

AI Adoption in Supply Chain Management among Lebanese Food and Beverage SMEs: Drivers, Barriers, and Strategic Implications

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Abstract. This study examines the integration of Artificial Intelligence (AI) in Supply Chain Management (SCM) among small and medium-sized enterprises (SMEs) in Lebanon's Food and Beverage (F&B) sector. Using a qualitative approach based on 45 semi-structured interviews, it explores the drivers, barriers, and strategic implications of AI adoption. Even though AI technologies offer significant opportunities, adoption remains uneven especially among SMEs. The findings reveal that participants recognize AI's potential to improve efficiency and competitiveness. Participants reported that AI enhances operational efficiency, cost optimization, and decision support. On the other hand, AI adoption remains limited by technical barriers, financial constraints, skill shortages, and low trust.

Based on the Technology Organization Environment (TOE) framework, the Resource-Based View (RBV), the Technology Acceptance Model (TAM), and Institutional Theory, the study highlights that successful AI integration depends on several factors. These factors include technological readiness, organizational capabilities, managerial acceptance, and institutional pressures. It suggests enhancing digital infrastructure, developing human capital, and improving governance frameworks to support SMEs.

Keywords: Artificial Intelligence; Supply Chain Management; F&B; SMEs; Technology Adoption.

1. Introduction

With recent technological developments, Artificial Intelligence (AI) has emerged as a transformative force across many industries including supply chain management (SCM). The increasing volatility of global markets and rising customer expectations have pushed firms to seek new ways to increase efficiency. AI's capabilities including predictive analytics, machine learning, and real-time decision support offer promising solutions to global challenges (Jahin et al., 2023).

Technological innovations such as blockchain, IoT, robotics and Large Language Models (LLMs) are being introduced in SCM. These technologies are supporting SCM in different functions including demand forecasting, supplier relationships, and logistics optimization.

AI has emerged as one of the most transformative trends especially in SCM. AI has the capacity to optimize supply chain processes. It can also improve forecasting accuracy and decision-making (Akanbi et al., 2024). While AI is frequently described as transformative, its impact varies significantly depending on organizational size. Research consistently shows that large multinational enterprises are advancing AI adoption in SCM at a substantially faster pace than SMEs (OECD, 2025; Ivanov et al., 2024). SMEs face a distinct set of structural barriers that limit their ability to keep pace, including high implementation and infrastructure costs, shortages of data science and AI talent, regulatory compliance burdens, and concerns about algorithmic transparency and accountability (Hendriksen, 2023).

Lebanon's F&B sector represents a particularly significant yet understudied context for AI adoption. The sector is the largest contributor to Lebanon's industrial output, accounting for approximately 38% of industrial production and 2.9% of GDP, with an estimated market size of USD 1.6 billion (IDAL, 2019). The sector comprises around 1,245 registered agri-food companies, and food industries represent approximately 19% of all manufacturing firms in the country (IDAL, 2019). SMEs are the backbone of Lebanon's economy more broadly, constituting 95% of all businesses, contributing over 40% of GDP, and employing around 50% of the workforce (World Bank, 2018; Lebanese Ministry of Economy and Trade, 2018). Yet Lebanon's broader economic environment severely constrains the digital transformation of these firms. Since the onset of the financial crisis in 2019, the Lebanese pound has lost over 95% of its pre-crisis value, and annual inflation reached 221% in 2023, with food prices alone surging by 208% that year (Macrotrends, 2024; BLOMINVEST, 2023). Lebanon imports more than 80% of its food supply, leaving F&B supply chains acutely vulnerable to external shocks; the 2020 Beirut port explosion, the COVID-19 pandemic, and the war in Ukraine compounded these vulnerabilities and exposed chronic weaknesses in supply chain resilience (Carnegie Endowment, 2023; IPC, 2023). On the digital infrastructure side, Lebanon ranks 92nd out of 132 economies in the Global Innovation Index 2023, with fixed broadband speeds well below regional averages and 5G penetration under 1% (WIPO, 2023; Freedom House, 2024). These structural conditions economic instability, fragile supply chains, and limited digital infrastructure - make Lebanon's F&B SMEs a compelling yet challenging environment for AI adoption. Recent systematic evidence confirms that advanced analytics and AI-driven tools in food supply chains offer significant potential for demand forecasting, inventory optimisation, and operational decision-making, yet adoption remains constrained by data quality challenges and infrastructure limitations (Le & Dam, 2025).

A growing body of research documents AI's applications mainly in large multinational firms. Less attention has been paid to adoption barriers faced by SMEs, and existing studies rarely address SMEs operating in developing economies under conditions of economic instability and infrastructure constraints. Lebanon's F&B sector presents a particularly distinctive context: persistent economic crises, severe supply chain disruptions, limited digital infrastructure, and resource-constrained SMEs create adoption challenges that differ fundamentally from those documented in developed-market settings. Understanding AI trends and challenges within this context can provide targeted guidance for practitioners seeking to leverage AI's benefits under adversity. This study aims to fill that gap through a qualitative investigation focusing on SMEs in Lebanon's F&B sector.

Despite these benefits, AI adoption in SCM entails significant challenges that must be addressed to realize its potential. Cybersecurity risks are among the most pressing: integrating AI with interconnected supply chain systems expands attack surfaces and increases vulnerability exposure, particularly for firms lacking dedicated security capabilities (Mullet et al., 2021; Layode, 2024). Transparency and governance present a parallel challenge, as the opacity of AI-generated recommendations can erode managerial trust and raise ethical concerns around accountability and data privacy (Hendriksen, 2023; Modgil et al., 2022). Sustainability integration adds further complexity, requiring that AI systems be designed to optimize not only efficiency but also environmental outcomes such as carbon footprint reduction and resource utilization (Layode, 2024). Addressing these challenges is essential for firms seeking to leverage AI to improve efficiency, customer satisfaction, and long-term competitiveness.

1.1 Need for the Study

SCM has become an important determinant of organizational success. In today's highly competitive markets, companies face several challenges. Some of these challenges include pressure to meet customer expectations and reduce operating cost. Previous supply chain approaches used manual processes and historical data. They struggled to provide the flexibility and precision required by current dynamic markets.

Current AI tools offer good opportunities for SCM. These tools can improve organizational performance. The benefits of AI implementation in SCM can be clearly noticed in the improved decision-making process in addition to optimized production and logistics. AI can also enhance customer service and improve inventory management. However, many organizations are still in the early stages of AI adoption. There is limited research on how these technologies impact supply chain efficiency and organizational competitiveness.

This study aims at examining the ways in which AI can be integrated into various aspects of SCM. AI adoption can have a big impact on SCM functions. Some of these functions can include procurement, production, distribution and retail. The findings of this study aim to provide practical insights for managers and policymakers and at the same time to help increase organizational efficiency.

