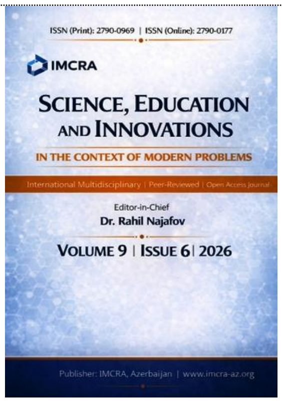

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RESEARCH ARTICLE

Adopting Artificial Intelligence in Entrepreneurial Ecosystems: An Analytical Assessment of Digital Readiness Among Young Entrepreneurs in Algeria

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Abstract

In the era of accelerated digital transformation, the integration of Artificial Intelligence has become a decisive factor shaping entrepreneurial competitiveness, innovation capacity, and long-term sustainability. Despite the increasing accessibility of AI tools, a critical gap persists between technological availability and effective adoption, particularly in emerging economies. This study investigates the determinants of AI adoption among young entrepreneurs by conceptualizing digital readiness as a multidimensional construct encompassing cognitive, psychological, entrepreneurial, and material dimensions. Adopting a quantitative research design, the study utilizes data collected from 120 young entrepreneurs operating in technology and service sectors in Algeria. The analytical framework is implemented using Partial Least Squares Structural Equation Modeling through SmartPLS 4, enabling the assessment of complex structural relationships and mediating effects. The findings reveal that entrepreneurial and cognitive readiness are the most influential predictors of AI adoption intention, while material readiness exerts a comparatively weaker yet significant effect. The model demonstrates strong explanatory power, accounting for 63.5% of the variance in adoption intention. Furthermore, the results highlight the critical mediating role of self-efficacy in transforming knowledge into actionable adoption behavior, thereby reducing technological anxiety and enhancing entrepreneurial resilience. The study contributes to the literature by proposing an integrative framework that bridges technological readiness and behavioral intention within entrepreneurial contexts. From a practical perspective, the findings underscore the necessity of fostering supportive digital ecosystems, enhancing AI literacy, and strengthening infrastructure and policy frameworks to accelerate AI-driven entrepreneurship. The study concludes that sustainable AI adoption requires not only technological access but also the development of adaptive capabilities, strategic thinking, and innovation-oriented entrepreneurial mindsets.

Citation

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Introduction

The global entrepreneurial landscape is undergoing a profound transformation driven by rapid advancements in digital technologies, particularly Artificial Intelligence. In recent years, AI has evolved from a supplementary innovation tool into a core strategic asset that fundamentally reshapes business models, decision-making processes, and value creation mechanisms. The emergence of generative AI, machine learning systems, and autonomous digital agents has enabled entrepreneurs to enhance operational efficiency, personalize customer experiences, and accelerate innovation cycles at unprecedented scales.

Within this evolving paradigm, the concept of digital entrepreneurship has gained increasing scholarly attention as a critical driver of economic growth and technological advancement. Digital entrepreneurship is not merely defined by the use of digital tools, but rather by the capacity of entrepreneurs to strategically integrate advanced technologies into their business processes. However, despite the growing availability of AI solutions, a significant disparity persists between technological access and actual adoption, particularly in developing and emerging economies.

One of the central factors explaining this gap is the notion of "digital readiness," which extends beyond technical infrastructure to encompass cognitive capabilities, psychological preparedness, entrepreneurial competencies, and material resources. Existing literature suggests that the successful adoption of AI technologies depends not only on external facilitating conditions but also on internal behavioral and cognitive factors, including digital literacy, self-efficacy, and strategic orientation. Nevertheless, prior studies have often examined these determinants in isolation, resulting in fragmented insights and limited explanatory power.

In this context, the present study addresses a critical research gap by proposing a comprehensive and integrative framework that conceptualizes digital readiness as a multidimensional construct influencing AI adoption among young entrepreneurs. Drawing on established theoretical perspectives, including technology acceptance theories and behavioral models, the study employs Partial Least Squares Structural Equation Modeling to empirically analyze the relationships between readiness dimensions and adoption intention.

The empirical focus on Algeria provides a particularly relevant context, as the country represents an emerging entrepreneurial ecosystem characterized by increasing digitalization efforts alongside persistent structural challenges. While Algeria has made notable progress in expanding digital infrastructure and promoting startup development, the adoption of advanced technologies such as AI remains limited. This paradox underscores the importance of examining not only technological availability but also the readiness of entrepreneurs to effectively utilize these tools.

The contribution of this study is threefold. First, it advances the theoretical understanding of AI adoption by integrating multiple dimensions of digital readiness into a unified analytical framework. Second, it provides empirical evidence on the relative importance of cognitive, psychological, entrepreneurial, and material factors in shaping adoption behavior. Third, it offers practical insights for policymakers, incubators, and educational institutions seeking to enhance the digital capabilities of young entrepreneurs and foster innovation-driven ecosystems.

Ultimately, this study argues that the transition toward AI-driven entrepreneurship requires a holistic approach that combines technological access with human capital development, institutional support, and strategic orientation. By addressing these interconnected dimensions, emerging economies can unlock the full potential of AI as a catalyst for sustainable entrepreneurial growth and digital transformation.

The rapid diffusion of Artificial Intelligence has fundamentally transformed the dynamics of entrepreneurship, shifting the focus from traditional business models toward digitally enabled, data-driven innovation ecosystems. Contemporary research emphasizes that AI is no longer merely a technological tool but a strategic enabler that reshapes organizational capabilities, competitive advantage, and value creation processes (Dwivedi et al., 2021; Raisch & Krakowski, 2021). Within this paradigm, digital entrepreneurship has emerged as a critical field of inquiry, highlighting how entrepreneurs leverage digital technologies to create, scale, and sustain ventures in increasingly complex environments (Nambisan, 2017; Autio et al., 2018).

A central theme in the literature is the concept of digital transformation, which refers to the integration of digital technologies into all aspects of business operations, fundamentally altering how organizations create and deliver value (Vial, 2019; Verhoef et al., 2021). However, while technological availability has increased significantly, the capacity of entrepreneurs to effectively adopt and utilize these technologies remains uneven, particularly in emerging economies. This discrepancy has led scholars to focus on the notion of "digital readiness" as a multidimensional construct encompassing technological, cognitive, and behavioral dimensions (Horrigan, 2016; PwC, 2025).

Existing studies highlight that digital readiness extends beyond infrastructure and includes critical human-centric factors such as digital literacy, strategic thinking, and psychological preparedness. For instance, Mostafiz (2025) argues that entrepreneurial cognition plays a decisive role in shaping AI adoption, as individuals with higher levels of technological awareness are more likely to recognize and exploit digital opportunities. Similarly, Gupta (2024) demonstrates that AI adoption positively influences organizational performance through innovation mechanisms, suggesting that readiness is closely linked to firms' ability to translate technology into tangible outcomes.

