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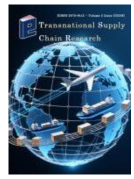

Research Article

AI-Driven Leadership in Manufacturing Supply Chains: A Systematic Literature Review, Research Gaps Analysis, and Exploratory Study of Egyptian Manufacturing Firms

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KEYWORDS

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ABSTRACT

Artificial intelligence (AI) is increasingly transforming manufacturing supply chains by enabling predictive analytics, intelligent automation, real-time visibility, data-driven decision-making, and adaptive coordination. Yet, the realization of sustained value from AI extends beyond technological adoption and depends on leadership capabilities that strategically align AI with organizational objectives, orchestrate technological and human resources, establish governance mechanisms, and reconfigure organizational capabilities. Despite the growing body of research on AI-enabled supply chains, the literature remains fragmented and largely technology-centric, with insufficient attention to the leadership mechanisms through which AI capabilities are translated into organizational and supply-chain outcomes, particularly in emerging-economy manufacturing contexts. This study addresses this gap through a two-stage design that integrates a systematic literature review of research published between 2011 and 30 May 2026 with exploratory empirical evidence from 60 senior managers across 15 Egyptian manufacturing firms. The review synthesizes research across key supply-chain functions to identify dominant themes, theoretical perspectives, methodological patterns, and unresolved research gaps, while the empirical inquiry examines AI maturity, leadership practices, and barriers to implementation and scaling. The findings reveal a persistent technology–leadership asymmetry, with limited scholarly attention to strategic AI leadership, governance, organizational readiness, resource orchestration, and human–AI collaboration. Empirical evidence further indicates heterogeneous levels of AI maturity, while legacy systems, fragmented data infrastructures, weak governance, organizational inertia, skills shortages, and leadership capability gaps constrain effective implementation. Integrating these insights, the study conceptualizes AI-driven leadership as a higher-order dynamic capability through which leaders sense AI-enabled opportunities and threats, seize them through strategic resource orchestration and governance, and reconfigure organizational and supply-chain capabilities to enhance intelligence, resilience, agility, and adaptability. The study advances AI and supply-chain scholarship by positioning leadership as a critical micro-foundation of AI-enabled transformation and extending the dynamic capabilities perspective to the emerging-economy manufacturing context.

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1. Introduction

The rapid diffusion of artificial intelligence (AI) and digital technologies is fundamentally reshaping supply chain management (SCM), driving a structural paradigm shift from static, rule-based decision-making toward autonomous, data-driven, and adaptive systems. In increasingly volatile, interconnected, and disruption-prone environments, traditional SCM approaches are no longer sufficient to ensure efficiency, responsiveness, and resilience. Instead, firms are progressively shifting toward AI-enabled infrastructures that transform fragmented and high-velocity data into real-time decision intelligence, enabling end-to-end visibility, predictive responsiveness, and system-wide optimization. This transformation reflects a fundamental reconfiguration of supply chain decision-making logic, from reactive control mechanisms toward anticipatory and autonomous orchestration. Against this backdrop, this study examines how AI is transforming SCM, the technological and analytical foundations enabling this transition, the barriers constraining adoption, and the implications for resilience, performance, and innovation [1-3].

SCM integrates procurement, production, inventory, logistics, and distribution processes to optimize cost, efficiency, and service performance through coordinated flows of materials, information, and financial resources. However, its effectiveness is increasingly constrained by structural interdependencies and data sensitivity, where small disturbances propagate across multi-tier networks, amplifying delays, inefficiencies, and systemic disruptions. At the system level, SCM has evolved into a complex adaptive network shaped by globalization, demand volatility, and recurrent disruptions across distributed value chains. Fragmented production systems, global sourcing, and multi-tier supplier ecosystems intensify interdependencies and systemic risk exposure, making responsiveness, visibility, and coordination central determinants of competitiveness. Moreover, globalization, e-commerce expansion, and increasing customer expectations for speed, customization, and reliability have further intensified operational complexity, reinforcing lean and agile paradigms as dominant yet increasingly strained design logics [4]. However, traditional forecast-driven planning systems remain fundamentally limited under uncertainty due to their reliance on stability assumptions, which are increasingly misaligned with today's dynamic and disruptive environments. This structural misalignment necessitates a shift toward adaptive, intelligence-enhanced decision-support systems that can learn continuously and respond in real time.

