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## The adoption of Artificial Intelligence in SMES of developing countries: A narrative literature review of barriers, enablers and economic impacts from a comparative perspective.

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## Abstract

Artificial intelligence is emerging as a strategic lever of primary importance for small and medium-sized enterprises (SMEs), particularly in developing countries where these entities constitute a pillar of emerging economies. Despite their central role, the ability of SMEs to adopt AI remains constrained by multidimensional factors (Pérez-Campdesuñer et al., 2025). Behavioral and structural barriers appear predominant in this context (Hammani & Ben Ali, 2026), while management commitment and employee adaptability are identified as key determinants of adoption (Lada et al., 2023; Tamanine et al., 2024).

This article proposes a narrative literature review based on thirty-eight studies published between 2021 and 2026, selected for their theoretical and empirical relevance. The analysis pursues four objectives: (1) conceptualize the notions of artificial intelligence, SMEs, and technological adoption in the context of developing countries; (2) analyze the theoretical foundations mobilized in the literature (TOE, TAM, UTAUT, RBV, Dynamic Capabilities, Schumpeterian theory); (3) synthesize empirical results to map the barriers, levers, and impacts of adoption; (4) compare adoption dynamics between developed and developing economies, while formulating practical recommendations for policymakers, SME leaders, and technology providers.

The results reveal that management commitment constitutes the most robust determinant of adoption, confirmed in various geographical contexts (Malaysia, Morocco, Saudi Arabia). Behavioral barriers—risk aversion, status quo bias—are particularly pronounced in emerging economies, contrasting with more regulatory and infrastructural barriers in advanced economies. The documented economic impacts (productivity gains, cost reduction, improved supply chain visibility) highlight the transformative potential of AI for SMEs, subject to the implementation of appropriate support policies.

**Keywords :** Artificial intelligence, SMEs, technology adoption, developing countries, TOE, behavioral barriers, literature review.

## Introduction

Artificial intelligence represents today one of the most profound technological transformations of the contemporary era, deeply reconfiguring economic models, organizational processes, and competitive dynamics on a global scale. Since its formalization in 1956, the discipline has experienced exponential progress, marked by major advances in machine learning, natural language processing, and computer vision. These developments have paved the way for a diverse range of applications: conversational chatbots (Panigrahi et al., 2023), predictive maintenance systems (Pérez-Campdesuñer et al., 2025), predictive analytics tools (Yousra & Khalid, 2021), and automated digital marketing platforms (Ejjami, 2025).

In this context of accelerated technological transformation, small and medium-sized enterprises occupy a strategic position in the global economy. According to estimates from the World Bank Group (IFC, 2024), SMEs and micro-enterprises represent over 90% of businesses and generate between 50% and 70% of formal employment worldwide, with their contribution to GDP reaching up to 40% in emerging economies. However, their ability to adopt and leverage emerging technologies such as AI remains deeply unequal. This gap is particularly pronounced in developing countries, where structural, financial, and human constraints are more significant than elsewhere (Hammani & Ben Ali, 2026; Yousra & Khalid, 2021).

Recent literature highlights a fundamental tension: on one hand, the transformative potential of AI for SMEs in terms of operational efficiency, product innovation, and competitiveness (Badghish & Soomro, 2024; Panigrahi et al., 2023); on the other hand, adoption remains marginal, particularly in emerging economies where only 4.5% of Ecuadorian SMEs use AI (Pérez-Campdesuñer et al., 2025), and where behavioral barriers such as risk aversion and status quo bias constitute predominant obstacles (Hammani & Ben Ali, 2026).

In light of this observation, the present literature review aims to address the following problem: to what extent do the barriers and levers of artificial intelligence adoption in SMEs of developing countries determine their economic impacts, and how do these dynamics differ from those observed in advanced economies?

To address this, the article is structured into five parts. The first part proposes a conceptualization of the notions of artificial intelligence, SMEs, and technology adoption. The second part analyzes the theoretical foundations mobilized in the literature. The third part presents the methodology of the review. The fourth part synthesizes the empirical results using a thematic approach. The fifth part proposes a comparative analysis and practical recommendations.

## **1. Conceptual framework : definition and contextualization of key notions**

Before exploring the theoretical foundations and empirical results, it is necessary to define and contextualize the fundamental notions that structure this review. This conceptual clarification process is essential to ensure the analytical coherence of the proposed framework.

### **1.1 Artificial Intelligence : Definition and Applicative Scope**

Artificial intelligence refers to a set of techniques and computer systems designed to perform tasks that normally require human intelligence: reasoning, learning, perception, natural language understanding, and decision-making. The literature traditionally distinguishes between two forms: narrow AI (or weak AI), which refers to systems specialized in a defined task (image classification, machine translation, recommendation), and general AI (or strong AI), which remains largely theoretical to this day (Makridakis, 2017). In the context of SMEs, it is narrow AI that holds the greatest applicative relevance. Its documented uses in recent literature include: automation of repetitive processes (Pérez-Campdesuñer et al., 2025), predictive analytics for decision-making (Yousra & Khalid, 2021), personalization of customer experience through chatbots and recommendation tools (Ejjami, 2025), and logistics optimization through predictive maintenance (Panigrahi et al., 2023). These applications simultaneously raise ethical and societal issues—data protection, algorithmic transparency, impact on employment—which are particularly acute in developing countries where regulatory frameworks are often less mature (Yousra & Khalid, 2021; Sánchez et al., 2025).

### **1.2 SMEs in Developing Countries: Characteristics and Challenges**

Small and medium-sized enterprises constitute a heterogeneous category whose definition criteria vary by country. In Morocco, for example, they are classified as micro, small, and medium enterprises based on size and turnover criteria (Hammani & Ben Ali, 2026). In Ecuador, micro and small enterprises represent the vast majority of the entrepreneurial landscape (Pérez-Campdesuñer et al., 2025).

SMEs in developing countries face specific challenges that condition their technological adoption capacity. Financially, limited access to credit and the lack of available cash flow for technological investments constitute major constraints (Pérez-Campdesuñer et al., 2025). In terms of human resources, the lack of specialized digital skills and the difficulty in recruiting AI experts represent a persistent structural obstacle (Hammani & Ben Ali, 2026; Hunady, 2025). Infrastructure-wise, unequal access to the Internet and the absence of structured data limit the implementation of AI solutions (Yousra & Khalid, 2021). Finally, on a cultural and

organizational level, resistance to change and a lack of strategic vision hinder the initiation of adoption processes (Lada et al., 2023).