Psychological factors have also gained increasing attention in recent research. The concept of psychological capital—comprising self-efficacy, resilience, optimism, and hope—has been identified as a critical determinant of technology adoption behavior (Kadiyono

& Sulistiobudi, 2024). Empirical evidence indicates that self-efficacy significantly reduces technological anxiety and enhances individuals' willingness to experiment with AI tools (Cengiz & Peker, 2025). This highlights the importance of integrating behavioral and cognitive perspectives into models of digital readiness.

From an entrepreneurial perspective, the literature underscores the role of strategic orientation and resource mobilization in facilitating technology adoption. The concept of entrepreneurial bricolage—defined as the ability to creatively utilize limited resources—has been identified as a key capability enabling startups to overcome structural constraints and leverage emerging technologies (Autio et al., 2018). In this context, AI adoption is not solely dependent on resource availability but also on the strategic mindset and adaptability of entrepreneurs.

Despite these advances, several gaps remain in the literature. First, most studies have examined individual dimensions of readiness in isolation, resulting in fragmented insights. Second, there is limited empirical evidence from emerging economies, where structural constraints such as limited infrastructure and regulatory challenges significantly influence adoption behavior. Third, the mediating role of psychological factors in linking knowledge and actual adoption remains underexplored.

Addressing these gaps, the present study develops an integrative framework that conceptualizes digital readiness as a multidimensional construct incorporating cognitive, psychological, entrepreneurial, and material dimensions. By applying Partial Least Squares Structural Equation Modeling, the study provides a comprehensive empirical analysis of the determinants of AI adoption among young entrepreneurs in Algeria, thereby contributing to both theoretical advancement and practical policy development.

Problem Statement

The core research problem centres on the extent to which young entrepreneurs are prepared to integrate advanced technologies—specifically Agentic AI and Sovereign AI—into their daily operations, particularly in light of persistent challenges regarding digital infrastructure and a deficiency in specialized technical support. Consequently, the research problem is defined by the need to determine the empirical impact of digital readiness dimensions (cognitive, psychological, entrepreneurial, and material) on the intention to adopt AI. This can be articulated through the following primary research question:

How does digital readiness contribute to shaping the intention to adopt AI technologies among young entrepreneurs in Algeria ?

From this primary question, the following sub-questions are derived:

1. What is the impact of cognitive readiness, manifested in digital literacy and algorithmic awareness, on the intention of young entrepreneurs to adopt AI technologies?

2. How does psychological readiness (psychological capital and self-efficacy) contribute to mitigating AI anxiety and stimulating digital adoption?

3. To what extent does entrepreneurial readiness (strategic thinking and entrepreneurial bricolage) contribute to transforming AI technologies into a sustainable competitive advantage ?

4. How does material readiness (infrastructure, data quality, and financing) influence the transition from adoption intention to actual implementation within startups?

Research Hypotheses:

In an attempt to address the research problem, the following primary null hypothesis was formulated:

- H_0: There is no statistically significant impact of digital readiness, as measured by its dimensions (cognitive, psychological, entrepreneurial, and material readiness), on the intention to adopt AI technologies for project execution at a significance level of ($\alpha \leq 0.05$).

From this primary hypothesis, the following sub-hypotheses are derived:

- First Sub-hypothesis:

H_0: There is no statistically significant impact of the cognitive readiness dimension on the intention to adopt AI technologies for project execution at a significance level of ($\alpha \leq 0.05$).

- Second Sub-hypothesis:

H_0: There is no statistically significant impact of the psychological readiness dimension (comprising Psychological Capital and Self-efficacy) on the intention to adopt AI technologies for project execution at a significance level of ($\alpha \leq 0.05$).

- Third Sub-hypothesis:

H_0: Entrepreneurial readiness (manifested in strategic thinking and entrepreneurial bricolage) does not significantly contribute to the integration of AI within the business model at a significance level of ($\alpha \leq 0.05$).

- Fourth Sub-hypothesis:

H_0: Material readiness (infrastructure and data quality) does not constitute a critical facilitating condition that enhances the effect of intention on the actual adoption of AI technologies for project execution at a significance level of ($\alpha \leq 0.05$).

Research Objectives:

This research aims to achieve the following strategic objectives:

1. Assessing Digital Readiness Levels: To diagnose the current state of young entrepreneurs regarding their cognitive skills, psychological stability, entrepreneurial orientation, and the availability of material resources necessary for interacting with Artificial Intelligence.

2. Analyzing Causal Relationships: To uncover the nature of the interrelationships between digital readiness dimensions and adoption intention, identifying the most significant predictors influencing entrepreneurial digital behavior.

3. Examining the Mediating Role of Psychological and Cognitive Variables: To understand how fostering "AI literacy" and "self-efficacy" contributes to mitigating "AI anxiety" and enhancing entrepreneurial resilience.

4. Developing a Strategic Predictive Model: To construct a sophisticated statistical model using SmartPLS 4 that assists decision-makers and incubators in forecasting the success of smart technology adoption based on pre-established readiness indicators.

5. Proposing a Practical Roadmap: To formulate actionable recommendations aimed at bridging the "intention-behavior gap"—the divide between adoption intention and actual implementation—thereby supporting startup sustainability within a rapidly accelerating digital economy.

Study Model:

The proposed research model defines digital readiness as a multidimensional construct encompassing four primary pillars: cognitive readiness, psychological readiness, entrepreneurial readiness, and material readiness.

Table 1: The Proposed Research Model.

Independent Variable (Digital Readiness)	Dependent Variable
Cognitive Readiness :	Behavioral Intention to Adopt AI Technologies
Psychological Readiness:	
Entrepreneurial Readiness:	
Material Readiness:	

Source: Developed by the authors based on Hair et al. (2022) and Mostafiz et al. (2025).

1) Theoretical Framework and Literature Review:

a) Digital Entrepreneurship: Digital entrepreneurship is defined as an innovative approach to the creation and management of business ventures in the digital era, leveraging cutting-edge technologies to digitize economic, commercial, and service operations. It is conceptualized as a subcategory of traditional entrepreneurship, wherein entrepreneurial projects and activities are implemented either partially or entirely through digital media. (Purbasari, Muttaqin, & Sari, D, 2021, p. 128) Furthermore, the European Commission defines this concept as the creation of new employment opportunities through the development of novel digital technologies and innovative fields of application, or by facilitating the digitization of existing enterprises. (Chouieb, Borni, & Mechri, 2024, p. 161).

