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FRUGAL INNOVATION, IOT, AND IA: THE ROLE OF LEADERSHIP AND TUNISIAN PERSPECTIVES

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ABSTRACT

Frugal innovation, which is sometimes referred to as frugal engineering or innovation centered on simplicity and effectiveness, is a method of development and problem resolution that relates to straightforward, accessible, and impactful solutions. Most investigations in this domain have concentrated on the difficulties encountered in developing nations, where limitations in resources and restricted access to technology, infrastructure, and financial capital create hurdles in implementing expensive or intricate solutions. This investigation looks into how Internet of Things (IoT) technologies and artificial intelligence (AI) applications influence frugal innovation within the context of a developing nation, specifically focusing on Tunisia for empirical evidence. It also explores the moderating effect of leadership (LD) in the relationship between frugal innovation, IoT, and AI. Utilizing a participant group of 160 individuals from Tunisia and employing structural equation modeling (SEM) through SmartPLS, the findings indicate that IoT and AI serve as significant indicators of frugal innovation. The data suggests that organizations could gain from harnessing the potential provided by these technologies to enhance their ability for frugal innovation and boost their competitive edge in a swiftly changing technological landscape. Additionally, the research emphasizes the significance of adopting technology and the potential influence leadership has in incorporating advanced technologies like IoT and AI frameworks into managerial practices. In conclusion, it offers various managerial recommendations, addresses the research's limitations, and identifies directions for future research, especially concerning the specificities and context of Tunisia.

KEYWORDS: Frugal Innovation, IoT, AI, Leadership, Tunisia, SEM, SmartPLS.

1. INTRODUCTION

The primary objective of frugal innovation is to design simple, accessible, and resource-efficient solutions for contexts characterized by limited resources (Hossain, 2018; Hossain et al., 2023). According to Sarkar and Mateus (2022) and Weyrauch and Herstatt (2017), it enables businesses to unlock the potential of innovative ideas and technologies through simplicity, accessibility, and ingenuity, delivering inclusive and sustainable solutions that benefit society in both developed and developing countries (Bhatti, 2012).

The integration of artificial intelligence (AI) and the Internet of Things (IoT) significantly enhances frugal innovation, enabling the creation of simple and affordable solutions in resource-constrained environments. Initially focused on developing countries, this powerful combination is now expanding its reach to areas such as health, education, and infrastructure. The IoT network of connected objects facilitates data-driven applications remote monitoring, predictive maintenance while AI improves resource allocation and personalizes solutions. Together, AI and IoT reduce costs and increase impact through automation and more efficient service delivery.

Entrepreneurial knowledge (ES) is a key component of low-cost innovation combining IoT and AI (Karyaningsih, 2020; Roxas, 2014). In response to market demands, leaders who can effectively leverage limited resources identify opportunities and develop scalable and affordable solutions (Karyaningsih, 2020; AlMulhim, 2021). This approach fosters sustainable solutions to global challenges, driving rapid iterations, positive societal impacts, and rapid market adoption. By identifying unmet needs and orchestrating collaboration to maximize their impact, frugal innovation driven by the ecosystem can improve solutions for low-income populations.

This study, focused on the use of frugal innovation, AI, and IoT in Tunisian SMEs, explores the relationships between these dimensions. Previous work has shown how AI and IoT can stimulate frugal innovation by optimizing resource use and developing practical and affordable solutions to societal challenges (Azzawi et al., 2016). However, most of these studies have focused on developed countries, neglecting the perspectives of developing economies. This research aims to fill this gap by providing data from the Tunisian context.

The crucial role of Tunisian SMEs in the country's economy underscores the relevance of this study (Zhu et al., 2012; Huang and Mirza, 2023). Their actions in innovation, exports, and job creation demonstrate their capacity to accelerate economic growth and global trade. Tunisia's size, economic vitality, and rapid technological progress make it a relevant framework for analyzing the influence of AI and IoT on frugal innovation.

This study examines key relationships, grounded in resource-based theory (RBV)

1. How IoT influences frugal innovation.
2. How AI influences frugal innovation.
3. How leadership (LD) shapes the interaction between IoT and frugal innovation.
4. How leadership (LD) shapes the relationship between AI and frugal innovation.

