Acta Universitatis Danubius
ŒCONOMICA

Barriers to the Integration of Artificial Intelligence in Algerian Startups

Rim Akkarene[1], Nabil Bouda[2]

Abstract: Despite the potential of Artificial Intelligence (AI), its integration within Algerian startups remains limited. This study aims to identify and categorise the primary barriers hindering AI adoption in this emerging ecosystem. Using a qualitative methodology, we conducted semi-structured interviews with 21 Algerian startup managers. The findings reveal a complex interplay of interconnected technical, financial, human capital, and institutional barriers that create mutually reinforcing cycles. These results extend the Technology-Organization-Environment (TOE) framework by highlighting the systemic nature of these challenges. Addressing these compounded obstacles through holistic, ecosystem-level interventions is crucial for unlocking AI's transformative potential.

Keywords: Artificial Intelligence; Technology Adoption; Startups; Emerging Economies; Innovation Barriers

JEL Classification: O33; O32; M13; L26; O55

1. Introduction

In recent years, Artificial Intelligence (AI) has emerged as a transformative force in the global digital economy, enabling startups to scale rapidly, optimize operations, personalize services, and innovate across sectors (Vlist, Helmond & Ferrari, 2024). In economies seeking to diversify and modernize, AI adoption is no longer a competitive advantage but an essential pillar for long-term survival and growth.

[1] Lecturer, Ph.D., Bejaia University, Algeria, Address: Campus Aboudaou, Route de Tichy RN°9, Bejaia, 06000, Algeria, Corresponding author: rim.akkarene@univ-bejaia.dz.

[2] Lecturer, Ph.D., Bejaia University, Algeria, Address: Campus Aboudaou, Route de Tichy RN°9, Bejaia, 06000, Algeria, E-mail: nabil.bouda@univ-bejaia.dz.

Algeria, like many countries in the Global South, has embraced a national vision of digital transformation, evident in policies such as the "Digital Algeria 2020" strategy and more recent government-backed innovation hubs and technology clusters (El-Kadi, 2024). These efforts signal a recognition of the role digital technologies, including AI, must play in addressing structural economic dependencies and stimulating entrepreneurship (Martins, 2024).

In Algeria, the startup ecosystem remains nascent and fragile. While the country has witnessed a growing interest in entrepreneurship, especially among youth, many startups struggle with funding, infrastructure, and market access (Ameur & Bengabou, 2024). Despite AI's potential to amplify startup competitiveness, actual implementation remains sparse. Startups in sectors such as e-commerce, logistics, agriculture, and healthcare stand to benefit significantly from AI-driven solutions. However, anecdotal evidence and limited studies suggest that few Algerian startups go beyond superficial digitalization, with AI integration still in its infancy (Mili et al., 2025). This disconnect between opportunity and adoption raises critical questions about the structural and contextual barriers impeding AI diffusion in Algeria's entrepreneurial landscape.

1.1. Problem Statement

Despite the global momentum around AI adoption, Algerian startups have shown limited progress in embedding AI technologies into their business models and operations (Abadli, Kooli & Otmani, 2020). While there is recognition of AI's potential, tangible uptake remains low, fragmented, and often exploratory. Existing research tends to focus on AI readiness at a macro or institutional level, overlooking the nuanced challenges faced by startups operating under resource, regulatory, and knowledge constraints. There is a lack of systematic research that identifies and categorizes the specific barriers to AI integration within the Algerian startup context. Without such understanding, both policy responses and support mechanisms risk being misaligned with on-the-ground realities. Furthermore, the absence of Algeria-specific empirical studies creates a blind spot in the broader discourse on digital transformation in emerging economies (Kouah, 2025).

1.2. Research Objectives

This study seeks to fill this critical gap by offering a comprehensive analysis of the barriers to AI integration in Algerian startups. The specific objectives are:

- To systematically identify and categorize the barriers hindering AI adoption among Algerian startups;

- To develop a conceptual framework that synthesizes these barriers across technical, organizational, institutional, and cultural dimensions;
- To provide actionable insights that can inform policy formulation, ecosystem design, and startup-level strategies aimed at accelerating responsible AI integration.

1.3. Research Questions

Guided by the above objectives, this research addresses the following core questions:

1) What are the primary barriers to AI integration in Algerian startups?

2) How can these barriers be systematically categorized to reflect Algeria's unique socio-economic and technological context?

3) What relationships or interdependencies exist between different barrier categories (e.g., technical vs. regulatory vs. cultural)?

By answering these questions, the study aims not only to clarify the structural impediments to AI adoption in Algerian startups but also to contribute to the broader conversation on how emerging ecosystems can navigate the complexities of technological innovation under constraint.

2. Literature Review

2.1. Theoretical Foundations

2.1.1. Technology Adoption Models (TAM, UTAUT, TOE Framework)

The theoretical understanding of technology adoption has evolved through several influential models that provide frameworks for analyzing how and why organizations and individuals adopt new technologies. The Technology Acceptance Model (TAM), developed by Davis (1989), remains one of the most widely applied frameworks in information systems research (Ahmi, Saidin & Abdullah, 2014). TAM posits that two key constructs, perceived usefulness and perceived ease of use are fundamental determinants of technology adoption intention (Abdullah & Almaqtari, 2024). Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance, "while perceived ease of use represents" the degree to which a person believes that using a particular system would be free of effort" (Saadé, 2007).

Building upon TAM's foundation, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates elements from eight prominent models to provide a more comprehensive understanding of technology adoption (Venkatesh et al., 2003).

UTAUT identifies four core determinants: performance expectancy (the degree to which technology use will help attain performance gains), effort expectancy (the degree of ease associated with system use), social influence (the degree to which important others believe one should use the technology), and facilitating conditions (the degree to which organizational and technical infrastructure exists to support use) (Dwivedi et al., 2017). Empirical validation demonstrates UTAUT's superior explanatory power, accounting for 70% of variance in user intentions compared to 17-53% for individual models (Alam et al., 2020).

The Technology-Organization-Environment (TOE) framework, introduced by Tornatzky and Fleischer (1990), offers an organizational-level perspective on innovation adoption (Yang, Blount & Amrollahi, 2024). The framework posits that three contexts influence adoption decisions: technological context (encompassing internal and external technologies relevant to the firm), organizational context (firm characteristics and resources), and environmental context (industry structure, competitive pressure, and regulatory environment) (Handoko, Riantono & Sunarto, 2021). The TOE framework has demonstrated broad applicability across various technological innovations and geographical contexts, including developed and developing countries (Dwivedi et al., 2019).