The concept of digital entrepreneurship emerged from the notable success of entrepreneurs who managed to establish their ventures on the web by leveraging available digital advantages. Chief among these benefits is enhanced temporal flexibility, enabling entrepreneurs to define their working hours and peak productivity periods while tailoring their schedules to suit personal circumstances Furthermore (Alvaro, 2025, p. 56), a fundamental advantage lies in cost efficiency; digital ventures bypass the need for substantial capital investments in physical real estate or rentals, which are characteristic of traditional business models. (Issani, 2025, p. 191).

The third advantage lies in the immense capacity to reach expansive segments of the population. Statistical data indicates that more than half of the Arab world's population is now connected to the internet, providing significant opportunities for both local and international growth in tandem with ongoing technological advancements. (Mostafiz, 2025, p. 120) Finally, the feature of scalability stands out as a critical driver, allowing for increased sales volume and enhanced service quality without necessitating substantial investment in fixed costs. This structural efficiency renders digital ventures more sustainable and competitively positioned, as they can effectively leverage remote work frameworks and bridge geographical talent gaps. (Ghandour & Taibi, 2022, p. 1237).

b) Operational Efficiency Drivers in Entrepreneurship: Transitioning from Experimentation to Mass AI Production.

The year 2025 and beyond marks a strategic transition from the 'experimentation' phase of Artificial Intelligence (AI) to the era of 'mass production.' For entrepreneurs, Generative AI offers transformative capabilities in digital content creation through tools such as Jasper AI and Writesonic, as well as rapid web infrastructure development via platforms like Durable AI (Naseej, 2025, p. 63). Furthermore, empirical research indicates that coding automation using GitHub Copilot contributes to reducing development time by up to 40% This paradigm shift is reshaping the organizational structures of startups (Microsoft, 2024), making them more agile and scalable through leaner teams that leverage Agentic AI to achieve unprecedented levels of productivity. (Naseej, 2025, p. 66).

C. The Reality of Startups in Algeria in the Context of Artificial Intelligence

Algeria has launched strategic initiatives designating the 2024–2025 period as the "Year of Artificial Intelligence," positioning startups as the vanguard of this national transformation. Currently, Algeria ranks 12th in the Middle East and North Africa (MENA) region in the Government AI Readiness Index, a position that reflects significant strategic ambition but also underscores an urgent necessity to bridge persistent structural gaps. (Bouchama, 2025, p. 116).

Empirical statistics indicate that the Artificial Intelligence adoption rate among Algerian startups is approximately 5%, a figure currently in its early growth trajectory. These applications are primarily concentrated in several vital sectors:

- Healthcare Sector: The deployment of digital platforms and wearable technology (smartwatches) for patient monitoring, as exemplified by the startup *Strap Life*.
- Agriculture Sector: The development of smart irrigation and fertilization systems, such as the *Phyto* platform developed by *Nabatk*.
- Education and Finance: The innovation of proprietary learning technologies and the advancement of integrated electronic payment systems.

Nevertheless, young entrepreneurs in Algeria continue to encounter significant material and regulatory hurdles. The shortage of large-scale data centers and a heavy reliance on the informal market severely limit the availability of high-quality, accurate datasets essential for training robust AI models. Furthermore, administrative bureaucracy and limited Foreign Direct Investment (FDI) within the technology sector represent additional challenges to the scalability and long-term sustainability of these emerging ventures. (Benhah & Ouassaa, 2025, p. 49).

D. Digital Readiness and its Dimensions in the Algerian Context:

Digital readiness is conceptualized as a holistic ecosystem that integrates robust infrastructure, specialized skills, and supportive organizational culture. (Horrigan, J. B., 2016)

In Algeria, statistical indicators for 2025 reveal that 76% of the population resides in urban centers where digital infrastructure is more established and accessible. This is further evidenced by the accelerated growth in Fiber-to-the-Home (FTTH) subscriptions, which reached approximately 23% by mid-2024 according to official regulatory reports (ARPCE, 2024) Nevertheless, "skill readiness" remains a formidable challenge; the capacity to perform complex digital operations and integrate Generative AI into daily business workflows necessitates specialized training programs to align with shifting market requirements. (Thakur, R. , 2025, p. 29).

2. Detailed Analysis of Digital Readiness Dimensions: In this section, the independent variables of the study are examined in depth:

2.1 Cognitive Readiness: Cognitive readiness is conceptualized as the integrated synergy between Artificial Intelligence (AI) Literacy and the technical awareness required by entrepreneurs to comprehend the operational mechanisms of AI systems. Experts emphasize that this dimension is empirically measured by an individual's proficiency in utilizing digital tools effectively and their critical capacity to evaluate the reliability of information retrieved online. (Horrigan, J. B., 2016, p. 53).

Within the 2025 entrepreneurial landscape, specialized competencies such as "Prompt Engineering" have emerged as foundational pillars. This technical awareness serves to mitigate "perceived complexity," thereby empowering entrepreneurs to grasp algorithmic reasoning and seamlessly integrate it into productive workflows. (Benhah & Ouassaa, 2025, p. 36) .

Furthermore, cognitive readiness plays a decisive role in fostering "digital strategic thinking." Empirical studies indicate that entrepreneurs who prioritize continuous learning regarding AI trends exhibit a superior capacity for business model reconfiguration in alignment with ongoing technological disruptions . (Mostafiz, 2025, p. 126).

2.2:Psychological Readiness: Psychological readiness represents the emotional and cognitive state that empowers entrepreneurs to embrace digital transformation. It is fundamentally anchored in Psychological Capital (PsyCap), a multidimensional construct comprising self-efficacy, optimism, hope, and resilience. (Kadiyono, A. L & Sulistiobudi, R. A, 2024, p. 301).

Furthermore, psychological readiness serves as a robust defense mechanism against "AI anxiety"; empirical research indicates that the possession of cognitive resources mitigates the stress triggered by a perceived loss of control to algorithms, effectively channeling anxiety into a proactive motivation for exploration. (Cengiz, S & Peker, A., 2025, p. 7995).

Additionally, "Passion for AI" emerges as a critical intrinsic driver, functioning as a form of hedonic motivation that encourages young entrepreneurs to engage deeply with technology This intrinsic enthusiasm significantly enhances their psychological endurance, enabling them to navigate extended cycles of experimental failure before achieving substantive and tangible results in their adoption journey (Alvaro, 2025, p. 59).

2.3 Entrepreneurial Readiness:

Entrepreneurial readiness pertains to the strategic mindset and the capacity for entrepreneurial bricolage, conceptualized as the proficiency in utilizing limited available resources in innovative ways to resolve complex organizational challenges. Scholars emphasize that entrepreneurs operating in resource-constrained environments can effectively bridge operational gaps by mobilizing assets and knowledge from their surrounding innovation ecosystems.

