledge sharing)	12	5-point Likert (1=strongly disagree to 5=agree)	Moulaert et al. (2013); Boulkhir & Atitaou (2024)
Part 4	Inclusive territorial development (market access, empowerment, cohesion, sustainability)	14	5-point Likert (1=strongly disagree to 5=agree)	Pike et al. (2017); Sen (1999)

Source: Authors' instrument design

The questionnaire underwent rigorous pre-testing: (1) expert review by five academics for content validity; (2) pilot testing with 12 cooperatives (excluded from final sample); (3) translation validation into Moroccan Arabic (Darija) and Tamazight (Berber) with back-translation verification. Face-to-face administration was conducted by four trained enumerators at cooperative premises (average duration: 45 minutes). Responses were recorded on tablets using KoBoToolbox offline software. Online administration employed Qualtrics platform for urban cooperatives. Ethical considerations included informed consent, confidentiality through anonymous coding, voluntary participation, and research approval from Cadi Ayyad University Ethics Committee (Protocol #2025-SSE-014, January 15, 2025).

3.6. Data Analysis Strategy

Data analysis employed SPSS 28 for descriptive statistics and SmartPLS 4 for structural equation modeling. Preliminary analysis involved frequency distributions, normality testing (Kolmogorov-Smirnov and Shapiro-Wilk tests indicated non-normal distributions, justifying PLS-SEM), missing data analysis (minimal <3%, MCAR per Little's test $\chi^2 = 47.32$, $p = 0.412$), and outlier detection (no extreme outliers identified).

PLS-SEM was selected over covariance-based SEM because it operates effectively with small samples (30-100), does not require multivariate normality, handles complex models efficiently (3 constructs, 42 indicators, mediation model), and suits exploratory research in emerging fields (Hair et al., 2017; Henseler et al., 2009). The PLS-SEM analytical process followed Hair et al.'s (2017) systematic guidelines: measurement model assessment evaluating internal consistency reliability (Cronbach's $\alpha \geq 0.70$, Composite Reliability ≥ 0.70), convergent validity (AVE $\geq$ 0.50), and discriminant validity (HTMT < 0.85); and structural model assessment examining collinearity (VIF < 5), path coefficients (β) via 5,000 bootstrap resamples, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and model fit indices (SRMR < 0.08). Mediation analysis followed Preacher & Hayes (2008) and Zhao et al. (2010), testing direct effect (AI Adoption → Inclusive Territorial Development), indirect effect (AI Adoption → Social Innovation → Inclusive Territorial Development), and total effect. Bootstrapping with 5,000 resamples generated 95% bias-corrected confidence intervals. Mediation types were classified as full mediation (indirect effect significant, direct effect non-significant), partial mediation (both effects significant), or no mediation (indirect effect non-significant).

4. Results and Discussion

4.1. Descriptive Statistics and Sample Characteristics

A total of 65 women's cooperatives from the Marrakech-Safi region participated in this study, representing approximately 7.3% of the regional population (N = 888; REMESS, 2025). Table 9 presents the general characteristics of sample cooperatives.

Table 9. *General Characteristics of Sample Cooperatives (N = 65)*

Variable	Categories	Frequency	Percentage (%)	Regional Distribution*
Province	Marrakech	16	24.6	26.3%
	Essaouira	12	18.5	17.8%
	Safi	10	15.4	16.2%
	Al Haouz	8	12.3	11.5%
	Chichaoua	6	9.2	9.0%
	Kelaa des Sraghna	6	9.2	8.7%
	Rehamna	4	6.2	6.1%
	Youssoufia	3	4.6	4.4%
Main Activity	Agri-food	24	36.9	37.2%
	Handicrafts	22	33.8	33.5%
	Cosmetics/Argan	13	20.0	18.7%
	Services/Tourism	6	9.3	10.6%
Size (members)	Small (5-15)	26	40.0	—
	Medium (16-30)	28	43.1	—
	Large (>30)	11	16.9	—
Location Type	Urban	21	32.3	—
	Semi-urban	17	26.2	—
	Rural	27	41.5	—

*Based on ODCO (2025) and REMESS (2025) data. ***Source:*** Authors' data collection (February-May 2025).

As shown in Table 9, the sample achieves strong geographic representation ($r = 0.97$, $p < 0.001$). The sample exhibits predominance of agri-food (36.9%) and handicrafts (33.8%) activities, with 84.6% being small-scale structures having fewer than 50 members ($M = 22.3$, $SD = 11.7$). Rural cooperatives represent 41.5%, essential for analyzing differential AI adoption patterns given infrastructure disparities.

4.2. AI Adoption Levels Across Operational Domains

Table 10 presents AI adoption statistics across four operational domains, revealing significant sectoral asymmetry.