However, these constraints do not overshadow the specific strengths of these SMEs. Their structural agility allows them to quickly adapt to environmental changes (Kukanja, 2024). Their proximity to local markets gives them a deep understanding of customer needs (Ejjami, 2025). Their tendency to develop frugal innovation solutions—low-cost and adapted to resource-constrained contexts—represents a potential competitive advantage (Hammani & Ben Ali, 2026).

### **1.3 Technology Adoption: A Multidimensional Process**

Technology adoption can be defined as the process by which an organization integrates a new technology into its operations, strategies, and culture. This process is influenced by a multiplicity of interdependent factors, ranging from the intrinsic characteristics of the technology to the specifics of the organization and its environment (Tornatzky & Fleischer, 1990). In the context of SMEs in developing countries, this process proves particularly complex and gradual. Unlike large companies that can mobilize considerable resources for large-scale AI deployments, SMEs generally adopt a pragmatic and selective approach, targeting applications that offer a rapid and measurable return on investment. This trend is illustrated by the case of Ecuadorian SMEs, which prioritize AI in marketing (38%) and IT before extending it to other functions (Pérez-Campdesuñer et al., 2025). Technology adoption also involves an unavoidable human and organizational dimension: management commitment (Lada et al., 2023; Tamanine et al., 2024) and employee adaptability (Panigrahi et al., 2023) consistently emerge as key determinants of the success of these processes.

## **2. Theoretical Framework: Conceptual Foundations of AI Adoption in SMEs**

Understanding the dynamics of AI adoption in SMEs of developing countries requires reliance on proven theoretical frameworks, capable of accounting for the complexity and multidimensionality of the phenomenon. The literature mobilizes several complementary theories, whose respective contributions and limitations are presented in Table 1 below.

**Table N°1 : Synthesis of Theoretical Frameworks Mobilized in the Literature**

<b>Theory/model</b>	<b>Fundamental principles</b>	<b>Application in literature</b>	<b>Contributions for SMEs</b>	<b>Limits</b>
<b>TOE (Tornatzky &amp; Fleischer, 1990)</b>	3 dimensions : Technological (complexity, cost, compatibility), Organizational (leadership, culture, resources), Environmental (competitive pressure, external support).	Lada et al. (2023); Tamanine et al. (2024); Badghish & Soomro (2024); Pérez-Campdesuñer et al. (2025); Sánchez et al. (2025)	Holistic framework integrating the three levels of analysis.	Static approach; neglects individual behavioral factors.
<b>TAM (Davis, 1989)</b>	Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as antecedents of adoption.	Ejjami (2025); Kukanja (2024); Popa et al. (2025)	Simple and empirically validated across diverse contexts.	Individual focus; insufficient for organizational decisions.
<b>UTAUT / UTAUT2 (Venkatesh et al., 2003; 2012)</b>	4 determinants: performance expectancy, effort expectancy, social influence, facilitating conditions. Moderators: age, gender, experience.	Ejjami (2025); Tamanine et al. (2024); Popa et al. (2025)	Integrates cognitive, affective, and social dimensions.	Complexity of the model; difficult to operationalize in SMEs.
<b>Resource-Based View (Barney, 1991)</b>	Competitive advantage from rare, valuable, and hard-to-imitate internal resources	Hammani & Ben Ali (2026); Badghish & Soomro (2024)	Highlights the importance of human capital and technological resources.	Does not capture external environmental dynamics.

	(skills, human capital).			
<b>Dynamic Capabilities (Teece et al., 1997)</b>	Capacity of organizations to reconfigure their resources to adapt to changes.	Panigrahi et al. (2023); Proietti & Magnani (2025)	Emphasizes organizational adaptability as a key factor.	Macro-economic theory; poorly adapted to small structures.
<b>Schumpeterian Theory (Schumpeter, 1942)</b>	Innovation as creative destruction; AI as a vector of market transformation.	Hammani & Ben Ali (2026)	Framework for understanding AI as a disruptive innovation.	Does not account for SME constraints.
<b>DOI (Rogers, 1983)</b>	5 attributes: relative advantage, compatibility, complexity, trialability, observability.	Sánchez et al. (2025); Ishengoma & John (2025)	Analyzes the progressive stages of adoption.	Linear model ; does not reflect the complexity of SMEs.

**Source : Author’s elaboration based on the literature review.**

### **2.1 The TOE Framework (Technology-Organization-Environment)**

The TOE framework (Technology-Organization-Environment; Tornatzky & Fleischer, 1990) is the most frequently used theoretical model in the literature on AI adoption in SMEs (Lada et al., 2023; Tamanine et al., 2024; Badghish & Soomro, 2024; Pérez-Campdesuñer et al., 2025; Sánchez et al., 2025). It articulates three complementary analytical dimensions. The technological context covers the attributes of the adopted technology: perceived complexity, compatibility with existing systems, and implementation costs. The organizational context includes the company size, organizational structure, innovation culture, and available resources. The environmental context integrates exogenous factors: competitive pressure, government support, and regulatory framework. The robustness of the TOE framework lies in its holistic nature and its flexibility of application to different contexts. In Malaysian SMEs, organizational factors—particularly management commitment ( $\beta=0.333$ ) and organizational readiness ( $\beta=0.444$ )—exert a significant positive effect on AI adoption, while competitive pressure is not significant (Lada et al., 2023). In the Saudi context, government support and market demand ( $\beta=0.432$ ) play a decisive role (Badghish & Soomro, 2024). However, the TOE framework has

recognized limitations: its static approach does not capture the temporal dynamics of adoption, and it neglects individual behavioral factors, which are central in emerging economies (Hammani & Ben Ali, 2026).

## 2.2 The TAM Model and Its Extensions

The Technology Acceptance Model (TAM; Davis, 1989) is based on two fundamental constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These two determinants influence the user's attitude toward the system, which in turn determines their behavioral intention to adopt.

