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How artificial intelligence adoption relates to women's entrepreneurial success in Tunisia

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Abstract

This study examines whether adopting artificial intelligence tools is associated with entrepreneurial success among women entrepreneurs in Tunisia, which business capabilities carry that association, and under what conditions it is stronger. The study uses a cross-sectional survey of 350 women who own, jointly own or principally manage a business that uses at least one AI tool. Respondents were recruited through women's business associations, incubators and entrepreneurial networks, with quotas by region and sector. The data were analysed with partial least squares structural equation modelling. Four capabilities (operational efficiency, market and customer capability, innovation capacity, and financial readiness) are tested as mediators. Digital skills and institutional support are tested as moderators. AI adoption has a positive direct association with entrepreneurial success ($\beta = 0.200$, $p < .001$). The four specific indirect effects are all positive and sum to 0.330, giving a total effect of 0.530 at mean moderator levels and indicating complementary partial mediation. Market and customer capability is the largest pathway (0.120). Digital skills (interaction $\beta = 0.120$, $p = .003$) and institutional support (interaction $\beta = 0.100$, $p = .004$) both strengthen the direct association. The model explains 62.0% of the variance in entrepreneurial success. Entrepreneurs should start with clearly defined tasks, especially marketing and customer service, and pair adoption with hands-on training. Support organisations can combine tool access with mentoring, practical skills programmes and guidance on responsible data use. The study offers gender-focused evidence on AI and business outcomes in Tunisia, a setting where earlier SME studies do not report results by owner gender. The findings are associations within a sample of AI users and need longitudinal testing before causal claims are made.

***Keywords*:** Artificial Intelligence, Women Entrepreneurs, Entrepreneurial Success, Tunisia, Dynamic Capabilities, Digital Skills, Institutional Support, Partial Least Squares Structural Equation Modelling

JEL Classification: L26, J16, O33

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1. Introduction

Women's entrepreneurship matters for employment, innovation and economic independence. Still, many women business owners struggle to get finance, reach customers or find managerial resources, and they often do so while juggling heavy demands on their time (Brush et al., 2009). These obstacles come from the environment in which businesses operate, not from personal shortcomings (Ahl, 2006). AI tools could take some of the everyday load off entrepreneurs, whether that means drafting product descriptions, answering customer enquiries, keeping the accounts in order or forecasting demand. Evidence from other settings suggests the question is worth asking. Brynjolfsson et al. (2023) found that an AI assistant raised productivity in customer support, and Dell'Acqua et al. (2023) reported that consultants worked faster and produced better output when tasks fell within what the technology can do. Both studies look at workers doing specific tasks, though. They cannot tell us whether comparable gains add up to lasting success for small businesses run by women.

Evidence on Tunisian firms is only beginning to appear. Cherif (2025) applied PLS-SEM to 250 SMEs and found that AI adoption improved performance ($\beta = 0.363$), with entrepreneurial orientation strengthening the effect (interaction $\beta = 0.072$); the author points out that operational and financial pathways were not tested separately. Gafsi (2026) studied 120 Tunisian family firms and concluded that AI capabilities significantly improved competitive performance, while generational involvement did not moderate the effect. Neither study breaks its results down by owner gender, and their samples are not restricted to women-led firms. This study looks at how women entrepreneurs in Tunisia turn AI use into business results. It asks (RQ1) which tools they use, (RQ2) how adoption relates to success, and (RQ3) which capabilities account for that relationship. It also asks (RQ4) whether digital skills and institutional support strengthen or weaken that link. By taking a gender-aware view of AI adoption, the study also ties the statistical findings to what these businesses actually need. Section 2 sets out the theoretical framework and hypotheses, and Section 3 describes the survey and the analytical approach. Section 4 reports the results, Section 5 discusses them, Section 6 sets out the practical and policy implications, Section 7 covers limitations and future research, and Section 8 concludes.