1.2 Research Objectives

1. To explore AI applications in SCM across different functions.
2. To examine the benefits of AI integration in SCM on organizational performance and competitiveness.
3. To identify the challenges organizations face in AI adoption.
4. To analyze how organizational size, industry sector, and regional context influence AI adoption.
5. To provide practical recommendations for businesses and policymakers to support AI adoption in SCM.

1.3 Research Questions

1. How is AI currently being applied across different functions of supply chain management?
2. What benefits do organizations achieve from integrating AI in their supply chains?
3. What are the main challenges organizations face when adopting AI in SCM?
4. How do these challenges differ across SMEs compared to larger organizations?
5. How do regional and organizational contexts shape perceptions and adoption of AI in SCM?
6. What strategies can facilitate AI adoption in supply chains in SMEs?

1.4 Theoretical Framework

The study integrates four complementary frameworks, each assigned to a distinct explanatory role in the analysis of AI adoption among Lebanese F&B SMEs:

- **TOE framework** (Tornatzky and Fleischer, 1990) explains the macro-level conditions shaping AI adoption, specifically technological infrastructure readiness and organizational capacity. In this study, TOE accounts for findings related to firms' digital maturity, resource availability, and the broader environmental pressures unique to Lebanon's F&B sector.

TAM (Davis, 1989) explains managerial acceptance of AI tools. Specifically, TAM is applied to findings concerning perceived usefulness, trust, and transparency, capturing why managers embrace or resist AI-generated recommendations despite recognizing their potential value.

- **Institutional Theory** (DiMaggio and Powell, 1983) explains the external pressures driving or constraining AI adoption. This study uses Institutional Theory to interpret findings related to coercive pressures from regulators, normative pressures from industry peers, and mimetic pressures arising from competitive imitation within Lebanon's F&B sector.
- **Resource-Based View (RBV)** (Barney, 1991) explains variation in AI adoption outcomes through internal capabilities. RBV is applied to findings concerning skill availability, data infrastructure, and organizational competencies, arguing that SMEs possessing superior technological and human resources are better positioned to leverage AI as a source of sustained competitive advantage.

Together, these four frameworks provide a multi-level lens: TOE addresses contextual readiness, RBV addresses internal capabilities, TAM addresses perceived usefulness and trust, and Institutional Theory addresses the external pressures that collectively shape AI adoption behavior among SMEs in Lebanon's F&B sector.

2. Literature Review

AI is an innovative technology that is capable of changing a wide range of industries including SCM. Companies that digitize processes can improve their bottom lines and please their customers (Samuels et al., 2024; Kumar et al., 2021). This literature review seeks to integrate existing research and identify critical insights into how AI technologies affect supply chain operations.

The increasing popularity of AI is mainly due to the use of Big Data, complex algorithms, and enhanced processing power and storage. AI systems are increasingly integrated into digital systems, that can significantly influence human decision-making processes (Duan et al., 2019).

During the last decades, the world witnessed a move towards digitalization. Four new-age technologies stand out: the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and blockchain. According to Gartner's Hype Cycle for Emerging Technologies, IoT, AI, Machine Learning, and blockchain are in the breakthrough stage with widespread use expected to come ahead (Gupta et al., 2022). These technologies are commonly regarded as the way of the future, and they serve as the foundation for other trends predicted to gain a big influence in the coming years (Kumar et al., 2021).

2.1 Overview on AI in Supply Chain Management

SCM has experienced a significant transformation over the years. Most of the transformation was focused on the management of resources to generate and distribute value to consumers (Mukhamedjanova, 2020). To improve organizational efficiency and competitiveness, many organizations have realized the importance of incorporating SCM principles (Kumar et al., 2021; Mukhamedjanova, 2020). SMEs in emerging market contexts have increasingly adopted SCM strategies to improve corporate performance and gain competitive advantages (Belhadi et al., 2021). The main aim behind SCM is to provide value to both customers and stakeholders (Mukhamedjanova, 2020).

The use of AI in supply chain management has recently received a lot of interest in the academic literature. There has been a lot of research on the positive effects of AI on supply chain operational efficiency, sustainability, and strategic innovation (Samuels et al., 2024). AI applications may make supply chains and organizations more flexible and resilient. This flexibility is highly useful in times of disruption like the COVID-19 pandemic. Optimizing supply chains with AI-driven predictive analytics

is essential for improving operational efficiencies, cutting costs, and satisfying customers (Nzeako, 2024).

As supply networks move from Industry 4.0 to Industry 6.0, AI becomes more significant. SCM performance is being enhanced by using AI such as artificial neural networks (ANN), genetic algorithms (GA), virtual reality (VR), and artificial immune systems (AIS) (Mohsen, 2023). According to Samuels et al., 2024; integrating AI and ML with HR can create a win-win situation where technology and human imagination work together to achieve more efficiency in supply chains.

2.2 Drivers of AI Adoption in SCM

A consistent theme across the literature is that AI adoption in SCM is driven primarily by the promise of operational efficiency, cost reduction, and enhanced decision-making. AI-powered systems enable more accurate demand forecasting, inventory optimization, and supply chain visibility by processing large datasets and identifying patterns that traditional methods cannot detect (Belhadi et al., 2021; Coleman et al., 2023; Adenekan, 2024). Machine learning models improve forecasting accuracy by combining historical sales data with real-time variables such as weather conditions and promotional campaigns, directly reducing waste and improving responsiveness to market changes (Nzeako, 2024). These efficiency gains align with the Resource-Based View (RBV), which frames AI-driven capabilities as strategic assets that generate sustained competitive advantage when embedded in organizational processes (Barney, 1991; Samuels et al., 2024).

Beyond efficiency, AI is a significant driver of supply chain resilience. AI tools - including Bayesian Networks, ensemble models, Artificial Neural Networks, and Large Language Models - enable firms to anticipate and respond to supply disruptions, demand volatility, and environmental risks (Kasaraneni, 2021; Belhadi et al., 2021; Krishnamoorthy, 2024). During crisis periods such as the COVID-19 pandemic, AI-enabled supply chains demonstrated markedly greater adaptability than those relying on traditional methods (Mukherjee et al., 2024). Across procurement, logistics, and customer relationship management, AI similarly drives value through route optimization, automated supplier selection, and personalized customer engagement (Khadem et al., 2023; Yandrapalli, 2023; Min, 2010). Collectively, these findings suggest that the primary drivers of AI adoption converge on a single logic: the ability to convert data into faster, more accurate, and more cost-effective decisions across the supply chain.

2.3 Barriers to AI Adoption in SCM

Despite strong evidence of AI's potential, the literature identifies a persistent set of barriers that slow adoption, particularly among resource-constrained organizations. Financial constraints are the most frequently cited obstacle: the substantial upfront investment required for AI infrastructure, data systems, and specialist talent alongside ongoing maintenance costs - places adoption out of reach for many firms, especially SMEs, for which the return on investment is often unclear (Tyagi et al., 2020). Skill shortages compound this challenge: the specialized expertise required to design, deploy, and maintain AI systems is scarce, forcing many organizations to depend on external consultants rather than developing internal capabilities (Banur, 2024; Hendriksen, 2023).