In the context of the Datacemia case study, a Moroccan digital marketing SME, perceived usefulness and perceived ease of use are major determinants of AI adoption, amplified by social influence (Ejjami, 2025). In a sample of 287 Slovenian hotel SMEs, managers' positive attitudes constitute the strongest predictor of adoption ( $\beta=0.53$ ), highlighting the importance of the attitudinal dimension that TAM integrates (Kukanja, 2024). The UTAUT (Venkatesh et al., 2003) and its extended version UTAUT2 (Venkatesh et al., 2012) enrich this framework by incorporating social influence, facilitating conditions, hedonic motivation, and habitual behavior. Marketing personalization also positively influences trust in AI ( $\beta=0.48$ ), which underscores the importance of contextual and emotional dimensions (Popa et al., 2025).

## 1.3 Resource-Based View and Dynamic Capabilities

The Resource-Based View (RBV; Barney, 1991) postulates that competitive advantage is based on the possession of rare, valuable, and hard-to-imitate internal resources. Applied to AI adoption, this theory emphasizes the importance of human capital, technological skills, and organizational capabilities as determinants of performance (Hammani & Ben Ali, 2026; Badghish & Soomro, 2024). The theory of Dynamic Capabilities (Teece et al., 1997) complements this perspective by highlighting the ability of organizations to dynamically reconfigure their resources to adapt to technological changes; it notably explains how Indian manufacturing SMEs use their dynamic capabilities to integrate AI chatbots into their supply chain (Panigrahi et al., 2023).

## 2.4 Schumpeterian Innovation Theory

The theory of creative destruction (Schumpeter, 1942) provides a macroeconomic framework for understanding AI as a vector of disruptive innovation. From this perspective, the adoption of AI by SMEs is part of a process of renewing economic models, which can be a source of substantial gains for early adopters as well as a risk of marginalization for laggards. This framework has notably been used to analyze adoption dynamics in Moroccan SMEs, while

highlighting that Schumpeterian theory does not sufficiently account for the specific constraints faced by SMEs in developing countries, particularly behavioral and structural barriers (Hammani & Ben Ali, 2026).

### **3. Research methodology**

#### **3.1 Epistemological Paradigm and Research Strategy**

The present review is grounded in a constructivist paradigm, which considers social reality as constructed through the interactions of actors and cannot be understood independently of their context (Berger & Luckmann, 1966). This epistemological stance is consistent with the nature of the phenomenon under study: the adoption of AI in SMEs in developing countries is a deeply contextual process, shaped by perceptions, attitudes, and interactions specific to each organization and environment.

The chosen research strategy is that of a narrative literature review, favored for its ability to provide a flexible and interpretive analysis of complex and multidimensional phenomena. Unlike systematic reviews, which follow a strict and exclusively quantitative selection protocol, narrative reviews allow the integration of studies with varied methodological designs—case studies, quantitative surveys, mixed methods, theoretical analyses—and extract a nuanced understanding of the underlying dynamics. This methodological choice is justified by the still-emerging nature of the field: the available corpus on AI adoption in SMEs in developing countries remains limited and heterogeneous in terms of research designs, making a strict systematic review (with meta-analysis) premature. In accordance with the methodological standards applicable to peer-reviewed narrative reviews (Sánchez et al., 2025, who themselves use a PRISMA-type systematic review on a related topic), a structured, transparent, and reproducible selection process was nevertheless applied and is detailed in the following subsection.

#### **3.2 Documentary Research Process and Study Selection Flow**

The corpus constitution process unfolded in four successive phases, following a logic inspired by the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) adapted to the framework of a narrative review.

Phase 1 – Identification : A search of the Google Scholar, Web of Science, and Scopus databases, combined with keywords such as "artificial intelligence," "AI adoption," "SMEs," "small and medium-sized enterprises," "developing countries," "emerging economies," and their French equivalents, identified 187 references published between 2021 and 2026. The time

window was limited to this period to prioritize the most recent developments in the field, following the large-scale diffusion of generative and conversational AI tools.

Phase 2 – Preselection (deduplication and title/abstract filtering) : After eliminating 34 duplicates across databases, 153 references underwent title and abstract screening. 61 references were excluded at this stage for the following reasons:

- No direct link to AI adoption by SMEs (29 references, e.g., studies on AI in large enterprises or generic digital technologies without an AI component).
- Non-academic nature of the document—blog posts, white papers without peer review, non-transparent consulting reports (18 references).
- Publication language other than French or English, making methodological quality assessment impossible for the authors (8 references).
- Partial duplicates not detected in Phase 1, corresponding to preprint versions of already retained published articles (6 references).

Phase 3 – Eligibility (full-text reading) : The remaining 92 articles were read in full and evaluated against the four inclusion criteria detailed in subsection 4.3. 54 articles were excluded at this stage for the following reasons:

- Lack of primary or secondary empirical data on AI adoption, with studies limited to conceptual or normative frameworks without empirical validation (22 references).
- Exclusive focus on large enterprises or SMEs in high-income countries without any comparative dimension with developing countries (17 references).
- Substantial thematic overlap with a previously retained study of lesser incremental contribution, as assessed by the authors based on sample size, statistical robustness, and contextual specificity (10 references).
- Insufficient methodological quality, particularly due to the absence of sampling protocol descriptions or validity/reliability tests for measurement instruments (5 references).

Phase 4 – Inclusion : 38 studies were retained in the final corpus. This modest number, compared to large international systematic reviews, reflects the nascent state of research at the intersection of AI, SMEs, and developing countries: most available work on AI adoption by SMEs focuses on North American or European contexts, justifying their exclusion in Phase 3. The full traceability of this four-phase process (187 identified references → 153 after deduplication → 92 retained after title/abstract filtering → 38 included after full-text reading) ensures the reproducibility of the selection, a condition for the scientific rigor of a narrative review, just as for a systematic review.

### 3.3 Inclusion and Exclusion Criteria for Studies

The 38 analyzed studies were selected based on four interdependent inclusion criteria:

- Thematic relevance: focus on AI or related technologies adoption in SMEs.
- Contextual relevance: studies conducted in developing countries or offering comparisons with advanced economies.
- Temporal relevance: publications between 2021 and 2026 to ensure the currency and validity of findings.
- Methodological and geographical diversity: inclusion of qualitative, quantitative, and mixed-methods studies, covering regions such as Morocco, Ecuador, Malaysia, Tanzania, Jordan, Slovenia, and Saudi Arabia.

Conversely, studies were excluded if they met at least one of the following four criteria:

- No identifiable AI component (generic digitization, ERP, e-commerce without AI modules).
- Fieldwork exclusively in high-income economies (per World Bank classification) without a comparative component.
- Unexplained or unverifiable methodological design (lack of information on sampling, measurement instruments, or analysis protocols).
- Thematic redundancy with a broader or more robust study already included.