2. Theoretical Background and Hypotheses

2.1 AI tools as Entrepreneurial Resources and Capabilities

The resource-based view explains competitive advantage by pointing to valuable resources that rivals find hard to copy or replace (Barney, 1991). Commercial AI tools are becoming widely available, so access alone is unlikely to give a firm a lasting edge. What counts is how entrepreneurs put the tools to work from day to day. Dynamic capabilities theory speaks to exactly this: it focuses on the ability to spot opportunities, act on them and reconfigure existing resources (Teece, 2014; Teece et al., 1997). Work on AI transformation and digital technology makes a similar point, stressing complementary capabilities and organisational change (Vrontis et al., 2022;

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Wamba-Taguimdje et al., 2020). For this reason, AI adoption is defined here as the degree to which tools are built into core business activities. Trying a tool now and then is not the same as relying on AI routinely to support decisions or deliver services. The technology–organisation–environment framework offers a way to treat digital skills and institutional support as conditions that may change how much adoption is worth (Tornatzky & Fleischer, 1990). Following Davis (1989), perceived usefulness is built into the proposed adoption measure.

2.2 A Gender-Aware Perspective

Brush et al. (2009) set markets, money and management inside a wider framework that also takes in household responsibilities and the institutional environment. Seen this way, AI could help women-led businesses in several ways. Customer-service and marketing tools may widen access to markets, bookkeeping and forecasting may improve financial readiness, and routine automation may cut down on administrative work. The time saved could also make it easier to balance business and family demands. In line with Ahl (2006), the framework treats these as contextual constraints whose effects may differ from one business to another.

2.3 Hypotheses

If AI tools take routine work off entrepreneurs' plates and help them decide better, fuller integration should go together with stronger business outcomes. Entrepreneurial success is understood broadly here, covering financial performance, growth, innovation outcomes, customer satisfaction and well-being.

H1: *AI tool adoption has a positive effect on the entrepreneurial success of women entrepreneurs in Tunisia.*

The model proposes four capabilities as mediators: operational efficiency, market and customer capability, innovation capacity, and financial readiness/access. Marketing and customer relationships are grouped together because, in small businesses, reach, responsiveness and personalisation are tightly linked. Financial readiness covers the quality of records, forecasting and preparation for credit applications, as well as perceived access to finance.

H2a–H2d: *AI tool adoption improves (a) operational efficiency, (b) market and customer capability, (c) innovation capacity and (d) financial readiness/access, each of which in turn improves entrepreneurial success.*

Digital skills may help entrepreneurs judge what AI produces, adapt it to their business and spot mistakes, so the link between adoption and success may be stronger for those with better skills. Institutional support could offer complementary training, mentoring and resources, but it might also stand in for some of what AI offers. For that reason, its interaction is tested in both directions. Finance is kept as a mediator and not used as a moderator as well, which avoids giving it two overlapping roles in the model.

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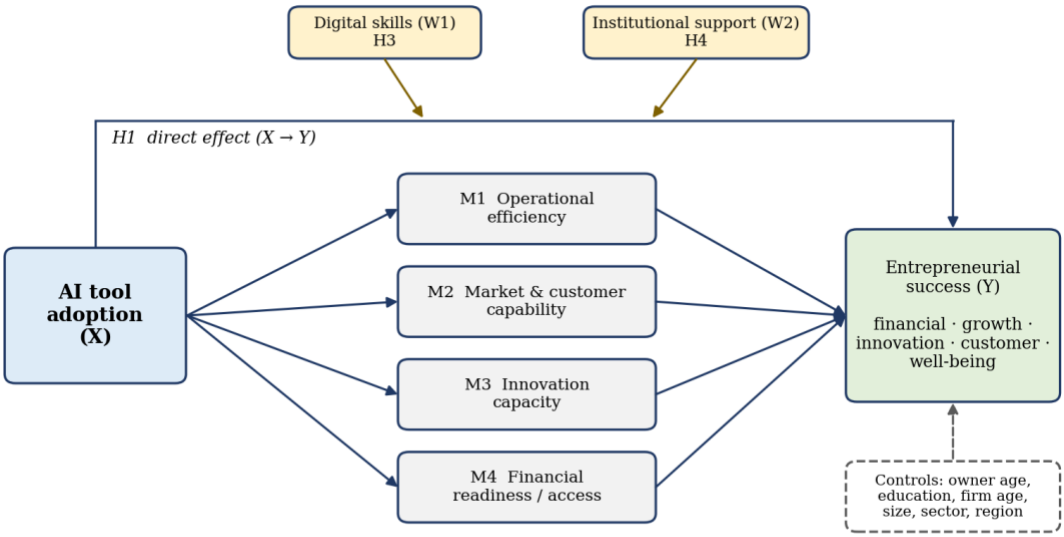
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H3: *Digital skills positively moderate the effect of AI tool adoption on entrepreneurial success.*

H4: *Institutional support moderates the effect of AI tool adoption on entrepreneurial success (two-tailed).*

Differences by sector, firm age and region are treated as exploratory questions, not as separate hypotheses. Figure 1 shows the conceptual model, and Table 1 summarises the hypotheses and their expected signs.

