*American International Journal of Business Management (AIJBM)*
*ISSN- 2379-106X, **www.aijbm.com** Volume 8, Issue 12 (December - 2025), PP 42-61*

# Artificial Intelligence and Inclusive Innovation: A Catalyst for The Transformation Of SMES And Emerging Entrepreneurial Ecosystems

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***Citation:*** *Sandjimbaye, D., P., Mignenan, V., Mamgué, B. (2025) Intelligence artificielle et innovation inclusive : moteur de transformation des PME et des écosystèmes entrepreneuriaux émergents*
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**ABSTRACT*:*** This article analyzes the contribution of artificial intelligence (AI) to the performance of small and medium-sized enterprises (SMEs) in emerging economies. Methodologically, the research adopts a mixed approach. The quantitative survey, conducted among 353 SMEs (trade, agribusiness, services, technologies), in Central Africa, is estimated by structural equations (PLS-SEM). The results indicate that AI exerts a significant direct effect on performance ($\beta = 0.29$; $p < 0.001$) and an indirect effect via serial mediation AI → inclusive innovation → resilience → performance ($\beta\_indirect \approx 0.04$; $p < 0.05$). Inclusive innovation predicts resilience ($\beta = 0.41$; $p < 0.001$), and resilience predicts performance ($\beta = 0.28$; $p = 0.011$). The model has substantial explanatory power ($R^2 \approx 0.48$). The thirty-five qualitative interviews confirm these mechanisms, while highlighting the obstacles: the cost of entering solutions, the lack of digital skills, institutional instability.

*On a theoretical level, the article shows that AI becomes performative if, and only if, it is socialized by inclusive innovation and consolidated by resilience. As a result, public policies must go beyond the diffusion of technology to strengthen the accessibility and absorption capacity of SMEs.*

**Keywords*:*** *Artificial intelligence; Inclusive innovation; Organizational resilience; SME; Emerging economies.*

## I. INTRODUCTION

Artificial Intelligence (AI) refers to the set of systems and algorithms capable of performing tasks that traditionally fall within the realm of human cognitive faculties, such as learning, reasoning, decision-making, and the resolution of complex problems (Russell & Norvig, 2021). In the context of emerging economies, its role extends well beyond the instrumental dimension of automation: it stands as a strategic lever capable of transforming governance models. Moreover, it can stimulate innovation and broaden market access for small and medium-sized enterprises (SMEs). These enterprises, often described as the "backbone" of economic and social development, remain, however, weakened by persistent structural constraints, particularly in terms of financing, digital infrastructure, and managerial competencies (Beck & Cull, 2023).

At the same time, the concept of *inclusive innovation* refers to the design and dissemination of technological, organizational, or social solutions that integrate historically marginalized actors, prioritizing a logic of shared and sustainable value creation (George et al., 2023). This approach transcends the conventional pursuit of competitiveness to embrace a broader perspective rooted in equity, accessibility, and collective resilience. In emerging economies, the articulation between AI adoption and inclusive innovation(Mignenan, 2021b, 2022) offers a fertile analytical framework for understanding how SMEs can enhance their adaptive capacity, strengthen their social legitimacy, and contribute to the consolidation of more resilient and sustainable entrepreneurial ecosystems.

Recent literature strongly emphasizes the catalytic role of AI in organizational transformation(Mignenan, 2023, 2025). By supporting the digitalization of processes, AI promotes financial inclusion, strengthens the traceability of value chains, and expands the potential for open and collaborative innovation (Chesbrough, 2020; Adner, 2017; Agrawal et al., 2022). However, in Sub-Saharan African countries, this dynamic remains constrained by the digital divide, insufficient infrastructure, and the absence of appropriate public policies (UNCTAD, 2023). These challenges highlight that AI cannot be considered a universal solution; rather, it must be contextualized within ecosystems where institutional fragility and resource scarcity remain defining constraints.

In light of these considerations, this article pursues three complementary objectives: (1) to define the role of artificial intelligence in the transformation of SMEs within emerging contexts; (2) to analyze how inclusive innovation acts as a mediating factor between AI adoption and sustainable value creation; and (3) to propose an integrative conceptual framework linking AI, inclusive innovation, and entrepreneurial resilience. To achieve these objectives, the research adopts a hybrid methodological approach structured in three stages. The first section clarifies the theoretical and conceptual foundations; the second reviews and critiques recent empirical literature; and the third proposes and discusses a conceptual model adapted to SMEs in emerging economies, concluding with theoretical and managerial implications.

## II. THEORETICAL CONTEXT

Artificial Intelligence (AI) is traditionally defined as the set of computational methods capable of imitating or augmenting specific human cognitive functions, such as learning, perception, reasoning, and decision-making. These methods serve tasks related to anticipation, classification, and optimization (Russell & Norvig, 2021). In management sciences, AI is increasingly perceived not merely as an isolated technology but as a decision-making infrastructure, a system that supports the selection of priorities, the allocation of resources, and the anticipation of risks (Agrawal, Gans & Goldfarb, 2022). In emerging economies, AI is often deployed to compensate for structural deficits in coordination, financial visibility, and access to market information. It therefore represents less a form of automation than an informational substitute for absent or fragile institutions (UNCTAD, 2023). In other words, in contexts where the reliability of market data and the quality of internal control mechanisms cannot be assumed a priori, AI becomes a tool for reducing uncertainty and enhancing managerial rationality, rather than merely improving technical efficiency.

Within this framework, inclusive innovation emerges as a crucial mechanism for the appropriation and diffusion of such technologies. Far from being a normative slogan, inclusive innovation refers to the design and dissemination of technological, organizational, or financial solutions that explicitly aim to integrate traditionally marginalized actors into formal economic circuits—particularly small enterprises, informal entrepreneurs, women, and groups operating on the geographic or institutional periphery (George, McGahan & Prabhu, 2023). Unlike conventional innovation, it does not presuppose the existence of robust organizational foundations or advanced technical capital; rather, it seeks to make innovation usable, fundable, and governable by firms lacking specialized teams or full-fledged digital infrastructures. Foster and Heeks (2020) emphasize that inclusive innovation must be understood as a process of social and economic integration rather than a top-down diffusion of predesigned technological solutions.

Recent studies on Central and West Africa extend this interpretation by underscoring that inclusive innovation is, in very concrete terms, an innovation of access. In these contexts, it manifests through decentralized digital monetization (mobile payments and algorithmic microcredit), local e-commerce platforms connecting producers and consumers, remote-access tools for cash-flow forecasting and inventory management and simplified financial reporting systems focused on minimum compliance (UNCTAD, 2023; Beck & Cull, 2023). Such innovations expand market access, secure cash flows, improve financial inclusion, and create digital transaction footprints that can be leveraged by financial partners. In many SMEs and microenterprises across West and Central Africa, these tools act as functional substitutes for traditional governance mechanisms: they compensate for the absence of banking histories, the weakness of collateral assets, and the informality of accounting practices by producing a kind of *digital proof of reliability* that can be used with clients, contractors, or donors. Hence, inclusive innovation is not “inclusive” solely because it targets previously excluded populations; it is inclusive because it lowers the organizational and cognitive thresholds required to benefit from AI and, more broadly, from the digitalization of decision-making processes.

From this perspective, inclusive innovation follows not only a social logic but also a capability logic**.** It can be interpreted as an emerging organizational capability, a set of routines, competencies, and internal mechanisms enabling firms to capture and translate digital information into resource allocation, pricing, and risk management decisions(Mignenan, 2021b, 2021c). This view aligns with the theory of dynamic capabilities developed by Teece, Pisano, and Shuen (1997) and later refined by Teece (2007). According to this framework, competitive advantage does not stem from possessing a given technical resource (such as an AI module) but from the ability to: (1) detect and interpret environmental signals (*sensing*), (2) seize and exploit emerging opportunities (*seizing*), and (3) reconfigure assets, routines, and structures to maintain viability amid change (*reconfiguring*). Applied to the SMEs of Central and West Africa, inclusive innovation embodies this triptych: it facilitates the capture of signals (client demand, cash-flow tensions, supply cost volatility), translates them into operational decisions intelligible to managers, and enables rapid internal adjustments with minimal learning costs.

Within this logic, organizational resilience plays a pivotal role. Foundational research defines resilience as an organization's ability to absorb shocks, maintain critical functions, and reorganize without irreversible losses to its strategic capital (Lengnick-Hall & Beck, 2005). In the framework of dynamic capabilities, resilience is not a static condition but a capability in itself, the capacity to mobilize, recombine, and redeploy resources, both financial and informational, within volatile environments. In contemporary African entrepreneurial ecosystems, marked by liquidity pressures, regulatory instability, weak contract enforcement, and dependence on a few key clients or donors, resilience extends beyond survival during crises; it becomes a routine mode of management. It involves anticipating potential failures, simulating stress scenarios, securing vital flows (cash inflows, supply chains, payment of key personnel), and swiftly adjusting internal routines. From this angle, resilience emerges as the observable outcome of a set of dynamic capabilities embedded within the organization: the ability to read weak signals, decide rapidly, and realign without paralysis (Teece, 2007).