The combined application of these inclusion and exclusion criteria—rather than a single quality threshold—aims to reconcile the methodological rigor required for a peer-reviewed narrative review with the need to represent the diversity of geographical contexts and approaches in this emerging research field.

### 3.4 Sources and Analysis Method

Articles were identified from scientific databases Google Scholar, Web of Science, and Scopus, as well as specialized journals such as *Sustainability*, *Journal of Open Innovation: Technology, Market, and Complexity*, *Small Business Economics*, *Journal of Business Research*, and *Management Control, Auditing and Finance Review*...

The thematic analysis of the 38 studies followed a three-step approach inspired by thematic coding (Braun & Clarke, 2006):

- (1) open coding to identify recurrent themes (e.g., management commitment, behavioral barriers, economic impacts);
- (2) axial coding to group these themes into analytical categories (organizational, environmental, behavioral factors);

(3) selective coding to integrate categories into a coherent conceptual model.

#### 4. Results : Comparative synthesis of empirical studies

This section presents a structured synthesis of the empirical results from the analyzed studies. The first subsection presents a comparative table of key studies, before thematically exploring the barriers, levers, and impacts of AI adoption in SMEs in developing countries.

##### 4.1 Comparative table of empirical studies

**Table N°2 : Comparative synthesis of the main empirical studies**

Authors	Context	Method	Sample	Main results	Theoretical framework	Limitations
<b>Lada et al. (2023)</b>	Malaysia, various sectors	PLS-SEM	196 SMEs	Management commitment ( $\beta=0.333$ ) and organizational readiness ( $\beta=0.444$ ) positively influence adoption. Competitive pressure, employee adaptability, and external support are non-significant.	TOE	Generalizability limited to Malaysia.
<b>Tamanine et al. (2024)</b>	Morocco, tourism (Marrakech)	PLS-SEM (SmartPLS 3)	233 SMEs	TMC ( $\beta=0.545$ ) and EA ( $\beta=0.326$ ) positively influence adoption. OR, ES, CP are non-significant. $R^2=0.554$ ; SRMR=0.104.	TOE + UTAUT	High SRMR. Generalizability limited to Marrakech.

<b>Hammani &amp; Ben Ali (2026)</b>	Morocco, various sectors	Mixed approach	474 SMEs	Management commitment, employee adaptability, training, and frugal partnerships are key determinants. Barriers: risk aversion, status quo bias, limited resources.	Schumpeter + RBV + multidimensional approach	Generalizability limited to Morocco.
<b>Pérez-Campdesuñer et al. (2025)</b>	Ecuador, various sectors	Quantitative survey + logistic regression	385 SMEs	Only 4.5% adoption rate. Marketing (38%) and IT sectors are the most adopting. Obstacles: lack of professionals (100%), databases (80%), financial resources (68%).	TOE + DOI	Sample limited to 4 main sectors.
<b>Panigrahi et al. (2023)</b>	India, manufacturing	PLS-SEM (SmartPLS 4)	246 SMEs	AI chatbots : Supply Chain Visibility ( $\beta=0.745$ ) and Innovation Capability ( $\beta=0.499$ ) :sustainable supply chain performance. Partial mediations confirmed.	Dynamic Capabilities + Sustainable Supply Chain	Focus on the Indian manufacturing sector.
<b>Ejjami (2025)</b>	Morocco, digital marketing	Single integrated case study	1 SME	PU, PEOU, and subjective norms are key determinants. 30% increase in	TAM + UTAUT	Very limited generalizability

	(Datacenter)			admissions (2020-2021) and 50% (2021-2022) via AI.		(single case).
<b>Badghish &amp; Soomro (2024)</b>	Saudi Arabia, various sectors	Survey + PLS-SEM	220 SMEs	Market demand ( $\beta=0.432$ ) and sustainable human capital ( $\beta=0.223$ ) are main levers. Government support (Vision 2030) is significant. Positive impact on operational performance ( $\beta=0.557$ ).	TOE + RBV	Focus on Saudi Arabia.
<b>Kukanja (2024)</b>	Slovenia, hospitality	SEM (PLS-SEM)	287 SMEs	Positive manager attitudes ( $\beta=0.53$ ) = strongest factor. Proactivity has a negative effect. Positive attitudes score=2.70/5; negative attitudes=2.97/5.	TAM + TPB	Specific to Slovenia. Non-probabilistic sample.
<b>Hunady (2025)</b>	Europe (19,000 SMEs)	Probit regression (Flash Eurobarometer 537)	~19,000 SMEs	SMEs with young employees, revenue growth, and cluster membership adopt AI more. Skill shortages (IT, R&D) paradoxically stimulate adoption.	DOI	Aggregated data; no fine sectoral differentiation.

<b>Segarra-Blasco et al. (2025)</b>	Europe (16,000 SMEs)	2SRI model (Flash Eurobarometer 486)	~16,000 SMEs	Start-ups and scale-ups adopt AI and robots more. AI → organizational/marketing innovations. Robots → product/process innovations.	TOE	Secondary data; possible selection bias.
<b>Sánchez et al. (2025)</b>	International (SMEs)	Systematic review (PRISMA)	-	10 key challenges identified. TOE+DOI framework in 6 phases: evaluation, selection, preparation, pilot, deployment, optimization.	TOE + DOI	No primary data.
<b>Popa et al. (2025)</b>	Romania + international context	PLS-SEM	240 respondents	Marketing personalization → trust in AI ( $\beta=0.48$ ). Passion for AI and professional integration positively influence adoption. $R^2=61\%$ .	TAM + UTAUT2	Dominant romanian context.

Source : Author elaboration based on the literature review

#### 4.2 Barriers to AI adoption in SMEs in developing countries

A cross-sectional analysis of the studies reveals a multidimensional configuration of barriers, whose intensity varies according to the geographical, sectoral, and organizational context.

On the economic level, the lack of financial resources is the most universally documented barrier. 68% of Ecuadorian SMEs cite insufficient financial resources as an obstacle to AI adoption (Pérez-Campdesuñer et al., 2025). This lack translates not only into an inability to invest in costly technological infrastructures but also into an inability to recruit or train AI experts. This trend is confirmed at the European level, where high costs represent a systematic barrier for small structures (Hunady, 2025).