Cybersecurity presents a distinct barrier as AI integration expands the attack surface of supply chain systems. Intelligent supply chains that fuse physical operations with digital networks are inherently vulnerable: a breach in any single node can propagate across the entire system, and many organizations lack the internal expertise to manage these risks effectively (Mullet et al., 2021; Umran et al., 2021; Layode, 2024). Data quality and interoperability further impede adoption; AI models require large volumes of clean, structured data, yet many firms - particularly in developing economies - operate with fragmented legacy systems that cannot support seamless data integration (Modgil et al., 2021; Banur, 2024). Organizational resistance to change, employee coordination challenges, and limited leadership commitment round out the internal barriers that delay or derail AI implementations (Hendriksen, 2023).

2.4 Contextual Influences on AI Adoption

The literature increasingly recognizes that AI adoption does not occur in a vacuum: organizational size, industry characteristics, and regional context all shape the pace and nature of adoption. The Technology-Organization-Environment (TOE) framework provides a useful lens here, highlighting how technological readiness, organizational capacity, and environmental pressures interact to determine adoption outcomes (Tornatzky and Fleischer, 1990). Larger firms with dedicated IT departments, established data infrastructure, and greater financial resources are consistently better positioned to adopt AI than SMEs, which face resource constraints across all three dimensions (OECD, 2025). This asymmetry is especially pronounced in the F&B sector, where supply chains are characterized by perishability, demand volatility, and thin profit margins that simultaneously create strong incentives for AI adoption and limit the resources available to pursue it (Belhadi et al., 2021; Samuels et al., 2024).

Regional and institutional contexts add further complexity. Institutional Theory explains how coercive pressures from regulators, normative pressures from industry peers, and mimetic pressures from competitive imitation collectively shape firms' AI decisions (DiMaggio and Powell, 1983). In developing economies marked by economic instability, fragmented digital infrastructure, and weak governance frameworks, these institutional pressures often operate inconsistently, creating an environment in which adoption is simultaneously incentivized by competitive necessity and constrained by systemic limitations (Ganesh and Kalpana, 2022). Lebanon's F&B sector exemplifies this dynamic: firms operate under conditions of currency devaluation, energy scarcity, import dependency, and limited regulatory digitization, all of which modulate how contextual factors translate, or fail to translate, into AI capability (Mukhamedjanova, 2020).

2.5 Trust, Transparency, and Human-AI Collaboration

Trust emerges as a cross-cutting theme in the AI adoption literature, with significant implications for both individual acceptance and organizational outcomes. The Technology Acceptance Model (TAM) posits that perceived usefulness and ease of use are the primary determinants of technology acceptance (Davis, 1989); however, research in AI-driven SCM increasingly shows that trust, understood as confidence in the reliability, explainability, and fairness of AI outputs, mediates this relationship (Kwak and Lee, 2022; Hendriksen, 2023). Managers who cannot understand or interrogate how an AI system arrives at a recommendation are less likely to act on it, even when they acknowledge its potential value. This "black-box" problem is particularly acute in high-stakes domains such as procurement and demand forecasting, where incorrect AI outputs carry direct financial consequences (Modgil et al., 2022; Richey, 2023).

The literature also highlights the importance of human-AI collaboration as a condition for sustainable adoption. Rather than replacing human judgment, effective AI implementations tend to augment managerial decision-making by surfacing insights that human analysts would miss while preserving space for human oversight and contextual interpretation (Samuels et al., 2024; Hendriksen, 2023). Firms that invest in transparency mechanisms, including explainable AI interfaces, governance frameworks, and staff training, report higher levels of employee acceptance and more sustained adoption outcomes (Modgil et al., 2022; Mullet et al., 2021). Conversely, organizations that deploy AI without adequate attention to trust-building and change management tend to encounter resistance that undermines adoption regardless of the system's technical performance. Trust is therefore not merely an ethical concern but a practical precondition for realizing the operational benefits that drive AI adoption in the first place.

2.6 Gaps

From the literature, three main gaps emerge:

- Most studies focus on large corporations; little is known about how SMEs, specifically in the F&B sector, perceive and adopt AI in SCM.

- Few studies examine how regional economic, political, and infrastructural conditions shape AI readiness and trust.
- While literature outlines AI's benefits, there is limited research on the lived experiences of managers who balance enthusiasm with practical constraints.

3. Research Methodology

This study adopts an interpretivist philosophical stance, consistent with its qualitative research design. Semi-structured interviews are conducted to explore how professionals experience and interpret the integration of AI within supply chain management. Interpretivism places an intense focus on understanding the unique experiences, meanings, and environments of persons. Thus, it is a good fit for our objective of learning more about how professionals view and interact with AI integration in their supply chain management processes. In addition to interviewing AI adopters, the study also includes professionals who have chosen not to implement AI solutions. This enables a comparative understanding of both acceptance and resistance. This approach facilitates a deeper examination of the organizational and social dynamics influencing AI integration, as well as the human factors that shape technological adoption decisions.

3.1 Data Collection

This study adopts an inductive research strategy grounded in qualitative interviews to examine the impact of AI tools on SCM. The inductive approach enables the collection of experience-based data driven directly from participants. This approach allows patterns and themes to emerge from the field rather than being imposed. Interview questions were designed to capture participants' perspectives, challenges, and practical insights regarding AI implementation in SCM. Through systematic coding and thematic analysis, the study seeks to identify key factors shaping AI adoption. Context-sensitive theoretical insights reflecting the realities faced by SCM professionals will be generated as well. This approach supports a flexible and empirically grounded investigation of AI integration within organizational settings.

It is very important to understand how AI tools are currently applied and how supply chain managers perceive these technologies. This study offers valuable perspectives on the uses of AI and its influence on the efficiency of supply chain operations. It also emphasizes the extent of knowledge and awareness among supply chain experts to adopt AI tools. Challenges and barriers that businesses face throughout the implementation of AI technologies are identified as well. Thereby providing insights to develop effective strategies to overcome these challenges.

Due to the exploratory nature of this study, a qualitative research approach is ideal for this study. Interviews allow for an in-depth exploration of participants' experiences and perceptions. They also help in capturing insights that structured quantitative methods may overlook. Semi-structured interviews were selected because they balance guidance with flexibility. Such interviews assisted in enabling participants to elaborate on both specific applications and broader implications of AI in SCM.

Artificial Intelligence in SCM is a complex subject that encompasses a range of technology, procedures, and human interactions. Semi-structured interviews help researchers in exploring these insights by providing participants with the opportunity to provide detailed perspectives regarding their experiences. This approach enables the gathering of comprehensive and insightful information that not only identifies the practical uses of AI but also considers the surrounding elements that impact its implementation. Such elements can include organizational culture, technology readiness, and employees' attitudes.