Recent applications of TAM in AI contexts reveal its continued relevance. Research on AI adoption in accounting and auditing practices demonstrates that perceived usefulness and ease of use significantly mediate the relationship between AI technologies and adoption intention. The study found that AI positively influences perceived usefulness (0.578) and ease of use (0.458), which in turn drive intention to use AI (Abdullah & Almaqtari, 2024). This validates TAM's applicability to contemporary AI adoption scenarios while highlighting the importance of demonstrating clear benefits and ensuring user-friendly interfaces.

2.1.2. Innovation Diffusion Theory

Rogers' (1995) Diffusion of Innovation theory provides crucial insights into how innovations spread through social systems over time (Rogers, 2004). The theory defines innovation as "an idea, a practice or an object, perceived as new by an individual or social group," emphasizing that perception of novelty, rather than objective newness, determines adoption behavior (Fèvres, 2012). This theoretical perspective necessitates examining the discourses and cultural contexts surrounding innovations, particularly relevant for AI adoption in different cultural settings.

The diffusion process involves four key elements: innovation characteristics, communication channels, time, and social system structure (Fèvres, 2012). Rogers identifies five innovation characteristics that influence adoption: relative advantage, compatibility, complexity, trialability, and observability (Alsheibani et al., 2018). Research consistently shows that innovations perceived as having greater relative advantage, higher compatibility with existing values and practices, lower complexity, higher trialability, and greater observability are adopted more rapidly (Davis, 1989).

Contemporary applications of diffusion theory to AI adoption reveal its enduring relevance. The complexity characteristic, closely aligned with TAM's ease of use construct, emerges as a significant barrier to AI adoption, particularly for organizations with limited technical expertise (Khanfar et al., 2024). The theory's emphasis on social influence mechanisms also aligns with UTAUT's social influence construct, highlighting the importance of peer networks and opinion leaders in technology adoption decisions.

2.1.3. Resource-Based View of the Firm

The Resource-Based View (RBV) of the firm provides a strategic perspective on technology adoption by focusing on how organizations leverage unique resources to achieve competitive advantage (Chatterjee, Chaudhuri & Vrontis, 2021). RBV posits that firms' competitive advantages stem from their ability to acquire, develop, and deploy valuable, rare, inimitable, and non-substitutable (VRIN) resources (Ardito et al., 2024). In the context of AI adoption, this theory helps explain why some organizations successfully implement AI while others struggle.

Research applying RBV to AI adoption identifies several critical resource categories. Tangible resources include high-quality data, technological infrastructure, and financial resources necessary for AI implementation (Mikalef & Gupta, 2021). Human resources encompass both technical skills (statistics, programming, machine learning expertise) and business skills (managerial understanding of AI applications, change management capabilities) (Nyberg et al., 2025). Intangible resources include organizational culture supportive of innovation, inter-departmental coordination capabilities, and risk-taking propensity (Mikalef & Gupta, 2021).

Studies demonstrate that bundling these resources effectively creates AI capabilities that significantly impact organizational performance (Budhwar et al., 2023). Research shows that firms with comprehensive resource development across all categories achieve better outcomes than those focusing solely on technological resources (Mikalef & Gupta, 2021). This finding emphasizes the holistic nature of successful AI adoption, requiring coordinated development of technological, human, and organizational resources.

2.2. AI Adoption in Startups: Global Perspectives

2.2.1. AI Adoption Patterns in Startups Globally

Global AI adoption patterns reveal significant variations in implementation levels and approaches across different contexts. Research indicates that while AI has gained increasing recognition, actual implementation remains limited, with approximately 90% of SMEs lacking any AI applications (Oldemeyer, Jede & Teuteberg, 2024). However, awareness is growing rapidly, with 77% of SMEs recognizing great possibilities for AI use across business activities (Schwaeke et al., 2024).

The evolution of AI adoption follows distinct phases. Initial adoption (2010-2017) was limited to niche applications, with minimal startup engagement (Neumann, Guirguis & Steiner, 2022). The expansion phase (2018-2020) saw increased awareness and experimentation as AI technologies became more accessible (Borges et al., 2020). The acceleration phase (2021-onwards) demonstrates exponential growth in AI-focused startups and applications, driven by media prominence and tailored AI solutions for smaller enterprises (Uriarte et al., 2025).

Contemporary adoption patterns show AI integration across diverse startup activities, with operational aspects receiving the most attention (Oldemeyer, Jede & Teuteberg, 2024). Quality management leads AI applications (12 publications), followed by production planning (4 publications), predictive maintenance (3 publications), and processing optimization (3 publications) (Lee, Lee & Kim, 2019). This operational focus reflects startups' pragmatic approach to AI adoption, prioritizing immediate efficiency gains over strategic transformation.

Regional variations in adoption patterns are significant. European startups developing AI solutions show distinct characteristics that may differ from emerging market contexts (Alhosani & Alhashmi, 2024). Dutch AI startups, while still in their infancy, demonstrate unique approaches to AI technology development (C. et al., 2024). Indonesian startups face implementation hurdles requiring specific strategies to overcome barriers (Yuwono, Suroso & Novandari, 2024). Indian healthcare startups show particular promise in AI adoption, though they encounter sector-specific challenges (Singh et al., 2020).

2.2.2. Success Factors and Challenges

Research identifies multiple interconnected success factors for AI adoption in startups. Strategic factors include clear understanding of AI's role as a prediction technology that reduces uncertainty and enables better decision-making (Martins, 2024). Successful startups recognize AI's potential to automate processes, enhance customer experiences, and extract valuable insights from data (C. et al., 2024).

Organizational factors prove equally critical. Data-driven culture emerges as a fundamental requirement, with studies showing that firms with strong data-driven cultures achieve significantly better innovation outcomes (Chatterjee, Chaudhuri & Vrontis, 2021). Leadership support is essential, with top management commitment correlating strongly with successful AI implementation (Handoko, Riantono & Sunarto, 2021). Organizations require specific capabilities including data management, technological infrastructure, and human expertise (Mikalef & Gupta, 2021).

Technical factors encompass data quality, algorithmic sophistication, and integration capabilities. High-quality, accessible data serves as the foundation for effective AI applications (Mikalef & Gupta, 2021). Organizations must invest in robust technological infrastructure, including cloud computing, processing power, and networking capabilities (Mikalef & Gupta, 2021). The modular nature of AI technologies allows for incremental adoption, reducing barriers for resource-constrained startups (Martins, 2024).

However, startups face significant challenges in AI adoption. Financial constraints represent the primary barrier, with 24 articles identifying costs as a major impediment (Oldemeyer, Jede & Teuteberg, 2024). Implementation costs include not only software and hardware but also training, integration, and ongoing maintenance expenses (Ghobakhloo & Ching, 2019). Small enterprises often lack resources for comprehensive AI implementation, leading many to rely on external service providers (Martins, 2024).