Figure 1 presents an overview of AI-driven leadership in manufacturing supply chains, illustrating how leadership capabilities orchestrate the strategic integration of artificial intelligence across key supply chain functions, including demand forecasting, procurement, production planning, inventory management, logistics, and customer relationship management. It highlights the role of AI-driven leadership in aligning AI technologies with organizational strategy, governance, digital infrastructure, and human capabilities to enable effective implementation and value creation. The figure further emphasizes the importance of organizational enablers, including robust data infrastructure, workforce competencies, cross-functional collaboration, and continuous learning, in supporting AI-enabled transformation. Collectively, these interconnected elements enhance decision quality, operational efficiency, supply chain resilience, organizational agility, and customer value, establishing AI-driven leadership as a strategic capability for developing intelligent, adaptive, and sustainable manufacturing supply chains.

1.1. Artificial Intelligence as a Transformative Enabler of SCM

Artificial intelligence represents a foundational technological shift in SCM, enabling a transition from descriptive and predictive analytics toward prescriptive and autonomous decision-making systems. Through machine learning, natural language processing, and intelligent automation, AI enables optimization, coordination, and automation across interconnected supply chain processes [5]. More critically, AI transforms heterogeneous and large-scale data into actionable intelligence, thereby enhancing decision quality, operational efficiency, responsiveness, and resilience [6,7].

From a resilience perspective, AI-driven analytics enhance anticipatory capabilities by enabling early detection of disruption risks and weak signals [8], while organizational capabilities in data governance and knowledge integration strengthen adaptive capacity under uncertainty [9,10]. Collectively, these developments indicate a shift toward intelligence-driven supply chains, where computational capability, operational execution, and organizational learning increasingly co-evolve as an integrated system.

AI-enabled SCM is grounded in interdisciplinary foundations spanning operations research, computer science, and industrial engineering, reflecting a transition from deterministic optimization toward complex adaptive systems. Classical techniques such as linear programming, stochastic optimization, nonlinear modeling, and combinatorial optimization remain essential; however, their integration with AI enables scalable and robust decision-support systems for high-dimensional and uncertain supply chain environments [11,12].

Machine learning strengthens SCM by capturing nonlinear dependencies in large-scale datasets, improving forecasting accuracy, demand planning, and inventory optimization [13]. Advanced methods—including neural networks, support vector machines, ensemble learning, and decision trees—enhance predictive performance and risk detection, while reinforcement learning, multi-agent systems, swarm intelligence, and game theory enable decentralized, adaptive, and sequential decision-making under uncertainty [14]. Despite these advancements, current applications remain fragmented across functional domains, with limited integration into unified strategic decision-making architectures and operational implementation pathways [15,16].

This technological evolution is further reinforced by Industry 4.0 enablers, including IoT, blockchain, additive manufacturing, and advanced tracking systems, which enhance visibility, traceability, and coordination across supply chain networks [5]. Blockchain improves transparency and trust by reducing information asymmetry [17], while IoT and big data infrastructures enable real-time monitoring and scalable analytics [18]. When integrated with digital twins and multi-agent systems, these technologies enable autonomous and self-organizing supply chain ecosystems, although adoption is constrained by cost, interoperability challenges, and system complexity [19].

From a performance perspective, AI enhances resilience by improving preparedness, alertness, and agility [20,21], while automation strengthens coordination, risk response, and operational efficiency [22,23]. Empirical studies confirm improvements in supply chain performance through predictive and self-learning systems [24,25], as well as gains in innovation and competitiveness [26]. However, AI's role in resilience under environmental dynamism remains insufficiently theorized, despite strong evidence that uncertainty significantly shapes supply chain performance outcomes [27-29].