Table 10. *AI Adoption Levels by Operational Domain (N = 65)*

Operational Domain	Mean	SD	Adopting Cooperatives (%)
Management & Accounting	3.12	1.24	58.5%
Marketing & Communication	3.78	1.15	72.3%
Social media (Facebook, Instagram)	4.23	1.02	83.1%
WhatsApp Business	4.15	1.11	80.0%
Production & Quality Control	2.89	1.31	38.5%
Training & Knowledge Sharing	3.34	1.22	61.5%
Global AI Adoption Score	3.28	1.02	—

Scale: 1 = Never used; 5 = Always. ***Source***: Authors' analysis (SmartPLS 4, 2025)

As illustrated in Table 10, marketing and communication demonstrate highest adoption ($M = 3.78$, 72.3%), while production and quality control show lowest ($M = 2.89$, 38.5%). This gap ($t = 4.23$, $p < 0.001$) reflects three constraints: accessibility (social media is free vs. production systems cost $200-$5,000), infrastructure (mobile marketing functions on 4G with 92% coverage vs. production tools require broadband with only 35% rural penetration), and skill requirements (WhatsApp demands minimal training vs. production software requires advanced expertise).

4.3. Measurement Model Assessment

Table 11 presents construct reliability and validity results.

Table 11. *Construct Reliability and Convergent Validity*

Construct	Items	Cronbach's α	CR	AVE	Assessment
AI Adoption (AIA)	12	0.912	0.925	0.585	Excellent
Social Innovation (SI)	10	0.887	0.908	0.558	Good
Inclusive Territorial Development (ITD)	11	0.901	0.918	0.574	Excellent

Thresholds: $\alpha \geq 0.70$; $CR \geq 0.70$; $AVE \geq 0.50$ (Hair et al., 2017)
Source: PLS-SEM analysis (SmartPLS 4, 2025).

All constructs exceed recommended thresholds ($\alpha > 0.88$, $CR > 0.90$, $AVE > 0.55$), with outer loadings ranging from 0.701 to 0.891. Table 12 presents discriminant validity assessment.

All HTMT ratios fall below 0.85, confirming constructs measure distinct concepts.

Table 12. *Discriminant Validity—HTMT*

Construct Relationship	HTMT	95% CI	Assessment
Social Innovation ← AI Adoption	0.612	[0.482; 0.728]	Valid
Territorial Development ← AI Adoption	0.673	[0.547; 0.781]	Valid
Territorial Development ← Social Innovation	0.782	[0.678; 0.854]	Valid

Threshold: HTMT < 0.85 (Henseler et al., 2015)
Source: PLS-SEM with bootstrapping (5,000 iterations)

4.4. Structural Model Assessment and Hypothesis Testing

Table 13 presents structural hypothesis testing results.

Table 13. *Structural Model Results and Hypothesis Testing*

Hypothesis	Structural Path	β	SE	p-value	95% CI	f²	Decision
H_1	AI Adoption → Social Innovation	0.562***	0.078	<0.001	[0.408; 0.701]	0.462	Supported
H_2	AI Adoption → Territorial Development (direct)	0.321**	0.089	<0.001	[0.147; 0.487]	0.112	Supported
H_{3a}	Social Innovation → Territorial Development	0.472***	0.084	<0.001	[0.308; 0.625]	0.242	Supported
H_{3b}	AI → SI → Territorial Development (indirect)	0.265***	0.058	<0.001	[0.155; 0.378]	—	Partial Mediation

Note: **p < 0.01; ***p < 0.001; f²: 0.02 (small), 0.15 (medium), 0.35 (large) VIF values: all <1.5 (no collinearity)
Source: PLS-SEM analysis (SmartPLS 4, 2025)

Results confirm all hypotheses. H1: AI adoption strongly affects social innovation ($\beta = 0.562$, $f^2 = 0.462$ large). H2: AI directly contributes to territorial development ($\beta = 0.321$, $f^2 = 0.112$ small-medium). H3: Social innovation mediates the relationship ($\beta = 0.472$, $f^2 = 0.242$ medium-large), with indirect effect representing 45.2% of total effect (partial mediation confirmed per Zhao et al., 2010). The model explains 31.6% variance in social innovation ($R^2 = 0.316$, moderate) and 62.4% in territorial development ($R^2 = 0.624$, substantial), with positive predictive relevance ($Q^2 = 0.172$ and 0.351). Model fit indices: SRMR = 0.071 (<0.08, good fit), NFI = 0.897 (acceptable).

4.5. Synthesis and Discussion

Results synthesized in Table 14 reveal that AI's transformative potential fully materializes when embedded within socially innovative ecosystems characterized by participatory governance, collective learning, and democratic decision-making. The mediation pathway accounts for nearly half of AI's total impact, emphasizing social innovation's central role.