A total of 45 comprehensive interviews were conducted with supply chain professionals, data analysts, and AI specialists from SMEs operating across F&B sector in Lebanon. Table 1 presents participants profiles.

Participants were selected through purposive sampling to capture the full spectrum of AI adoption stages, current adopters, firms actively planning adoption, and non-adopters within Lebanon's F&B SME sector. This deliberate cross-sectional design was theoretically motivated: non-adopters and planning-stage firms were intentionally included because their perspectives on barriers, resource constraints, and adoption intentions are central to understanding why AI uptake remains uneven. The selection criterion was direct professional responsibility for supply chain operations, demand forecasting, procurement, or technology decision-making within an SME, irrespective of the firm's current level of AI implementation. Participants without active AI adoption were therefore qualified to speak to perceived barriers, organizational readiness, and the contextual factors shaping adoption decisions insights that are equally analytically valuable as those from current adopters.

Table 1: Participant Demographic Profile

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	28	62.2
	Female	17	37.8
Position	Supply Chain Manager	15	33.3
	Operations Manager	10	22.2
	Procurement Manager	6	13.3
	Logistics Coordinator	5	11.1
	Data Analyst	5	11.1
	AI / Digital Transformation Specialist	4	8.9
Years of Experience	1–5 Years	8	17.8
	6–10 Years	14	31.1
	11–15 Years	13	28.9
	More than 15 Years	10	22.2
Organization Size	Small Enterprise (10–49 Employees)	20	44.4
	Medium Enterprise (50–249 Employees)	25	55.6
AI Adoption Status	Currently Using AI Tools	29	64.4
	Planning to Adopt AI	10	22.2
	No Current AI Adoption	6	13.4

3.2 Data Analysis

Thematic saturation was monitored iteratively throughout the data collection process. After approximately 38 interviews, no substantively new themes, codes, or contradictory perspectives were emerging across successive transcripts. The remaining interviews were conducted to confirm this saturation and to ensure adequate coverage of participants at different AI adoption stages (current adopters, planners, and non-adopters). The final sample of 45 interviews was therefore considered sufficient to achieve thematic saturation within the bounded context of Lebanon's F&B SME sector, consistent with recommendations for purposive qualitative samples in organizational research (Braun and Clarke, 2006; Guest et al., 2006).

A semi-structured interview format was used to facilitate open-ended discussions while ensuring consistency throughout all interviews. The interview questions aimed to gather insights regarding participants' experiences with AI-driven forecasting. Challenges were addressed and the perceived benefits and limitations of AI integration in supply chain decision-making were discussed. The inquiries also examined the influence of AI on forecasting precision, mitigation, and the overall resilience of the

supply chain. The duration of each interview ranged from 40 minutes to one hour, providing participants enough opportunity to deliver comprehensive responses.

Interviews were conducted between January 2026 and April 2026. Participants were recruited through purposive sampling via professional networks, industry associations, and direct organizational contact. Interviews took place in person at participants' workplaces. The interviews were conducted in English, with Arabic responses subsequently translated into English by the researcher. With participants' prior informed consent, all interviews were audio-recorded to ensure accuracy. Recordings were transcribed verbatim and reviewed for completeness before thematic analysis commenced. Ethical approval was obtained from Notre Dame University and all participants provided informed consent confirming their voluntary participation and the confidentiality of their responses.

3.3 Thematic Map and Code

The analysis followed Braun and Clarke's (2006) six-phase framework for thematic analysis: familiarization with the data, generation of initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. This approach was selected because the aim was not to test a predetermined hypothesis but to allow patterns and meanings to emerge inductively from participants' narratives.

Coding was led by the primary researcher (first author), who read and re-read all 45 transcripts before generating an initial set of descriptive codes directly from the data. All codes and their associated transcript segments were managed and stored in QDA Miner software, which facilitated the systematic organization of codes into sub-themes and themes across the full corpus of interviews.

To strengthen coding credibility, a second researcher, a co-author with prior experience in qualitative supply chain research, independently coded a purposively selected subset of ten transcripts (approximately 22% of the corpus), covering participants across all three adoption stages (current adopters, planners, and non-adopters). Neither coder consulted the other's codes during this independent phase. Inter-coder reliability was then assessed using Cohen's kappa, yielding a coefficient of $\kappa = 0.81$, which indicates strong agreement (Landis and Koch, 1977). Coding disagreements, primarily concerning the boundary between the Barriers and Contextual Influences themes, were resolved through structured discussion between the two researchers until consensus was reached. All final decisions and the rationale for boundary cases were documented in QDA Miner's memo function to maintain an audit trail. The remaining 35 transcripts were coded by the primary researcher, with periodic cross-checks against the agreed coding framework to ensure consistency throughout the analysis.