1.2. Adoption Barriers and Research Gaps

Despite its transformative potential, AI adoption in SCM is constrained by financial, technical, and organizational barriers, including high implementation costs, cybersecurity risks, data privacy concerns, skill shortages, fragmented systems, and interoperability limitations. Legacy infrastructures and poor data quality further hinder scalability and integration [30]. Although AI enables a shift toward autonomous decision-making, most supply chains remain at early maturity stages due to technical, ethical, and organizational constraints. Challenges related to explainability, governance, accountability, and system integration complexity further necessitate structured implementation approaches [31,32].

More broadly, the literature remains fragmented across analytics, machine learning, and automation domains, lacking system-level theoretical integration linking technological capability, organizational readiness, and performance outcomes. From this synthesis, five key research gaps emerge: lack of integrated frameworks linking AI, SCM strategy, and performance outcomes; limited understanding of AI maturity toward autonomous supply chains; scarcity of longitudinal empirical evidence on resilience and sustainability impacts; absence of standardized AI-specific performance metrics; and underdeveloped socio-technical dimensions, including governance, ethics, and human–AI collaboration.

1.3. Research Objectives and Contributions

From a theoretical perspective, this gap reflects a broader limitation in the existing SCM and digital transformation literature, in which AI is often treated as a set of tools rather than as a capability embedded within organizational and managerial structures. This study addresses this limitation by drawing on dynamic capabilities theory and socio-technical systems thinking, positioning AI adoption as a capability-building and system-orchestration process rather than a purely technological implementation challenge.

Against this backdrop, this study conceptualizes AI-driven leadership as a higher-order dynamic capability that enables the integration, alignment, and scaling of AI within supply chain systems. AI-driven leadership is defined as the organizational capability to orchestrate technological, data, and human resources to achieve adaptive, resilient, and intelligence-driven supply chain performance. This perspective shifts the analytical focus from isolated technology deployment to capability orchestration, where leadership acts as the central mechanism enabling value realization from AI investments.

Accordingly, this study aims to advance the understanding of AI-driven leadership in manufacturing supply chains through a systematic literature review complemented by exploratory evidence from Egyptian manufacturing firms.

RO1: To synthesize the literature on AI-driven leadership in manufacturing supply chains.
RO2: To identify the theoretical, methodological, and empirical gaps in the existing literature.
RO3: To examine the key drivers and barriers affecting AI adoption in Egyptian manufacturing firms.
RO4: To develop an integrated conceptual framework and a transformation roadmap for AI-driven leadership in manufacturing supply chains.

The study addresses the following research questions:
RQ1: How is AI applied across manufacturing supply chain functions?
RQ2: What theoretical, methodological, and empirical gaps characterize the existing literature?
RQ3: What factors drive or constrain AI adoption in Egyptian manufacturing firms?
RQ4: How can AI-driven leadership be conceptualized as a higher-order dynamic capability for manufacturing supply chain transformation?

The remainder of the paper is organized as follows: Section 2 reviews the literature; Section 3 presents the gap analysis; Section 4 outlines the methodology; Section 5 develops the conceptual framework and transformation roadmap; and Section 6 concludes the study.