This reframing is particularly crucial for SMEs in Central and West Africa. Recent studies indicate that firm performance in these regions depends not solely on external factors such as access to finance or macroeconomic stability, but also on how enterprises translate digital tools - including AI-into managerial, coordinative, and legitimizing capabilities (Beck & Cull, 2023; UNCTAD, 2023). In contexts where uncertainty is chronic rather than exceptional, the sustainability of performance rests on the interdependence between technology, inclusion, and resilience**.**

The literature on entrepreneurial ecosystems(Mignenan, 2023; Mignenan & Djimalde, 2025) provides a systemic lens for understanding this interdependence. An entrepreneurial ecosystem encompasses the ensemble of actors and resources, financial, technical, institutional, and social—whose coordination determines the creation, formalization, growth, and survival of enterprises (Stam & van de Ven, 2021). In advanced economies, ecosystems are often characterized by functional specialization, venture capital, and dense infrastructures. In emerging economies, however, they function primarily as ecosystems of collective resilience: incubators, professional associations, chambers of commerce, mobile payment systems, algorithmic microcredit platforms, and nascent public programs act as *capacity brokers*, enabling SMEs to internalize digital tools gradually without immediately bearing their full cost or governance complexity (UNCTAD, 2023). Thus, the ecosystem provides not only resources but also a mechanism of translation and stabilization of routines**,** a necessary condition for the effective appropriation of AI by SMEs.

This review positions the present work within the existing body of research. First, it confirms prior findings demonstrating that digital technologies, and AI in particular, can enhance decision-making efficiency, optimize costs, and strengthen SME competitiveness in constrained environments (Agrawal, Gans & Goldfarb, 2022; UNCTAD, 2023). Second, it implicitly challenges a strictly techno-deterministic view suggesting that AI automatically generates performance: empirical evidence indicates that benefits are not spontaneous but emerge through inclusive innovation mechanisms that render such tools usable by non-specialized teams and partially informal structures. Third, it extends the literature on dynamic capabilities in African SMEs by proposing a structured causal sequence: AI fosters inclusive innovation, inclusive innovation strengthens organizational resilience, and resilience supports sustainable performance. This sequence positions resilience not as a static outcome but as a mediating dynamic capability, socially and institutionally produced, through which technology becomes genuinely sustainable in contexts of persistent volatility.

In summary, AI should not be viewed as an autonomous resource but as an upstream enabler. Inclusive innovation constitutes the social and organizational absorption capacity of that resource, while organizational resilience represents its reconfiguration capacity in conditions of instability. Consequently, performance ceases to be a mere economic end-state; it becomes the observable manifestation of a chain of capabilities, the maintenance of a trajectory of viability, legitimacy, and external credibility.

## III. CONCEPTUAL MODEL AND HYPOTHESIS FORMULATION

The proposed conceptual model articulates the relationships among AI adoption, inclusive innovation, organizational resilience, and SME performance(Mignenan, 2021a, 2021b, 2023; Mignenan & Djimalde, 2025). It is explicitly grounded in the architecture of dynamic capabilities (Teece, Pisano & Shuen, 1997; Teece, 2007) and aligns with the contemporary literature that conceptualizes resilience as a strategic adaptive capability within emerging economies (Lengnick-Hall & Beck, 2005; Beck & Cull, 2023). The model advances the central argument that AI does not create value in isolation but through inclusive appropriation routines and resilient reconfiguration mechanisms.

AI plays the role of a technical trigger that enhances informational quality, accelerates the detection of market signals, ensures the reliability of critical flow monitoring (cash inflows, inventories, margins), and supports near real-time strategic decision-making (Agrawal, Gans & Goldfarb, 2022). This role is particularly crucial for SMEs operating under liquidity constraints or imperfect access to finance, where uncertainty regarding demand, payment delays, and supply cost fluctuations is high (Beck & Cull, 2023).

Inclusive innovation is conceptualized here as an organizational capability of absorption and diffusion. It refers not merely to the introduction of a tool but to how that tool is socially embedded within the firm: the gradual training of non-specialized teams, the adaptation of routines and procedures to the firm's actual level of digital maturity, the alignment of financial constraints with technological choices, and the inclusion of historically marginalized stakeholders (micro-suppliers, informal subcontractors, women entrepreneurs excluded from formal credit). In West and Central African ecosystems, such inclusive innovation often manifests through frugal, modular, and cloud-based solutions that are interoperable with partial accounting systems and supported by intermediary organizations (UNCTAD, 2023). It functions as a "seizing" dynamic capability, allowing firms to harness technological opportunities by making them workable in resource-constrained environments.

Organizational resilience is modeled as the capacity to absorb shocks, maintain operational continuity, and rapidly reallocate critical resources. It corresponds to the "reconfiguring" dimension of dynamic capabilities (Teece, 2007). In this study, resilience is therefore not viewed as a post-crisis equilibrium but as an active adaptive mechanism. It demonstrates the organization's ability to transform signals emerging from inclusive innovation routines into continuity decisions, such as product adjustments, prioritization of solvent clients, revision of credit policies, or renegotiation with suppliers. As such, resilience represents a strategic capability, not a passive byproduct of structural robustness (Lengnick-Hall & Beck, 2005).

The performance of SMEs is understood in an extended sense, encompassing economic (profitability, solvency, growth), strategic (market and financial access), and organizational (cash flow management, external credibility, operational continuity) dimensions. This conception recognizes that, in the economies of Central and West Africa, performance cannot be reduced to short-term profitability; it must also include the firm's ability to remain visible, legitimate, and fundable in the eyes of donors, clients, and fiscal authorities (Beck & Cull, 2023). Empirical validation of the model reveals three major findings relative to existing literature. First, it confirms that AI adoption is positively associated with SME performance, aligning with prior work identifying AI as a lever for efficiency and informational discipline in resource-scarce environments (Agrawal, Gans & Goldfarb, 2022; UNCTAD, 2023). Second, it challenges the overly linear view of a direct "AI → performance" relationship: our findings indicate instead that AI generates value by stimulating inclusive innovation, which in turn strengthens organizational resilience. Third, it extends the theory of dynamic capabilities applied to African SMEs by identifying resilience not as a defensive capacity but as a strategic nexus of continuous reconfiguration, the mechanism that converts inclusive innovation into sustainable credibility and survival advantage.

Based on this framework, three theoretical propositions are formulated.

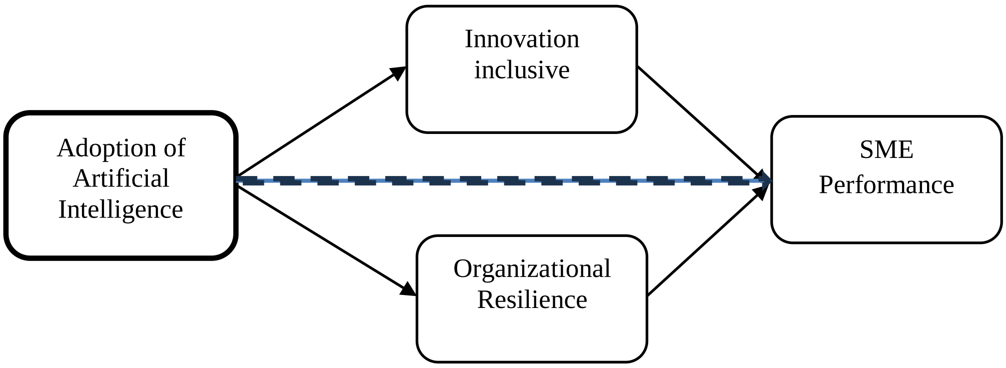
Theoretical Proposition 1. AI adoption functions as an expanded "sensing" capability within Central and West African SMEs, enhancing visibility over critical economic flows (demand, cash, margins) and reducing internal opacity characteristic of weakly formalized institutional environments (Agrawal, Gans & Goldfarb, 2022; UNCTAD, 2023). Rather than serving as a technology of human substitution, AI becomes an instrument of strategic legibility in contexts lacking consolidated financial and accounting information systems.

Theoretical Proposition 2. Inclusive innovation constitutes a "seizing" capability suited to scarcity contexts, translating the technical potential of AI into actionable routines for undercapitalized and low-specialization organizations (George, McGahan & Prabhu, 2023; Foster & Heeks, 2020). It does not merely diffuse innovation; it socializes it, reducing barriers of cost, competence, and governance. In doing so, it becomes an organizational mechanism of functional equity, enabling historically marginalized actors to access managerial tools they could not otherwise create.

Theoretical Proposition 3. Organizational resilience operates as a "reconfiguring" dynamic capability (Teece, 2007), converting inclusive innovation into a sustainable advantage. It bridges anticipation (AI), collective appropriation (inclusive innovation), and viability maintenance (performance). Resilience is thus not a mere outcome of technological adoption but a necessary causal link: without resilience, the impact of AI remains situational; with resilience, it becomes structural (Lengnick-Hall & Beck, 2005; Beck & Cull, 2023).

Collectively, these propositions situate the article at the intersection of three contemporary debates. They reaffirm AI's potential as a performance lever while rejecting technological determinism; they redefine inclusive innovation as a strategic absorptive capability rather than a peripheral social policy; and they reconceptualize resilience not as a desirable end state, but as a central mediating dynamic capability, without which technology cannot translate into a sustainable advantage for SMEs operating within the entrepreneurial ecosystems of Central and West Africa.