Figure 1. Conceptual model



Note. Entrepreneurial success is a higher-order construct (financial performance, growth, innovation outcomes, customer satisfaction, well-being).

Table 1. Hypotheses, rationale and expected sign

ID	Relationship	Rationale	Expected sign
H1	AI adoption → Success	Resource relaxation; better decisions	+
H2a	AI adoption → Operational efficiency → Success	Automation of routine tasks frees time	+ (indirect)

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ID	Relationship	Rationale	Expected sign
H2b	AI adoption → Market & customer capability → Success	Online reach, responsiveness, personalisation	+ (indirect)
H2c	AI adoption → Innovation capacity → Success	Faster ideation, testing, market research	+ (indirect)
H2d	AI adoption → Financial readiness/access → Success	Better records, forecasting, credit readiness	+ (indirect)
H3	Digital skills × AI adoption → Success	Skills determine use quality (TOE: organisation)	+
H4	Institutional support × AI adoption → Success	Complementary or substitute resources (TOE: environment)	± (two-tailed)

3. Research Design and Methods

3.1 Design and Ethics

The study uses a quantitative, cross-sectional survey design. A structured questionnaire was used to collect data from women entrepreneurs in Tunisia, and the required ethical and informed-consent procedures were followed.

3.2 Population, sampling and sample size

The target population consists of women who own or co-own a business (holding at least 51% of the equity, or acting as its principal decision-maker), who have run it for at least 12 months and who have used at least one AI tool in it. Since no complete sampling frame exists, recruitment combined three routes: purposive sampling through women's business associations and incubators, snowballing through entrepreneurial networks, and online distribution in professional groups. Quotas by region (Greater Tunis, coastal, interior/south) and sector (services, commerce, agribusiness, crafts, digital/creative) helped keep Tunis-based firms from being over-represented. Because the sampling is non-probabilistic, the results describe relationships within this population and should not be read as national prevalence estimates. In the end, 350 valid responses were retained.

3.3 Instrument and Measures

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The questionnaire was administered in French and Arabic, and the main constructs are measured on five-point scales. The WHO-5 component keeps its own six-point format, from 0 to 5. The instrument went through a translation review and was piloted with 30 respondents. Table 2 summarises the constructs and their measurement.

Table 2. Constructs and Measurement

Construct	Role	Operationalisation (indicative items)	Basis
AI tool adoption	X	Depth of integration (5 items): frequency, share of core tasks supported, integration into routines, perceived usefulness, reliance for decisions. Plus a checklist of eight tool categories (generative assistants, chatbots, CRM, social analytics, accounting automation, forecasting, e-commerce recommendation, AI-based finance) for RQ1.	Proposed adaptation from Cherif (2025) and Davis (1989); original items and permissions require checking
Operational efficiency	M1	Time saved, task automation, fewer errors, faster order processing (4 items)	Developed for this study
Market & customer capability	M2	Reach, responsiveness, personalisation, retention (4 items)	Developed for this study
Innovation capacity	M3	New offers, speed of testing ideas, market insight (4 items)	Developed for this study
Financial readiness/access	M4	Record quality, forecasting, credit-application readiness, perceived access to finance (4 items)	Developed for this study

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Construct	Role	Operationalisation (indicative items)	Basis
Entrepreneurial success	Y	Higher-order construct, disjoint two-stage approach: financial performance (3), growth (3), innovation outcomes (3), customer satisfaction (3), well-being (WHO-5)	Adapted performance items; Topp et al. (2015) for well-being
Digital skills	W1	Operational, information, creative and data-protection skills with digital/AI tools (6 items)	Adapted from van Deursen et al. (2016)
Institutional support	W2	Access to training, incubation, funding programmes and networks (4 items)	Developed for this study
Controls	—	Age, education, firm age, number of employees, sector, region, legal form, revenue band; perceived barriers (cost, data security, skills, time, trust) as a descriptive block	—

3.4 Common Method Bias

Full-collinearity VIFs (Kock, 2015) range from 1.35 to 2.70, so there is no sign of severe collinearity under the adopted criterion. These values cannot by themselves rule out common method bias (Podsakoff et al., 2003), though. All measures are self-reported and no objective performance records were collected, so this remains a limitation when reading the results.