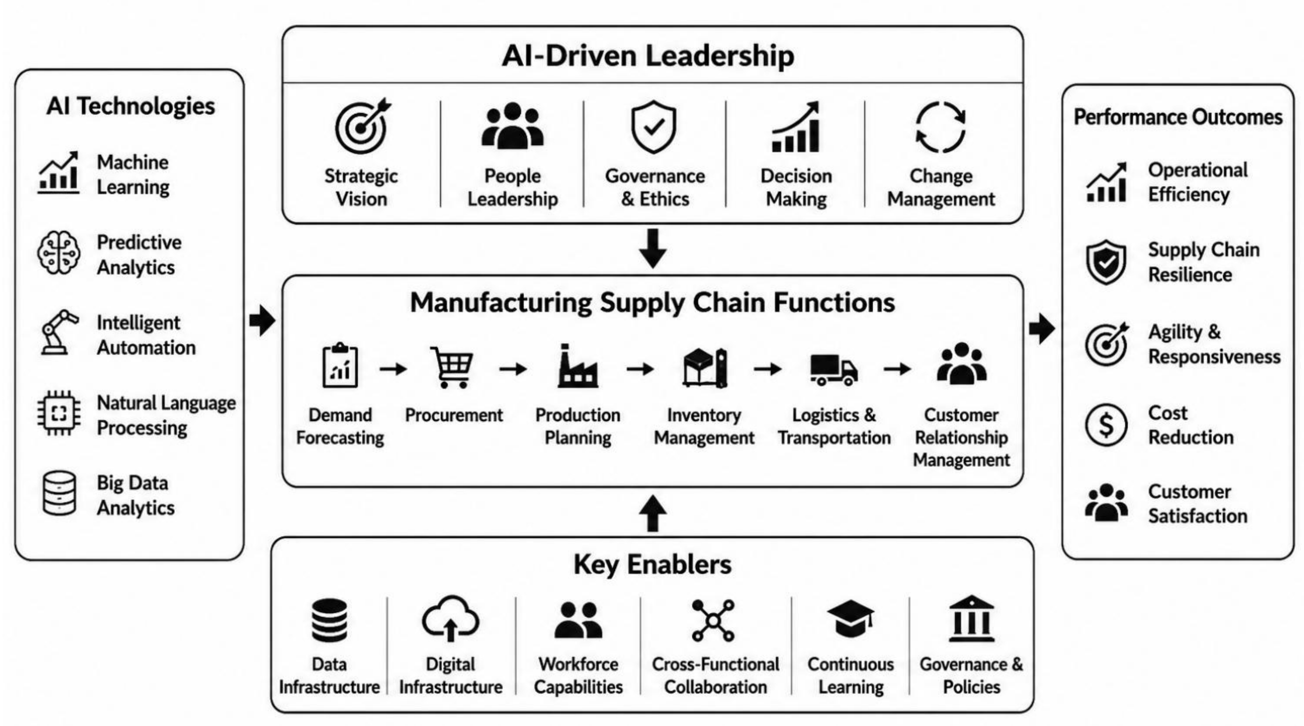

Figure 1. Overview of AI-driven leadership in manufacturing supply chains.

2. Literature Review

This study employs a Systematic Literature Review (SLR) to identify, synthesize, and critically evaluate the scholarly evidence on AI-driven leadership in manufacturing supply chains published between 2011 and 30 May 2026. This period captures the progressive development of artificial intelligence (AI), Industry 4.0, digital transformation, and intelligent supply-chain management. The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to strengthen methodological rigor, transparency, and reproducibility [33]. The review process comprises six stages: (1) data sources and search strategy, (2) eligibility criteria, (3) study screening and selection, (4) quality assessment, (5) data extraction and synthesis, and (6) methodological positioning.

1) Data Sources and Search Strategy: A comprehensive search was conducted across Scopus, Web of Science Core Collection, ScienceDirect, IEEE Xplore, Emerald Insight, SpringerLink, Taylor & Francis Online, Wiley Online Library, and Google Scholar, providing broad disciplinary coverage across manufacturing, supply chain management, operations management, information systems, digital transformation, and AI. The search strategy incorporated terms relating to artificial intelligence, AI-driven leadership, digital leadership, machine learning, manufacturing, manufacturing supply chains, supply chain management, Industry 4.0, smart manufacturing, and digital transformation, combined using Boolean operators (AND/OR), phrase searching, and truncation where supported. Searches were restricted to English-language, peer-reviewed journal articles published between 2011 and 30 May 2026. To ensure full reproducibility, the complete database-specific Boolean search strings are reported in Supplementary Material. Backward and forward citation searching was also undertaken for relevant seminal, highly cited, and recent studies to identify additional eligible publications.