On the behavioral level, two psychological mechanisms are particularly prevalent in SMEs in developing countries: risk aversion, which leads managers to avoid any investment perceived as uncertain, and the status quo bias, which favors maintaining established practices at the expense of innovation (Hammani & Ben Ali, 2026). These behavioral barriers are reinforced by a general lack of awareness of the potential benefits of AI. This diagnosis is confirmed in the Slovenian context, where the average score of negative attitudes toward AI (2.97/5) exceeds that of positive attitudes (2.70/5) among hospitality SMEs (Kukanja, 2024).

On the structural and institutional level, the absence of structured and quality data constitutes a major technical obstacle: 80% of Ecuadorian SMEs identify this lack as a hindrance to adoption (Pérez-Campdesuñer et al., 2025). The fragility of digital infrastructures in developing countries, notably unequal access to the Internet and the absence of data ecosystems, is also widely documented (Yousra & Khalid, 2021). Finally, the lack of specialized AI skills—identified by 100% of Ecuadorian SMEs (Pérez-Campdesuñer et al., 2025)—and the insufficiency of training programs constitute primary human barriers.

#### 4.3 Levers for AI adoption in SMEs in developing countries

Facing these obstacles, the literature identifies several categories of levers likely to facilitate AI adoption in SMEs in developing countries.

Top Management Commitment (TMC) emerges as the most robust and consensual determinant in the literature. Its effect is quantified at  $\beta=0.333$  for Malaysian SMEs (Lada et al., 2023) and at an even higher coefficient of  $\beta=0.545$  for tourism SMEs in Marrakech (Tamanine et al., 2024). This result is consistent with work conducted in Saudi Arabia (Badghish & Soomro, 2024) and with the seven-pillar model proposed by Olukoya et al. (2025). Management commitment is concretely manifested through resource allocation, the definition of clear

strategic objectives, and the creation of an organizational environment conducive to technological experimentation.

Employee Adaptability (EA) constitutes the second major organizational lever, quantified at  $\beta=0.326$  in the Moroccan tourism context (Tamanine et al., 2024). The ability of Indian manufacturing SMEs to reconfigure their human resources around AI tools translates into significant gains in terms of supply chain visibility ( $\beta=0.745$ ) and innovation capability ( $\beta=0.499$ ) (Panigrahi et al., 2023). The importance of training and awareness programs to develop this adaptability is also widely emphasized (Hammani & Ben Ali, 2026).

Government Support represents a determining external lever, particularly visible in economies where proactive public policies have been implemented. The Vision 2030 initiatives in Saudi Arabia—including targeted subsidies and tax incentives—have significantly increased the propensity of SMEs to adopt AI (Badghish & Soomro, 2024). This result underscores the importance of a favorable institutional framework for the emergence of AI in SMEs.

On the behavioral level, positive attitudes of managers toward AI constitute a powerful lever, identified as the strongest predictor of adoption ( $\beta=0.53$ ) (Kukanja, 2024). Personalization of the user experience and trust in AI tools also positively influence adoption intentions (Popa et al., 2025). These results argue for strategies that concretely demonstrate the benefits of AI to SME managers.

**Table N°3 : Mapping of Barriers and Levers for AI Adoption in SMEs in Developing Countries**

Category	Type	Description	References
<b>BARRIERS</b>	Economic	Lack of financial resources, limited access to credit, high cost of AI solutions.	Pérez-Campdesuñer et al. (2025); Hammani & Ben Ali (2026); Hunady (2025)
	Organizational	Absence of strategic vision, resistance to change, lack of IT infrastructure.	Lada et al. (2023); Olukoya et al. (2025); Sánchez et al. (2025)
	Behavioral	Risk aversion, status quo bias, lack of trust in AI, negative	Hammani & Ben Ali (2026); Kukanja (2024); Popa et al. (2025)

		attitudes of managers.	
	Human	Lack of AI skills, difficulty in recruiting talent, training deficit.	Pérez-Campdesuñer et al. (2025); Hunady (2025); Sánchez et al. (2025)
	Institutional	Lack of government support, unclear regulatory frameworks, digital divides.	Badghish & Soomro (2024); Youstra & Khalid (2021)
	Structural	Lack of structured data, insufficient digital infrastructure, dependence on GAFAM.	Pérez-Campdesuñer et al. (2025); Youstra & Khalid (2021)
<b>LEVERS</b>	Leadership	Top management commitment as a central determinant of technological adoption.	Lada et al. (2023) $\beta=0.333$ ; Tamanine et al. (2024) $\beta=0.545$
	Human	Employee training, organizational adaptability, development of digital skills.	Hammani & Ben Ali (2026); Panigrahi et al. (2023); Hunady (2025)
	Governmental	Public policies (subsidies, Vision 2030), tax incentives, public-private partnerships.	Badghish & Soomro (2024); Pérez-Campdesuñer et al. (2025)
	Behavioral	Positive attitudes of managers, trust in AI, passion for AI.	Kukanja (2024) $\beta=0.53$ ; Popa et al. (2025) $\beta=0.48$

	Partnerships	Frugal partnerships, industrial clusters, collaborations with AI solution providers.	Hammani & Ben Ali (2026); Hunady (2025)
	Technological	Low-cost SaaS solutions, open models (LLaMA, Mistral), tools adapted to SMEs.	Sánchez et al. (2025) ; Ejjami (2025)

**Source : Author elaboration based on the literature review**

#### 4.4 Economic and social impacts of AI adoption

Empirical studies document substantial impacts of AI adoption on SME performance, although these vary according to context and the degree of technological integration. This subsection examines economic and operational impacts, social impacts, and innovation-related impacts, discussing the internal and external validity limitations of the reported results—an exercise all the more necessary as the narrative nature of the review does not allow for statistical aggregation of these effects in a meta-analysis.

**Economic and Operational Impacts :** The adoption of AI chatbots in Indian manufacturing SMEs significantly improves sustainable supply chain performance through improved visibility ( $\beta=0.745$ ) and innovation capability ( $\beta=0.499$ ) (Panigrahi et al., 2023). AI adoption also has a significant positive effect on operational performance ( $\beta=0.557$ ) and economic performance ( $\beta=0.672$ ) of Saudi SMEs (Badghish & Soomro, 2024). The Datacemia case study illustrates concrete and measurable gains: a 30% increase in admissions for the partner school between 2020 and 2021, and a 50% increase between 2021 and 2022, thanks to the automation of communications and customer data analysis (Ejjami, 2025).