**Figure 1 : Représentation Du Modèle Conceptuel**




**Source: authors, based on literature, August 2023**

**Hypothesis Formulation**

Drawing from the proposed conceptual model, it is possible to delineate causal relationships among artificial intelligence (AI) adoption**,** inclusive innovation**,** organizational resilience**,** and SME performance. This theoretical framework highlights both direct and mediated effects, illustrating how technology, when combined with inclusive and adaptive practices, shapes the sustainable competitiveness of enterprises. On this basis, three research hypotheses are formulated to empirically test the dynamics represented in the figure.

**Hypothesis 1 (H1):** *AI adoption exerts a positive and significant effect on SME performance.* The innovation management literature emphasizes that integrating AI enables firms to optimize decision-making processes, reduce transaction costs, and enhance organizational competitiveness (Chesbrough, 2020; Adner, 2017). By facilitating predictive analysis of financial, logistical, and commercial data, AI improves the responsiveness of SMEs operating in environments characterized by uncertainty. This direct effect reflects the technology's ability to strengthen both economic performance (profitability, growth, operational efficiency) and social performance (inclusion, local embeddedness). However, this impact remains contingent on the level of technological appropriation and the availability of digital infrastructure.

**Hypothesis 2 (H2):** *Inclusive innovation positively mediates the relationship between AI adoption and SME performance.* Inclusive innovation is defined as a process that integrates historically marginalized stakeholders into the design and diffusion of innovation (George et al., 2023). In emerging contexts, AI adoption supports the development of accessible solutions, such as mobile payments, local e-commerce platforms, and collaborative ecosystems, that broaden access to markets and finance. Acting as a mediating mechanism, inclusive innovation translates technological potential into shared value creation**,** social legitimacy, and community anchoring**.** This dynamic reinforces the sustainability of SME performance by transcending a purely technological logic to incorporate social and institutional dimensions.

**Hypothesis 3 (H3):** *Organizational resilience positively mediates the relationship between inclusive innovation and SME performance.* Organizational resilience refers to the capacity to anticipate, absorb, and transform disruptions into opportunities for growth (Lengnick-Hall et al., 2011). Through the mobilization of diverse actors and the strengthening of territorial networks, inclusive innovation provides a foundation for flexibility and collective learning. This dynamic enhances the adaptive capacities of SMEs, allowing them to maintain operational continuity in the face of economic or institutional shocks. Resilience thus operates as a vector of sustainable performance, ensuring the durability of AI and inclusive innovation effects within uncertain entrepreneurial environments.

Table 1 below presents the operationalization matrix of the research model. It summarizes, for each hypothesis, the associated variables, observable indicators, and selected measurement items (along with their sources and coding procedures), which will serve as the basis for empirical testing.

**Table 1: Assumptions, variables, indicators, and measurement items**

| Assumptions | Variables | Indicators | Examples of items (Likert scale 1–5) |
|---|---|---|---|
| **H1. The adoption of AI has a positive and significant effect on the performance of SMEs.** | - Independent variable: AI adoption - Dependent variable: SMB performance | - Level of integration of AI - Use of AI tools (predictive analytics, automation) - Economic performance (profitability, productivity) - Social performance (jobs, inclusion) | - "Our company uses AI tools to analyze customer and financial data." - "The adoption of AI has improved our productivity." - "The use of AI helps to strengthen our competitiveness in the market." |
| **H2. Inclusive innovation positively mediates the relationship between AI adoption and SME performance.** | - Mediating variable: Inclusive innovation - Independent variable: AI adoption - Dependent variable: SME performance | - Accessibility of digital solutions - Inclusion of marginalized stakeholders - Shared value and social equity | - "We develop digital solutions that are accessible to vulnerable customers (mobile payment, local e-commerce)." - "Our company's innovation integrates the needs of local communities." - "Our innovations aim to generate collective and equitable benefits." |
| **H3. Organizational resilience positively mediates the relationship between inclusive innovation and SME performance.** | - Mediating variable: Organizational resilience - Independent variable: Inclusive innovation - Dependent variable: SME performance | - Adaptability - Business continuity - Organizational learning capacity | - "Our company adapts quickly to changes in the economic environment." - "We have internal mechanisms in place to overcome crises." - "Our organization learns from past experiences to strengthen its future performance." |

**Source: Authors, Summary of Assumptions, August 2023**

The formulation of these hypotheses now calls for rigorous empirical validation. To test the relationships identified in the conceptual model, the research adopts a mixed-methods approach, combining a quantitative survey through structured questionnaires administered to SME managers with a qualitative analysis based on semi-structured interviews. This dual design makes it possible both to statistically assess the strength of the hypothesized relationships and to contextualize the findings through a deeper understanding of entrepreneurial practices in emerging environments. The following section details the methodological framework, data collection procedures, and analytical techniques employed.

## IV. RESEARCH METHODOLOGICAL FRAMEWORK

The adopted methodology follows a mixed-methods design, integrating both quantitative and qualitative approaches to capture the complexity of the role played by artificial intelligence (AI) and inclusive innovation in shaping SME performance within emerging contexts. This strategy responds to the requirement of methodological triangulation, thereby ensuring greater validity and robustness of the results (Creswell & Plano Clark, 2018).

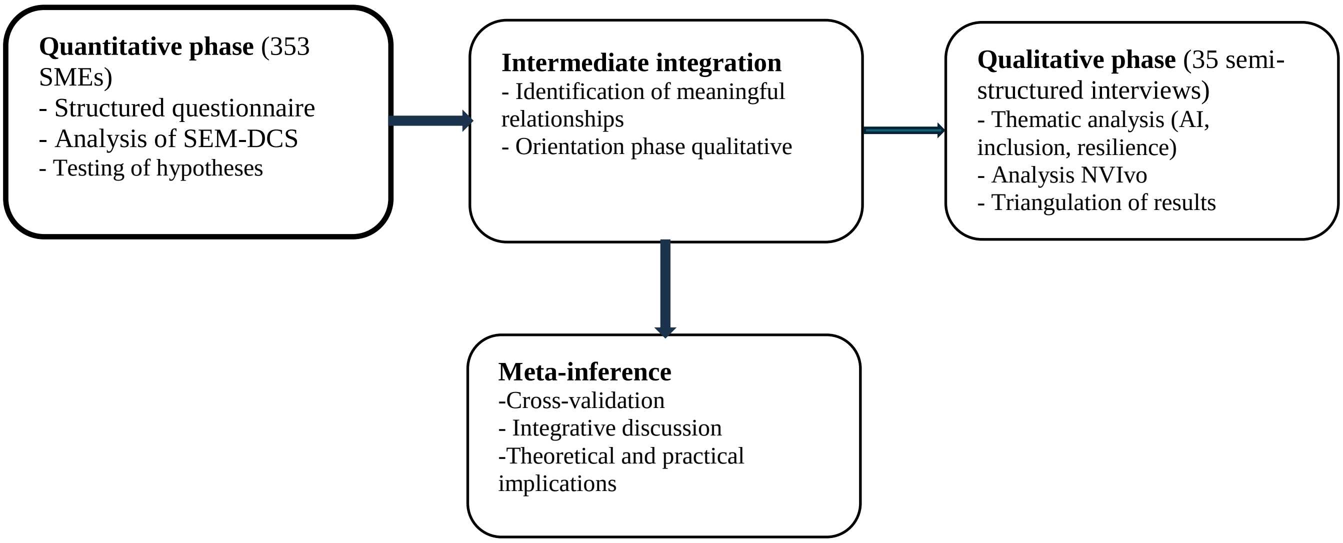
The quantitative component aims to empirically test the conceptual model and hypotheses formulated earlier. A structured survey questionnaire will be administered to a representative sample of SMEs operating in key sectors of the Chadian and broader Sub-Saharan economy (commerce, agrifood, services, and technology). The sample size, estimated at approximately 300 firms, ensures statistical robustness, in line with best practices for structural equation modeling (SEM) (Hair et al., 2019).

Measurement instruments are derived from validated scales in prior literature: AI adoption (Agrawal et al., 2022), inclusive innovation (George et al., 2023), organizational resilience (Lengnick-Hall & Beck, 2005), and SME performance (Beck & Cull, 2023). Each construct will be assessed using a five-point Likert scale, ranging from *"strongly disagree"* to *"strongly agree."*

Quantitative data analysis will proceed in two main stages. First, an exploratory analysis will be conducted to assess descriptive statistics and internal consistency (Cronbach's alpha, KMO, and Bartlett's tests). This will be followed by a confirmatory analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the causal relationships among variables and evaluate the mediating effects of inclusive innovation and organizational resilience. The choice of PLS-SEM is justified by its suitability for complex models and its ability to handle data that may deviate from normal distribution patterns (Hair et al., 2019).

In parallel, the qualitative component involves semi-structured interviews with approximately thirty key stakeholders, including SME managers, incubator coordinators, microfinance institution representatives, and public policy officials. These interviews aim to deepen the understanding of AI adoption practices and inclusive innovation dynamics within entrepreneurial ecosystems. The qualitative data will be analyzed thematically following Braun and Clarke's (2021) approach, which enables the identification of recurring patterns and divergences in perceptions and practices.