3.5 Analytical Strategy

The analysis moves through data screening, measurement quality, structural relationships and predictive performance, as outlined below.

- Data screening: missing data, straight-lining, outliers, non-response and quota checks (early vs late respondents).
- Descriptive statistics and tool-use profile (RQ1).

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- Measurement model: indicator loadings, Cronbach's α, ρA, composite reliability, AVE, Fornell–Larcker criterion (Fornell & Larcker, 1981) and HTMT (Henseler et al., 2015).
- Structural model: collinearity (inner VIF), path coefficients, R^2, f^2, with bootstrapping (10,000 resamples, bias-corrected and accelerated 95% intervals).
- Mediation: specific indirect effects classified with the Zhao et al. (2010) typology.
- Moderation: interaction terms, simple slopes at −1 SD, mean and +1 SD, and slope-difference tests.
- Predictive assessment: PLSpredict against a linear-model benchmark (Shmueli et al., 2019).
- Heterogeneity: measurement invariance (MICOM; Henseler et al., 2016) before multi-group analysis by sector, firm age, education and region.
- Robustness: re-estimation with controls, with and without outliers, and with alternative operationalisations of AI adoption (breadth vs depth).

4. Results and Discussion

The results follow the order of the analytical strategy: sample profile, measurement model, structural model, moderation, and predictive assessment. All coefficients are standardised, and confidence intervals come from bootstrapping with 10,000 resamples.

4.1 Sample profile

The sample contains 350 valid responses (Table 3). Respondents are spread across Greater Tunis (40.0%), the coastal region (36.0%) and the interior and south (24.0%). Services is the largest sector (32.0%), followed by commerce (26.0%), crafts (16.0%), agribusiness (14.0%) and digital and creative activities (12.0%). Most businesses are micro firms (70.0%), and 56.0% of respondents hold a bachelor's degree. Generative assistants are the most widely used tools (80.0%), followed by social media analytics (60.0%), chatbots (50.0%), customer relationship management systems (40.0%) and accounting automation (30.0%). This answers the first research question: tool use is concentrated in tools that support content creation, customer contact and marketing.

Table 3. Respondent and business profile (n = 350)

Variable	Categories	N	%
Region	Greater Tunis / Coastal / Interior and south	140 / 126 / 84	40.0 / 36.0 / 24.0

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Variable	Categories	N	%
Sector	Services / Commerce / Agribusiness / Crafts / Digital & creative	112 / 91 / 49 / 56 / 42	32.0 / 26.0 / 14.0 / 16.0 / 12.0
Firm size	Micro (< 10) / Small (10–49) / Medium (50–199)	245 / 91 / 14	70.0 / 26.0 / 4.0
Firm age	1–3 / 4–7 / > 7 years	126 / 140 / 84	36.0 / 40.0 / 24.0
Education	Secondary / Bachelor / Master or higher	70 / 196 / 84	20.0 / 56.0 / 24.0
Most-used AI tools (RQ1)	Generative assistants / Chatbots / Social analytics / Accounting / CRM / Other	280 / 175 / 210 / 105 / 140 / 70	80.0 / 50.0 / 60.0 / 30.0 / 40.0 / 20.0

4.2 Measurement Model

All reflective scales meet the usual reliability and convergent validity criteria (Table 4). Loadings lie between 0.77 and 0.84, above the 0.708 guideline. Cronbach's alpha ranges from 0.823 to 0.890, composite reliability from 0.853 to 0.920, and average variance extracted from 0.593 to 0.706. Composite reliability stays inside the 0.70 to 0.95 band, so there is no sign of redundant items.