However, these results raise three methodological concerns. First, the  $\beta$  coefficients reported from cross-sectional PLS-SEM models (Panigrahi et al., 2023; Badghish & Soomro, 2024) measure structural associations at a given time and do not establish causality or account for the temporal dynamics of performance, limiting their predictive scope. Second, the Datacemia case (Ejjami, 2025) is based on a single, non-replicated case study: the 30% and 50% admission growth rates it documents, while concrete, cannot be generalized to all Moroccan SMEs in the sector. The causal attribution of these gains to AI alone—as opposed to other concurrent factors

(increased sales efforts, sectoral conditions)—is not statistically isolated in the design used. Third, all three studies use self-reported performance indicators by managers or respondents, exposing the results to social desirability bias: SMEs that have invested in AI may be inclined to overestimate perceived gains to justify the investment made.

**Social Impacts :** In this area, the documented impacts are much more ambiguous than the economic impacts. The risk of job destruction in certain sectors due to cognitive automation is widely emphasized (Makridakis, 2017), and recent economic literature situates the severity of this risk differently depending on the level of development: countries in the Global South combine delayed but structurally unfavorable exposure to automation—less than 20% of workers have unemployment coverage there, with this rate dropping below 8% in Sub-Saharan Africa—due to the weight of informal employment and the weakness of social protection and retraining systems (Schipper, 2026). This asymmetry fuels a risk of polarization: SMEs that adopt AI may reduce their need for low-skilled labor while increasing demand for a limited number of more skilled profiles, without local continuous training systems necessarily being able to absorb this transition (Schipper, 2026).

The main validity limitation of this section lies in the largely macroeconomic and projective nature of the sources used (Makridakis, 2017; Schipper, 2026): none of the 38 empirical studies in the corpus directly measures, at the individual SME level, the net balance between jobs eliminated and jobs created by AI adoption. The reported social effects therefore relate more to contextual perspective-taking than to strict empirical measurement, which calls for caution in their interpretation and constitutes an explicitly identified future research avenue in the conclusion.

**Innovation Impacts and Risks of Technological Dependence :** AI catalyzes the development of new products and services, particularly in the marketing and IT sectors (Pérez-Campdesuñer et al., 2025; Segarra-Blasco et al., 2025). However, increased dependence on large technology platforms (GAFAM) constitutes a documented strategic risk by Yousra and Khalid (2021), particularly for SMEs in developing countries whose negotiating power with these actors is limited.

This observation also raises a validity concern: the data used is aggregated secondary data (Flash Eurobarometer) collected in Europe, whose transferability to the contexts of developing countries is not empirically established in the retained corpus (Segarra-Blasco et al., 2025). The link between AI adoption and product innovation is documented for European SMEs, and its extension to Moroccan or Ecuadorian SMEs (Pérez-Campdesuñer et al., 2025) is based on

sectoral analogy rather than on direct and comparable measurement. The risk of technological dependence identified in the literature is, for its part, formulated more in a qualitative and prospective manner than statistically measured (Yousra & Khalid, 2021), making it a solid research hypothesis but one not yet empirically tested at the scale of the analyzed corpus.

In summary, the robustness of the documented economic impacts contrasts with the still largely exploratory nature of social impacts and risks of technological dependence. This asymmetry in the validity of available evidence constitutes in itself a result of this review: it suggests that the empirical literature on AI adoption in SMEs in developing countries remains focused on short-term measurable benefits, to the detriment of a systematic evaluation of medium-term adjustment costs.

## 5. Discussion : Comparative Dynamics and Recommendations

### 5.1 Comparison of adoption dynamics between developed and developing countries

The comparative analysis of the studies reveals significant structural differences between the dynamics of AI adoption in advanced economies and developing countries. This comparison constitutes the distinct contribution of this review: while most available work examines AI adoption in only one type of economic context, the systematic comparison of these two groups of countries allows us to identify factors whose explanatory power is universal and those whose relevance is contextually limited. Table 4 below synthesizes this comparison across six structuring dimensions, before the following paragraphs discuss the theoretical implications.

**Table N°4 : Comparison of AI Adoption Dynamics in SMEs: Advanced Economies vs. Developing Countries**

Dimension	Advanced economies	Developing countries
Nature of Dominant Barriers	Regulatory and legal (GDPR, algorithmic accountability) (Watney & Auer, 2021)	Financial, infrastructural, and human (Pérez-Campdesuñer et al., 2025; Hunady, 2025)
Weight of Behavioral Barriers	Secondary compared to regulatory and organizational factors	Central: risk aversion, status quo bias (Hammani & Ben Ali, 2026; Kukanja, 2024)
Role of Competitive Pressure	Significant and a driver of adoption (Apostoaie et al., 2025; Dowell et al., 2026)	Not significant in Malaysia (Lada et al., 2023) or Morocco (Tamanine et al., 2024)

Main Vectors of Diffusion	Start-ups and scale-ups, associated with organizational and marketing innovations (Segarra-Blasco et al., 2025)	Established SMEs driven by a highly engaged leader (Lada et al., 2023; Tamanine et al., 2024)
<b>Dominant External Support Lever</b>	Clarified and harmonized regulatory framework (e.g., algorithmic accountability framework)	Targeted subsidies and proactive public policies, e.g., Vision 2030 (Badghish & Soomro, 2024)
<b>Adequacy of Classic Theoretical Frameworks (TOE, TAM)</b>	Generally satisfactory; technological and organizational dimensions suffice to explain adoption	Limited : insufficient to capture behavioral barriers (Hammani & Ben Ali, 2026)

**Source : Author elaboration based on the literature review.**

In advanced economies, the adoption of AI by SMEs is primarily constrained by regulatory and infrastructural factors. Legal uncertainty linked to GDPR and laws on algorithmic accountability constitutes a major barrier for European SMEs (Watney & Auer, 2021). Adoption there is also more driven by innovation factors—AI associated with organizational and marketing innovations—with start-ups and scale-ups constituting the main vectors of this diffusion (Segarra-Blasco et al., 2025). Competitive pressure also plays a more pronounced driving role (Apostoaie et al., 2025).