The methodology is rigorous, describing the sampling, data collection, and analysis. After presenting the results and their theoretical and managerial implications, limitations are discussed, and avenues for future research are proposed.

2. LITERATURE REVIEW

The Resource-Based View (RBV) theory is a management framework that highlights the strategic importance of a company's internal resources and capabilities in achieving a sustainable competitive advantage through various techniques and methods (Kruesi and Bazelmans, 2023; Wernerfelt, 1984). Developed by researchers Jay Barney and Birger Wernerfelt in the 1980s, RBV primarily emphasizes the heterogeneity of companies' resource endowments, allowing them to outperform their competitors (Wernerfelt, 1984). The theory posits that resources must be valuable, rare, inimitable, and non-substitutable to serve as sources of competitive advantage (Wernerfelt, 1984). RBV guides managers in identifying and exploiting their unique resources to create distinct value propositions, adapt to changing environments, and ensure long-term success in highly competitive markets (Kraaijenbrink et al., 2010).

This theory provides a fruitful model for conducting further research on the theme of AI and IoT by studying frugal innovation (Gupta et al., 2018; Stroumpoulis et al., 2022). It also helps researchers connect critical resources and capabilities, including IoT and AI technologies, to yield intriguing results from multiple countries (Gupta et al., 2018). Additionally, RBV aids researchers in identifying unique assets that can lead to successful and thriving frugal innovations (Soni and T. Krishnan, 2014). RBV's focus on achieving sustainable competitive advantage guides researchers in exploring how frugal innovators can create long-term value and scale their solutions effectively (Madhani, 2010). RBV helps analyze the link between entrepreneurial knowledge, resource heterogeneity, and the ability to adapt to dynamic frugal environments, shedding light on factors that enable positive outcomes in these innovative contexts (Madhani, 2010; Rodríguez-Espíndola et al., 2022). Therefore, it would be relevant to empirically study the link between IoT, AI, and entrepreneurial knowledge towards frugal innovation from the perspective of Chinese SMEs. To this end, the author proposes certain hypotheses, explained below and highlighted in Figure 1.

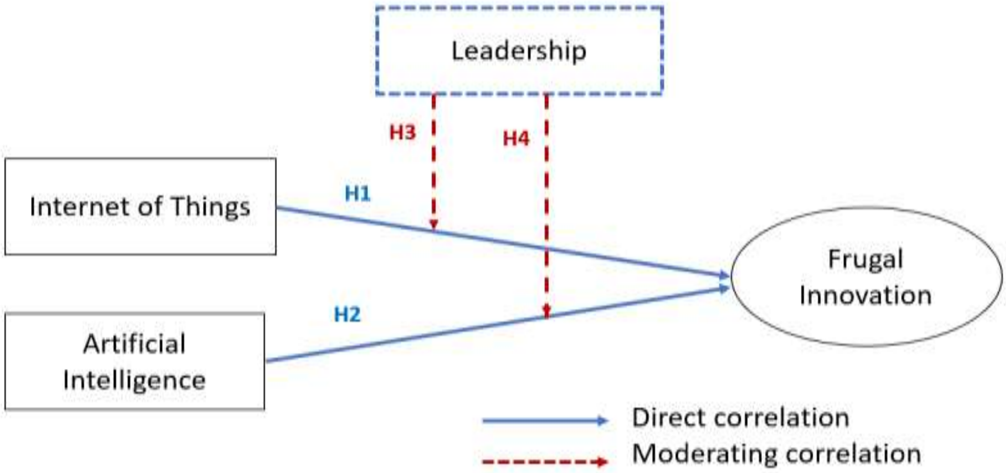

Figure 1: Conceptual Model.