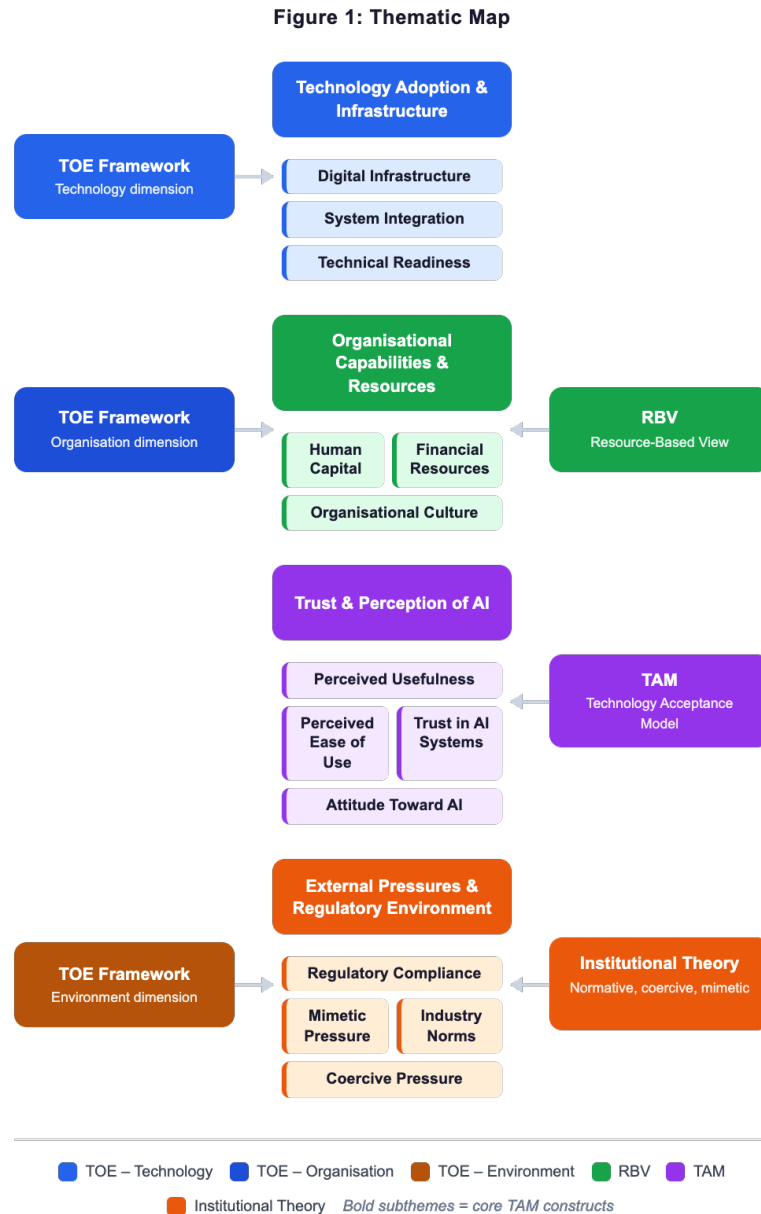


Fig.1: Thematic Map

The primary themes identified through this process were organized around four thematic clusters: Applications and Benefits, Barriers and Challenges, Contextual Influences, and Trust in AI. Figure 1 presents the thematic map, and Table 2 provides a full breakdown of themes, sub-themes, and codes as structured within QDA Miner.

The findings were further validated through analytical triangulation, comparing themes emerging from the interview data against relevant literature and industry reports on AI adoption in SCM which supported the credibility of the interpretations.

Table 2: Final Coding Hierarchy from QDA Miner Analysis

Themes	Sub-Theme/Code
Applications and benefits	Operational Efficiency, Decision Support, Cost and Resource Optimization, Customer Value, Innovation & Competitive Advantage
Barriers and challenges	Financial Constraints, Technical Barriers, Human and Skill Barriers, Organizational Resistance, Data Quality and Accessibility Issues
Contextual influences	Economic Environment, Government & Regulatory Frameworks, Industry Dynamics, Organizational Size & Maturity, Cultural Factors
Trust and perception	Perceived Reliability, Transparency and Explainability, Human Oversight, Ethical & Privacy Concerns, Trust Development

Table 2 outlines the main themes and sub-themes identified through qualitative analysis of interviews and secondary data concerning AI-enabled supply chain transformation in the Food and Beverage (F&B) sector. The themes illustrate the primary patterns and conceptual categories that impact AI adoption in SCM. Each sub-theme or code offers specific insights that explains the detailed perspectives, experiences, and realities of industry participants.

4. Findings

4.1 Introduction

This section presents the results of interviews with supply chain professionals from SMEs operating in the F&B sector in Lebanon. Participants shared common perspectives on AI adoption and its impact in Lebanese SMEs. The findings are organized thematically around applications and benefits, barriers and challenges, contextual influences, and trust in AI. Figure 2 states the distribution of total code mentions highlighted by participants regarding AI Adoption in SCM. Code mentions were counted as the total number of coded text segments assigned to each code across all 45 transcripts in QDA Miner. Where a participant returned to the same topic in distinct parts of the interview, each segment was counted separately, meaning multiple mentions from the same participant are included in the totals. Code frequency should therefore be interpreted as an indicator of thematic prominence, reflecting how recurrently a topic surfaced across the corpus, rather than as a direct measure of relative importance.

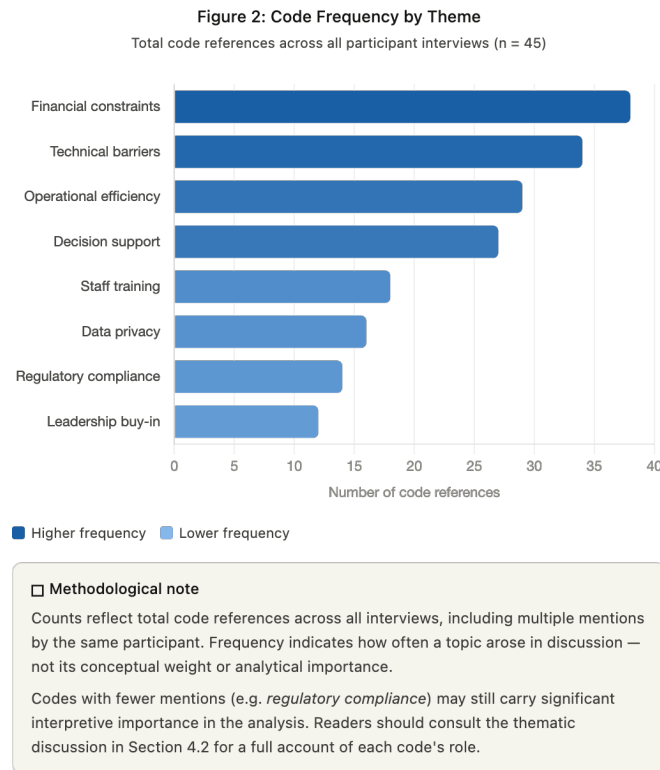


Fig.2: Code Frequency by theme

The results from the thematic analysis indicate that the implementation of Artificial Intelligence in Supply Chain Management in Lebanon's Food and Beverage sector is affected by several factors. These factors include technological readiness, organizational maturity, financial capacity, human skills, ethical considerations, and environmental pressures. Figure 2 illustrates both enablers and inhibitors of AI adoption. Enablers include decision support, cost optimization, and operational efficiency, alongside inhibitors, such as technical barriers, financial constraints, and data quality issues.

Four theoretical frameworks are employed to thoroughly analyze these findings including the Technology Organization Environment (TOE) framework, the Resource-Based View (RBV), the Technology Acceptance Model (TAM), and Institutional Theory. These theories explain how technological, organizational, and contextual factors interact together to shape AI adoption behavior in the Lebanese F&B supply chain ecosystem.

4.2 Thematic Findings

The analysis of interviews identified four interrelated themes that clarify how organizations experience the integration of Artificial Intelligence in supply chain management:

- Applications and benefits
- Barriers and challenges
- Contextual influences
- Trust and perception

These themes offer a comprehensive understanding of the strategic potential of AI implementation in SCM.

4.2.1 Theme 1: Applications and Benefits of AI in SCM

The main aim behind questions that belong to theme 1 was to understand what organizations gain from AI adoption and how it can be applied to the SCM. It was very clear from all participants that they were aware of the importance of AI adoption in SCM and its impact on organizational efficiency, decision-

making, cost optimization, and customer value. Most interviewees highlighted the benefits of AI tools when they were integrated into their supply chains. A clear improvement in demand forecasting, inventory optimization, and logistics coordination was pointed out by participants.

The evidence supports the argument that when firms possess AI resources and knowledge, they can realize significant performance improvements through AI-driven SCM. On the other hand, despite the clear strategic value of AI tools in Supply chain management remains limited due to certain challenges and barriers that face SMEs.