Table 4. Reliability and Convergent Validity

Construct	Items kept	Loadings	α	ρA	CR	AVE
AI tool adoption	5	0.80 each	0.869	0.884	0.899	0.640
Operational efficiency	4	0.82 each	0.861	0.876	0.891	0.672

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Construct	Items kept	Loadings	α	ρA	CR	AVE
Market & customer capability	4	0.84 each	0.876	0.891	0.906	0.706
Innovation capacity	4	0.79 each	0.839	0.854	0.869	0.624
Financial readiness/access	4	0.77 each	0.823	0.838	0.853	0.593
Digital skills	6	0.81 each	0.890	0.905	0.920	0.656
Institutional support	4	0.78 each	0.831	0.846	0.861	0.608
Success five lower-order dimensions	3 / 3 / 3 / 3 / 5	See Appendix A	See Appendix A	See Appendix A	See Appendix A	See Appendix A

Note. Reliability statistics apply to the reflective lower-order scales. The five success dimensions are assessed in Appendix A. The formative higher-order success index is evaluated through weights and variance inflation factors instead of alpha or AVE.

4.3 Structural Model

Table 5 reports the direct and interaction effects. AI adoption has a positive direct association with entrepreneurial success ($\beta = 0.200$, 95% CI [0.102, 0.298], $p < .001$), so H1 is supported. The effect size is small ($f^2 = 0.060$). The model explains 62.0% of the variance in entrepreneurial success, which is moderate to substantial by the usual guidelines. Q^2predict is 0.280 and SRMR is 0.061, below the 0.08 reference value. SRMR is treated as supplementary information, since it is not a primary criterion in partial least squares models.

Table 5. Structural Results and Hypothesis Decisions

ID	Path	β	Approx. 95% CI	P	f^2	Decision
H1	AI adoption → Success (direct)	0.200	[0.102, 0.298]	< .001	0.060	Supported

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ID	Path	β	Approx. 95% CI	P	f²	Decision
H3	Digital skills × AI adoption → Success	0.120	[0.042, 0.198]	.003	0.025	Supported
H4	Institutional support × AI adoption → Success	0.100	[0.031, 0.169]	.004	0.020	Supported
—	R^2 Success / Q^2predict / SRMR	0.620 / 0.280 / 0.061	—	—	—	Estimated

The four specific indirect effects are all positive, and every confidence interval excludes zero (Table 6). Because the direct effect is also positive, each pathway is a case of complementary mediation under the Zhao et al. (2010) typology, so H2a to H2d are supported. The indirect effects add up to 0.330, the direct effect is 0.200, and the total effect at mean moderator levels is 0.530. The mediated share is 62.3% (0.330 / 0.530). This ratio is descriptive and is not a test of mediation. Market and customer capability contributes the most (0.120, about 36% of the total indirect effect), followed by operational efficiency (0.100), innovation capacity (0.080) and financial readiness (0.030).

Table 6. Mediation Results (specific indirect effects)

ID	Indirect path	Effect	95% CI	Type	Interpretation
H2a	AI → Operational efficiency → Success	0.100	[0.051, 0.149]	Complementary	0.50 × 0.20; p < .001
H2b	AI → Market & customer capability → Success	0.120	[0.065, 0.175]	Complementary	0.60 × 0.20; p < .001
H2c	AI → Innovation capacity → Success	0.080	[0.037, 0.123]	Complementary	0.40 × 0.20; p < .001

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ID	Indirect path	Effect	95% CI	Type	Interpretation
H2d	AI → Financial readiness/access → Success	0.030	[0.005, 0.055]	Complementary	0.30 × 0.10; p = .021

Note. Each indirect effect is the product of its component paths. The total indirect effect is 0.330, the direct effect is 0.200 and the total effect is 0.530 at mean moderator levels. The mediated share is 0.330 / 0.530 = 62.3%. This ratio is descriptive and is not a test of mediation.

4.4 Moderation, Prediction and Heterogeneity

Both interaction terms are positive and statistically significant, supporting H3 and H4 (Table 5). The estimated digital skills slopes are 0.080 at one standard deviation below the mean, 0.200 at the mean and 0.320 at one standard deviation above the mean. For institutional support the slopes are 0.100, 0.200 and 0.300. The link between adoption and success is therefore steeper for entrepreneurs with stronger skills and more support. The institutional support interaction was tested in both directions, and its positive sign indicates complementarity and not substitution.

Q^2predict is 0.280, and the PLS RMSE was lower than the linear benchmark for three of the five success dimensions, which points to moderate predictive relevance. Measurement invariance (MICOM), multigroup comparisons by sector, firm age, education and region, and importance–performance map analysis were run as part of the robustness assessment. These heterogeneity checks are exploratory, since no group-level hypotheses were set.