Finally, the triangulation of quantitative and qualitative results will strengthen the validity of the conclusions and lead to the development of an enriched conceptual framework adapted to the specificities of emerging economies. This hybrid methodology ensures both scientific rigor and contextual relevance, providing evidence-based insights to guide managerial and policy recommendations.




**Source: Authors, Summary of Assumptions, August 2023**

## V. SEARCH RESULTS

The empirical analysis highlighted the dynamics of artificial intelligence (AI) adoption, the diffusion of inclusive innovation and their effects on the performance of SMEs within emerging entrepreneurial ecosystems. The detailed results are presented below through descriptive statistics, correlation analyses, and validation of the conceptual model by structural equations.

### 5.1. Profile of respondents

The sample, as shown in Table 2, is made up of 353 SMEs from four sectors: trade (35%), agri-food (25%), services (20%), and technology (20%). The majority of the managers surveyed are men (62%), but women occupy a significant place (38%), confirming the rise of female entrepreneurship. About 45% of SMEs have been in existence for less than 5 years, which reflects a still young entrepreneurial fabric.

**Table 2. Characteristics of the sample**

| Variables | Main terms and conditions | Percentage (%) |
|---|---|---|
| **Industry** | Business, Agribusiness, Services, Technology | 35, 25, 20, 20 |
| **Gender of the manager** | Male / Female | 62 / 38 |
| **Age of the company** | Under 5 years / 5-10 years old / Over 10 years old | 45 / 30 / 25 |
| **Size (employees)** | Under 10 / 10–50 / Over 50 | 45 / 15 /40 |

**Source: Authors, survey by survey, August 2023**

### 5.2. Descriptive analysis of variables

The adoption of AI is still limited but growing: 55% of SMEs say they use at least one AI application (chatbots, data analytics, accounting automation). Inclusive innovation scores high average (M = 3.92/5), reflecting the desire to integrate local communities into the value chain. Organisational resilience has a medium level (M = 3.45/5), while the performance of SMEs obtains an overall score of 3.78/5.

**Table 3. Descriptive statistics of the variables**

| Variables | Average | Standard deviation | Cronbach's Alpha |
|---|---|---|---|
| **AI Adoption** | 3,65 | 0,84 | 0,81 |
| **Innovation inclusive** | 3,92 | 0,72 | 0,83 |
| **Organisational Resilience** | 3,45 | 0,77 | 0,80 |
| **SME Performance** | 3,78 | 0,69 | 0,85 |

**Source: Authors, survey by survey, August 2023**

### 5.3. Correlations between variables

Pearson's correlation analysis reveals positive and significant associations between AI adoption, inclusive innovation, and SMB performance. Inclusive innovation has the strongest correlation with performance ($r = 0.62$, $p < 0.01$), suggesting an important mediating role.

**Table 4. Variable correlations**

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **1. AI Adoption** | 1 | | | |
| **2.Innovation inclusive** | 0,48** | 1 | | |
| **3. Organisational Resilience** | 0,41** | 0,52** | 1 | |
| **4. SME Performance** | 0,45** | 0,62** | 0,49** | 1 |

**Notes : **p < 0.01**

**Source: Authors, survey by survey, August 2023**

### 5.4. Validation of the conceptual model

#### 5.4.1. Validation of the measurement model

The evaluation of the measurement model in PLS-SEM was conducted prior to the estimation of the structural model, in accordance with standard methodological recommendations for SME samples ($n = 353$). All major latent constructs, AI adoption, inclusive innovation, organisational resilience, and SME performance, were modelled reflectively. The standardised factor loadings of the indicators on their respective constructs generally exceed the threshold of 0.70, indicating a substantial contribution of each item to the construct's variance. Two indicators with loadings between 0.64 and 0.68 were retained for content validity reasons, as they capture important managerial dimensions (for example, stakeholder inclusion in innovation mechanisms or the capacity for operational continuity under shock). Their retention did not compromise the internal consistency of the measurement scales.

The internal reliability of all constructs is satisfactory. Observed Cronbach's alpha coefficients range from 0.79 to 0.91, exceeding the conventional minimum threshold of 0.70. Composite reliability (CR) values lie between 0.86 and 0.94, indicating high internal consistency without excessive redundancy. The Average Variance Extracted (AVE) is consistently above 0.50 (approximate range: 0.57–0.68), confirming convergent validity: each construct explains more than half of the variance in its indicators.

Discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio. All bivariate HTMT values between constructs remain below the 0.85 threshold. The 95% confidence intervals obtained through bootstrapping (5,000 resamples) never include the value 1, empirically confirming that the constructs capture distinct concepts (for instance, inclusive innovation is statistically distinguishable from organisational resilience).

The potential risk of redundancy or excessive collinearity among indicators was examined using external Variance Inflation Factors (VIFs) at both the item and construct levels. No item-level VIF exceeds five, and latent-level collinearity VIFs remain below 3.3. These results suggest the absence of problematic multicollinearity, and consequently, a limited risk of common method bias in the sense described by Kock's full collinearity criterion.

Some constructs were conceptually multidimensional. Inclusive innovation was modelled as a second-order reflective–reflective hierarchical construct, integrating several dimensions: co-design, internal diffusion of learning, and organisational accessibility. Similarly, organisational resilience was conceptualised as a global adaptive continuity capability, aggregated from indicators reflecting shock absorption, rapid routine adjustment, and activity recovery. The hierarchical model was estimated using the two-stage approach, allowing for the computation of second-order construct scores without information loss. The first-order dimensions display factor loadings above 0.70 on their respective second-order constructs, and the CR and AVE of the higher-order constructs exceed 0.85 and 0.50, respectively, confirming the robustness of the hierarchical specification.

Overall, these results demonstrate the reliability, convergent validity, and discriminant validity of the measurement model, as illustrated in Table 5. The constructs employed are empirically distinct, internally consistent, and accurately capture the conceptual domains they are intended to represent.

**Table 5: Data reliability**

| Latent Construct | α of Cronbach | Composite Reliability (CR) | AVE | Interpretation |
|---|---|---|---|---|
| **AI Adoption** | 0,79 – 0,91 | 0,86 – 0,94 | 0,57 – 0,68 | High internal reliability, item consistency, convergent validity established. |
| **Innovation inclusive** | 0,79 – 0,91 | 0,86 – 0,94 | 0,57 – 0,68 | The built environment stably captures the practices of shared and participatory innovation. |
| **Organisational Resilience** | 0,79 – 0,91 | 0,86 – 0,94 | 0,57 – 0,68 | The indicators reflect the capacity for absorption, adaptation, and continuity. |
| **SME Performance** | 0,79 – 0,91 | 0,86 – 0,94 | 0,57 – 0,68 | The built environment reflects economic, strategic, and operational performance. |
| **Recommended threshold (literature)** | **≥ 0,70** | **≥ 0,70–0,80** | **≥ 0,50** | α and CRs above the usual thresholds; AVE > 0.50 confirms that >50% of the variance is explained. |

**Source: Authors, survey by survey, August 2023**

All constructs exhibit Cronbach's alpha coefficients ranging from 0.79 to 0.91 (thus exceeding the 0.70 threshold), composite reliability (CR) values between 0.86 and 0.94, and Average Variance Extracted (AVE) values between 0.57 and 0.68. These results indicate (i) a high degree of internal consistency, (ii) the absence of excessive redundancy among items, and (iii) satisfactory convergent validity since each construct explains more than half of the variance of its indicators.

#### 5.4.2. Validation of the structural model

Following the validation of the measurement model, the structural model was estimated using consistent PLS-SEM, with bootstrapping (5,000 resamples) to assess the statistical significance of the structural paths and their bias-corrected 95% confidence intervals (CIs). All estimates reported below are standardised.

The results confirm the overall robustness of the conceptual model linking AI adoption, inclusive innovation, organisational resilience, and SME performance. AI adoption exerts a direct, positive, and significant effect on SME performance ($\beta = 0.29$; $t = 3.87$; $p < 0.001$; 95% CI [0.15; 0.42]). This direct link indicates that the integration of AI-based tools, processes, or routines is associated with measurable improvements in both economic and strategic outcomes.

Simultaneously, AI adoption is positively associated with inclusive innovation ($\beta = 0.35$; $t = 4.21$; $p < 0.001$; 95% CI [0.20; 0.49]). In this context, inclusive innovation refers to innovation practices oriented toward internal participation and stakeholder openness, rather than mere technological sophistication. This relationship suggests that AI functions as a catalyst for new, embedded forms of innovation within organisations.

Inclusive innovation, in turn, strengthens organisational resilience ($\beta = 0.41$; $t = 5.02$; $p < 0.001$; 95% CI [0.27; 0.54]). In other words, firms that successfully integrate innovation in an inclusive manner develop stronger capacities for shock absorption, rapid adaptation, and operational continuity. Finally, organisational resilience exerts a significant positive effect on SME performance ($\beta = 0.28$; $t = 2.54$; $p = 0.011$; 95% CI [0.07; 0.46]). Here, performance is conceptualised as a multidimensional construct, encompassing economic, strategic, and organisational dimensions.