This theme was the most prominently coded cluster in the QDA Miner analysis, generating 203 coded segments across five sub-themes (Operational Efficiency, Decision Support, Cost and Resource Optimization, Customer Value, and Innovation and Competitive Advantage) and drawing on contributions from 41 of 45 transcripts. Its near-universal presence across the corpus reflects the strong consensus among participants regardless of adoption stage that AI holds significant strategic potential for F&B supply chains. The following quotations are representative of the range of participant responses under this theme.

Quote 1 (Participant 7 - Supply Chain Manager): "AI has significantly improved our demand forecasting accuracy. Previously, we relied on historical sales records and intuition, but AI allows us to identify trends and seasonal fluctuations much faster, which has reduced inventory shortages and excess stock."

Quote 2 (Participant 15 - Operations Manager): "One of the biggest advantages of AI is its ability to support decision-making. Managers now have access to real-time information that helps us react quickly to changes in customer demand and supplier performance."

Quote 3 (Participant 23 - Logistics Coordinator): "AI has helped us optimize delivery schedules and warehouse operations. We are using fewer resources while maintaining service quality, which has contributed to lower operational costs and better customer satisfaction."

Quote 4 (Participant 33 - IT Manager): "Since integrating AI into our procurement process, we have been able to identify reliable suppliers more quickly and reduce lead times considerably. The competitive advantage is real companies that do not adopt these tools will struggle to keep pace with what customers now expect in terms of speed and availability."

4.2.2 Theme 2: Barriers and Challenges to AI Adoption

Although the advantages of AI are well known, companies face several obstacles that restrict its extensive use. Questions covering the second theme were designed to discover the barriers and challenges organizations face during AI adoption into SCM.

Despite the clear strategic importance of AI tools, organizational adoption remains slow. Several participants discussed how implementation barriers were prevalent and frequently outweighed perceived advantages. The main obstacles facing AI adoption include financial constraints, technical barriers, human and skill shortages, and organizational resistance. According to participants, high implementation cost of AI tools and data integration were among the biggest challenges that SMEs were facing. Many respondents also discussed the lack of in-house experience to implement AI into SCM. Some also noted resistance to change that their organizations faced while trying to adopt AI.

These results highlight that financial capability, digital maturity, and change management are critical factors in assessing AI adoption readiness. Addressing these obstacles requires strategic investment, leadership involvement, and personnel development.

This theme was the second most prominently coded cluster in the QDA Miner analysis, generating 189 coded segments across four sub-themes (Financial Constraints, Technical Barriers, Human and Skill Shortages, and Organizational Resistance) and drawing on contributions from 43 of 45 transcripts. Its near-universal presence encompassing adopters, planners, and non-adopters alike underscores that

barriers to AI adoption are pervasive and cross-cutting within this sector. The following quotations are representative of the range of participant responses under this theme.

Quote 1 (Participant 11 - SME Owner): "The cost of implementing AI solutions is still a major challenge for small businesses like ours. Between software, infrastructure, and employee training, the investment is difficult to justify in the current economic environment."

Quote 2 (Participant 19 - Procurement Manager): "We do not have enough employees with the technical skills required to manage AI systems. Even when we invest in technology, we still depend heavily on external consultants."

Quote 3 (Participant 31 - Supply Chain Analyst): "Resistance to change remains a problem. Some employees are worried that AI will replace their jobs, while others simply prefer to continue using traditional processes that they are familiar with."

Quote 4 (Participant 6 - Finance Director): "Beyond the upfront cost, our biggest obstacle has been data quality. Our existing systems generate inconsistent and incomplete records, and AI tools simply cannot perform without clean, structured data. Fixing our data infrastructure turned out to be a prerequisite we had not budgeted for."

4.2.3 Theme 3: Contextual and Environmental Influences

The external environment significantly impacts decisions regarding AI adoption. The main aim behind questions related to the third theme was to understand the impact of AI integration into SCM on local SMEs operating across F&B sector in Lebanon. The main environmental elements identified were economic instability, regulatory uncertainty, competitive dynamics, and organizational maturity. Participants discussed that AI adoption decisions were mainly influenced by the internal capacities of SMEs. Government regulations played an important role as well. Because of the high volatility in the Lebanese market due to political and economic instability, participants agreed on the negative impact of these factors on AI investments. They stated that even though the government is encouraging such initiatives, but due to high volatility, SMEs operating in Lebanon are hesitant to adapt AI tools in their SCM. On the other hand, industry competitiveness and customer expectations act as motivating factors, prompting enterprises to implement AI-driven solutions to maintain relevance.

This theme was the third most prominently coded cluster in the QDA Miner analysis, generating 156 coded segments across four sub-themes (Economic Instability, Regulatory Uncertainty, Competitive Dynamics, and Organizational Maturity) and drawing on contributions from 38 of 45 transcripts. Contextual and environmental factors surfaced consistently across participant accounts regardless of firm size or adoption stage, reflecting the pervasive influence of Lebanon's macroeconomic and institutional environment on technology decision-making. The following quotations are representative of the range of participant responses under this theme.

Quote 1 (Participant 5 - General Manager): "The Lebanese economic crisis has made long-term technology investments very risky. Even when companies recognize the value of AI, uncertainty often delays implementation decisions."

Quote 2 (Participant 27 - Operations Director): "The lack of clear regulations and government support creates hesitation among SMEs. Many businesses are unsure about data governance requirements and the future direction of digital transformation policies."

Quote 3 (Participant 38 - Supply Chain Consultant): "Competition within the market is pushing companies toward AI adoption. Customers expect faster service and better availability of products, and businesses are under pressure to respond more efficiently."

Quote 4 (Participant 17 - Warehouse Manager): "The energy crisis in Lebanon has made it very difficult to rely on digital systems consistently. Power outages and connectivity interruptions disrupt AI-dependent processes at critical moments. Until basic infrastructure improves, AI adoption for SMEs like ours will always remain partial and unstable."

4.2.4 Theme 4: Trust and Perception of AI

A common theme across participants was trust and perception. Participants expressed mixed feelings regarding the reliability and ethical implications of AI systems. Theme four discusses the importance of the human factor in AI acceptance. Despite the importance of AI tools and their positive influence on organizational performance, trust remains a common concern across all participants. Managers discussed the importance of AI tools on various operational functions but according to the participants, AI tools cannot be fully autonomous decision makers. Some participants mentioned that they still doubt some of the AI tools and they spend extra time checking their validity. On the other hand, concerns related to data privacy and lack of human insights were prominent across participants especially those who work for companies with limited technical understanding of AI operations. Participants who had prior experience with AI technologies showed greater confidence, emphasizing perceived reliability, and ethical compliance as key to building trust.

This theme was the fourth most prominently coded cluster in the QDA Miner analysis, generating 142 coded segments across five sub-themes (Perceived Reliability, Transparency and Explainability, Human Oversight, Ethical and Privacy Concerns, and Trust Development) and drawing on contributions from 37 of 45 transcripts. Trust emerged as a cross-cutting concern that shaped adoption attitudes independently of financial or technical capacity, appearing prominently in the accounts of both current adopters and non-adopters. The following quotations are representative of the range of participant responses under this theme.