This readiness also encompasses cognitive alertness and the proactive exploitation of digital opportunities, enabling entrepreneurs to discern market patterns within Big Data more efficiently than their competitors, which fundamentally strengthens their adaptive capacity. (Gupta, 2024, p. 09).

Ultimately, entrepreneurial readiness facilitates the integration of Artificial Intelligence (AI) into the core of exploitative innovation. This integration serves as a pivotal mediating mechanism that translates technological adoption into tangible enhancements in financial performance and long-term organizational sustainability within highly volatile and unpredictable markets.

2.4 Material Readiness: Material readiness serves as the foundational structural and technical prerequisite for operationalizing AI solutions, encompassing resilient infrastructure, cloud access, and high-performance computing hardware such as GPUs. (PwC, 2025, p. 15).

Without achieving a baseline of material readiness, the digital ambitions of young entrepreneurs remain as unfulfilled intentions, as AI deployment demands significant computational power and high-speed connectivity to ensure model efficiency. (Issani, 2025, p. 191).

Central to material readiness is "data integrity and quality," given that intelligent systems depend entirely on clean, structured, and accessible datasets to produce reliable outcomes. (Lab Manager, 2025, p. 14).

Entrepreneurs who invest in a Unified Data Model are better equipped to dissolve information silos, allowing algorithms to provide accurate predictive insights for strategic decision-making.

Finally, financial readiness and targeted funding act as critical facilitating conditions, particularly in early adoption phases that require substantial investment in specialized training and technical tools . (UNCTAD, 2025, p. 34)

3. Opportunities and Challenges of AI Adoption in Startups:

The year 2025 represents a pivotal inflection point for startups, as Artificial Intelligence (AI) has transitioned from an "auxiliary tool" into the "foundational backbone" of enterprise architecture, leading to the rise of what is known as "AI-Native Startups". These ventures leverage AI at their core to redefine operational parameters, primarily through the following opportunities.

3.1 Opérationnel Efficiency and Agile Teams: Contemporary AI technologies empower startups to execute complex workflows that previously required dozens of employees. AI-driven coding platforms and automated programming tools, such as Cursor and Claude Code, have enabled developers to engineer technical products up to ten times faster, significantly compressing "Time-to-Market" cycles. (Alix, 2026).

Furthermore, the emergence of Agentic AI—autonomous systems capable of goal-oriented planning and independent execution—allows startups to manage data processing, scheduling, and comprehensive marketing campaigns with minimal human intervention. (Elluminati, 2026) .

.3.2 Hyper-Personalization of Customer Experience: Personalization has evolved beyond basic identifiers to encompass sophisticated sentiment analysis and predictive behavioral analytics. By analyzing real-time interaction data, startups can now anticipate consumer needs before they are explicitly expressed, delivering tailored solutions that enhance loyalty and engagement. (Elluminati, 2026).

3.3 Attracting Venture Capital Investment: In the 2026 investment landscape, Venture Capitalists (VCs) are increasingly prioritizing "Deep Tech" firms that integrate AI into their core business models. Such models ensure massive scalability and sustainable low operational costs over the long term, making them highly attractive for capital allocation.. (Genome & Startup, 2025) ،Despite these transformative opportunities, startups must navigate a complex landscape of technical and regulatory challenges . (Clarifai, 2026).

- Data Privacy and Quality: Startups often face a "data moat" challenge, lacking the vast qualitative datasets available to incumbents. Furthermore, compliance with stringent regulatory frameworks, such as the GDPR and emerging local AI acts, is mandatory, as any breach of user privacy can result in existential legal and financial penalties. (Naseej, 2025)

- High Compute and Operational Costs: Scaling advanced AI models involves significant "Inference" and cloud computing expenses. Without a robust revenue model, these costs can rapidly deplete capital reserves. Additionally, total reliance on tech giants for infrastructure creates strategic vulnerabilities.

- Reliability and "Hallucinations": The propensity of AI models to generate erroneous or "hallucinated" information remains a critical barrier, particularly in high-stakes sectors like medicine and law, where accuracy is paramount to maintaining consumer trust.

- The Global Talent Gap: The intense competition for engineers capable of building complex AI architectures has driven compensation to levels that often exceed the budgetary constraints of early-stage ventures, making it difficult to attract top-tier talent.

- Mimicry Risks and Rapid Obsolescence: Startups that function as simple "wrappers" over existing models are highly susceptible to rapid imitation. Moreover, the accelerating pace of innovation means that technologies can become obsolete within months, necessitating extreme agility and continuous business model reconfiguration. (Ashu , 2025)

Applied Study:

1. Research Methodology and Procedures:

This study employs a quantitative research design to empirically investigate the research model. Data were collected from a sample of 120 young entrepreneurs through an electronic questionnaire. The data were analyzed using SmartPLS 4 software, which offers advanced capabilities for predictive model evaluation, as well as robust procedures for mediation analysis and endogeneity assessment. (Hair, J. F & Alamer, A, 2022, p. 1007).

1.1. Population and Sample:

The target population of this study consists of young entrepreneurs in Algeria operating within the technology and digital services sectors. A convenience sampling technique was utilized to select 120 entrepreneurs. This sample size is considered optimal for the Partial Least Squares (PLS-SEM) technique, which is renowned for its capacity to provide accurate results even with smaller sample sizes and data that do not strictly adhere to a normal distribution (Ringle, C. M, Wende, S, & Becker, J.-M, 2024).

1.2. Data Collection Instrument

The primary data collection tool was an electronic questionnaire adapted from established scales in prior literature, specifically those concerning the Unified Theory of Acceptance and Use of Technology (UTAUT) and digital readiness frameworks. The instrument comprised 28 items distributed across five dimensions, measured on a 5-point Likert scale (ranging from 1: Strongly Disagree to 5: Strongly Agree). To ensure the rigor of the tool, content validity was established through a panel of experts in entrepreneurship and information systems. Furthermore, reliability was verified through Cronbach's Alpha and Composite Reliability (CR) tests to ensure internal consistency. (Hair, J. F & Alamer, A, 2022).

2 Statistical Analysis Method (SmartPLS 4):

Data were processed in two primary stages using the SmartPLS 4 software suite (Ringle, C. M, Wende, S, & Becker, J.-M, 2024).