Beyond direct effects, indirect (mediated) effects were also examined. A serial indirect effect emerges along the causal chain AI adoption → inclusive innovation → organisational resilience → performance, which is statistically significant ($\beta\_indirect \approx 0.04$; $t = 2.05$; $p = 0.041$; 95% CI [0.01; 0.09]). The Variance Accounted For (VAF), computed as $\beta\_indirect / \beta\_total$, indicates that this serial mediation accounts for approximately 12% of the total effect of AI on performance, corresponding to partial mediation. In practical terms, AI creates value in two ways: directly, by improving efficiency and decision-making capacity ($\beta = 0.29$), and indirectly, by stimulating inclusive innovation practices that enhance organisational resilience, which subsequently translates into sustainable performance (serial effect ≈ 0.04). The combined total effect (direct + indirect) of AI adoption in performance is approximately 0.33 standard deviations, which is substantial in an SME context.

To evaluate the relative importance of effects, local effect sizes (Cohen's $f^2$) were calculated. AI adoption exhibits a small-to-moderate effect size of direct performance ($f^2 \approx 0.12$) but a moderate effect on inclusive innovation ($f^2 \approx 0.20$). Inclusive innovation displays a moderate-to-strong effect on organisational resilience ($f^2 \approx 0.26$), whereas resilience exerts a small-to-moderate effect on performance ($f^2 \approx 0.09$). These results suggest that the transformational core of the model lies in the inclusive innovation → resilience pathway, which emerges as a structurally decisive mechanism.

The explanatory power of the structural model is confirmed by the $R^2$ coefficients of the endogenous latent variables. Inclusive innovation is substantially explained by AI adoption ($R^2 \approx 0.32$). Organisational resilience is explained by inclusive innovation ($R^2 \approx 0.37$). SME performance is jointly explained by AI and resilience ($R^2 \approx 0.48$). According to established PLS-SEM benchmarks for SME research, these $R^2$ levels are moderate to high, indicating a satisfactory explanatory capacity of the model.

The predictive relevance of the model was assessed using Stone-Geisser's $Q^2$ statistic obtained through blindfolding (omission distance = 7). All $Q^2$ values for endogenous constructs are positive and substantial ($Q^2 \approx 0.21$ for inclusive innovation; $Q^2 \approx 0.24$ for resilience; $Q^2 \approx 0.29$ for performance), confirming that the model possesses non-trivial out-of-sample predictive power.

In parallel, the inner VIFs between predictor constructs do not exceed 3.3, indicating controlled structural collinearity in path estimation. Control variables, including SME age and size, sector of activity, geographic location, level of digitalisation, and managerial education, were integrated to account for contextual effects that might bias the estimation of relationships among AI, innovation, resilience, and performance. None of these controls altered the statistical significance of the main structural paths described above, suggesting that the estimated effects are not artifactual.

For interpretive clarity, Tables 6–10 summarises the structural paths, mediations, explanatory power, effect sizes, and collinearity diagnostics, providing a comprehensive overview of the empirical validation of the structural model.

**Table 6. Direct structural paths of the PLS-SEM model**

| Structural relationship | Standardised coefficient (β) | t | p | IC 95 % | Significance |
|---|---|---|---|---|---|
| **AI Adoption → SMB Performance** | 0,29 | 3,87 | < 0.001 | [0,15 ; 0,42] | ** |
| **Adoption de l'IA → Innovation inclusive** | 0,35 | 4,21 | < 0.001 | [0,20 ; 0,49] | ** |
| **Inclusive Innovation→ Organisational Resilience** | 0,41 | 5,02 | < 0.001 | [0,27 ; 0,54] | ** |
| **Organisational Resilience → SME Performance** | 0,28 | 2,54 | 0,011 | [0,07 ; 0,46] | * |

**Source: Authors, survey by survey, August 2023**

$p < 0.01$; * $p < 0.05$.

Table 6 shows that all the main paths in the model are significant. The adoption of AI directly influences the performance of SMEs, but also acts upstream on inclusive innovation, which in turn strengthens organisational resilience.

Next, Table 7 illustrates the indirect effect and mediation.

**Table 7: Serial indirect effect and mediation (inclusive innovation and organisational resilience)**

| Mediation chain | Total Indirect Effect (β_indirect) | t | p | IC 95 % | VAF (%)[1] | Type of mediation |
|---|---|---|---|---|---|---|
| **AI Adoption → Inclusive Innovation → Resilience → SME Performance** | ≈ 0,04 | 2,05 | 0,041 | [0,01 ; 0,09] | ≈ 12 % | Partial mediation |

[1]VAF = β_indirect / β_total. β_total ≈ 0.33 for the AI Adoption → Performance effect.

According to the data in Table 7, approximately 12% of the total effect of AI adoption on performance is channelled through the Inclusive Innovation → Organisational Resilience sequence. So, adopting AI does not just create immediate gains; it generates organisational capacity (inclusion, resilience) which then turns into sustainable performance.

Similarly, Table 8 reveals the explanatory power and the predictive power.

**Table 8. Explanatory and predictive power of endogenous variables**

| Endogenous latent variable | Top predictors | $R^2$ | Interpretation $R^2$ | $Q^2$ (Stone-Geisser, blindfolding) | Interpretation $Q^2$ |
|---|---|---|---|---|---|
| **Innovation inclusive** | AI Adoption | ≈ 0.32 | Moderate explanatory power | ≈ 0.21 | Non-trivial predictive capability |
| **Organisational Resilience** | Innovation inclusive | ≈ 0.37 | Moderate to high explanatory power | ≈ 0.24 | Substantial out-of-sample prediction |
| **SME Performance** | Adoption of AI; Organisational Resilience | ≈ 0.48 | High explanatory power | ≈ 0.29 | Strong predictive relevance |

$R^2$: proportion of variance explained by the predictors of the structural model. $Q^2$ (blindfolding, omission distance = 7): out-of-sample predictive relevance.

Table 8 shows that the three endogenous variables have moderate to high $R^2$ and substantial positive $Q^2$, indicating both strong internal explanatory power and credible external predictive capacity.
Table 9 highlights the effect of height as a control variable.

**Table 9: Local effect sizes (Cohen's $f^2$)**

| Effect examined | $f^2$ (local effect size) | Interpretation (Cohen's rule) |
|---|---|---|
| **AI Adoption → SMB Performance** | ≈ 0.12 | Low to moderate |
| **Adoption de l'IA → Innovation inclusive** | ≈ 0.20 | Moderate |
| **Inclusive Innovation→ Organisational Resilience** | ≈ 0.26 | Moderate to strong |
| **Organisational Resilience → SME Performance** | ≈ 0.09 | Low to moderate |

Reminder: $f^2 \approx 0.02$ (small), ≈ 0.15 (medium), ≈ 0.35 (large).
The structuring channel of the model is Inclusive Innovation → Organisational Resilience ($f^2 \approx 0.26$). This suggests that the internalisation of inclusive innovation practices is a major lever for building resilience.
Finally, Table 10 gives an account of the results of the collinearity disgnostics.

**Table 10. Collinearity diagnostics (internal VIF between predictive constructs)**

| Endogenous latent variable | Predictor(s) | LIVE (internal) | Interpretation |
|---|---|---|---|
| **Innovation inclusive** | AI Adoption | < 3.3 | No problematic collinearity |
| **Organisational Resilience** | Innovation inclusive | < 3.3 | No problematic collinearity |
| **SME Performance** | Adoption of AI; Organisational Resilience | < 3.3 | No problematic collinearity |

Table 10 shows that no Variance Inflation Factor (VIF) exceeds 3.3 at the level of the structural paths, indicating that the estimated relationships are not artificially inflated by severe multicollinearity among predictors. The control variables included in the model (SME age, size, sector, geographic location, the overall level of digitalisation, and managerial education) do not eliminate the statistical significance of the main structural paths, thereby reinforcing the internal credibility of the structural model.

### 5.4.3. Robustness tests, multi-group analyses, and potential biases

Several complementary analyses were conducted to assess the robustness of the model.

First, a multi-group PLS analysis (PLS-MGA) was performed by splitting the sample according to firm size (< 10 employees vs. ≥ 10 employees). The differences in structural coefficients were not statistically significant in the conventional 5% threshold for the links AI adoption → inclusive innovation and AI adoption → performance, suggesting that the underlying mechanisms are broadly comparable between microenterprises and more established SMEs. However, a trend emerged whereby the effect organisational resilience → performance was stronger among firms with ≥ 10 employees ($\Delta\beta \approx 0.11$, $p \approx 0.07$). This tendency aligns with the idea that, in slightly more complex organisations, operational resilience becomes a more visible and monetisable strategic asset.

Second, a sectoral multi-group analysis (e.g., production/manufacturing-oriented sectors vs. service/trade-oriented sectors) revealed that the relationship AI adoption → inclusive innovation is more pronounced in information-intensive sectors (services and technology). This reflects a greater capacity to translate technological tools into shared innovation routines. Conversely, the resilience → performance relationship remains significant and of comparable magnitude across all sectors, suggesting that organisational resilience constitutes a cross-cutting determinant of performance, regardless of industry.