Trust emerged as a prominent theme across interviews, yet it is analytically misleading to treat it as a single construct. The data reveal at least five distinct dimensions of trust, each arising from different concerns and carrying different implications for practice.

The first is trust in data participants' confidence that the inputs feeding AI systems are accurate, complete, and free from bias. This dimension points managers toward data governance frameworks, regular audits, and clear documentation of data provenance as preconditions for AI adoption. The second is trust in algorithms, referring to participants' need for transparency and explainability in how AI models reach their outputs. Where this trust was absent, participants reported resistance to acting on AI-generated recommendations, suggesting that explainable AI tools and human-in-the-loop oversight mechanisms are not optional additions but organisational necessities.

A third dimension concerns trust in vendors confidence that third-party providers are reliable, ethical, and committed for the long term. This form of trust shaped procurement decisions and risk perceptions in ways that trust in technology alone cannot explain, and points to the importance of robust service-level agreements and vendor due diligence. Fourth, several participants expressed uncertainty about trust in employees' ability to use AI responsibly, raising questions about whether staff had sufficient literacy to interpret, question, or override AI outputs. This dimension calls for structured training programmes and acceptable-use policies rather than technological fixes. Finally, participants spoke to trust in regulatory and data protection systems their confidence, or lack of it, that existing legal frameworks adequately govern AI use. This dimension connects individual organisational decisions to the broader institutional environment and suggests that managers should actively monitor regulatory developments, such as the EU AI Act, rather than treating compliance as a static baseline.

Treating these five dimensions as a single "trust" construct risks obscuring the different causal mechanisms at play and producing recommendations that are too generic to be actionable. The discussion that follows addresses each in turn.

Quote 1 (Participant 9 - Supply Chain Manager): "AI provides useful recommendations, but I still believe that final decisions should remain in the hands of experienced managers. Human judgment is essential, especially in uncertain situations."

Quote 2 (Participant 21- Data Analyst): "I trust AI when it comes to processing large amounts of information, but I need transparency regarding how the system arrives at its recommendations before relying on it completely."

Quote 3 (Participant 42 - SME Owner): "My biggest concern is data privacy. Sharing sensitive operational information with AI systems raises questions about security and confidentiality that many small businesses are not prepared to address."

Quote 4 (Participant 30 - Operations Supervisor): "Trust in AI has built up gradually within our team. At the beginning, staff were skeptical and would frequently override AI recommendations to follow their own judgment. Over time, as the system proved consistently accurate, confidence grew. Building that trust required patience and a sustained track record of reliable results."

5. Discussion

This research investigates the drivers, barriers and strategic implications of Artificial Intelligence (AI) adoption in Supply Chain Management (SCM) by Small and Medium Enterprises (SMEs) in the Food and Beverage (F&B) industry in Lebanon. The results reveal that AI is progressively being viewed as a useful tool for improving operational efficiency, decision-making, cost reduction, and customer value. Despite the recognized benefits, the adoption of AI is still hindered by financial limitations, technical barriers, skill shortages, organizational resistance, and issues of trust and transparency.

The following discussion interprets the four empirical themes through the study's theoretical frameworks, the Resource-Based View (RBV), the Technology-Organization-Environment (TOE) framework, Institutional Theory, and the Technology Acceptance Model (TAM). Whereas the Findings section reports what participants observed and experienced, this section explains why those patterns emerge and what they mean in relation to existing theory and prior literature.

The results of the benefits of AI are consistent with the Resource-Based View (RBV), which claims that organizations possessing valuable technological and human resources can gain sustainable competitive advantages. Participants noted enhancements in demand forecasting, inventory optimization, and logistics coordination. These results are consistent with earlier studies that emphasized AI's role in driving operational excellence and supply chain performance (Belhadi et al., 2021; Joel, 2024; Abaku, 2024). The findings suggest that AI capabilities can become strategic resources when supported by suitable organizational competencies.

The barriers identified in this study are consistent with the Technology-Organization-Environment (TOE) framework. Financial limitations, lack of technical expertise and digital maturity were found to be important barriers to adoption. These findings are in line with previous studies that have found that SMEs struggle to adopt advanced technologies because of resource constraints and implementation costs (Tyagi et al., 2020; Umran et al., 2021). SMEs in Lebanon face the additional challenges of economic instability and limited access to technological resources, unlike larger organizations.

Institutional Theory holds that organisations are shaped not only by internal resources or technological capabilities, but by the broader institutional environment in which they operate. Scott (2001) distinguishes three mechanisms through which this environment exerts pressure: coercive, normative, and mimetic. Applying this framework precisely to the present findings requires mapping each empirical observation onto the appropriate mechanism rather than treating institutional forces as a general backdrop.

Regulatory uncertainty, as described by participants, reflects a condition of weak or inconsistent coercive pressure. Coercive pressure operates through mandates, legislation, and formal sanctions imposed by governments or regulatory bodies. Where these are absent, contradictory, or in flux as participants reported in relation to AI governance organisations face not the pressure to conform but an absence of clear signals, which itself becomes a barrier to adoption. Limited government support

functions similarly: it reflects a failure of coercive institutions to actively incentivise or structure AI uptake, leaving organisations without the scaffolding that regulatory frameworks can provide.

Industry competition, by contrast, maps more precisely onto mimetic pressure. DiMaggio and Powell (1983) argue that organisations imitate peers when facing uncertainty about best practice. Participants who reported monitoring competitors' AI investments, or delaying adoption until others had demonstrated viability, were responding to mimetic cues rather than regulatory mandates. This distinction matters because the appropriate managerial response to mimetic pressure building sector-level intelligence and engaging with industry benchmarks differs substantially from responses to coercive pressure.

Finally, professional expectations among staff, clients, or sector bodies reflect normative pressure, which operates through shared standards of appropriate behaviour embedded in professional communities and training systems. Where participants described feeling that AI adoption was expected of a credible, modern organisation, or where staff resistance drew on professional norms about human judgement, these responses are best understood as normative rather than regulatory or competitive in origin.

Distinguishing these three mechanisms is not merely a theoretical exercise. Coercive, normative, and mimetic pressures call for different organisational responses: regulatory engagement and compliance readiness; professional development and cultural change; and strategic positioning relative to industry peers, respectively. Conflating them under the broad label of "institutional pressure" risks producing recommendations that are misaligned with the actual source of constraint.