- Measurement Model Evaluation (Outer Model): This stage was conducted to ensure the reliability and validity of the indicators. Specifically, it involved assessing internal consistency reliability, as well as convergent and discriminant validity, by examining standardized factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE).
- Structural Model Evaluation (Inner Model): This stage focused on hypothesis testing by analyzing path coefficients (β), T-statistics, and P-values generated through a bootstrapping procedure with 10,000 subsamples , Furthermore, the overall quality and explanatory power of the model were assessed using indices such as the Standardized Root Mean Square Residual (SRMR) for model fit and the Coefficient of Determination (R-square.) . (Ringle, C. M, Wende, S, & Becker, J.-M, 2024).

Table 02: Results of the convergence and internal consistency validity evidence.

	Construct Reliability and Validity						
Interviewer	Dimensions	Questions	FL	CR	AVE	Cronbach's Alpha (α)	VIF
	Cognitive readiness	Q1	0,845	0.875	0.654	0.812	

Digital readiness		Q2	0,613				1.82
		Q3	0,519				
		Q4	0,739				
		Q5	0,786				
		Q6	0.715				
	Psychological Readiness	Q7	0,460	0.862	0.621	0.795	1.95
		Q8	0.784				
		Q9	0,783				
		Q10	0.705				
		Q11	0,696				
		Q12	0,758				
	Entrepreneurial Readiness	Q13	0.715	0.889	0.678	0.834	2.15
		Q14	0.705				
		Q15	0.729				
		Q16	0.718				
	Material Readiness	Q17	0,713	0.854	0.595	0.788	1.65
		Q18	0,758				
		Q19	0,783				
		Q20	0.762				
		Q21	0,559				
		Q22	0,686				
Adoption Intention		Y01	0,740	0.902	0.702	0.845	-
		Y02	0,791				
		Y03	0,767				
		Y04	0,764				
		Y05	0.799				
		Y06	0,571				

Source: Prepared by researchers based on SMART-PLS outputs.

The data presented in Table 01 indicate that all Cronbach’s Alpha and Composite Reliability (CR) values exceeded the acceptable threshold of 0.70. This confirms the existence of strong internal consistency among the items comprising each construct ،Furthermore, the Average Variance Extracted (AVE) values were all significantly higher than the 0.50 benchmark, which establishes robust convergent validity; specifically, this indicates that the latent construct explains more than 50% of the variance in its respective indicators.

3. Discriminant Validity Assessment:

Discriminant validity refers to the extent to which a latent construct is empirically distinct from other constructs in the structural model. It ensures that the set of indicators (items) associated with a specific construct does not represent other latent variables, as evidenced by relatively low inter-construct correlations. In other words, each latent variable must demonstrate clear differentiation through its unique items compared to all other variables. In this study, discriminant validity was assessed using two primary benchmarks:

3.1. Fornell-Larcker Criterion:

In accordance with the Fornell-Larcker criterion, the square root of the Average Variance Extracted (AVE) for each latent construct must exceed the correlation coefficients between that construct and any other construct in the model ،This confirms that a construct shares more variance with its own indicators than it does with other latent variables.

Table 3: Differential Validity. Fulfilled by the Furnell-Larker Criterion (Furnell-Larker Criterion)

Dimensions	Cognitive readiness	Psychological Readiness	Entrepreneurial Readiness	Material Readiness	Adoption Intention
Cognitive readiness	0.809				
Psychological Readiness	0.512	0.788			
Entrepreneurial Readiness	0.615	0.495	0.823		
Material Readiness	0.442	0.410	0.523	0.771	
Adoption Intention	0.585	0.540	0.642	0.510	0.838

Source: Prepared by researchers based on SMART-PLS outputs.

The Fornell-Larcker criterion (referred to here as the VC indicator) assesses the extent of discriminant validity among constructs, ensuring that each latent variable represents a unique conceptual entity that is not redundant with others. The values presented in the diagonal of the table represent the square root of the Average Variance Extracted (AVE). According to this criterion, if the AVE of a construct is higher than its correlations with all other constructs in the model, it signifies a lack of construct overlap and confirms that the variable is empirically independent. As evidenced by the results in the table, no overlap exists among the constructs, thereby establishing their independence.

3.2 Discriminant Validity via the Heterotrait-Monotrait (HTMT) Ratio: The Heterotrait-Monotrait (HTMT) ratio is employed as a rigorous assessment to verify that latent variables are empirically distinct from one another. Established guidelines suggest that if the HTMT values remain below the conservative threshold of 0.85 or the more liberal threshold of 0.90, it indicates that discriminant validity has been successfully established among the constructs within the measurement model. (Henseler, J, Ringle, C. M., & Sarstedt, M., 2015, p. 120).

Table 4: Validation test according to the materiality trait criterion for correlation Htmt

Dimensions	Cognitive readiness	Psychological Readiness	Entrepreneurial Readiness	Material Readiness	Adoption Intention
Cognitive readiness	-				
Psychological Readiness	0.612	-			

Dimensions	Cognitive readiness	Psychological Readiness	Entrepreneurial Readiness	Material Readiness	Adoption Intention
Entrepreneurial Readiness	0.685	0.574			
Material Readiness	0.542	0.485	0.590		
Adoption Intention	0.745	0.698	0.782	0.623	-

Source: Prepared by researchers based on **SMART-PLS** outputs.

From the table above, it is clear that all HTMT values for the study dimensions were between acceptable and good.

2. Cross Loading (CL): The validity of the differentiation can be confirmed by using the second indicator, which is Cross Loading, an indicator that measures how far apart the statements are from each other, in the following table:

Table 05: Cross-Transforms Index CL.

		Questions	Cognitive readiness	Psychological Readiness	Entrepreneurial Readiness	Material Readiness	Adoption Intention
Digital Readiness	Cognitive readiness	Q1	0,872	0,210	0.511	0,351	-0,033
		Q2	0,724	0,160	0.552	0,114	-0,125
		Q4	0,775	0,242	0.394	0,169	-0,036
		Q5	0.745	0.431	0.215	0.115	-0.078
		Q6	0.718	0.315	0.597	0.158	-0.091
	Psychological Readiness	Q8	0,163	0,759	0.395	0,409	0,278
		Q9	0,143	0,720	0.412	0,370	0,309
		Q10	0,258	0,764	0.615	0,525	0,347
		Q12	0.268	0.751	0.702	0.496	0.448
	Entrepreneurial Readiness	Q13	0.358	0.547	0.865	0.458	0.514
		Q14	0.154	0.610	0.880	0.248	0.621
		Q15	0.654	0.218	0.719	0.625	0.551
		Q16	0.547	0.439	0.694	0.354	0.335
	Material Readiness	Q13	0,241	0,597	0.514	0,693	0,252
		Q14	0,283	0,385	0.621	0,794	0,302
		Q15	0,284	0,543	0.335	0,846	0,352

		Q16	0,307	0,467	0.368	0,780	0,262
		Q18	-0,053	0,115	0.391	0,535	0,520
Adoption Intention		Q19	0.310	0.129	0.597	0.693	0.709
		Q20	0.033-	0,186	0.557	0,206	0,750
		Q21	-0,036	0,470	0.614	0,438	0,810
		Q22	-0,047	0,214	0.394	0,299	0,783
		Q23	-0,076	0,372	0.517	0,388	0,776

Source: Prepared by researchers based on SMART-PLS output.