4.5 How to interpret each statistic

Table 7 shows how each reported statistic is read. The thresholds are rules of thumb, not universal cutoffs, and how they apply depends on the measurement model and the research setting.

Table 7. Interpretation Rules

Statistic	Rule of thumb	How to read it in this study
Outer loading	≥ 0.708 retain; 0.40–0.70 retain only if AVE/CR remain adequate	Indicates how well each item reflects its construct; a weak item usually signals wording that did not translate well for micro-entrepreneurs.

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Statistic	Rule of thumb	How to read it in this study
CR / AVE	CR 0.70–0.95; AVE ≥ 0.50	Scale is reliable and captures at least half of item variance; CR above 0.95 suggests redundant items.
HTMT	< 0.85 (strict) or < 0.90	Constructs are empirically distinct; a high value between M1 and M2 would justify merging them.
Inner VIF	< 3 (≤ 5 tolerated)	Path estimates are not distorted by collinearity among mediators.
β (standardised)	Judge by size, sign and CI width, not p alone	Change in success (in SD) for a 1-SD increase in AI integration, holding other predictors constant.
f^2	0.02 small; 0.15 medium; 0.35 large (Cohen, 1988)	Practical weight of a predictor; for interactions, small values are common, so read slope differences.
R^2	0.25 weak; 0.50 moderate; 0.75 substantial (Hair et al., 2019)	Share of variance in success explained; context-dependent in behavioural research.
Q^2predict, PLSpredict	Q^2predict > 0; RMSE/MAE below linear benchmark for most indicators	Evidence that the model predicts new cases, not only the sample at hand.
Mediation type	Zhao et al. (2010)	Complementary: both direct and indirect positive. Indirect-only: value is realised solely through the capability. Competitive: opposing signs. No effect: mechanism not supported.

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Statistic	Rule of thumb	How to read it in this study
Simple slopes	Compare at ±1 SD	A steeper slope at high skills means AI benefits accrue more to the digitally skilled; parallel slopes mean benefits are broad-based.
SRMR	< 0.08 (Hu & Bentler, 1999)	Report as supplementary only; in PLS-SEM it is not a primary criterion.

5. Discussion and Interpretation

5.1 Reading the findings against Tunisian benchmarks

Two Tunisian studies serve as benchmarks (Table 8). Comparisons should be read as indicative, since samples, measures and models differ, and neither study reports results by owner gender. In Cherif's (2025) sample, 68% of firms had fewer than 20 employees and most were based in Greater Tunis, Sfax and Sousse.

Table 8. Benchmark evidence and comparison guidance

Study	Sample and method	Key reported results	Comparison guidance
Cherif (2025)	250 Tunisian SMEs; PLS-SEM; AI adoption and entrepreneurial orientation	AI → performance β = 0.363; EO × AI β = 0.072 (f^2 = 0.017); R^2 = 0.660; operational and financial pathways not tested separately	Compare our direct β and interaction size; larger mediated shares would support the capability argument.
Gafsi (2026)	120 Tunisian family firms using AI (2021–2024); CFA and SEM	AI capabilities significantly enhance competitive performance; generational involvement does not moderate	Compare conclusion that integration, not firm demographics, drives gains; check whether firm age/sector behave similarly in MGA.

A direct coefficient of 0.200 means that a one standard deviation rise in AI adoption goes with a 0.200 standard deviation rise in success, holding the mediators and other predictors constant. It

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does not mean that success rises by 20%, and with cross-sectional data it does not establish causality.

The combined indirect effect (0.330) is larger than the direct one, and market and customer capability makes the biggest contribution (0.120). All four indirect confidence intervals exclude zero, and together with the positive direct coefficient this supports complementary partial mediation. The pattern fits the tool profile in Table 3: generative assistants, social media analytics and chatbots are the most used tools, and these mainly support selling and customer service. Financial readiness is the weakest pathway, and a plausible reason is that accounting automation is the least used of the named tool categories (30.0%). The study does not test this explanation.