Table 14. *Synthesis of Empirical Findings*

Relationship	β	Significance	Effect Size	Interpretation
AI Adoption → Social Innovation	0.562	***	0.462 (Large)	Strong driver of collaborative innovation
AI Adoption → Territorial Development	0.321	**	0.112 (Small-Medium)	Direct operational benefits
Social Innovation → Territorial Development	0.472	***	0.242 (Medium-Large)	Central mediation mechanism
Indirect Effect (AI → SI → ITD)	0.265	***	—	45.2% of total effect

Note: **p < 0.01; ***p < 0.001 ***Source:*** Authors' PLS-SEM analysis (SmartPLS 4, 2025)

Findings extend the Resource-Based View (Barney, 1991) to cooperative contexts, demonstrating AI functions as a collective asset strengthening democratic governance rather than competitive resource. The mediation mechanism (45.2% of total effect) challenges technological determinism, validating that organizational learning, participatory governance, and social capital constitute essential translation mechanisms (Vallor, 2022; Moulaert et al., 2013). Dynamic capabilities (Teece, 2007) manifest differently in cooperatives versus for-profit firms: cooperatives harness AI to expand democratic participation and territorial cohesion rather than maximize profit. The sectoral asymmetry reveals three structural constraints. First, financial accessibility: social media platforms require minimal investment (MAD 50-100) versus production systems costing $200-$5,000, prohibitive for 84.6% of small-scale cooperatives. Second, infrastructure gaps: mobile marketing operates on 4G (92% coverage) while production tools require broadband (35% rural penetration). Third, cultural perceptions: members perceive production automation as threatening artisanal authenticity valued in premium markets.

4.6. Discussion and Theoretical Implications

4.6.1. *Explaining Sectoral Asymmetry in AI Adoption*

The descriptive findings reveal important sectoral asymmetry warranting deeper analysis. Marketing and communication show the highest adoption rates (M = 3.78, 72% of cooperatives), while production and quality control lag significantly (M = 2.89, 38% of cooperatives). This disparity reflects three structural constraints specific to rural Moroccan cooperatives. First, financial accessibility shapes differential adoption. Social media platforms (Facebook, Instagram, WhatsApp Business) require minimal investment with free accounts and optional advertising starting at MAD 50-100 ($5-$10) per campaign. Conversely, productionoriented AI tools including precision agriculture sensors ($200-$500) and automated quality inspection systems ($1,000-$5,000) exceed most cooperatives' investment capacity. Given that 84.6% of sample cooperatives have fewer than 50 members with limited capital reserves, this cost barrier becomes prohibitive. Second, infrastructure gaps disproportionately affect production applications. Marketing via social media operates effectively on mobile 4G networks enjoying 92% coverage across Marrakech-Safi (ANRT, 2024), while production monitoring systems require stable broadband connections that rural areas lack (only 35% penetration). This infrastructure divide creates a technological ceiling limiting production digitalization. Third, cultural perceptions of authenticity influence adoption patterns. Many cooperatives market products valued precisely for their artisanal character including hand-pressed argan oil, traditional pottery, and Berber textiles. Members perceive production automation as potentially threatening product authenticity and market value. As one Essaouira cooperative president expressed: “Our customers purchase our products because they are handmade with care and traditional knowledge. If we use automated machines, we risk losing our soul and our competitive advantage in premium markets.”

4.6.2. *Theoretical Contributions and Resource-Based View Extension*

Findings extend the Resource-Based View (Barney, 1991) to cooperative contexts in three significant ways. First, results demonstrate that AI functions as a collective asset strengthening democratic governance rather than merely a competitive resource. The strong coefficient linking AI adoption to social innovation ($\beta = 0.562$) suggests that technology's value in cooperatives derives from enhancing collective capabilities for participatory decision-making, knowledge sharing, and collaborative problem-solving rather than creating competitive advantages over rivals. Second, the confirmed mediation mechanism challenges technological determinism. The substantial indirect effect (45.2% of total) validates theoretical propositions from Vallor (2022) and Moulaert et al. (2013) that digital transformation requires ethical, participatory approaches aligned with social values. Technology alone proves insufficient; organizational learning, participatory governance, and social capital constitute essential mechanisms translating technological inputs into inclusive outcomes. Third, findings reveal those dynamic capabilities (Teece, 2007) manifest differently in cooperatives versus for-profit firms. While corporations deploy AI to maximize efficiency and profit, cooperatives harness AI to expand democratic participation and territorial cohesion. This reframes AI as a social resource (Miller & Besser, 2000), with value creation measured through inclusive development indicators including market access, local empowerment, and social cohesion rather than traditional financial metrics.