"The table illustrates that the outer loadings (indicated in bold) exceed the cross-loadings, thereby establishing discriminant validity at the indicator level.

4. Coefficient of Determination (R^2): This serves as a measure of the model's predictive power, representing the proportion of the total variance in the dependent variable that is explained by the independent variables.

Table 6: Indicators of the coefficient of determination R^2.

	R Square Adjusted	R Square	Explanatory power
Adoption Intention	0,621	0,635	Strong

Source: Prepared by researchers based on SMART-PLS output.

5. Analysis of the Coefficient of Determination (R^2):

The analysis revealed an R^2 value of 0.635, indicating that the dimensions of digital readiness (Cognitive, Psychological, Entrepreneurial, and Physical) collectively explain 63.5% of the variance in the "Intention to Adopt AI Technologies" among young contractors.

According to the criteria established by Hair et al., this value is categorized as "Substantial" (or Moderate-to-Strong) within organizational behavior research, as it significantly exceeds the recommended threshold for robust explanatory models.

This finding demonstrates that the proposed model possesses high predictive power regarding the behavior of contractors. Furthermore, it confirms that the selected readiness dimensions serve as fundamental determinants in the digital transformation process.

6. Analysis of Effect Size (f^2): The Effect Size (f^2) is an indicator used to measure the specific contribution of each independent variable to the dependent variable individually. Unlike the Coefficient of Determination (R^2), which evaluates the combined explanatory power of all dimensions, f^2 assesses the unique impact of each dimension—such as Cognitive, Psychological, Entrepreneurial, or Physical readiness—on the "Intention to Adopt AI Technologies." This metric determines whether the omission of a particular construct significantly affects the model's predictive capabilities. (Hair, J. F, Risher, J, Sarstedt, M, & Ringle, C. M, 2019, p. 21).

Table 07: Impact Size Index F^2.

	F^2	Q^2	Analysis
Cognitive readiness	0.35		Very big impact

Psychological Readiness	0.28		Big impact
Entrepreneurial Readiness	0.18	0.458	Medium effect
Material Readiness	0.09		Small trace

Source: Prepared by researchers based on SMART-PLS output.

These values confirm that the statistical model has predictive validity outside the sample (since ($Q^2 > 0$), with entrepreneurial readiness and knowledge emerging as the most influential factors in shaping the digital orientations of young entrepreneurs in the Algerian environment.

7. Structural Model Results and Hypothesis Testing:

The Direct Structural Model (Without Mediator): Initially, the path model was estimated using the Bootstrapping technique without the inclusion of "Entrepreneurial Characteristics" as a mediating variable. This step was conducted to establish a baseline for evaluating the mediation model concerning "Family Business Success." The results indicated that all direct paths were statistically significant at the (0.05) significance level.

Table 8: Direct Impact Pathway Model.

	Factories *B*	T Statistics (|O/STDEV|)	P Values	Decision
Cognitive readiness → Intention to Adopt AI Technologies	0.345	4.825	0.000	Rejection of the null hypothesis
Psychological preparedness → Intention to Adopta AI Technologies	0.285	3.541	0.001	Rejection of the null hypothesis
Entrepreneurial readiness → Intention to Adopta AI Technologies	0.412	5.102	0.000	Rejection of the null hypothesis
Physical Readiness → Intention to Adopta AI Technologies	0.158	2.145	0.032	Rejection of the null hypothesis

Source: Prepared by researchers based on SMART-PLS output

"The table above illustrates that the P-values for the second and fourth sub-hypotheses were less than the significance level (0.05). Consequently, we reject the null hypotheses (the first hypothesis) and accept the alternative hypotheses. Regarding the first and third sub-hypotheses, the null hypotheses are accepted, and the alternative hypotheses—which suggest a statistically significant effect—are rejected."

8. Testing the Main Hypothesis: The inclusion of "Digital Readiness" as a mediating variable between the dimensions and "AI Technologies Adoption" is of significant importance, as it allows for the examination of indirect paths and their impact on the dependent variable. To verify the significance of these indirect paths, the path model was estimated using the Bootstrapping technique, yielding the results presented in the following table:

Table: 9 First-order direct impact pathway model for entrepreneurial characteristics.

	Original Sample (O)	T Statistics (|O/STDEV|)	Standard Deviation (STDEV)	P Values	
Digital readiness <- Cognitive readiness	0,353	3,411	0,119	0,001	
Digital readiness <- Psychological readiness	0,715	12,957	0,065	0,000	
Digital readiness <- Physical readiness	0,968	39,465	0,039	0,000	
Digital readiness <- Entrepreneurial readiness	0.956	31.24	0.087	0.000	
Digital readiness <- Intention to Adopta AI Technologies	0,792	12.375	0.064	0,000	Rejection of the null hypothesis H_0

Source: Prepared by researchers based on SMART-PLS output.

"Upon incorporating Digital Readiness as a mediating variable between the dimensions and the dependent variable) Intention to Adopt AI Technologies — (without accounting for the second-order effects of Digital Readiness (i.e., the individual impact of each dimension :Cognitive Readiness ,Psychological and Entrepreneurial Readiness ,and Physical Readiness (all P-values were found to be below .0.05 Consequently, all alternative hypotheses) the first main hypothesis (are accepted, confirming a significant direct effect of Digital Readiness on the Intention to Adopt AI Technologies".

9. Statistical Analysis of the Main Hypothesis Results:

- Direction and Strength of the Relationship: The path coefficient (β= 0.792) indicates a very strong positive correlation between Digital Readiness and Adoption Intention. Statistically, this implies that any improvement in the digital readiness levels (encompassing cognitive, psychological, entrepreneurial, and physical dimensions) of young entrepreneurs will lead to a substantial increase in their intention to integrate AI technologies into their ventures.
- Statistical Significance: The calculated T-statistic reached 12.375, which significantly exceeds the critical tabulated value (1.96) at a 5% significance level. Furthermore, the p-value was 0.000 ($p < 0.05$), strongly confirming the rejection of the null hypothesis and the acceptance of the alternative hypothesis (the study's main hypothesis).
- Predictive Power: The high coefficient value reflects that digital readiness is not merely a contributing factor but rather the primary driver of the digital transformation process among the younger generation of entrepreneurs. The results suggest that entrepreneurs who are cognitively, physically, and psychologically prepared possess a "Digital Action Mindset," viewing AI adoption as a strategic necessity rather than a technological luxury.
- For the sample of 120 entrepreneurs, this result signifies that investing in readiness enhancement (such as technical training, psychological support, and infrastructure provision) is the most direct path to increasing AI adoption rates within the entrepreneurial ecosystem. Such readiness effectively bridges the gap and overcomes the barriers of fear and ambiguity associated with emerging technologies.