The study also provides evidence of all three institutional pressure types identified by DiMaggio and Powell (1983). Coercive pressures were evident in participants' references to regulatory uncertainty, government policy unpredictability, and tax frameworks that constrained investment capacity; several managers noted that the absence of clear AI governance frameworks made strategic planning difficult. Normative pressures emerged from industry associations, professional training programmes, and cross-sector knowledge exchanges, through which AI adoption was increasingly positioned as a competitive standard for food and beverage operations. Mimetic pressures were reflected in participants' accounts of monitoring competitors' digital investments and using peer practices as benchmarks for their own adoption decisions, particularly under conditions of environmental uncertainty. Together, these three mechanisms illustrate how institutional conditions in Lebanon shape the pace and scope of AI integration in SME supply chains, and extend Institutional Theory by documenting how coercive, normative, and mimetic pressures interact in a fragile-economy context where top-down regulatory support remains limited.

Trust was also a significant factor in AI adoption decisions, and these findings can be interpreted through the lens of the Technology Acceptance Model (TAM), which holds that perceived usefulness and perceived ease of use are the two primary determinants of technology adoption intentions (Davis, 1989). Participants' emphasis on the operational benefits of AI such as demand forecasting accuracy, cost reduction, and real-time logistics coordination aligns with TAM's construct of perceived usefulness; organizations adopted or planned to adopt AI because they believed it would improve their supply chain performance. Conversely, concerns about the complexity of AI tools, the need for specialist technical skills, and difficulties in interpreting AI-generated outputs correspond to TAM's construct of perceived ease of use, which multiple participants identified as a meaningful barrier. Trust and reliability, while not original TAM constructs, function here as antecedents to perceived usefulness: participants were only willing to act on AI recommendations when they trusted the system's outputs. The findings thus extend TAM by demonstrating that in high-uncertainty environments such as the Lebanese F&B sector, organizational trust-building mechanisms including transparency, explainability, and human oversight mediate the relationship between perceived usefulness and actual adoption behaviour.

Overall, this study contributes to advancing the knowledge on AI-enabled supply chain transformation by providing empirical evidence from SMEs operating in a developing economy. The results indicate that the successful adoption of AI requires the integration of technological readiness, organizational capabilities, managerial support, and institutional conditions. The Lebanese context demonstrates that the adoption of AI is not just a technological choice but also a strategic and environmental choice that is influenced by economic realities, resource availability and organizational culture.

6. Conclusion

This study investigated the integration of Artificial Intelligence into Supply Chain Management within Lebanon's Food and Beverage sector. The study focuses on AI applications, benefits, challenges, and contextual influences. Utilizing the integrated Technology Organization Environment (TOE) framework, the Technology Acceptance Model (TAM), and Institutional Theory, the study provided a multi-level explanation linking technological readiness, managerial cognition, and institutional legitimacy.

The findings indicate some optimism among SMEs in AI adoption into their supply chain management. The findings indicate that although AI offers significant potential for improving operational efficiency, cost reduction, decision-making, and consumer value, its implementation is still in the early stages, restricted by internal and external obstacles. Managers acknowledge the potential benefits of AI adoption while expressing reservations related to financial, infrastructural, and trust-related limitations. AI Adoption is not rejected but deferred. Most firms prioritize digitization prior to exploring advanced AI.

Empirical evidence indicates that financial limitations, expertise deficiencies, data quality problems, and organizational opposition are significant barriers to AI integration. Furthermore, the Lebanese economic ecosystem and deficient digital policy framework intensify uncertainty. However, companies that show preparedness and flexibility experience reported improvements in supply chain agility and strategic performance, as described by participants across the study.

The study indicates that effective AI integration into the supply chain necessitates not only technology but also organizational learning, cultural adaptability, and a supportive institutional framework. Internal resources should be synchronized with external opportunities. This can help companies attain resilience and sustain competitive edge in an increasingly data-driven global marketplace.

7. Recommendations

To effectively incorporate AI into Lebanon's food and beverage supply chains, managers are advised to begin with low-cost, bounded AI pilots rather than enterprise-wide deployments. Demand forecasting modules and inventory optimisation tools are well-suited entry points because they produce measurable results within a short operational cycle and require limited upfront infrastructure. Where capital constraints are acute, SMEs should explore shared AI platforms and cooperative data arrangements with peer firms or sector associations, reducing per-firm licensing and integration costs while generating the pooled datasets that machine-learning models require. Supplier data standardisation should be treated as a prerequisite: establishing common data exchange formats across the supply chain for orders, inventory levels, and delivery status, maximises the accuracy and usefulness of any AI-generated forecast. Phased implementation is recommended, progressing from back-office demand planning, through logistics optimisation, to customer-facing applications only once internal data quality and staff readiness are confirmed. Employee training should be delivered through formal partnerships with Lebanese universities, vocational institutes, or technology vendors offering subsidised upskilling programs, rather than ad hoc in-house courses. Leadership commitment remains essential to reduce

resistance to change, and governance protocols for data privacy, algorithmic transparency, and human oversight should be formalised before AI tools are scaled.

On the policy side, policymakers should develop sector-specific incentive mechanisms to lower the cost of AI adoption for Lebanese F&B SMEs, including tax credits for qualifying digital investments, subsidised access to cloud computing infrastructure, and co-funded AI training partnerships between universities and industry associations. A national supplier data standardisation protocol for the food and beverage sector would reduce the integration costs that participants identified as a primary barrier. Policymakers should also establish or designate regional digital innovation hubs where SMEs can pilot AI tools in a shared environment, access technical advisory services, and collaborate on common data challenges. Given the regulatory uncertainty participants cited, clear AI governance guidelines covering data ownership, algorithmic accountability, and cross-border data transfer would reduce managerial hesitancy and encourage long-term investment planning.

Several limitations of this study should be acknowledged when interpreting the findings. First, the study employs a purely qualitative design based on semi-structured interviews, which does not permit causal inference or statistical generalisation; the findings reflect participants' perceptions and self-reported experiences rather than objective performance data, and the reported benefits of AI adoption cannot be independently verified through this method alone. Second, as with all interview-based research, the data are subject to social desirability bias and recall bias: participants may have over- or under-stated their organisations' AI capabilities or the severity of the challenges they encountered. Third, the study is geographically and sectorally bounded, focusing exclusively on SMEs operating in the Lebanese food and beverage industry. Lebanon's specific economic conditions including currency instability, energy scarcity, import dependency, and regulatory uncertainty may not be representative of other MENA contexts or of the F&B sector in more stable economies, limiting the transferability of the findings. Fourth, purposive sampling, while appropriate for qualitative inquiry, introduces the possibility that participants with a particular interest in or awareness of AI adoption were over-represented, which could skew the picture of both drivers and barriers. Taken together, these limitations mean that the findings should be read as contextually specific insights into one under-researched setting rather than universally generalisable conclusions, and future research employing mixed or quantitative methods across broader geographic and sectoral samples would complement and extend the present work.

Future studies should focus on integrating quantitative in addition to qualitative approaches in studying the impact of AI adoption into SCM. Studies should also include other sectors across the MENA region. Researchers can also explore ethical and social dimensions focusing on cultural, ethical and societal perceptions that can influence AI acceptance across different regions of the world.

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