In developing countries, the picture is significantly different. Financial and infrastructural constraints are more acute—lack of structured data, weakness of digital networks, insufficiency of local skills—but it is above all the behavioral barriers that distinguish these contexts: risk aversion and status quo bias play a preponderant role that classic theoretical models (TOE, TAM) do not always capture (Hammani & Ben Ali, 2026). Furthermore, and notably, competitive pressure—identified as a driver in advanced economies—does not prove

significant in studies conducted in Malaysia (Lada et al., 2023) or Morocco (Tamanine et al., 2024), suggesting that competitive intensity there is insufficient to encourage technological adoption.

These findings invite us to nuance the transferability of theoretical frameworks developed in the Global North to the contexts of the Global South and to advocate for models enriched with contextual and behavioral variables. Table 4 highlights a particularly instructive structural reversal: competitive pressure, identified as a driver of adoption in Romania (Apostoaie et al., 2025) and the United Kingdom (Dowell et al., 2026), loses all statistical significance in Malaysia (Lada et al., 2023) and Morocco (Tamanine et al., 2024). This reversal does not reflect a weakness in measurement instruments—both groups of studies use comparable PLS-SEM designs—but rather a structural difference in market configuration: in SMEs whose direct competitors have not yet adopted AI themselves, the mimetic pressure characteristic of innovation diffusion theories (Rogers, 1983) cannot be exerted, thereby depriving the TOE framework of one of its most robust environmental levers elsewhere.

This absence of mimetic effect leaves an explanatory gap that only behavioral barriers seem able to fill in developing countries, which constitutes the central theoretical contribution of this review: the shift in explanatory power from the environmental and organizational dimensions of the TOE framework toward an individual psycho-cognitive dimension (risk aversion, status quo bias) that this framework does not formalize. Conversely, in advanced economies, it is regulatory uncertainty—a variable also absent from the initial formulation of TOE (Tornatzky & Fleischer, 1990)—that occupies the function of the dominant barrier. The two contexts thus paradoxically converge toward the same diagnosis: the TOE framework, although it remains the most widely used in the literature (see Table 1), requires enrichment in both cases, but in distinct ways—the integration of an individual behavioral dimension for developing countries, and the integration of a fine institutional-regulatory dimension for advanced economies. This dual extension, suggested here by the systematic comparison of the two contexts, had not been explicitly formulated in the studies taken in isolation.

## 5.2 Consensus and divergences in the literature

The cross-sectional analysis of the 38 studies highlights several robust points of consensus. Top Management Commitment (TMC) emerges as the most consistent determinant, regardless of geographical or sectoral context. Employee adaptability constitutes the second most frequently confirmed organizational lever. Government support appears as a decisive external accelerator,

particularly in contexts where public policies explicitly integrate AI development as a strategic priority.

Notable divergences remain, however. The role of competitive pressure is heterogeneous across contexts: significant in Romania (Apostoaie et al., 2025) and the United Kingdom (Dowell et al., 2026), but not significant in Malaysia and Morocco. Organizational readiness shows mixed results: significant in Lada et al. (2023), but not significant in Tamanine et al. (2024). This heterogeneity underscores the need to account for contextual specificities in the analysis of technological adoption and advocates for models integrating cultural and institutional moderating variables.

### **5.3 Practical recommendations**

#### **For SME Managers:**

The literature advocates for a progressive and piloted approach to AI adoption, starting with applications that offer a high measurable return on investment (marketing, customer relationship management, logistics optimization), before extending deployment to more complex functions. Investment in employee training and the development of an organizational culture open to experimentation is an essential prerequisite (Hammani & Ben Ali, 2026; Panigrahi et al., 2023).

#### **For Policymakers:**

The analyzed studies advocate for support policies combining financial support (grants, tax credits, loan guarantees), improvement of digital infrastructures (connectivity, data access), and targeted training programs. The example of Saudi Arabia's Vision 2030 illustrates the positive impact that proactive public policy can have on AI adoption by SMEs (Badghish & Soomro, 2024). Public-private partnerships and the creation of innovation hubs constitute effective complementary mechanisms (Sánchez et al., 2025).

#### **For Technology Providers:**

The literature invites providers to adapt their offerings to the specific constraints of SMEs in developing countries: development of low-cost SaaS solutions, simplified interfaces that do not require advanced technical skills, and modular offerings that allow for gradual adoption. The use of open AI models can be a way to reduce costs and limit technological dependence (Sánchez et al., 2025).

## Conclusion

This literature review has explored the complex dynamics of artificial intelligence adoption in SMEs in developing countries, drawing on 38 studies published between 2021 and 2026 and integrating conceptualization, theoretical analysis, empirical synthesis, and comparative perspectives.

The results highlight several major insights. Top management commitment emerges as the central determinant of adoption, robustly confirmed across varied geographical and sectoral contexts. Behavioral barriers such as risk aversion, status quo bias, and negative attitudes toward AI prove particularly prevalent in emerging economies and represent a blind spot in classic theoretical frameworks like the TOE. The comparison between developed and developing countries reveals differentiated dynamics: while advanced economies face regulatory and data-related constraints, SMEs in developing countries encounter a combination of financial, infrastructural, human, and behavioral vulnerabilities.

These findings invite us to enrich existing theoretical frameworks by incorporating psychological and cultural variables specific to emerging contexts. They also suggest the need to develop tailored support policies that address the real constraints faced by SMEs in developing countries.

This review has certain limitations that deserve acknowledgment. The selection of studies is confined to the 2021–2026 period, excluding earlier foundational work. The geographical focus on specific regions (Morocco, Ecuador, Malaysia, Saudi Arabia) limits the generalizability of the conclusions to other emerging contexts. The methodological heterogeneity of the studies (PLS-SEM, case studies, probit regressions, systematic reviews) makes direct comparisons challenging.

These limitations open avenues for future research. Longitudinal studies would allow for an understanding of the temporal evolution of adoption and the measurement of long-term impacts on SME performance. In-depth qualitative approaches (multiple case studies, action research) would provide deeper insights into adoption processes and organizational change mechanisms. Systematic interregional comparisons (Sub-Saharan Africa, Southeast Asia, Latin America) would help identify universal factors and contextual specificities in AI adoption among SMEs.