2.1. The Internet of Things (IoT) and Frugal Innovation

The relationship between IoT and frugal innovation (FI) is envisioned as symbiotic, with each concept enhancing and complementing the other (Azzawi et al., 2016; Park et al., 2018; Park et al., 2022). For instance, FI involves developing affordable and economical solutions to meet the needs of populations with limited resources, such as those in developing countries (Bhatti, 2012). IoT can play a crucial role in managing resource use, reducing waste, and streamlining processes, thereby contributing to the creation of more cost-effective products and services (Sullivan et al., 2023). IoT technologies enable devices to be connected for data sharing and communication with each other (Sullivan et al., 2023). Such connectivity can enhance the accessibility of frugal innovation by making organizations more user-friendly and adaptable to various contexts (Park et al., 2018). Frugal innovation is recognized as a continuous development process where innovations are refined over time (Hossain, 2018). On the other hand, IoT can gather valuable data from the interactions and patterns of numerous users, allowing innovators to make data-driven decisions to reshape frugal solutions more realistically (Park et al., 2018; Park et al., 2022). Experts suggest that IoT can enable frugal innovation to be customized to meet the needs and preferences of individuals (Furini et al., 2020). The adaptability of IoT can enhance frugal innovation more effectively by reaching a broader audience and improving the lives of many people in various regions worldwide (Tiwari, 2021). Additionally, frugal innovation is highly concerned with the optimization of resource usage, including energy, materials, and water (Soni and T. Krishnan, 2014). IoT provides real-time data on resource usage, which can be used to identify inefficiencies and preserve resources effectively (Furini et al., 2020; Park and al., 2018). It is suggested that IoT could be used to create smart infrastructure for frugal innovations (Furini et al., 2020).

However, numerous studies highlight concerns regarding frugal innovation and the IoT from various perspectives and in different regions of the world, with mixed encouraging results (Azzawi et al., 2016; Park et al., 2018; Thakare and al., 2022). Most of the previous researchers suggested further research in this area to obtain diverse results. Similarly, Resource Value Theory (RVT) offers a theoretical framework for evaluating frugal innovation and the IoT by highlighting the importance of valuable resources and capabilities (Kruesi and Bazelmans, 2023; Madhani, 2010). According to Madhani (2010) and Wernerfelt (2014), using RVT allows researchers to identify essential resources, assess their complementarity, and analyze how this contributes to maintaining a sustainable competitive advantage (Abushakra, A and Nikbin, D, 2019).

Resource-Based Value (RBV) theory offers a better understanding of how businesses can use resources to promote cost-effective and socially responsible IoT-based frugal solutions (Wernerfelt, 1984). Researchers have the opportunity to conduct more in-depth studies using RBV principles to identify the key elements for success and promote the development of sustainable and innovative frugal practices in the IoT field (Gupta et al., 2018; Madhani, 2010). In this way, the Internet of Things and artificial intelligence can lead to significant positive changes, particularly in addressing social and economic challenges in resource-constrained situations (Altmann, p and Engberg, R, 2016). Currently, the author proposes the following hypothesis to empirically verify the results from the perspective of Tunisian small and medium-sized enterprises (SMEs), referencing the links above and the arguments supporting RBV and the researchers' recommendations.

H1: The Internet of Things (IoT) is positively correlated with frugal innovation.

2.2. *Artificial Intelligence (AI) and Frugal Innovation*

The mutually reinforcing relationship between artificial intelligence (AI) and frugal innovation is likely, as AI can enrich and improve the principles and practices of frugal innovation (Govindan, 2022; Jabeur et al., 2022). According to the literature, artificial intelligence can improve processes and automate tasks in the field of frugal innovation, leading to increased efficiency and reduced costs (Thakare et al., 2022). Through AI-driven automation, it is possible to produce, distribute, and maintain frugal solutions more efficiently, thus facilitating access for organizations to resource-constrained populations (Govindan, 2022; Masanja and Mkumbo, 2020). According to Masanja and Mkumbo (2020), frugal innovation is data-driven in order to create context-appropriate and cost-effective solutions. AI has the capacity to analyze large datasets, identify trends, and extract valuable insights to inform the development of frugal innovation (Alliance, 2020). Artificial intelligence can help personalize and adapt frugal innovation to individual needs (Alliance, 2020; Govindan, 2022). According to Govindan (2022), AI can play a role in improving the use of scarce resources in the field of frugal innovation. Thus, through the use of advanced analytics and intelligent algorithms, artificial intelligence can identify resource optimization opportunities, leading to reduced waste and lower resource consumption (Alliance, 2020).