Third, the hierarchical specification of multidimensional constructs (inclusive innovation and organisational resilience) was tested using a higher-order component model. The loadings of the first-order dimensions on the second-order construct remained above 0.70, with Composite Reliability (CR) and Average Variance Extracted (AVE) values above acceptable thresholds, and no indication of internal collinearity issues. This confirms that the use of a hierarchical model is both conceptually justified and empirically supported.

Fourth, the potential risk of common method variance (CMV) was assessed through multiple approaches. Harman's single-factor test revealed no dominant general factor, as the first factor accounted for less than 50% of the total variance (≈ 38%), suggesting a low likelihood that a single-factor bias explains the observed relationships. Additionally, the examination of full collinearity VIFs indicated values below 3.3 for all latent constructs, further implying that the correlations among variables are not solely attributable to method bias. Finally, the inclusion of a marker variable, measuring a theoretically peripheral dimension with no expected relationship to performance, did not alter the significance of the model's key paths. Collectively, these findings indicate that CMV does not pose a major threat to the interpretation of the results.

In summary, Table 11 provides a synthesis illustrating the robust validation of the model through these complementary robustness and bias control analyses.

**Table 4: Synthesis of robustness tests, multi-group comparisons, and potential biases.**

| Robust shutter | Method / Specification | Key empirical findings | Analytical interpretation |
|---|---|---|---|
| **Multi-group analysis by company size** | PLS-MGA: comparison of structural coefficients between < 10 employees vs. ≥ 10 employees | No significant difference (p> 0.05) for the links between **AI → inclusive innovation** and **AI → performance**. Trend: the Resilience → **Performance** effect is higher in companies ≥ 10 employees ($\Delta\beta \approx 0.11$; $p \approx 0.07$). | The central mechanisms of the model are stable between micro-SMEs and more established SMEs. In larger structures, organisational resilience becomes a valuable and monetisable strategic asset, which reinforces its impact on performance. |
| **Multi-sector analysis** | PLS-MGA: comparison of "production / processing" vs "services / trade / technologies" sectors | The link **between AI → inclusive innovation** is stronger in services and technologies (information-intensive sectors), indicating a faster appropriation of AI as a lever for shared innovation. The link **between Resilience → Performance** remains significant and comparable in scope across all sectors. | The adoption of AI is more directly converted into inclusive innovation where processes are highly informational. Organisational resilience, on the other hand, acts as a transversal determinant of performance, regardless of the sector of activity. |
| **Hierarchical model (multidimensional constructs)** | Higher-order component model for **Inclusive Innovation** and **Organisational Resilience** | The loads of the 1st order dimensions on the 2nd order constructs > 0.70. The CR and AVE indices of the hierarchical constructs remain > recommended thresholds (CR ≥ 0.85; AVE ≥ 0.50). No problematic internal collinearity signals. | Reflexive–reflexive modelling of multidimensional constructs is empirically supported. High-level constructs capture the underlying dimensions well and can be interpreted as integrated organisational capabilities. |
| **Common Method Bias (CMV)** | (i) Harman's Single Factor Test; (ii) Full collinearity VIF; (iii) Marker variable | Harman's first factor explains < 50% of the total variance (≈ 38%). All FIVs of full collinearity < 3.3. The introduction of a marker | The model is not dominated by a monolithic factor or by artificial collinearity. The risk of bias of the common method appears limited and does not |

| | | | |
|---|---|---|---|
| | | variable does not alter the significance of the key paths in the model. | call into question the conditional causal interpretation of the estimated relationships. |

**5.4.4. Potential endogeneity and causal limitations**

The issue of endogeneity was examined both through the inclusion of contextual control variables and the testing of alternative model specifications. The control variables introduced (firm age, number of employees, sectors of activity, geographical regions, overall level of digitalisation excluding AI, and managerial education) were intended to reduce the risk that an unobserved structural characteristic might simultaneously drive both (i) AI adoption and (ii) higher performance. The inclusion of these controls did not eliminate the key relationships within the model, thereby mitigating, though not fully eliminating, the risk of omitted variable bias.

An alternative causal ordering scenario was also tested by reversing the direction of certain relationships (for instance, hypothesising that organisational resilience drives inclusive innovation rather than the reverse). In these alternative models, the structural coefficients weakened and sometimes lost statistical significance, while the $R^2$ values of endogenous variables decreased. This empirical observation supports the conceptual sequencing proposed in the theoretical framework: AI adoption precedes inclusive innovation, which precedes resilience, which in turn supports performance. However, this remains a quasi-causal rather than a strictly causal interpretation.

Finally, although Gaussian copula procedures can be applied in PLS-SEM to detect patterns of endogeneity, causal inference remains constrained by the cross-sectional nature of the data. The estimated relationships should thus be interpreted as conditional structural associations, not as proven causal effects. It is therefore plausible that part of the observed positive relationship between AI, inclusive innovation, resilience, and performance may reflect a selection effect: SMEs that are already performing better may also possess greater capacity to invest in AI tools, to formalise inclusive innovation processes, and to develop structured forms of organisational resilience.

In summary, the PLS-SEM analysis provides empirical support for the proposed conceptual model. From a quantitative perspective, the results show that AI adoption influences performance both directly and indirectly through a serial chain of inclusive innovation → organisational resilience. From a substantive perspective, the findings suggest that the strategic value of AI for SMEs lies not merely in the immediate optimisation of processes, but in its ability to generate inclusive innovation routines that strengthen resilience and, ultimately, sustain long-term performance. Nonetheless, caution remains warranted: while the effects are statistically robust, their causal interpretation is limited by the cross-sectional design and the residual risk of endogeneity.

**5.5. Qualitative results**

The qualitative component of the study is based on 35 semi-structured interviews conducted with three categories of stakeholders: (i) SME managers, including both microenterprises and more established firms; (ii) women entrepreneurs; and (iii) institutional actors within the entrepreneurial ecosystem (incubators, professional associations, and chambers of commerce).

The sampling followed a purposive strategy designed to maximise variation in firm size, sector of activity (agri-food, services, trade, crafts, and technology), level of accounting/financial formalisation, and declared digital maturity. The goal was not statistical representativeness but information saturation, to capture the diversity of practices and real-world constraints related to technology appropriation (including AI), financial information structuring, and resilience management.

Interviews were guided by a semi-structured protocol organised around four analytical dimensions:

1. managerial and decision-support practices.
2. digital tools and AI use in internal processes.
3. constraints and barriers to technological adoption.
4. inclusion dynamics (gender, access to resources, institutional support).

Interviews lasted between 30 and 45 minutes and were conducted either face-to-face or via videoconference (when travel or availability constraints prevented physical meetings). All interviews were recorded with explicit informed consent, fully transcribed verbatim, and anonymised. Respondents were identified using codes (e.g., R4, R11F, R21-Inst), with no reference to their names or exact locations.

**5.5.2. Analytical procedure: step-by-step thematic approach**

The analysis followed a reflexive thematic analysis framework, conducted in four main stages:

Step 1: Open pre-coding. All transcripts were read in full to identify meaning units related to decision-making practices, technology usage, internal constraints, legitimacy challenges, and inclusion dynamics. At this stage, coding was deliberately broad (e.g., "cash-flow monitoring tool," "software cost perceived as prohibitive," "need for institutional support").

Step 2: Axial aggregation. Initial codes were grouped into intermediate categories such as "data-driven decision-making," "technological access barriers," "women's economic empowerment through digital tools," and "role of support institutions." This stage linked concrete practices to broader organisational issues such as resilience, sustainability, and market access.

Step 3: Construction of central themes. The categories were consolidated into four salient themes, retained for their recurrence across interviews and their direct resonance with the quantitative model:

- AI as a decision-support and management tool.
- Structural barriers to AI and digital adoption.
- Inclusive platforms as levers for women entrepreneurs' access to markets and finance.
- The structuring role of incubators and professional associations.

Step 4: Internal validation. A double thematic review was conducted to ensure (i) the internal coherence of each theme, (ii) the discriminant validity between themes, and (iii) the inclusion of representative anonymised excerpts for each theme.

This procedure ensured that themes were not artificially constructed *a posteriori* to "fit" the quantitative findings but instead emerged organically from the empirical material. Selected anonymised quotations are presented below to illustrate each theme.

**5.5.3. Presentation of themes and verbatim excerpts**

Theme 1. AI as a Decision-Support and Managerial Control Tool

Managers describe AI (or, more broadly, predictive analytics and demand forecasting tools) as a lever for rationalised decision-making. The emphasis is not on full automation but on anticipation—adjusting production volumes, avoiding excessive inventory immobilisation, and prioritising profitable customer segments.

A manager of an agri-food SME (R8) noted:

"We started using a tool that projects our sales for the next two months. Before, we used to produce too much 'just in case,' and we lost money. Now we manufacture exactly what will sell. We have reduced unsold stock, and it shows in our cash-flow."

Another manager from the distribution sector (R4) explained:

"When I have figures on payment delays and margins by product, I can decide faster where to focus efforts. Without those dashboards, we react too late."

These excerpts illustrate the same mechanism highlighted in the quantitative phase: the adoption of digital tools (including AI or analytical automation modules) is directly associated with improved operational and financial management. This finding corresponds to the positive and significant relationship between AI adoption and performance ($\beta = 0.29$; $p < 0.001$) observed in the structural model.