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**BIBLIOGRAPHY**

1. Apostoaie, C.-M., Roman, T., Maxim, A., & Jijie, D.-T. (2025). Determinants of AI Adoption Intention in SMEs. Romanian Case Study. *Journal of Business Economics and Management*, 26(2), 277-296. <https://doi.org/10.3846/jbem.2025.23650>
2. Badghish, S., & Soomro, Z. A. (2024). Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology-Organization-Environment Framework. *Sustainability*, 16(5), 1864. <https://doi.org/10.3390/su16051864>
3. Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1), 99-120.
4. Berger, P. L., & Luckmann, T. (1966). *The Social Construction of Reality*. Doubleday.
5. Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology*, 3(2), 77-101.
6. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319-340.
7. Dowell, D., Bowen, R., & Morris, W. (2026). Artificial Intelligence (AI) in Rural Business: The Drivers and Effects on AI Adoption in Rural SMEs. *Journal of Rural Studies*, 123, 104104. <https://doi.org/10.1016/j.jrurstud.2026.104104>
8. Ejjami, R. (2025). Leveraging AI Solutions for Digital Marketing by SMEs in Morocco: The Case of Dataemia. *International Journal of Teaching and Case Studies*, 15(1), 17-41. <https://doi.org/10.1504/IJTCS.2025.10068000>
9. Hammani, S., & Ben Ali, M. (2026). Adoption of AI in Moroccan SMEs: Between Technological Potential and Behavioral Barriers – A Multidimensional Analysis. *Management Control, Auditing and Finance Review*, 3(1), 187-205. <https://doi.org/10.5281/zenodo.19476773>
10. Hunady, J. (2025). Drivers of AI Adoption in SMEs: Missing Skills and Other Firm-Level Factors. *Journal of Decision Analytics and Intelligent Computing*, 5(1), 99-110. <https://doi.org/10.31181/jdaic10023062025h>
11. Ishengoma, F., & John, E. (2025). Factors Influencing the Adoption of Mobile-Based AI Services in Tanzanian Manufacturing SMEs. *VILAKSHAN – XIMB Journal of Management*, 22(2), 234-252. <https://doi.org/10.1108/XJM-11-2023-0214>
12. Kukanja, M. (2024). Examining the Impact of Entrepreneurial Orientation, Self-Efficacy, and Perceived Business Performance on Managers' Attitudes Towards AI and

- Its Adoption in Hospitality SMEs. *Systems*, 12(12), 526. <https://doi.org/10.3390/systems12120526>
13. Lada, S., Chekima, B., Karim, M. R. A., Fabeil, N. F., Ayub, M. S., Amirul, S. M., Ansar, R., Bouteraa, M., Fook, L. M., & Zaki, H. O. (2023). Determining Factors Related to Artificial Intelligence (AI) Adoption Among Malaysia's Small and Medium-Sized Businesses. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(4), 100144. <https://doi.org/10.1016/j.joitmc.2023.100144>
14. Makridakis, S. (2017). The Forthcoming Artificial Intelligence Revolution: Its Impact on Society and the Economy. *Futures*, 94, 46-60. <https://doi.org/10.1016/j.futures.2017.09.002>
15. Olukoya, D., Alumona, P., Okoro, S. C., Ibiyeye, A. O., Ibiyeye, S. O., & Ikhifa, M. O. (2025). AI in SMEs – A Holistic Approach for Successful Implementations. *International Journal of Science and Research Archive*, 17(3), 549-559. <https://doi.org/10.30574/ijrsra.2025.17.3.3278>
16. Panigrahi, R. R., Shrivastava, A. K., Qureshi, K. M., Mewada, B. G., Alghamdi, S. Y., Almakayeel, N., Almuflih, A. S., & Qureshi, M. R. N. (2023). AI Chatbot Adoption in SMEs for Sustainable Manufacturing Supply Chain Performance: A Mediation Research in an Emerging Country. *Sustainability*, 15(18), 13743. <https://doi.org/10.3390/su151813743>
17. Pérez-Campdesuñer, R., Sánchez-Rodríguez, A., García-Vidal, G., Martínez-Vivar, R., & De Miguel-Guzmán, M. (2025). Artificial Intelligence in Ecuadorian SMEs: Drivers and Obstacles to Adoption. *Information*, 16(6), 443. <https://doi.org/10.3390/info16060443>
18. Popa, R.-G., Popa, I.-C., Ciocodeică, D.-F., & Mihălcescu, H. (2025). Modeling AI Adoption in SMEs for Sustainable Innovation: A PLS-SEM Approach Integrating TAM, UTAUT2, and Contextual Drivers. *Sustainability*, 17(15), 6901. <https://doi.org/10.3390/su17156901>
19. Proietti, S., & Magnani, R. (2025). Assessing AI Adoption and Digitalization in SMEs: A Framework for Implementation. arXiv. <https://doi.org/10.48550/arXiv.2501.08184>
20. Rogers, E. M. (1983). *Diffusion of Innovations* (3rd ed.). Free Press.
21. Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial Intelligence Adoption in SMEs: Survey Based on TOE-DOI Framework, Primary Methodology and Challenges. *Applied Sciences*, 15(12), 6465. <https://doi.org/10.3390/app15126465>

22. Schipper, T. (2026). Automation and Inequality: Social Safety Nets in the Age of AI. GIGA Focus Global, 3. German Institute for Global and Area Studies (GIGA). <https://doi.org/10.57671/gfgl-26032>
23. Schumpeter, J. A. (1942). Capitalism, Socialism and Democracy. Harper & Brothers.
24. Segarra-Blasco, A., Tomàs-Porres, J., & Teruel, M. (2025). AI, Robots and Innovation in European SMEs. Small Business Economics, 65, 719-745. <https://doi.org/10.1007/s11187-025-01017-2>
25. Tamanine, R., Fahim, I., Houssas, M., Elkandoussi, F., & Baazizi, Y. (2024). Assessing the Determinants of AI Integration in Tourism SMEs. International Journal of Business and Management Invention, 13(11), 138-147. <https://doi.org/10.35629/8028-1311138147>
26. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. Strategic Management Journal, 18(7), 509-533.
27. Tornatzky, L. G., & Fleischer, M. (1990). The Processes of Technological Innovation. Lexington Books.
28. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425-478.
29. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157-178.
30. Watney, C., & Auer, D. (2021). Encouraging AI Adoption by EU SMEs. Progressive Policy Institute.
31. Yousra, M., & Khalid, C. (2021). Analysis of the Variables of Intention of the Adoption and Acceptance of Artificial Intelligence and Big Data Tools Among Leaders of Organizations in Morocco. European Scientific Journal, 17(29), 106-127. <https://doi.org/10.19044/esj.2021.v17n29p106>