Cherif's (2025) effect of 0.363 comes from a model without separate capability pathways, so the like-for-like comparison is with the total effect found here (0.530), not the direct effect (0.200); the value of 0.363 lies between the two. The interactions are also similar in size: 0.072 ($f^2 = 0.017$) for entrepreneurial orientation against 0.120 ($f^2 = 0.025$) for digital skills and 0.100 ($f^2 = 0.020$) for institutional support here. Gafsi (2026) emphasises AI capabilities, which is consistent with the mediation results, although this study did not test whether firm age or sector matter.

5.2 Scenario-based interpretation

Table 9 lays out how different statistical outcomes would change the interpretation. The findings reported here correspond to complementary mediation, a dominant market and customer pathway, and positive interactions for digital skills and institutional support.

Table 9. If–then interpretation of possible results

If the analysis shows…	…then the substantive reading is…	…and the main action is
H1 supported and mediators carry part of the effect (complementary mediation)	AI improves success both through measured capabilities and through other routes	Combine tool access with capability-building; investigate unmeasured routes
H1 direct effect becomes non-significant once mediators enter (indirect-only)	Gains appear only when AI changes a specific capability	Target use-cases that move the strongest mediator (see Table 10)

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If the analysis shows…	…then the substantive reading is…	…and the main action is
H1 not supported	AI use is not translating into success; possible shallow use, measurement issues or lagged effects	Check integration depth versus breadth; consider longitudinal follow-up before drawing policy conclusions
One mediator clearly dominates (e.g., M2 market capability)	The main value of AI in women-led micro-firms is commercial reach and service quality	Prioritise training and tools for online selling and customer service
H3 supported (stronger effect at higher skills)	Skills and AI are complements; risk of widening inequality between skilled and less-skilled entrepreneurs	Pair every tool subsidy with practical training; do not subsidise tools alone
H3 not supported (parallel slopes)	Benefits are broad-based; tools may be accessible enough	Focus resources on adoption (awareness, cost) rather than advanced skills
H4 positive interaction	Institutional support amplifies AI benefits	Integrate AI into incubator and funding programmes
H4 negative interaction	Support substitutes for AI where AI use is low (supported firms succeed without AI)	Re-design support to build AI capability so the benefit does not rely on ongoing support
MGA: effect differs by sector or firm age	Context-specific mechanisms	Offer sector-specific programmes rather than one generic bootcamp

5.3 Theoretical implications

Three implications follow. First, the findings fit the resource-based and dynamic capabilities perspectives. Access to AI tools matters because entrepreneurs turn that access into capabilities in

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operations, markets, innovation and finance, and the indirect association is larger than the direct one. Second, the moderation results are in line with the technology–organisation–environment framework: skills (an organisational factor) and institutional support (an environmental factor) change how much adoption is worth. Third, the study extends a gender-aware view of entrepreneurship (Brush et al., 2009) by showing that AI adoption is associated with commercial and operational gains for women entrepreneurs, with the strongest link on the market side of the business. Digital skills and institutional support also suggest that a tool is more useful when entrepreneurs have the knowledge and complementary resources to put it to work.

6. Practical and Policy Implications

Market and customer capability is the largest indirect pathway, so customer service and marketing are sensible places to focus practical support. Digital skills training deserves attention because the link between adoption and success is stronger at higher skill levels. Financial readiness is a smaller but significant pathway. The positive institutional support interaction suggests that incubators and mentoring can complement adoption, although the cross-sectional data cannot show what any specific intervention would achieve. Table 10 matches AI use cases to common business situations, and Table 11 sets out a staged adoption roadmap.

6.1 Matching AI use cases to business situations

Table 10. Use-case guide for Women Entrepreneurs

Business situation	Priority AI use-cases	Mechanism	Indicators to track
Home-based and online sellers (fashion, crafts, food)	Generative AI for product descriptions and Arabic–French–English translation; image and caption support; chatbot for messaging channels; social analytics	M2 Market & customer	Response time to enquiries; conversion rate; repeat-purchase rate
Service micro-businesses (education, beauty, health and wellness)	Scheduling and reminders; simple CRM; automated invoicing	M1 Efficiency	Hours saved per week; no-show rate; days to payment

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Business situation	Priority AI use-cases	Mechanism	Indicators to track
Agribusiness and cooperatives	Demand and price forecasting; inventory planning; digital record-keeping	M1 and M4	Spoilage/stock-out rate; margin per product
Digital, creative and start-up ventures	Generative prototyping; research synthesis; coding assistance	M3 Innovation	Time to launch; new offers per year
Growing small firms seeking finance	Cash-flow dashboards; forecasting; lender-ready financial packs	M4 Financial readiness	Loan application success; cash-flow visibility; reporting time