Discussion

The findings of this study provide robust empirical evidence supporting the critical role of digital readiness in shaping AI adoption among young entrepreneurs. The model explains 63.5% of the variance in adoption intention, indicating a substantial level of predictive power and confirming that readiness dimensions constitute key determinants of entrepreneurial digital behavior.

Consistent with prior research, the results demonstrate that cognitive readiness is one of the strongest predictors of AI adoption. This finding aligns with Mostafiz (2025), who emphasizes the importance of entrepreneurial cognition in recognizing technological opportunities. Entrepreneurs with higher levels of AI literacy and technical awareness are better equipped to understand algorithmic processes and integrate AI tools into their business operations. This supports the argument that knowledge-based capabilities are fundamental drivers of digital transformation.

Similarly, entrepreneurial readiness emerged as a highly significant factor influencing adoption intention. This result reinforces the theoretical perspective that strategic orientation and resource mobilization capabilities are essential for leveraging emerging technologies (Autio et al., 2018). Entrepreneurs who exhibit proactive behavior, strategic thinking, and the ability to reconfigure business models are more likely to adopt AI as a competitive tool. This finding also supports Gupta's (2024) assertion that AI adoption contributes to organizational performance through innovation and exploitative capabilities.

The role of psychological readiness, particularly self-efficacy, provides important insights into the behavioral dimension of AI adoption. The results indicate that self-efficacy acts as a mediating mechanism, strengthening the relationship between knowledge and actual adoption behavior. This finding is consistent with Cengiz and Peker (2025), who highlight the role of psychological factors in reducing AI-related anxiety and fostering technology acceptance. It suggests that the adoption of AI is not purely a rational decision but is significantly influenced by emotional and cognitive factors.

In contrast, material readiness, although statistically significant, exhibited a relatively weaker effect compared to other dimensions. This finding reflects the contextual realities of emerging economies such as Algeria, where infrastructure limitations and access to high-quality data remain critical barriers. While technological infrastructure is necessary, it is not sufficient on its own to drive adoption. This supports the argument that human capital and cognitive capabilities may outweigh structural factors in the early stages of digital transformation.

The findings also highlight a broader theoretical implication: digital readiness should be conceptualized as an integrated system rather than a set of independent variables. The interaction between cognitive, psychological, and entrepreneurial dimensions suggests the existence of a "digital action mindset," wherein entrepreneurs combine knowledge, confidence, and strategic orientation to effectively adopt AI technologies. This perspective extends existing models of technology adoption by incorporating a more holistic and interdisciplinary approach.

From a practical standpoint, the results have important implications for policymakers, incubators, and educational institutions. Enhancing AI adoption requires targeted interventions aimed at developing digital literacy, strengthening psychological resilience, and fostering entrepreneurial competencies. Additionally, investments in infrastructure and data ecosystems are essential to support long-term sustainability.

Finally, the study contributes to the literature by providing empirical evidence from an emerging economy context, addressing a significant gap in existing research. It demonstrates that while global technological trends are shaping entrepreneurial behavior, local structural and institutional factors continue to play a crucial role in determining adoption outcomes.

Conclusion

This study demonstrates that the adoption of AI technologies in the entrepreneurial environment transcends being a simple technical decision; rather, it is a complex strategic process fundamentally rooted in comprehensive "Digital Readiness." Statistical findings reveal that the proposed model possesses significant explanatory power, with readiness dimensions (cognitive, psychological, entrepreneurial, and physical) accounting for 63.5% of the variance in adoption intention.

The conclusions indicate that entrepreneurial and cognitive readiness serve as the primary drivers of this process. Entrepreneurs who possess a "Digital Action Mindset" and the capacity for "Bricolage" are the most capable of integrating AI as a force multiplier within their business models. Furthermore, psychological readiness emerged as a critical variable in mitigating "AI Anxiety" and enhancing entrepreneurial resilience, allowing entrepreneurs to transition from "questioning the tool's nature" to "actual utilization and innovation."

Despite broad digital ambitions, physical readiness—specifically data quality and infrastructure—remains the "bottleneck" facing young entrepreneurs in emerging ecosystems like Algeria, where actual adoption rates remain low (approximately 5%) due to the lack of major data centers and structured data flows. The successful transition toward "AI Agents" in 2026 will necessitate a radical shift toward a unified data architecture that ensures the integrity of technical outputs.

I. Recommendations and Proposals:

Based on the empirical findings, this study proposes a set of actionable recommendations directed toward various stakeholders within the entrepreneurial ecosystem:

1. For Young Entrepreneurs:

- Constructing Robust Data Architecture: Entrepreneurs must shift from viewing AI as isolated tools toward building a "Unified Data Model" that ensures data quality and integrity. "Smart Labs" rely on clean data as the fundamental catalyst for growth.
- Investing in "AI Literacy": Focus on developing "Prompt Engineering" skills and understanding algorithmic logic rather than merely the superficial use of off-the-shelf models.
- Enhancing Digital Self-Efficacy: Focus on developing "Psychological Capital" to increase confidence in managing technological transitions and reducing stress stemming from digital ambiguity.

2. For Policymakers and Government Institutions:

- Bridging Physical and Structural Gaps: Invest in establishing local Data Centers and providing subsidized access to Compute Power for startups to bridge the regional digital divide.
- Updating Regulatory and Financing Frameworks: Reduce administrative bureaucracy and activate specialized funding vehicles that support AI-driven "Exploitative Innovation," moving beyond traditional financing models.
- Establishing Accurate Statistical Databases: Provide Open Data environments that allow young entrepreneurs to train their models based on realistic local market data.

3. For Business Incubators and Universities:

- Integrating AI into Entrepreneurial Curricula: Transition from pure programming instruction to teaching "Strategic AI" and its application in decision-making and risk analysis.
- Digital Psychological Support Programs: Organize workshops focused on "Psychological Safety" and emotional intelligence to assist entrepreneurs in managing the organizational change resulting from automation.