According to De Waal et al. (2019), artificial intelligence can foster the creation of affordable smart technologies that adhere to the principles of frugal innovation. However, several studies have demonstrated findings on the topic of artificial intelligence and frugal innovation, based on different perspectives and themes worldwide, with varying results (Alliance, 2020; De Waal et al., 2019; Stroumpoulis et al., 2022; Thakare et al., 2022; Wu, 2021). To ensure conclusive results, most researchers have suggested conducting further research in this area (Alliance, 2020; Stroumpoulis et al., 2022; Thakare et al., 2022). According to Baker and Ahmad (2010), the Resource-Based View (RBV) highlights the importance of identifying and leveraging the unique resources and capabilities available to organizations. To successfully carry out projects in the field of frugal innovation and AI, researchers can analyze which specific resources (such as AI expertise, data, and access to technology) and capabilities (such as AI development and integration with frugal solutions) are essential. According to Resource-Based Value (RBV) theory, companies develop various combinations of resources that actually lead to improved organizational performance (Bakar and Ahmad, 2010). RBV allows researchers to analyze how different organizations use AI to enhance their frugal innovation initiatives, and how these strategies impact competitive advantage and business success (Qaisar, I., Katarzyna, P., Andreas K., 2025). Thus, incorporating AI into agricultural innovation has the potential to improve the adoption of cost-effective, socially beneficial, and sustainable solutions. Artificial intelligence possesses skills in data analysis, automation, and optimization, which perfectly aligns with the goals of frugal innovation, thereby fostering the creation of innovative solutions (De Waal and al., 2019). Currently, the author proposes the following hypothesis to empirically verify the results from the perspective of Tunisian small and medium-sized enterprises, based on the previously mentioned links and the arguments supporting RBV.

H2: Artificial intelligence (AI) is positively correlated with frugal innovation.

2.3. *Moderating Role of (LD) Between AI, IoT, and Frugal Innovation*

In a frugal innovation approach associated with AI and IoT, leadership must be based on a theoretical framework built around several pillars. First, strategic vision and governance require the integration of AI and IoT technologies with the principles of frugal innovation, ensuring ethical considerations, data security, and the traceability of learning; reference works such as Davenport and Harris's (2007) Competing on Analytics and research on frugal innovation and the lean startup methodology (Ries, 2011) inform this direction. Second, team culture and leadership must foster reasoned experimentation, short MVP cycles, and cross-functional collaboration, supported by knowledge-sharing practices (Nonaka & Takeuchi, 1995). Third, skills and team development require data and AI literacy for non-technical staff, complemented by training in lean management and IoT, as highlighted in research on enterprise AI and IoT-related organizational capabilities (Davenport, 2018; Brousseau & Guercio, 2017). Fourth, organizational architecture and delivery demand an agile and modular organization, with reusable pipelines and plug-and-play architectures, in line with modularity principles and frameworks such as the NIST IoT Framework (2020). Fifth, data governance and ethics require clear rules on the use of IoT data and AI models, bias management, and traceability, aligned with AI ethics guidelines and GDPR/national data protection frameworks (Jobin, Ienca & Vayena, 2019; GDPR). Sixth, performance measurement and ROI involve balanced indicators combining rapid ROI, total cost of ownership, and the adoption and reuse of insights, drawing on frameworks such as the Balanced Scorecard and data-driven approaches (Kaplan & Norton, 1996; Marr, 2016). Seventh, risk management and resilience involve the proactive identification of risks (model drift, IoT failures, security) and mitigation and continuity plans, with monitoring and rollback practices (Anderson & Anderson, 2007; Hevner & Chatterjee, 2010).

Finally, communication and managerial sobriety require transparency regarding progress and limitations, pedagogical leadership, and the dissemination of learning through communities of practice (Al Hawamdeh, N., & Al-Edena, M. 2025). These elements intersect with advanced theoretical frameworks such as dynamic capability theory (DCT), digital transaction cost economics, user-centered design, and studies on trust and explainability in AI. For further exploration, one can refer to sources such as Davenport & Harris (Competing on Analytics, 2007), Ries (The Lean Startup, 2011), McAfee & Brynjolfsson (Big Data: The Management Revolution, 2012), Nonaka & Takeuchi (The Knowledge-Creating Company, 1995), the literature on AI ethics (Jobin, Ienca & Vayena, 2019), and data governance frameworks (ISO/IEC 38507, GDPR

Hypotheses: the role of the LD as a moderator

- H1: The leadership moderates the relationship between frugal innovation (IF) and the adoption/development of Internet of Things (IoT) technologies. Specifically, stronger EEs amplify the positive impact of frugal innovation on IoT adoption.
- H2: The leadership moderates the relationship between frugal innovation (IF) and artificial intelligence (AI) deployment. Specifically, a more supportive Policy, Finance, and Human Capital environment strengthens the translation of frugal innovations into AI applications.