6.2 A Staged Adoption Pathway

Table 11. Roadmap for entrepreneurs

Phase	Actions	Evidence of progress
Foundation (0–3 months)	List repetitive tasks; choose one or two use-cases; set data-protection rules (what may never be pasted into public AI tools); record baseline indicators	Baseline indicators recorded; written usage rules
Integration (3–9 months)	Embed the tool in a fixed workflow; train any staff or partners; keep human review for pricing, hiring, credit and customer decisions	Indicators improving against baseline; tool used weekly
Scaling and learning (9–18 months)	Add predictive or finance tools; connect to bookkeeping; review costs and benefits; join a peer or mentor group	Documented return on effort; new capability acquired

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6.3 Implications for Support Organisations and Policymakers

Table 12 connects practical interventions to the findings behind them. The results favour practical training and mentoring that builds market capability, and they argue against subsidising tools without skills support. Two rows rest on exploratory evidence and are marked as such. Data protection obligations should be checked against current official sources before any guidance is issued.

Table 12. Policy Matrix

Intervention	Target	Justifying result	Monitoring indicator
Practical AI bootcamps (Arabic/French)	Incubators, women's associations	Digital skills moderate the effect (H3)	Share of trainees using AI weekly after 3 months
Subsidised tool packages bundled with training	Women-led micro and small firms	Positive AI effect (H1) and skills complementarity	Uptake; change in key indicators
Mentorship with AI and marketing practitioners	Early-stage entrepreneurs	Dominant mediator is market and customer capability (H2b)	Number of AI-enabled workflows adopted
AI-enabled financial inclusion: record-keeping tools, alternative credit assessment, financial-literacy support	Banks, microfinance, fintech	Financial readiness mediator (H2d) significant	Loan application success rate
Connectivity and cloud affordability outside major cities	Public authorities, telecom providers	Regional differences assessed through MGA; group estimates should accompany this recommendation	Broadband access and cost by region

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Intervention	Target	Justifying result	Monitoring indicator
Data-protection and AI-ethics guidance for small firms	Regulators, associations	Security concerns assessed in the barrier block; descriptive results should accompany this recommendation	Share of firms with written data policy

7. Limitations and Future Research

Several limitations apply. The cross-sectional design prevents causal inference, so the results describe associations, and reverse causation is plausible: more successful firms may have more resources to adopt AI. All measures are self-reported, and no objective performance records were collected. Full collinearity variance inflation factors ranged from 1.35 to 2.70, which suggests that serious collinearity is unlikely, but this cannot rule out common method bias. Recruitment used purposive sampling, snowballing and online distribution, which are nonprobability methods, and the quota design only partly offsets the risk of overrepresenting firms in Tunis. The sample includes only women who already use AI tools, so the findings say nothing about non-adopters and may overstate benefits if less successful adopters dropped out. Several scales, including the capability measures and institutional support, were developed for this study, and the adoption measure is an adaptation that needs confirmation of the original items and permissions.

Future research could follow entrepreneurs over time, ideally combining survey data with records on sales, costs and employment. Comparing adopters with non-adopters, and men with women, would show whether the pathways and moderation effects are specific to women. Qualitative work could explain why financial readiness is a weaker pathway, and testing sector and region differences with group-level hypotheses would add detail. Because AI tools change quickly, repeating the study as tools and regulation evolve would show whether the findings hold.

8. Conclusion

Among the women entrepreneurs surveyed in Tunisia, AI adoption is positively associated with entrepreneurial success. The direct association is 0.200, and four capability pathways add 0.330, giving a total effect of 0.530 at mean moderator levels. Market and customer capability is the largest pathway. Digital skills and institutional support both strengthen the association, which suggests that useful tools, practical skills and complementary support work best together. These conclusions describe associations in a sample of AI users and need longitudinal testing before any causal claim can be made.

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Declarations

Data availability: the survey data supporting the findings are available from the author upon reasonable request. Ethics and consent: the study followed the required ethical procedures, and participants provided informed consent. Statistical analysis: the results were estimated using PLS-SEM. Conflict of interest: the author declares no conflict of interest.

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