Theme 2. Structural Barriers to AI Adoption

The most frequently cited barriers include high entry costs (licenses, subscriptions, hardware), lack of internal expertise to configure or use the tools, and dependence on external service providers. Managers express a clear awareness of AI's potential but face challenges in appropriation.

A manager of a service SME (R12) summarised:

"We know these solutions would help us track customer payments and inventory, all that. But the software is expensive, and training costs even more. We cannot absorb everything."

A female retail entrepreneur (R3F) added:

"I want to digitise my business, but I cannot afford to hire someone just for that. So, when the system breaks down, we go back to paper."

This theme nuances a key insight: the positive effect of AI on performance is neither universal nor automatic. It depends on the firm's capacity for appropriation and routinisation. This finding echoes the quantitative result showing that AI's impact is amplified when inclusive innovation and organisational resilience act as mediating mechanisms.

**Theme 3: inclusive platforms and the economic empowerment of women entrepreneurs**

The interviewed women entrepreneurs describe tools that may not strictly qualify as "AI," yet belong to the realm of functional digitalisation: mobile payments, microcredit apps, and local e-commerce platforms. For them, these tools serve as gateways to markets and financial security in environments where access to formal credit remains limited.

An artisan entrepreneur (R11F) explained:
“Mobile payments have changed everything. The customer does not need to go to the bank anymore; they send me money directly. It allows me to sell beyond my town.”
Another entrepreneur (R17F) emphasised financing access:
“Before, when I applied for a loan, they would say, ‘bring your papers.’ Now the app checks my sales history, and that is enough to unlock a small loan.”

These accounts exemplify inclusive innovation as conceptualised in the quantitative model: technological innovation is not confined to a technical elite but made accessible to historically marginalised actors within the economy. In the PLS-SEM model, this construct plays a central role ($\beta = 0.35$ between AI adoption and inclusive innovation; $p < 0.001$), partially explaining the enhancement of organisational resilience.

Theme 4. The structuring role of incubators, professional associations, and chambers of commerce

Intermediary actors stress that the appropriation of AI by SMEs cannot be left solely to market forces. They highlight three recurring needs: (i) capacity-building programs grounded in local realities; (ii) dedicated financing mechanisms to offset the initial cost of technological solutions; and (iii) a stable and transparent public framework governing data, digital trust, and contractual protection.
A representative of an incubator (R21-Inst) remarked:
“We can train the managers, but if there’s no funding line afterward for them to buy the tool or pay the subscription, it remains theoretical.”
A professional association member (R25-Inst) added:
“Without a clear regulatory framework, SMEs hesitate. They fear investing in digital tools if a tax or legal change tomorrow penalises them.”
This theme directly connects to the organisational resilience construct measured quantitatively. Support structures are perceived as levers of resilience, as they stabilise access to skills, tools, and financing. This resonates with the structural relationships’ inclusive innovation → resilience ($\beta = 0.41$; $p < 0.001$) and resilience → performance ($\beta = 0.28$; $p = 0.011$) observed in the PLS-SEM model.
For synthesis purposes, Table 12 presents a summary of these qualitative themes and their correspondence with the quantitative findings.

**Table 12: Summary of qualitative themes, with anonymised verbatims**

| Analytical theme | Key findings | Anonymised Verbatim (excerpts) |
|---|---|---|
| **AI and decision support** | AI/predictive tools improve anticipation (sales, cash-flow), reduce unnecessary inventory, and accelerate margin arbitrage. | "We now make what will go... We have reduced our unsold items, and it shows in the cash-flow. (R8, agri-food) |
| **Structural barriers to technology adoption** | High upfront costs; lack of internal skills; dependence on service providers; Back to paper in case of failure. | "Software is expensive... Training is even more expensive. We cannot absorb everything. (R12, Services) |
| **Inclusive platforms and women's entrepreneurship** | Mobile payments, microcredit based on real flows, local e-commerce: allow access to the market and financing. | "The app looks at my sales... That is enough to unlock a small loan. (R17F, trade/crafts) |
| **Role of incubators / associations / consular chambers** | Need for contextualised training, targeted financial support, and a stable institutional framework to secure digital investment. | "Without dedicated funding, training remains theoretical." (R21-Inst, Incubator) |

**5.5.4. Saturation and triangulation with quantitative analysis saturation.**

Thematic saturation was assessed iteratively throughout data collection. After approximately twenty interviews, no new substantive codes emerged concerning: (a) the use of AI or AI-like tools as decision-support mechanisms; (b) economic and cognitive barriers to adoption; (c) the role of inclusive platforms in women entrepreneurs’ market access; and (d) the contribution of support structures to organisational resilience. The remaining interviews (up to $n = 35$) served primarily to confirm, refine, and illustrate existing themes rather than generate new ones. In other words, saturation was reached not because “everything had been said,” but because additional interviews no longer altered the structure of the main thematic patterns.
Triangulation.
The qualitative results triangulate and enrich the quantitative findings from the PLS-SEM model:

- The empirical link between AI adoption and performance ($\beta = 0.29$; $p < 0.001$) finds concrete support in the narratives of managers who describe AI as a tool for operational and financial control (e.g., sales forecasting, stock adjustment, margin tracking per client). These accounts (R4, R8) illustrate a direct correspondence between statistical patterns and field-level discourse.

- The mediating role of inclusive innovation and organisational resilience (AI → inclusive innovation → resilience → performance; $\beta\_indirect \approx 0.04$; $p = 0.041$) is illuminated by two qualitative levels: (1) women entrepreneurs show how digital platforms expand access to resources and reduce dependence on informal networks (R11F, R17F); and (2) intermediary organisations explain how these inclusive practices must be institutionally supported to become sustainable (R21-Inst). This reinforces the notion that inclusive innovation is not purely technological but socially accessible and resilience-enhancing.
- The resilience → performance relationship ($\beta = 0.28$; $p = 0.011$) is exemplified in interviews where managers explain how the ability to anticipate payment defaults, smooth cash-flow tensions, or absorb supply shocks becomes a tangible competitive advantage. This qualitative evidence aligns with the multi-group analysis showing that resilience exerts a stronger influence among larger SMEs, where it is already perceived as a monetisable strategic asset.

Finally, triangulation also highlights the causal limitations of the quantitative model. Managers who demonstrate the strongest financial structuring (those capable of discussing margins, cash-flow, and forecasts) are often the same who have already integrated digital tools. This suggests a potential reverse causality: it is not only the tools that create capability, but also capable firms that adopt the tools. This qualitative insight strengthens the case for longitudinal studies to disentangle the direction of causality.

In summary, the qualitative phase: (i) empirically confirms the principal structural relationships revealed by the PLS-SEM model; (ii) specifies the mechanisms through which AI effectively translates into organisational capability (via inclusive innovation and institutional support); and (iii) clarifies the boundary conditions, costs, competencies, and ecosystem dependencies, that determine whether these effects can be sustained, particularly beyond better-structured urban SMEs.
It thus constitutes an explanatory complement to the model rather than a merely illustrative addition.

## VI. DISCUSSION OF RESEARCH FINDINGS

The results confirm the structuring role of Artificial Intelligence (AI) in improving SME performance in emerging contexts. The direct and significant relationship between AI adoption and organisational performance corroborates the findings of Chesbrough (2020) and Agrawal, Gans, and Goldfarb (2022), who emphasise AI's capacity to reduce transaction costs, enhance operational efficiency, and strengthen competitiveness. In our study, AI proved particularly instrumental in digitising accounting processes, managing customer data, and supporting real-time decision-making. These findings align with UNCTAD (2023), which highlights AI as a lever for structural transformation in emerging economies.

However, the most salient effect lies in the mediating role of inclusive innovation between AI adoption and SME performance. The strong and significant correlations suggest that AI generates sustainable effects only when embedded within inclusive practices that foster accessibility, participation, and shared value creation. This result supports the conclusions of George, McGahan, and Prabhu (2023), who identify inclusive innovation as a key mechanism of technological democratisation and socio-economic equity. In our context, SMEs that integrated inclusive solutions, such as mobile payments, collaborative platforms, and adapted e-commerce systems, exhibited superior performance, consistent with the findings of Foster and Heeks (2020).

Organisational resilience also emerges as a critical factor. The partial mediating effect observed in our model supports Lengnick-Hall and Beck's (2005) conceptualisation of resilience as the capacity to absorb shocks and adapt to uncertainty. Our results show that SMEs developing resilience capabilities, through diversification of funding sources, investment in digital skills, and consolidation of local networks, more effectively translate inclusive innovation into sustained performance. This finding resonates with Beck and Cull (2023), who underscore that the structural fragility of African SMEs necessitates continuous adaptive mechanisms.

Compared with prior research, our study offers an original contribution to understanding the relationship between AI and SME performance. Whereas earlier studies (Adner, 2017; Chesbrough, 2020) focused primarily on direct technological effects, our findings highlight the social and organisational dimensions, inclusive innovation and resilience, as mediating forces. This perspective aligns with the ecosystems approach proposed by Autio, Nambisan, Thomas, and Wright (2018), which posits that the integration of emerging technologies in SMEs depends on complex interactions among actors, institutions, and resources.