3. METHODOLOGY

During this study, several questionnaires were meticulously distributed to key stakeholders in the Tunisian market. Various methods were used to collect data, including online distribution via WeChat and email, as well as personal visits conducted with the assistance of colleagues. The author focused on the Tunisian market to confirm further empirical evidence from this market regarding how the integration of IoT and AI could play a crucial role in frugal innovation within it. The surveys were conducted individually, and 180 responses were successfully obtained. Finally, (N = 160) questionnaires were selected for data analysis after review and assessment of incorrectly completed information and other critical issues, such as incomplete responses, to ensure the authenticity of the feedback.

The researchers primarily used a five-point Likert scale based on previously published studies (Makkonen et al., 2016; Mehmood et al., 2019; Shahid et al., 2022; Younas et al., 2017). Furthermore, forty-nine questions comprised the main statements of the survey, while the respondents' profiles were assessed based on five characteristics.

3.1. Pilot Study

Furthermore, a pilot study is necessary before undertaking a large-scale survey to obtain improved and more fruitful results (Thabane et al., 2010). Forty-five questionnaires (n = 45) were examined for this purpose, and the results were evaluated based on criteria proposed by statisticians (Black and Babin, 2019; Hair, 2011).

According to Hair (2011), the current values are stable, with IoT at 0.695, AI at 0.755, LD at 0.698, and frugal innovation at 0.744 corresponding.

3.2. Measures

The Internet of Things (IoT) and artificial intelligence (AI) are used as standalone measures, frugal innovation as a dependent variable, and innovation management as a moderating variable. First, IoT was assessed using five items from a previous study (Umair et al., 2021). Next, AI was assessed using six items from a previous study (Schepman and Rodway, 2020). Then, LD was assessed using five items from previous studies (Roxas, 2014). Finally, frugal innovation was assessed using five items from previous studies (Levanen et al., 2016). Previous studies assessed all scales, with some items removed due to lower reliability resulting from the analytical techniques used, as follows.

3.3. Analysis Tools and Techniques

First, the author applied descriptive statistics to calculate basic statistics based on the information collected about participant profiles. Next, a correlation testing approach was applied to understand the interrelationships between the study variables. Third, discriminant validity was calculated and examined using two methods: the Fornell and Larcker method and the Heterotrait-Monotrait (HTMT) method (Ab Hamid et al., 2017; Fornell and Larcker, 1981a). Similarly, a convergent validity approach was performed according to suggested methods, such as the evaluation of AVEs, factor loadings, and reliability (Russell, 1978). A structural equation modeling (SEM) analysis was then performed using SmartPLS software to confirm the directional relationships between the variables (Ramayah et al., 2018). Calculating NIF and SRMR values is crucial to confirming the authenticity of the SEM model (Hu and Bentler, 1999). The recommended criteria for each analysis and index are reported as follows. For example, values should be between -1 and +1 in the Pearson correlation test (Cohen et al., 2009; Hair, 2011), factor loading and AVE values should be less than 0.5 (Hu and Bentler, 1999), reliability values should be greater than 0.7 (Hair, 2011), values should be less than 0.9 in the HTMT test (Henseler et al., 2015), and AVE square root results should be greater than the intervariable relationships for discriminant validity.

4. RESULTS

Table 1 presents the validity and reliability of the variables, as well as the means and standard deviations. As previously stated, factor loadings and AVE values should be less than 0.5, and reliability values greater than 0.7 (Hair et al., 2005).

Table 1: The Validity and Reliability of the Variables.