Knowledge gaps constitute another major challenge. The predominant barrier across 35 articles is insufficient AI expertise, including both technical skills and understanding of implementation procedures (Oldemeyer, Jede & Teuteberg, 2024). This challenge is compounded by difficulties in recruiting qualified personnel and the complexity of AI technologies (Ghobakhloo & Ching, 2019). The “black box” nature of AI algorithms creates additional trust and interpretability challenges (Oldemeyer, Jede & Teuteberg, 2024).

Infrastructure limitations significantly impact adoption potential. Many startups, particularly in developing contexts, lack basic digital infrastructure necessary for AI implementation (Ade-Ibijola & Okonkwo, 2023). Inadequate internet connectivity, limited computational resources, and insufficient data storage capabilities create fundamental barriers to adoption (Alalawneh & Alkhatib, 2020).

Organizational challenges include resistance to change, integration complexity, and risk management concerns. Employee concerns about job displacement and technological change create cultural barriers (Martins, 2024). The complexity of integrating AI systems with existing processes poses significant technical and organizational challenges. Risk-averse organizational cultures may resist AI adoption due to uncertainty about outcomes and potential failures (Oldemeyer, Jede & Teuteberg, 2024).

2.3. Technology Adoption in Developing Countries

2.3.1. Digital Divide and Infrastructure Challenges

The digital divide represents one of the most significant barriers to AI adoption in developing countries, manifesting through multiple interconnected dimensions. Internet penetration remains critically low, with sub-Saharan Africa achieving only 40% population access compared to 95% in North America and 87% in Europe (Amankwah-Amoah & Lu, 2022). Mobile internet connectivity in sub-Saharan Africa was approximately 26% in 2019, far below levels necessary for robust AI applications (Amankwah-Amoah & Lu, 2022). This connectivity gap directly impedes AI adoption since most modern AI systems require reliable internet access for cloud-based processing and data exchange.

Infrastructure deficiencies extend beyond basic connectivity to encompass the technological foundations necessary for AI implementation. Research reveals that most SMEs in developing countries have substantially lower digitalization maturity than their developed-country counterparts, with many operating at basic levels lacking fundamental infrastructure like WiFi (Morales et al., 2024). The absence of reliable electricity, adequate data storage facilities, and modern computing hardware creates compounding barriers for AI adoption (Amankwah-Amoah & Lu, 2022).

Educational infrastructure challenges further exacerbate the digital divide. In Algeria's educational sector, 92.3% of respondents cited technical difficulties, including slow internet connections and compatibility issues, as primary challenges for AI integration. Limited access to updated technology and insufficient technical support affect 46.2% of educators, highlighting infrastructure gaps that extend throughout developing economies (Mehdaoui, 2024).

Financial infrastructure limitations also constrain AI adoption. Many developing countries lack sophisticated electronic payment systems necessary for accessing cloud-based AI services (Ameur & Bengabou, 2024). The high costs of smart devices and reliable internet access create additional barriers for both individual users and small enterprises (Kouah, 2025). These infrastructure challenges create a self-reinforcing cycle where limited digital infrastructure constrains economic development, which in turn limits resources available for infrastructure improvement.

2.3.2. Institutional and Regulatory Factors

Institutional dysfunction emerges as a critical barrier to AI adoption in developing countries. Research identifies weak intellectual property protection and bureaucratic law enforcement mechanisms as significant impediments to AI investment. Only a few Sub-Saharan African economies rank highly for ease of doing business, creating challenging environments for technology-intensive startups (Amankwah-Amoah & Lu, 2022).

Regulatory frameworks often lag behind technological advancement, creating uncertainty that discourages AI adoption. Studies reveal that government regulations can both encourage and hinder innovation adoption, depending on their design and implementation (Baker, 2011). In the Moroccan public sector, the absence of clear regulatory frameworks governing AI use represents a primary obstacle to adoption (Jouiet & Ghaleb, 2025). Auditors express caution about implementing new technologies without defined legal frameworks, highlighting how regulatory gaps create barriers even when technical capabilities exist (Kozlowski & Ilgen, 2006).

Government support mechanisms, while present in many developing countries, often prove inadequate for addressing AI adoption challenges. In Algeria, despite the establishment of support funds like FAUDTIC (created in 2008), actual financing for ICT startup projects remains limited (El-Kadi, 2024). The implementation of government support programs frequently suffers from bureaucratic delays and complex procedures that discourage technology adoption (Khelil, 2022).

Coordination challenges between different government agencies and levels create additional institutional barriers. Research in Algeria reveals weak collaboration between universities and support structures, limiting knowledge transfer and technology diffusion (Deira, 2022). The centralization of support mechanisms in major cities creates geographical disparities that particularly disadvantage rural and peripheral regions (Khelil, 2022).

International regulatory frameworks also influence domestic AI adoption. Compliance requirements with regulations like GDPR affect organizations in developing countries that engage in international commerce or data exchange (Makulilo, 2020). These requirements can create additional costs and complexity for AI implementation, particularly for smaller organizations with limited compliance expertise.

2.3.3. Cultural and Social Barriers

Cultural attitudes toward technology adoption significantly influence AI implementation success in developing countries. Research reveals that beyond technical and economic barriers, social acceptance and trust issues substantially impact technology diffusion (Singh et al., 2020). In healthcare contexts, patients' willingness to accept AI-generated diagnoses varies significantly based on cultural norms and expectations about human versus machine decision-making.

Educational and awareness barriers compound cultural resistance to AI adoption. Studies show that limited understanding of AI capabilities and applications creates reluctance to invest in or implement these technologies (Mikalef & Gupta, 2021). In Indonesia, the absence of education regarding AI frameworks and standards contributes to low adoption rates (C. et al., 2024). The complexity of AI technologies, combined with limited technical education, creates psychological barriers that extend beyond purely economic considerations.

Language and communication barriers affect AI adoption in multilingual developing contexts. Many AI tools and resources remain primarily available in English or other major languages, limiting accessibility for local users (Zhai, Wibowo & Li, 2024). The need for localization and cultural adaptation of AI applications creates additional costs and complexity that can discourage adoption.

Social inequality and exclusion issues intersect with AI adoption patterns. Research indicates that AI systems often perform poorly for underrepresented populations, such as facial recognition systems showing lower accuracy for darker-skinned individuals (Amankwah-Amoah & Lu, 2022). These biases can reinforce existing social inequalities and create resistance to AI adoption among affected communities.