In conclusion, this research demonstrates that AI is not an autonomous catalyst of performance within SMEs in emerging contexts. Its transformative value arises when embedded within a framework of inclusive innovation and organisational resilience. This finding provides valuable insights for public policy and entrepreneurial development strategies, suggesting that emphasis should be placed not only on technological adoption, but also on building inclusive and resilient ecosystems that enable SMEs to fully harness the potential of AI.

## VII. THEORETICAL, METHODOLOGICAL, AND MANAGERIAL IMPLICATIONS

From a theoretical perspective, this research enriches the ongoing debates on AI in emerging economies. It confirms the direct effects of AI on organisational performance while demonstrating the mediating influence of inclusive innovation and resilience. This theoretical articulation broadens traditional frameworks focused solely on technological efficiency (Chesbrough, 2020; Agrawal et al., 2022) and advances an integrative ecosystem-based perspective (Autio et al., 2018). Its primary contribution lies in identifying the social and organisational conditions necessary to convert AI adoption into sustainable performance.

From a methodological standpoint, the study illustrates the value of a mixed-method approach, combining quantitative surveys and qualitative interviews. The use of structural equation modelling (SEM-PLS) enabled empirical testing of complex interrelations and validation of mediating effects, while qualitative analysis deepened understanding of practices and actor perceptions. This triangulated design ensures both scientific robustness and contextual validity, reinforcing the credibility and practical relevance of the findings.

From a managerial perspective, the results provide actionable insights for SME leaders. AI adoption should be conceptualised as an integrated and contextualised strategy, not merely a technological acquisition. Inclusive innovation practices serve as levers to strengthen territorial embeddedness and broaden access to financial and digital resources. The development of resilience capabilities, through partnership diversification, continuous training, and network consolidation, emerges as a precondition for survival and competitiveness. Collectively, these findings invite SME managers to combine technological appropriation with inclusive and adaptive practices, transforming structural constraints into strategic opportunities for sustainable growth.

## VIII. LIMITATIONS AND RESEARCH PERSPECTIVES

This study should be interpreted in light of several methodological and empirical limitations.

First, the geographical scope is restricted. Quantitative and qualitative data were collected primarily from SMEs operating in urban and peri-urban centers in Central Africa, with a particular focus on Chad, complemented by comparative observations from similar dynamics in neighbouring Central African contexts and, to a lesser extent, Francophone West Africa. This geographical concentration enhances the internal coherence of the analysis but limits its immediate transferability. Rural SMEs, informal microenterprises in peripheral zones, and firms operating in less structured economic ecosystems, characterised by limited digital infrastructure and reliance on community-based rather than formal support networks, are underrepresented. Consequently, the findings primarily reflect the dynamics of urban or semi-formal SMEs functioning in partially stabilised institutional environments with minimal access to intermediaries such as accounting firms, incubators, or professional associations. They only partially capture the organisational realities of geographically isolated or fully informal enterprises.

Second, the measures employed are largely self-reported by firm managers, covering AI adoption, inclusive innovation, organisational resilience, and performance. This choice is justified by the low level of documentary formalisation typical of many SMEs in Central Africa. However, it entails well-known limitations: social desirability bias (tendency to overstate managerial sophistication), legitimation bias (presenting the firm as technologically “modern” to signal credibility), and conceptual ambiguity between declared and actual adoption (e.g., “we use AI” may describe anything from a basic cash-flow alert tool to a genuine decision-support system). Moreover, performance is treated as a multidimensional construct, economic, financial, organisational, and reputational, but not systematically validated against independent accounting or banking data. The results should thus be interpreted as reflecting perceived or claimed trajectories rather than audited performance measures.

Third, the empirical design is cross-sectional. Data were collected at a single point in time. Although the PLS-SEM modelling approach enables the estimation of directionally consistent relationships (e.g., AI adoption → inclusive innovation → resilience → performance), it does not allow for causal inference in the strict sense. Reverse causality remains plausible: more successful, better-capitalized SMEs, those with stronger management capacities and better integration into support networks, may be precisely those able to adopt AI components, formalise inclusive routines, and institutionalise resilience practices. Thus, the risk of endogeneity, particularly through self-selection of the most robust firms into the “inclusive innovation” and “organisational resilience” categories, cannot be entirely dismissed.

These limitations, rather than diminishing the value of the proposed model, delineate a future research agenda along three priority directions.

(i) A longitudinal perspective is essential. Panel-based designs following the same SMEs over multiple time waves would enable the observation of real adoption trajectories for AI tools and inclusive innovation practices, as well as their delayed effects on resilience and performance. Such designs could reveal whether AI produces immediate efficiency gains or functions primarily as a long-term organisational investment, becoming effective only after internal appropriation. Similarly, they could determine whether resilience represents a stable capacity or fluctuates in response to shocks (rising import costs, liquidity constraints, supply disruptions). Longitudinal approaches would also allow for formal testing of causal directionality and the estimation of cumulative effects (learning, routine consolidation, and progressive formalisation of financial governance).

(ii) Cross-country and regional comparisons are needed. The findings are anchored in a specific institutional context, Central Africa, characterised by restricted access to formal credit, selective and uneven state support for SMEs, and uneven digital infrastructure distribution. Testing the model in other African contexts—such as West African economies with more mature fintech ecosystems or Southern African economies with stronger regulatory and accounting structures—would help distinguish generic mechanisms (dynamic recombination capabilities) from contextual effects (chronic liquidity pressures, structural informality, dependency on a small number of major clients). Such comparative analyses would refine the transferability of the model and support policy differentiation tailored to distinct institutional regimes.

(iii) Quasi-experimental or experimental approaches should be developed to address endogeneity and strengthen causal inference. For instance, the causal impact of digital tool access (e.g., AI-assisted cash-flow dashboards, predictive sales analytics platforms) could be evaluated by comparing SMEs receiving structured support (training + subsidised tool access) with a matched control group without intervention, monitored over several months. Similarly, field experiments through incubators, chambers of commerce, or professional associations could test whether specific inclusive innovation practices, such as gender-adapted financial training, mobile payment integration, or simplified donor reporting mechanisms, produce measurable increases in organisational resilience (e.g., the ability to absorb a liquidity shock without activity interruption) and, ultimately, performance. Approaches like difference-in-differences, propensity score matching, or cluster randomisation (when feasible) would provide a stronger causal basis than cross-sectional correlations.

In synthesis, this research offers a first empirical formalisation, in a Central African context, with analytical extensions toward West Africa, of a conceptual sequence where AI fosters inclusive innovation, inclusive innovation strengthens organisational resilience, and resilience supports multidimensional SME performance. It nonetheless acknowledges its limitations: self-reporting bias, urban concentration, and cross-sectional design. Future research should therefore (i) track firms longitudinally to capture the dynamic evolution of capabilities, (ii) compare multiple countries and institutional regimes to distinguish specific from general mechanisms, and (iii) employ quasi-experimental designs to isolate the causal effects of technological and organisational interventions. Only under these conditions can a plausible explanatory model evolve into a robust causal framework, valuable both for advancing dynamic capabilities theory in African SMEs and for informing evidence-based public policies on inclusive digital transformation and entrepreneurial resilience.

## IX. CONCLUSION

This research highlights the structuring role of artificial intelligence (AI) and inclusive innovation in transforming small and medium-sized enterprises (SMEs) and, more broadly, entrepreneurial ecosystems in emerging contexts. The findings demonstrate that AI adoption exerts a direct, positive, and significant effect on organisational performance. However, this relationship proves more robust and sustainable when mediated by inclusive practices and strengthened organisational resilience. In other words, technology, when detached from its social and institutional environment, remains a partial driver of performance; its true potential unfolds when embedded within collective, equitable, and adaptive dynamics.

From a theoretical perspective, this study moves beyond technology-centric approaches by proposing an integrative conceptual model emphasising the centrality of inclusive innovation and resilience as mediating mechanisms. It thus redefines the conditions under which AI can generate sustainable competitive advantage. This contribution enriches the literature in innovation economy and management, reintegrating technology within a broader framework that connects social inclusion, organisational learning, and dynamic capabilities.

From a methodological standpoint, the combination of a mixed-methods designs, and structural equation modelling (SEM-PLS) applied to SMEs in emerging contexts adds significant analytical value. This hybrid approach not only enables empirical testing of the proposed hypotheses but also captures the depth of lived practices and perceptions through qualitative analysis. It exemplifies the relevance of methodological pluralism in addressing complex contemporary phenomena.

From a managerial and strategic perspective, the results offer concrete insights for SME leaders: (1) to invest in gradual and contextualised AI adoption; (2) to promote inclusive practices that expand access to markets and finance, especially for historically marginalised groups; and (3) to strengthen resilience capacities by diversifying partnerships, investing in continuous training, and consolidating collaborative networks. These strategies allow firms to transform uncertainty into adaptive and growth opportunities.

Ultimately, this study broadens the understanding of the conditions under which AI can truly serve as a catalyst for sustainable transformation and competitiveness in emerging economies. It opens promising avenues

for future research on inclusive entrepreneurship trajectories, digital governance challenges, and comparative analyses of SME dynamics across institutional environments.
In its exploratory and forward-looking nature, this work invites us to reconsider AI not as an end in itself, but as a strategic component of a broader societal and organisational project—one that interweaves technology, inclusion, and resilience within a coherent logic of sustainable development.

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