ITEMS	Mean Value	SD	loading	AVE	Reliability
Artificial intelligence					
				0.833	0.877
IA-F1	5.206	1.356	0.694		
IA-F2	4.899	1.248	0.588		
IA-F3	5.893	1.364	0.628		
IA-F4	5.135	1.589	0.747		
IA-F5	5.106	1.540	0.404		
Internet of Things					
				0.809	0.776
IoT-F1	5.104	1.026	0.293		
IoT-F2	5.198	1.120	0.602		
IoT-F3	5.130	1.530	0.572		
IoT-F4	5.197	1.320	0.570		
IoT-F5	5.124	1.114	0.698		
Leadership				0.742	0.859
LD-F1	5.982	1.130	0.520		
LD-F2	5.132	1.120	0.430		
LD-F3	5.189	1.198	0.332		
LD-F4	5.130	1.197	0.518		
LD-F5	5.137	1.140	0.698		
Frugal Innovation				0.757	0.776
FI-F1	5.198	1.298	0.543		
FI-F2	5.124	1.351	0.665		
FI-F3	5.128	1.425	0.620		
FI-F4	5.198	1.577	0.644		
FI-F5	5.197	1.654	0.745		
FI-F6	5.123	1.344	0.698		
Values should be between 1 to +1 in Pearson testing.					

4.1. Pearson Correlation

The results of the correlation analysis, which confirm the relationships between the variables studied. Values range from -1 to +1; negative values indicate a negative correlation, low values indicate a weak correlation, and high values indicate a strong correlation (Fornell & Larcker, 1981a; Hair et al., 2019; Kline, 2005).

4.2. Discriminant Validity

Table 2 presents the values used to assess discriminant validity. Commonly proposed criteria include, for example, that the square roots of the AVEs must be greater than the interrelationships between constructs (Fornell & Larcker, 1981b). The bold values in the first row of each column represent the square roots of the AVEs; the regular values represent the interrelationships.

Table 2: Model of Discriminant Validity.

	IA	IF	IOT	LD
IA	0,767			
IF	0,849	0,634		
IOT	0,772	0,793	0,658	
LD	0,670	0,602	0,693	0,801
Note. Bold are square roots of AVEs, and rest are interrelationships.				

4.3. Heterotrait-Monotrait (HTMT) Analysis

In addition to the analysis by Fornell and Lacker (2001), HTMT analysis can be used to verify data validity by exploring similarities between constructs. According to the recommendation of Henseler et al. (2015), HTMT values should be < 0.90 (see Table 3). Current results support the validity of the HTMT model in the data, given the accuracy of the results.

Table 3: HTMT.

	IA	IF	IOT	LD
IA				
IF	0,089			
IOT	0,309	0,368		
LD	0,790	0,778	0,200	
Note. Values should be <0.09.				

Table 4 shows the directions of the main paths, based on the beta values from the SEM model. It is recommended to examine the CFI and SRMR to assess and analyze the validity of the SEM model. For example, NFI values should be > 0.90 and SRMR < 0.08 (Hu & Bentler, 1999). The current results are most consistent with these recommendations. A significant correlation between AI and IF was observed (β = 0.087; p = 0.001).

Based on these results, hypothesis H4 (AI → IF) is retained. These results also corroborate previous work that has demonstrated a positive correlation between AI and IF from various perspectives and on a global scale (AlMulhim, 2021; Cetindamar et al., 2020; Fischer et al., 2021; Giuggioli & Pellegrini, 2023; Haffar et al., 2021; Nassani et al., 2022; Roxas, 2014; Vrontis et al., 2022). Furthermore, the author did not detect any moderation, contrary to what was previously suggested.

5. DISCUSSION

H1: IoT is positively related to frugal innovation (FI). The results obtained after SEM implementation show a positive connection between IoT and FI (β = 0.087; p < 0.001). On this basis, H1 (IoT → FI) is accepted. The results corroborate previous studies that suggest a positive relationship between IoT and FI from various global perspectives (Azzawi et al., 2016; Bhatti, 2012; Furini et al., 2020; Hossain, 2018; Park et al., 2018; Park et al., 2022; Sullivan et al., 2023; Tiwari, 2021).

H2: AI is positively related to FI. The SEM results show a positive relationship between AI and FI (β = 0.094; p < 0.001).

Based on this, H2 (AI → FI) is accepted. The results support previous work that found a positive relationship between AI and FI (Alliance, 2020; Bakar & Ahmad, 2010; De Waal et al., 2019; Govindan, 2022; Masanja & Mkumbo, 2020; Thakare et al., 2022; Wu, 2021).

H3: Leadership (LD) moderates the relationship between IoT and FI. SEM indicates a positive modulation of leadership on the IoT → FI relationship (β = 0.021; p = 0.002). Based on this, H3 (LD × IoT → FI) is accepted.