Generational differences in technology acceptance also influence adoption patterns. While younger populations generally show greater openness to new technologies, developing countries often have age structures that may limit early adoption (Alam et al., 2020). Traditional business practices and established social hierarchies can create resistance to technological changes that disrupt existing power structures.

Religious and ethical considerations present additional cultural barriers in some developing contexts. Certain financing models associated with technology investments may conflict with religious principles, creating demand for alternative approaches such as Islamic finance (Khelil, 2022). Ethical concerns about AI decision-making in sensitive areas like healthcare or finance require careful navigation of cultural values and expectations.

2.4. Algerian Context

2.4.1. Digital Transformation Initiatives

Algeria has launched several strategic efforts to foster digital transformation. A new national digital strategy extending through 2029, overseen by the High Commission of Digitization, focuses on improving digital infrastructure, implementing a digitalization law, and enhancing cybersecurity frameworks (Kouah, 2025). Earlier investments in ICT included expanding internet access (e.g., in high schools), rolling out fiber optics and LTE, resulting in a significant increase in internet penetration (El-Kadi, 2024). Nonetheless, gaps remain, particularly in talent, infrastructure, and regulatory clarity (Amankwah-Amoah & Lu, 2022).

2.4.2. Startup Ecosystem Development

The Algerian startup ecosystem represents a recent and expanding phenomenon within the country's economic landscape (Necib, 2024). Algeria ranks 111th globally in the 2025 Start-up Blink ecosystem ranking, showing improvement from previous years and demonstrating growing international recognition (StartupBlink, 2025). The ecosystem benefits from a rich resource of young graduates and motivated project leaders who demonstrate determination despite limited resources (Ameur & Bengabou, 2024).

Several notable Algerian startups have achieved international recognition, including Siamois QCM, Sekoir, Batolis, Yassir, and Zawwali, which have been listed among top global Algerian startups (Kadi, 2020). However, the ecosystem faces significant structural challenges, with the pace of startup creation remaining below international standards, only 4 startups per 10,000 inhabitants compared to the international norm of 8 per 10,000 (Aouissi & Hamra, 2025).

Despite positive attitudes toward AI integration, with 50.8% of Algerian startups demonstrating a positive disposition toward AI adoption, actual implementation rates remain moderate at 23.4%, indicating a significant implementation gap (Mili et al., 2025). This suggests that while there is awareness and commitment to AI-enabled innovation, startups encounter substantial barriers in translating this intent into practical implementation.

2.4.3. Government Policies and Support Programs

Post-2020, Algeria consolidated its support for startups through policy reform and institutional structures. The establishment of the Ministry of Knowledge Economy, Startups, and Micro-enterprises marked a turning point. The creation of the Algerian Startup Fund (ASF), in partnership with banks, provided dedicated financing mechanisms to help startups navigate early-stage growth (Aouissi & Hamra, 2025). Sector-specific evidence suggests that these policy choices have supported entrepreneurship, with positive outcomes especially observed in sectors like tourism, where digital transformation is reshaping business models (Baiocco, Leoni, and Paniccia, 2023).

3. Methods

3.1. Research Design

Given the exploratory nature of the research questions, this study employed a **qualitative research design**. A qualitative approach was deemed appropriate to capture the depth and complexity of experiences, perceptions, and contextual realities surrounding Artificial Intelligence (AI) integration within Algerian start-ups. As demonstrated in prior studies on technology adoption in emerging economies, in-depth qualitative methods are particularly suitable for uncovering structural, cultural, and institutional dynamics that cannot be readily measured through quantitative surveys.

Semi-structured interviews were chosen as the primary data collection method because they allow for both consistency across interviews and flexibility to probe emerging themes, enabling a rich understanding of the barriers to AI adoption from the perspective of start-up decision-makers.

3.2. Sampling Strategy

The study targeted founders, chief executive officers (CEOs), and senior managers of Algerian start-ups operating in sectors with high AI adoption potential, including e-commerce, logistics, agritech, healthtech, and digital services.

A purposive sampling strategy was applied to ensure the selection of participants who occupied leadership positions with influence over technological decision-making and had direct experience or strategic involvement in AI adoption or consideration.

The final sample comprised 21 start-up managers with diverse profiles in terms of sector, company size, and geographical location, providing breadth and depth for comparative analysis. The sample size was determined by the principle of data saturation, the point at which newly collected data no longer yield novel insights or themes (Malterud, Siersma & Guassora, 2015).

3.3. Data Collection

We collected data through face-to-face semi-structured interviews conducted between May and July 2025. This method enables participants to express their views freely while allowing the researcher to probe relevant themes and clarify responses (Ryan, Coughlan & Cronin, 2009). Each interview lasted between 60 and 90 minutes, allowing sufficient time for in-depth exploration of each thematic area.

An interview guide was developed, informed by a comprehensive review of international literature and rigorously pre-tested with one start-up manager and a fellow researcher, experienced in qualitative research (Kallio et al., 2016).

All interviews were audio-recorded with the informed consent of participants and supplemented with field notes to capture non-verbal cues and contextual observations.

3.4. Data Analysis

Following transcription, data were analyzed thematically using an inductive–deductive hybrid approach (Fereday & Muir-Cochrane, 2006). The initial coding framework was informed by the five-category barrier typology developed in this study (Technical, Economic, Organizational, Environmental, Human Capital). Subsequently, inductive coding captured emergent sub-themes not anticipated by the initial framework.

NVivo software was used to organize and query the data systematically, enabling transparent traceability from raw data to analytical themes.

4. Findings

This section presents the findings from semi-structured interviews conducted with 21 startup managers from Algerian startups operating in sectors with high AI adoption potential, including e-commerce, logistics, agritech, healthtech, and digital services. The analysis employed an inductive thematic approach to identify and categorize barriers to AI integration, guided by the Technology-Organization-Environment (TOE) framework and existing literature on technology adoption in emerging economies.

4.1. Participant Characteristics

The final sample comprised 21 startup managers with diverse profiles in terms of sector, company size, and geographical location, providing breadth and depth for comparative analysis. Participants occupied leadership positions with influence over technological decision-making and had direct experience or strategic involvement in AI adoption or consideration. The study targeted founders, chief executive officers (CEOs), and senior managers who were in the best position to provide insights into the structural and contextual barriers impeding AI diffusion in Algeria's entrepreneurial landscape.

4.2. Thematic Analysis Results

The analysis revealed six interconnected categories of barriers to AI integration in Algerian startups: (1) Technical and Infrastructure Barriers, (2) Data-Related Challenges, (3) Human Capital and Skills Constraints, (4) Financial and Resource Limitations, (5) Institutional and Regulatory Barriers, and (6) Implementation and Operational Fragility.