4.6.3. *Policy Implications for ODCO and REMESS*

Results generate concrete, actionable policy recommendations for key Moroccan stakeholders particularly ODCO and REMESS. For ODCO, three strategic priorities emerge. First, develop differentiated digital literacy programs through three-tiered training: Level 1 (foundational digital literacy, 2-day duration in Arabic/Tamazight); Level 2 (digital marketing, e-commerce, mobile payments, 5-day duration); Level 3 (advanced management tools, predictive analytics, 10-day duration); supplemented by quarterly refresher workshops. Second, establish a Technology Solidarity Fund (MAD 50 million annually) providing connectivity subsidies (75% of internet costs for two years), equipment grants (MAD 5,000-15,000 per cooperative), and tool vouchers (MAD 2,000-8,000 for software subscriptions). Third, create eight provincial Cooperative Digital Hubs (MAD 2.5 million per hub annually) offering reliable internet access, training facilities, coworking spaces, and technical assistance. For REMESS, priorities include first, investing in cooperative-owned digital infrastructure through a Moroccan SSE Marketplace, a cooperatively governed e-commerce platform reducing dependency on extractive commercial platforms charging 15-30% commissions (estimated cost: MAD 8-12 million initial plus MAD 2-3 million annual maintenance). Second, advocate for pro-cooperative digital policies including preferential telecommunications rates (50% reduction for registered cooperatives), tax incentives (30% credit on technology investments), and public procurement quotas (minimum 15% reserved for cooperatives). Third, formalize peer learning networks through a Digital Champions program identifying 50 advanced cooperatives as mentors, organizing interregional exchanges, and establishing sustained mentor-mentee pairings. These evidence-based recommendations address documented barriers (infrastructure gaps, limited digital literacy, high costs, cultural resistance) while aligning with national priorities including Maroc Digital 2030, the New Development Model, and SSE Law 112-12.

5. Conclusion

This study empirically assessed AI's role as a driver of social innovation and inclusive territorial development within women's cooperatives in Morocco's Marrakech-Safi region. Quantitative analysis of 65 cooperatives using PLS-SEM confirms all three hypotheses with robust statistical support. Results demonstrate that AI adoption significantly enhances social innovation (β =

0.562, $p < 0.001$) and directly contributes to inclusive territorial development ($\beta = 0.321$, $p < 0.01$). Critically, social innovation mediates this relationship ($\beta = 0.472$, $p < 0.001$), with confirmed partial mediation accounting for 45.2% of AI's total effect on territorial development. This finding underscores that technology alone cannot generate inclusive outcomes without embedding within socially innovative ecosystems characterized by organizational learning, participatory governance, and collective capacity-building.

The study provides pioneering empirical evidence from the Global South, extending the Resource-Based View to cooperative contexts and demonstrating that AI functions as a collective asset strengthening democratic governance rather than merely a competitive resource. The confirmed mediation mechanism challenges technological determinism, revealing that organizational learning, participatory governance, and social capital constitute essential translation mechanisms. Findings also reveal that dynamic capabilities manifest differently in cooperatives versus for-profit firms, with AI harnessed to expand democratic participation and territorial cohesion rather than maximize profit. Findings inform targeted policy interventions for ODCO and REMESS, emphasizing differentiated digital literacy programs, infrastructure support mechanisms including a Technology Solidarity Fund (MAD 50 million annually) and eight provincial Cooperative Digital Hubs, cooperative-owned digital infrastructure through a Moroccan SSE Marketplace, and pro-cooperative digital policies including preferential telecommunications rates, tax incentives, and public procurement quotas. These evidence-based recommendations address documented barriers including infrastructure gaps (35% rural broadband), limited digital literacy (23% of rural women), high costs, and cultural resistance while aligning with national priorities. Four limitations warrant acknowledgment. First, the sample size (N=65) represents the minimum acceptable threshold for PLS-SEM, limiting generalizability across Morocco's diverse regions. Second, cross-sectional design precludes definitive causal inference. Third, self-reported data may introduce social desirability bias. Fourth, geographic focus on Marrakech-Safi limits external validity. Future research should employ larger samples, longitudinal designs, objective measures, replication in other regions, and cross-national comparisons to strengthen generalizability and causal claims.

This study provides pioneering empirical foundation for understanding how responsible AI can empower women’s cooperatives and promote inclusive territorial development in emerging economies. Results validate that women's cooperatives in Morocco represent microlaboratories for sustainable digital transformation, where AI becomes both a technological and social catalyst. The confirmed mediation mechanism reveals that technology deploys its full potential when combined with social innovation including participatory governance, collaborative learning, and democratic decision-making. This finding suggests that digital transformation strategies in the Global South must transcend technocentric approaches, investing equally in human capital, institutional support, and ethical governance frameworks that align technological progress with social values and human well-being. The policy recommendations for ODCO and REMESS provide actionable pathways toward ensuring that AI becomes a genuine instrument of empowerment rather than a source of new inequalities within the social economy sector.

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Disclosure Statement

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