H4: AI is positively related to FI. The SEM results show a positive relationship between AI and FI (β = 0.000; p = 0.001). Based on this, H4 (AI → FI) is accepted. The results support previous work showing a positive relationship between AI and FI (AlMulhim, 2021; Cetindamar et al., 2020; Fischer et al., 2021; Giuggioli & Pellegrini, 2023; Haffar et al., 2021; Nassani et al., 2022; Roxas, 2014; Vrontis et al., 2022).

Furthermore, no additional unanticipated moderation or interaction was detected in the preceding section.

Table 4: SEM Model Results.

Directions	Direct	Moderating	Sig.	S. E	Decision
H1:IoT → FI	0,087*	-	0.000		
H2:IA → FI	0,094*	-	0.000		
Effet modérateur 1 ->		0,021**	0.002	0,381	supported
Effet modérateur 2 ->		0,000***	0.001	0,042	supported
		Model fitness		0,042	supported
				0,076	supported
		NFI	0.938		
		SRMR	0.918		

ES =expected signs; S.E =standard errors; NFI must be >0.9; SRMR must < 0.08. *** sig at 0.05.

6. IMPLICATIONS

6.1. Theoretical Implications

From a theoretical perspective, this study enriches the literature on IoT, AI, LD, and frugal innovation by providing empirical evidence from SMEs in Tunisia. IoT and AI are proving crucial in the current business environment and support the achievement of frugal innovation.

The study contributes by demonstrating positive relationships between IoT and FI, as well as between AI and FI. Furthermore, it highlights the importance of LD as a moderator between IoT and FI, and between AI and FI, reinforcing the role of entrepreneurial leadership in the adoption and diffusion of innovative, low-cost technological practices.

Finally, LD emerges as a key factor in leveraging synergies between IoT/AI and frugal innovation, thus enriching the literature on leadership in technology SMEs in a competitive environment.

6.2. Managerial Implications

For business leaders, the results suggest investing in leadership development (LD) to maximize the benefits of IoT and AI technologies in terms of frugal innovation.

Leadership can facilitate technology monitoring, organizational agility, and resource management to optimize costs while improving performance and innovation.

Managers should promote leadership practices that foster communication, decentralized decision-making, and the ability to mobilize teams around resource-optimized IoT/AI projects.

7. CONCLUSION

This study highlights the crucial role of IoT and AI as catalysts for frugal innovation in the context of Tunisian SMEs. Empirical and theoretical findings converge to support the following:

IoT and AI are significant predictors of frugal innovation, enabling better resource allocation and simpler, more accessible solutions adapted to the constraints of emerging markets.

Leadership (LD) can moderate the relationship between IoT and AI on the one hand, and frugal innovation on the other, suggesting that effective leadership capabilities strengthen the adoption and integration of innovative technologies into management practices.

Technological adoption and strategic alignment between emerging technologies and organizational practices are essential to fostering the emergence of frugal solutions that benefit low-income populations and boost the competitiveness of SMEs.

Practical Implications

For Tunisian SME leaders:invest in leadership skills that support the implementation of IoT and AI solutions, facilitate change management, and promote low-cost pilot projects to demonstrate the value of frugal innovation.

For R&D managers and policymakers: promote approaches that integrate IoT and AI from the earliest stages of product development, focusing on resource access and efficiency.

For public policymakers and financial partners: encourage ecosystems that facilitate access to technology and capital for frugal projects, thereby stimulating digital inclusion and SME growth.

8. LIMITATIONS AND FUTURE DIRECTIONS

This study focuses on a specific context (Tunisian SMEs);results may differ in other sectors or developing countries. Cross-sectional or longitudinal studies would validate the robustness of the observed relationships. More detailed sectoral analyses (industry, services, agriculture) could shed light on the contextual determinants of frugal innovation. Examining other leadership variables (e.g., leadership style, organizational culture) could enrich our understanding of moderation mechanisms.

In summary, the strategic integration of IoT and

AI, supported by relevant leadership, offers a relevant and pragmatic path to accelerate frugal innovation in SMEs in Tunisia and, more broadly, in developing economies. This approach can not only improve operational efficiency and market access, but also contribute to positive societal outcomes by fostering affordable and sustainable solutions.

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