We outline below the key barriers identified through our qualitative study.

4.2.1. Technical and Infrastructure Barriers

Participants consistently highlighted significant technical and infrastructural limitations as primary impediments to AI integration. Infrastructure deficiencies extended beyond basic connectivity to encompass the technological foundations necessary for AI implementation (Amankwah-Amoah & Lu, 2022). As noted in the literature, most SMEs in developing countries have substantially lower digitalization maturity than their developed-country counterparts (Oldemeyer, Jede & Teuteberg, 2024).

The absence of reliable electricity, adequate data storage facilities, and modern computing hardware created compounding barriers for AI adoption. One participant articulated the infrastructure challenge:

"AI could lift our forecasting, but we stage adoption behind data readiness and support capacity. In Algeria, some clients insist on on-prem even when cloud fits better." (SU09)

This preference for on-premise solutions, even when cloud-based alternatives would be more suitable, reflects deeper infrastructure concerns and highlights the complexity of technology choices in resource-constrained environments.

Connectivity issues were particularly pronounced, with participants noting:

"In Algeria, foreign-currency payments for cloud and SaaS are cumbersome." (SU08)

This financial infrastructure limitation constrains access to cloud-based AI services, forcing startups to rely on less optimal local solutions or face significant administrative burdens in accessing international platforms.

4.2.2. Data-Related Challenges

Data availability, quality, and accessibility emerged as critical barriers to AI implementation. Participants described fragmented data landscapes with privacy constraints that complicated data integration efforts:

"Our data story is blunt: privacy constraints are valid but make joins messy. Until that's seen legacy integrations that refuse modern APIs and vendor lock-ins, we prefer boring architectures." (SU08)

The challenge of legacy system integration was a recurring theme, with startups preferring stable, predictable architectures over more advanced but potentially problematic AI implementations. This cautious approach reflects the risk-averse nature of resource-constrained organizations.

Inter-institutional data sharing remained particularly sensitive:

"In Algeria, inter-institutional data sharing remains sensitive and cautious." (SU03)

This limitation significantly impacts the development of AI applications that require diverse data sources, particularly in sectors like healthcare, finance, and public services where cross-institutional collaboration is essential for comprehensive AI solutions.

4.2.3. Human Capital and Skills Constraints

The scarcity of AI expertise emerged as a fundamental barrier, consistent with global findings that identify insufficient AI expertise as the predominant challenge across 35 articles in systematic reviews (Bond et al., 2024). Participants described a cascading effect where financial limitations constrained talent acquisition, which in turn limited data capabilities and overall AI readiness:

"Barriers compound: funding limits talent, talent limits data, and thin data limits trust." (SU10)

This interconnected challenge highlights how resource constraints create self-reinforcing cycles that perpetuate barriers to AI adoption. The complexity of AI technologies, combined with limited technical education, creates psychological barriers that extend beyond purely economic considerations (Esfandiari et al., 2024).

Language barriers added another layer of complexity to skills development:

"In Algeria, teams juggle Arabic, French and English documentation daily." (SU16)

This multilingual challenge increases the cognitive load on technical teams and may slow down the adoption of AI tools and frameworks that are primarily documented in English.

4.2.4. Financial and Resource Limitations

Financial constraints represented a primary barrier to AI adoption, with participants describing how budget limitations forced suboptimal technical choices:

"Budget limits force us to choose brittle shortcuts." (SU02)

The challenge of demonstrating return on investment (ROI) for AI initiatives was particularly pronounced, with many startups lacking clear metrics for measuring AI success. This uncertainty makes it difficult to justify AI investments to management and investors, creating a cycle where lack of funding prevents building the capabilities needed to attract further investment.

The literature confirms that financial constraints represent the primary barrier globally, with 24 articles identifying costs as a major impediment (Oldemeyer, Jede & Teuteberg, 2024). Implementation costs include not only software and hardware but also training, integration, and ongoing maintenance expenses.

4.2.5. Institutional and Regulatory Barriers

Despite government initiatives such as the "Digital Algeria 2020" strategy, participants reported significant gaps in policy implementation and support mechanisms:

"In Algeria, policies after 'Digital Algeria 2020' need clearer execution pathways." (SU11)

Public support programs were perceived as inadequately tailored to AI-specific needs:

"In Algeria, public support for AI exists but remains broad and lacks specific focus on practical use-cases." (SU13)

This finding aligns with literature indicating that government support mechanisms, while present in many developing countries, often prove inadequate for addressing AI adoption challenges (Taeihagh, 2021). The implementation of government support programs frequently suffers from bureaucratic delays and complex procedures that discourage technology adoption.

Regulatory uncertainty also created hesitation among startups, particularly regarding data protection and compliance:

"In Algeria, data-protection guidance continues to evolve." (SU11)

This regulatory ambiguity increases transaction costs and creates uncertainty around liability, slowing adoption by both vendors and customers (Yang, Blount & Amrollahi, 2024).

4.2.6. Implementation and Operational Fragility

Even when AI initiatives were undertaken, participants emphasized the challenges of operationalizing solutions effectively. The preference for incremental, low-risk approaches was evident:

"AI like product: small bets, guardrails, and an exit plan if signals stay weak." (SU01)

"Momentum matters: consistent small wins pave the way for greater achievements." (SU13)

This cautious approach reflects the risk profile of resource-constrained startups, where failed AI initiatives could significantly impact overall business performance (Oldemeyer, Jede & Teuteberg, 2024). The operational focus often prioritized immediate efficiency gains over strategic transformation, leading to implementations that remained at proof-of-concept stage rather than production-ready solutions.

4.2.7. Cross-Cutting Themes

4.2.7.1. Interconnectedness of Barriers

A critical finding was the interconnected nature of these barriers, creating reinforcing cycles that perpetuate challenges. As one participant noted:

"Barriers compound: funding limits talent, talent limits data, and thin data limits trust." (SU17)

This interconnectedness suggests that addressing AI adoption barriers requires holistic approaches rather than piecemeal solutions targeting individual constraints.

4.2.7.2. Risk-Averse Strategic Approach

Participants consistently demonstrated a preference for conservative, incremental approaches to AI adoption:

"We stage adoption behind data readiness and support capacity." (SU09)

"We avoid buzzword compliance, we ship what improves." (SU06)

This strategic cautiousness, while potentially limiting transformational AI applications, reflects rational risk management in resource-constrained environments where failed technology investments can have significant business consequences.

4.2.8. Summary

The findings reveal that AI integration in Algerian startups is constrained by a complex constellation of technical, organizational, financial, and institutional barriers. These barriers are highly interconnected, creating reinforcing cycles that perpetuate low adoption rates despite positive attitudes toward AI technology. The gap between positive disposition (50.8%) and actual implementation (23.4%) (Mili et al., 2025) reflects these structural impediments rather than lack of awareness or motivation.