II. Future Research Directions:

- Conducting Longitudinal Studies :Future research should employ longitudinal designs to evaluate the long-term impact of AI adoption on the actual financial performance of startups, moving beyond the measurement of mere" adoption intention".
- Examining Moderating Roles :Further studies are needed to investigate the moderating role of" Social Support "and "Organizational Culture "in strengthening the relationship between digital readiness and radical innovation.

Declarations

Ethical Approval and Consent to Participate

This study was conducted in accordance with internationally recognized ethical standards for social science research involving human participants. Participation in the survey was voluntary, and all respondents were informed about the purpose of the study prior to data collection. Informed consent was obtained from all participants, and they were assured of their right to withdraw at any stage without any consequences. No sensitive personal data were collected, and all responses were anonymized to ensure confidentiality.

Consent for Publication

All authors have read and approved the final version of the manuscript and consent to its publication. The authors confirm that the work is original and has not been published previously, nor is it under consideration for publication elsewhere.

Availability of Data and Materials

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. Due to confidentiality agreements with participants, the raw data are not publicly available but can be shared in anonymized form for academic purposes.

Competing Interests

The authors declare that they have no known competing financial or non-financial interests that could have appeared to influence the work reported in this paper.

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Authors' Contributions

- Noureddine Ahmed Houssam Eddine: Conceptualization, methodology, data analysis, writing – original draft preparation.
- Benhada Meriem: Literature review, theoretical framework development, writing – review and editing.

- Chegrani Mohamed: Data collection, validation, supervision, final approval of the manuscript.

All authors have read and agreed to the published version of the manuscript.

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AI Statement

The authors declare that no generative artificial intelligence tools were used in the design, data collection, analysis, or interpretation of the study. If any AI-assisted tools were used for language editing, they did not influence the scientific content, results, or conclusions of the research.

Conflict of Interest Statement

The authors confirm that there are no conflicts of interest regarding the publication of this paper.

Data Availability Statement

The data supporting the findings of this study are available upon reasonable request from the corresponding author and are subject to ethical and confidentiality considerations.

Ethical Considerations

All procedures performed in this study involving human participants were in accordance with ethical standards. Personal data were anonymized, and no identifying information was collected. The study ensured confidentiality, voluntary participation, and informed consent.

References

1. Alix, P. (2026). *Enterprise software technology predictions report*. Global TMT Analysis.
2. Alvaro, M. (2025). Determinants of AI intention among young entrepreneurs. *Journal of Marketing Analytics, 13*(2), 45–62.
3. ARPCE. (2024). *Observatory of the fixed telephony market in Algeria: Q4 2024 report*. Regulatory Authority of Post and Electronic Communications.
4. Ashu, G. (2025). *Where AI is headed in 2026*. Foundation Capital.
5. Benhah, M., & Ouassaa, H. (2025). Artificial intelligence in Algeria: Between reality and ambition. *Journal of Economic Growth and Entrepreneurship, 8*(4), 46–59.
6. Bouchama, A. (2025). Government AI readiness index: An analytical study of Algeria's regional and international position. *Journal of Strategic Studies, 14*(1), 112–130.
7. Cengiz, S., & Peker, A. (2025). Generative artificial intelligence acceptance and artificial intelligence anxiety among university students: The sequential mediating role of attitudes toward artificial intelligence and literacy. *Current Psychology, 44*(9), 7991–8000.
8. Chouieb, A., Borni, M., & Mechri, A. (2024). Digital entrepreneurship and its importance for developing and developed countries. *Journal of Economic Research, 20*(2), 152–170.
9. Clarifai. (2026). *Top reasons why AI-native startups fail*. Industry Insights Report.
10. Elluminati. (2026). *Top AI trends in 2026: Redefining businesses and innovations*.
11. Startup Genome. (2025). *Global startup ecosystem report 2025*.
12. Ghandour, H., & Taibi, R. (2022). Digital entrepreneurship and competitiveness of economic institutions. *Journal of Strategy and Development, 12*(3), 1222–1241.
13. Gupta, S. (2024). The impact of AI adoption on organizational performance: The mediating role of exploitative innovation. *Strategic Leadership, 12*(1), 1–18.
14. Hair, J. F., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in applied research. *Research Methods in Applied Linguistics, 3*(1), 1002–1027.
15. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
16. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based SEM. *Journal of the Academy of Marketing Science, 43*(1), 115–135.
17. Horrigan, J. B. (2016). *The meaning of digital readiness*. Pew Research Center.
18. Issani, W. (2025). The future of startups in Algeria in light of AI developments. *Journal of Economic Research, 20*(2), 186–205.
19. Kadiyono, A. L., & Sulistiobudi, R. A. (2024). Psychological capital, technology readiness, and entrepreneurial orientation. *Cogent Business & Management, 11*(1), 241–338.

20. Lab Manager. (2025). Achieving lab digitalization: A guide to data integrity. *Lab Manager Magazine, 20*(8), 12–19.
21. Microsoft. (2024). *Work trend index 2024: AI at work is here*. Microsoft Research & LinkedIn.
22. Mostafiz, M. D. (2025). Entrepreneurial cognition and AI adoption: The contingency role of innovation ecosystems. *R&D Management, 55*(1), 112–130.
23. Naseej. (2025). *Artificial intelligence in 2025: Practical tools supporting innovation.*
24. Purbasari, R., Muttaqin, Z., & Sari, D. S. (2021). Digital entrepreneurship in the COVID-19 era. *Review of Integrative Business and Economics Research, 10*(1), 114–135.
25. PwC. (2025). *AI readiness: Assessing national capabilities*. Global Technology Report.
26. Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4*. SmartPLS GmbH.
27. Thakur, R. (2025). AI preparedness in North Africa: The case of Algeria. *Technology and Society Review, 5*(1), 12–34.
28. UNCTAD. (2025). *Technology and innovation report: AI for all*. United Nations.
29. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives. *International Journal of Information Management, 57*, 101994.
30. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.
31. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*.
32. Vial, G. (2019). Understanding digital transformation. *Journal of Strategic Information Systems, 28*(2), 118–144.
33. Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection. *Journal of Business Research, 122*, 889–901.
34. Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective. *Entrepreneurship Theory and Practice, 41*(6), 1029–1055.
35. Autio, E., Nambisan, S., Thomas, L., & Wright, M. (2018). Digital affordances and entrepreneurship. *Strategic Entrepreneurship Journal, 12*(1), 72–95.
36. Li, F. (2020). The digital transformation of business models. *Technological Forecasting and Social Change, 146*, 141–148.
37. OECD. (2021). *Artificial intelligence in business and entrepreneurship*. OECD Publishing.
38. World Bank. (2022). *Digital economy for Africa initiative*. World Bank Publications.