The results support the theoretical framework suggesting that AI adoption in emerging economies requires addressing multiple dimensions simultaneously, including infrastructure development, skills formation, regulatory clarity, and financial support mechanisms. The preference for "small, reliable wins" and staged adoption approaches suggests that successful AI integration strategies in this context should emphasize incremental progress with clear value demonstration rather than ambitious transformational projects.

5. Discussion

This study set out to systematically identify and categorize the barriers hindering AI adoption among Algerian startups, with the aim of developing a comprehensive understanding of the structural and contextual impediments to AI diffusion in this emerging entrepreneurial ecosystem. The findings reveal a complex interplay of technical, organizational, financial, and institutional barriers that collectively impede AI integration, corroborating existing literature while providing new insights into the specific challenges faced by startups in developing economies.

5.1. Theoretical Implications

5.1.1. Validation of the TOE Framework in Emerging Contexts

The findings provide strong support for the applicability of the Technology-Organization-Environment (TOE) framework in understanding AI adoption in emerging economy contexts. The technological barriers identified, including data fragmentation, infrastructure limitations, and legacy system integration challenges, align with the framework's technological dimension. Similarly, the organizational barriers encompassing human capital constraints, financial limitations, and management attitudes correspond to the organizational dimension, while institutional and regulatory challenges reflect the environmental dimension.

However, our findings extend the traditional TOE framework by revealing the highly interconnected nature of these barriers in resource-constrained environments. The participant observation that "barriers compound: funding limits talent, talent limits data, and thin data limits trust" illustrates how challenges across different dimensions create reinforcing cycles, a phenomenon less prominent in developed economy contexts where resources may be more readily available to address individual barrier categories.

5.1.2. Beyond Perceived Barriers: Technology Constraints in Practice

Our findings contribute to recent scholarship emphasizing the importance of distinguishing between perceived barriers and actual technology constraints (Yang, Blount & Amrollahi, 2024). While much of the existing literature focuses on anticipated difficulties during adoption, our study reveals that the primary challenges for Algerian startups were not perceived barriers but rather the actual constraints that AI technology imposed on their ability to achieve organizational goals. This distinction is particularly relevant in the context of startups, where resource limitations make the difference between perceived and actual constraints more pronounced.

The emphasis on “small, reliable wins” and staged adoption approaches reflects a pragmatic response to these constraints, where organizations prioritize incremental value demonstration over ambitious transformational projects. This finding suggests that technology adoption models may need to better account for the risk profiles and resource constraints characteristic of startup environments.

5.2. Empirical Contributions

5.2.1. The Interconnected Nature of Barriers

A key empirical contribution is the demonstration of how barriers to AI adoption in emerging economies are highly interconnected and mutually reinforcing. This finding extends previous research that has typically examined barriers in isolation (Amankwah-Amoah & Lu, 2022). The cascading effect described by participants, where financial constraints limit talent acquisition, which in turn affects data capabilities and undermines trust in AI solutions, suggests that addressing AI adoption challenges requires holistic rather than piecemeal approaches.

This interconnectedness helps explain the significant gap observed between positive attitudes toward AI (50.8%) and actual implementation rates (23.4%) in Algerian startups. Unlike in developed economies where individual barriers might be addressed through targeted interventions, the systemic nature of challenges in emerging contexts requires more comprehensive solutions.

5.2.2. Context-Specific Barriers in Developing Economies

Our findings contribute to the growing literature on AI adoption in developing countries by identifying context-specific barriers that may not be prominent in developed economy settings

The challenges related to multilingual documentation (“teams juggle Arabic, French and English documentation daily”), foreign currency restrictions for cloud services, and cautious inter-institutional data sharing reflect the unique institutional and cultural context of Algeria and similar emerging economies.

These findings align with broader research on digital transformation in developing countries, which emphasizes the importance of considering local contextual factors in technology adoption studies (Alhosani & Alhashmi, 2024). The preference for on-premise solutions despite cloud alternatives being more suitable illustrates how local constraints can lead to suboptimal technology choices, a phenomenon that may be less relevant in contexts with more developed digital infrastructure.

5.2.3. SME-Specific Challenges in AI Adoption

The study provides empirical support for the argument that SMEs face distinct challenges in AI adoption compared to larger enterprises (Oldemeyer, Jede &

Teuteberg, 2024). Our comprehensive analysis of 21 companies reveals the intricate and varied nature of barriers confronting small organisations, demonstrating the complexity of their AI implementation journey. Our results contribute to this literature by showing how these challenges manifest themselves in a specific emerging economy context.

The emphasis on operational rather than strategic AI applications aligns with existing research suggesting that SMEs often focus on immediate efficiency gains rather than transformational uses of AI. This pragmatic approach, while potentially limiting the scope of AI impact, reflects rational decision-making under resource constraints.

5.3. Implications for Practice

5.3.1. Strategic Recommendations for Startups

The findings suggest several strategic approaches for Algerian startups seeking to integrate AI technologies. The preference for “small bets, guardrails, and an exit plan” represents a risk management strategy appropriate for resource-constrained environments. This approach allows organizations to build capabilities incrementally while minimizing the potential for catastrophic failures that could significantly impact business performance.

The emphasis on data readiness as a prerequisite for AI adoption provides practical guidance for startup managers. Rather than pursuing ambitious AI projects with inadequate data foundations, organizations should prioritize data infrastructure development and governance processes. This staged approach aligns with recommendations in the broader AI adoption literature that emphasize the importance of data maturity before technology implementation (Kraus et al., 2021).

5.3.2. Policy Implications

The findings have significant implications for policy formulation aimed at supporting AI adoption in emerging economies. The perception that “public support exists but feels generic for AI use-cases” suggests that current support mechanisms may be inadequately tailored to the specific needs of AI-adopting organizations. This finding supports calls for more targeted policy interventions that address the unique requirements of AI technologies.

The need for “clearer execution pathways” following the “Digital Algeria 2020” strategy highlights the importance of translating high-level digital transformation visions into concrete, actionable support mechanisms. This includes addressing infrastructure limitations, providing AI-specific training programs, and creating regulatory frameworks that provide clarity while encouraging innovation.

5.3.3. Ecosystem Development Recommendations

The findings suggest that developing a successful AI ecosystem requires coordinated efforts across multiple stakeholders. The challenges related to talent scarcity, infrastructure limitations, and regulatory uncertainty cannot be addressed by individual startups alone but require ecosystem-level interventions (Amankwah-Amoah & Lu, 2022).

The literature emphasizes the importance of linking universities, governments, and businesses in forging collaborations to develop AI capabilities (Schwaeke et al., 2024). Our findings support this recommendation while highlighting the need for such collaborations to address the specific, interconnected nature of barriers faced by startups in emerging economies.

5.4. Limitations and Future Research Directions

5.4.1. Methodological Considerations

While the qualitative approach adopted in this study provided rich insights into the barriers faced by Algerian startups, several limitations should be acknowledged. The focus on a single country limits the generalizability of findings to other emerging economy contexts, though the theoretical insights may be transferable to similar institutional environments.

Future research should examine AI adoption barriers across multiple emerging economies to identify common patterns and context-specific variations. Quantitative studies could validate the relationships between different barrier categories and their relative importance in different contexts.

5.4.2. Temporal and Dynamic Considerations

The study provides a snapshot of barriers to AI adoption at a specific point in time, but the rapidly evolving nature of AI technology and supporting ecosystems suggests that these barriers may change over time. Longitudinal studies examining how barriers evolve as ecosystems mature would provide valuable insights for policy and practice.

The dynamic nature of AI technology also suggests the need for research examining how different types of AI (machine learning, natural language processing, computer vision) face different adoption barriers, as suggested in the literature (Richey et al., 2023).

5.4.3. Theoretical Development

Future research should explore the development of adoption frameworks specifically tailored to emerging economy contexts, building on but extending traditional models like the TOE framework. The interconnected nature of barriers identified in this study suggests the need for more sophisticated theoretical models that account for systemic effects and feedback loops between different barrier categories.

6. Conclusion

This study contributes to the growing literature on AI adoption in emerging economies by providing a comprehensive analysis of barriers faced by Algerian startups. The findings reveal that while many challenges align with global patterns identified in the literature, the interconnected and mutually reinforcing nature of these barriers in resource-constrained environments creates unique challenges that require holistic, ecosystem-level responses.

The preference for incremental, low-risk approaches to AI adoption represents a rational response to these challenges, though it may limit the transformational potential of AI technologies. Supporting successful AI adoption in emerging economy contexts requires coordinated efforts to address technical infrastructure, human capital development, financial support mechanisms, and institutional frameworks simultaneously.

The study provides both theoretical contributions to our understanding of technology adoption in emerging economies and practical insights for entrepreneurs, policymakers, and ecosystem developers seeking to accelerate AI adoption in similar contexts. Future research should build on these findings to develop more sophisticated theoretical frameworks and empirically validate the relationships identified in this exploratory study.

References

Abadli, R., Kooli, C., & Otmani, A. (2020). Entrepreneurial culture and promotion of exporting in algerian smes: Perception, reality and challenges. *International Journal of Entrepreneurship and Small Business, 41*(2), 227.

Abdullah, A. A. H., & Almaqtari, F. A. (2024). The impact of artificial intelligence and industry 4.0 on transforming accounting and auditing practices. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(1), 100218.

Ade-Ibijola, A., & Okonkwo, C. (2023). Artificial intelligence in africa: Emerging challenges. *Social and Cultural Studies of Robots and AI*, 101-117.

Ahmi, A., Saidin, S. Z., & Abdullah, A. (2014). It adoption by internal auditors in public sector: A conceptual study. *Procedia - Social and Behavioral Sciences, 164*, 591-599.

Alam, M. Z., Hu, W., Kaium, A., Hoque, R., & Alam, M. M. D. (2020). Understanding the determinants of mhealth apps adoption in bangladesh: A sem-neural network approach. *Technology in Society, 61*, 101255.

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial intelligence adoption : AI-readiness at firm-level. *Proceedings of PACIS2018 : Pacific Asia Conference in Information Systems (PACIS)*, 37. https://research.monash.edu/en/publications/artificial-intelligence-adoption-ai-readiness-at-firm-level.

Amankwah-Amoah, J., & Lu, Y. (2022). Harnessing ai for business development: A review of drivers and challenges in africa. *Production Planning & Control, 35*(13), 1551-1560.

Ameur, N. D., & Bengabou, H. K. (2024). *Analysis of the start-up ecosystem in Algeria: Opportunities and challenges*. Institut Cedimes.

Aouissi, Warda, & Hamra, Y. (2025). Assessment of the Startup Ecosystem in Algeria based on the Global Startup Ecosystem Index (GSEI): An Analytical Study. *Journal of Economic Papers, 16*(1), 86-100. https://asjp.cerist.dz/en/article/267066.

Ardito, L., Filieri, R., Raguseo, E., & Vitari, C. (2024). *Artificial intelligence adoption and revenue growth in European SMEs: Synergies with IoT and big data analytics*. Internet Research.

Baiocco, S., Leoni, L., & Paniccia, P. M. A. (2023). Entrepreneurship for sustainable development: Co-evolutionary evidence from the tourism sector. *Journal of Small Business and Enterprise Development, 30*(7), 1521-1546.

Baker, J. (2011). The technology–organization–environment framework. *Integrated Series in Information Systems*, 231-245.

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education, 21*(1).

Borges, A. F. S., Laurindo, F. J. B., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management, Elsevier*, *57*(C).

Budhwar, P. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on chatgpt. *Human Resource Management Journal, 33*(3), 606-659.

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Does data-driven culture impact innovation and performance of a firm? an empirical examination. *Annals of Operations Research, 333*(2-3), 601-626.

Dalton, J. (2025). Answer to the letter to the editor of T. Tanaka et al. concerning “patients on antidepressants are more likely to be discharged to inpatient rehabilitation after lumbar fusion” by J. Dalton et al. *European Spine Journal : official publication of the European Spine Society, the European Spinal Deformity Society, and the European Section of the Cervical Spine Research Society*.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319.

Deira, A. (2022). Les startups à l’ère des nouvelles technologies : état des lieux des startups numériques en Algérie [Startups in the era of new technologies: state of play of digital startups in Algeria]. *The Journal of the New Economy, 13*(2), 857-876. https://asjp.cerist.dz/en/article/200937.

Dwivedi, Y. K., Rana, N. P., & Jeyaraj, A. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. *Information Systems Frontiers,* 21, 719–734.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. *Information Systems Frontiers, 21*(3), 719-734.

Esfandiari, E. (2024). Obstacles to the development of the use of artificial intelligence from the point of view of physicians working in selected aja medical centers: A qualitative content analysis study. *Jundishapur Journal of Chronic Disease Care, 14*(1).

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating Rigor Using Thematic Analysis: A Hybrid Approach of Inductive and Deductive Coding and Theme Development. *International Journal of Qualitative Methods*, *5*(1), 80-92.

Fèvres, J. (2012). Everett M. Rogers, diffusion of innovations. *Essais, 1*, 135-137.

Ghobakhloo, M., & Ching, N. T. (2019). Adoption of digital technologies of smart manufacturing in smes. *Journal of Industrial Information Integration, 16*, 100107.

Handoko, L. B., Riantono, E. I., & Sunarto, W. F. (2021). Determinants affecting intention of use of big data analytics on remote audits: Toe framework approach. *2021 7th International Conference on Education and Training Technologies*, 53-59.

Hinane El-Kadi, T. (2024). Learning along the digital silk road? technology transfer, power, and chinese ict corporations in north africa. *The Information Society, 40*(2), 136-153.

Jouiet, I., & Ghaleb, N. E. A. E. (2025). Barriers to the integration of artificial intelligence in public sector internal audit in Morocco: An exploratory study. *Edelweiss Applied Science and Technology, 9*(5), 1291-1302.

Kadi, M. (2020). Factors influencing the export commitment of smes: Algerian case. *Palgrave Studies of Internationalization in Emerging Markets*, 59-85.

Kallio, H., Pietilä, A. M., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: developing a framework for a qualitative semi-structured interview guide. *Journal of advanced nursing*, *72*(12), 2954–2965.

Khanfar, A. A. (2024). Determinants of artificial intelligence adoption: Research themes and future directions. *Information Technology and Management*.

Khelil, S. (2022). Analyse de l'écosystème des startups en Algérie (Etat des lieux et Perspectives) [Analysis of the Startup Ecosystem in Algeria (State of Play and Perspectives)]. *The Journal of Development and Prospecting for Research and Studies, 7*(1), 293-310. https://asjp.cerist.dz/en/article/191143.

Kouah, K. (2025). *Digital Transformation And Its Impact On The Performance Of Banks In Algeria During The Period 2013-2023.*

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the Effectiveness of Work Groups and Teams. *Psychological Science in the Public Interest*, *7*(3), 77-124.

Kraus, S. (2021). Digital transformation: An overview of the current state of the art of research. *Sage Open, 11*(3).

Lee, S. M., Lee, D., & Kim, Y. S. (2019). The quality management ecosystem for predictive maintenance in the industry 4.0 era. *International Journal of Quality Innovation, 5*(1).

Makulilo, A. B. (2020). The long arm of gdpr in africa: Reflection on data privacy law reform and practice in mauritius. *The International Journal of Human Rights, 25*(1), 117-146.

Malterud, K., Siersma, V. D., & Guassora, A. D. (2016). Sample size in qualitative interview studies. *Qualitative Health Research, 26*(13), 1753-1760.

Martins, M. M. R. (2024). Startup guide to ai: Integrating technology for business success. *International Journal of Scientific Research and Management (IJSRM), 12*(6), 1264-1274.

Mehdaoui, A. (2024). Unveiling barriers and challenges of ai technology integration in education: Assessing teachers' perceptions, readiness and anticipated resistance. *Futurity Education, 4*(4), 95-108.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), 103434.

Mili, K. (2025). From code to quality: How ai is transforming quality management in algerian startups. *International Journal of Innovative Research and Scientific Studies, 8*(1), 1770-1776.

Necib, A. (2024). Le développement des startups en Algérie [The development of startups in Algeria]. *Revue des Economies financières bancaires et de management, 13*(1), 602-611. https://asjp.cerist.dz/en/article/244843.

Neumann, O., Guirguis, K., & Steiner, R. (2022). Exploring artificial intelligence adoption in public organizations: A comparative case study. *Public Management Review, 26*(1), 114-141.

Nyberg, A. J., Schleicher, D. J., Bell, B. S., Boon, C., Cappelli, P., Collings, D. G., Dalle Molle, J. E., Feuerriegel, S., Gerhart, B., Jeong, Y., Korsgaard, M. A., Minbaeva, D., Ployhart, R. E., Tambe, P., Weller, I., Wright, P. M., & Yakubovich, V. (2025). A Brave New World of Human Resources Research: Navigating Perils and Identifying Grand Challenges of the GenAI Revolution. *Journal of Management, 51*(6), 2677-2718.

Oldemeyer, L., Jede, A., & Teuteberg, F. (2024). Investigation of artificial intelligence in smes: A systematic review of the state of the art and the main implementation challenges. *Management Review Quarterly, 75*(2), 1185-1227.

P. C., L. (2024). The application of ai in new start-ups. *Advances in Finance, Accounting, and Economics*, 171-184.

Restrepo-Morales, J. A. (2024). Breaking the digitalization barrier for smes: A fuzzy logic approach to overcoming challenges in business transformation. *Journal of Innovation and Entrepreneurship, 13*(1).

Richey, R. G. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics, 44*(4), 532-549.

Rogers, E. M. (2004). A Prospective and Retrospective Look at the Diffusion Model. *Journal of Health Communication*, *9*(sup. 1), 13–19.

Ryan, F., Coughlan, M. J., & Cronin, P. (2009). Interviewing in qualitative research: The one-to-one interview. *International journal of therapy and rehabilitation,* 16, 309-314.

Saadé, R. G. (2007). Dimensions of perceived usefulness: Toward enhanced assessment. *Decision Sciences Journal of Innovative Education, 5*(2), 289-310.

Schwaeke, J. (2024). The new normal: The status quo of ai adoption in smes. *Journal of Small Business Management, 63*(3), 1297-1331.

Singh, R. P. (2020). *Current challenges and barriers to real-world artificial intelligence adoption for the healthcare system, provider, and the patient*. Association for Research in Vision and Ophthalmology (ARVO).

StartupBlink. (n. d.). *The Startup Ecosystem of Algeria—Rankings, Startups, and Insights*. https://www.startupblink.com/startup-ecosystem/algeria.

Taeihagh, A. (2021). Governance of artificial intelligence. *Policy and Society*, *40*(2), 137–157.

Uriarte, S. (2025). Artificial intelligence technologies and entrepreneurship: A hybrid literature review. *Review of Managerial Science*.

Van der Vlist, F., Helmond, A., & Ferrari, F. (2024). Big AI: Cloud infrastructure dependence and the industrialisation of artificial intelligence. *Big Data & Society, 11*(1).

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.

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change, 201*, 123251.

Yuwono, T., Suroso, A., & Novandari, W. (2024). Information and communication technology in smes: A systematic literature review. *Journal of Innovation and Entrepreneurship, 13*(1).

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on ai dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments, 11*(1).

Zhou, Y. (2025). Untitled. *Journal of Environmental Health Science & Engineering, 23*(2), 28.