2) Eligibility Criteria: Predefined inclusion and exclusion criteria were established before screening to ensure consistency and alignment with the research objectives. Studies were eligible when they were English-language, peer-reviewed journal articles published between 2011 and 30 May 2026 and examined AI applications, AI-driven or digital leadership, intelligent decision-making, or AI-enabled transformation within manufacturing supply chains. Eligible studies were required to provide empirical, conceptual, theoretical, or review-based evidence relevant to leadership, organizational capabilities, governance, AI adoption, or supply-chain transformation. Studies were excluded if they were conference proceedings, books, book chapters, dissertations, editorials, technical reports, duplicate publications, or focused exclusively on algorithm development or technical optimization without meaningful organizational, managerial, leadership, or supply-chain implications.

3) Study Screening and Selection: The initial search identified 165 records. Following the removal of 28 duplicates, 137 unique records proceeded to title and abstract screening, resulting in the exclusion of 74 records that did not meet the predefined eligibility criteria. The remaining 63 studies underwent full-text assessment. Backward and forward citation searching subsequently identified 16 additional potentially relevant studies, resulting in 79 full-text records for detailed evaluation. Following full-text assessment, 8 studies were excluded because of limited conceptual relevance (n = 3), insufficient methodological rigor (n = 2), inadequate manufacturing supply-chain focus (n = 2), or duplicate findings (n = 1). Consequently, 71 studies met the eligibility and quality requirements and were included in the final qualitative synthesis. The complete screening and selection process is presented in the PRISMA 2020 flow diagram (Figure 2).

4) Quality Assessment: The methodological quality of the included studies was assessed using a structured appraisal framework adapted from established SLR guidance. Each study was evaluated against five criteria: research relevance, theoretical contribution, methodological rigor, transparency of data collection and analysis, and clarity of findings. Each criterion was scored on a three-point scale (0 = not satisfied, 1 = partially satisfied, and 2 = fully satisfied), producing a maximum score of 10. This procedure enhanced the consistency, credibility, and methodological robustness of the evidence base.

5) Data Extraction and Synthesis: A standardized data-extraction protocol was applied to all studies retained for synthesis to ensure systematic and comparable evidence capture. Extracted information included publication characteristics, research objectives, theoretical foundations, methodological approaches, AI technologies, leadership dimensions, manufacturing and supply-chain functions, implementation drivers and barriers, organizational capabilities, and principal findings. The extracted evidence was analyzed using descriptive and thematic synthesis to identify publication trends, theoretical perspectives, methodological patterns, AI application areas, leadership capabilities, organizational readiness factors, implementation barriers, and research gaps. Particular attention was given to the extent to which existing studies connect AI adoption with leadership, organizational capability development, governance, and supply-chain outcomes. The resulting synthesis provided the evidence base for developing the study's AI-driven leadership framework and transformation roadmap.

6) Methodological Positioning: The study adopts a theory-building mixed-evidence approach that integrates the SLR with exploratory empirical evidence from Egyptian manufacturing firms. The SLR establishes the broader theoretical foundation by consolidating fragmented knowledge on AI-driven leadership and AI-enabled manufacturing supply chains, while the empirical component examines how these insights manifest within an emerging-economy manufacturing context. Importantly, the empirical analysis complements and extends, rather than reproduces, the analysis reported in [74], with a distinct focus on AI-driven leadership, capability development, and supply-chain transformation. Integrating the two evidence streams enables the study to identify and contextualize four mutually reinforcing capability domains—digital/data, organizational, human, and strategic governance capabilities—and to translate these insights into the proposed conceptual framework and transformation roadmap. This positioning establishes a clear distinction between evidence synthesized from the existing literature and the novel empirical and theoretical contribution of the present study.

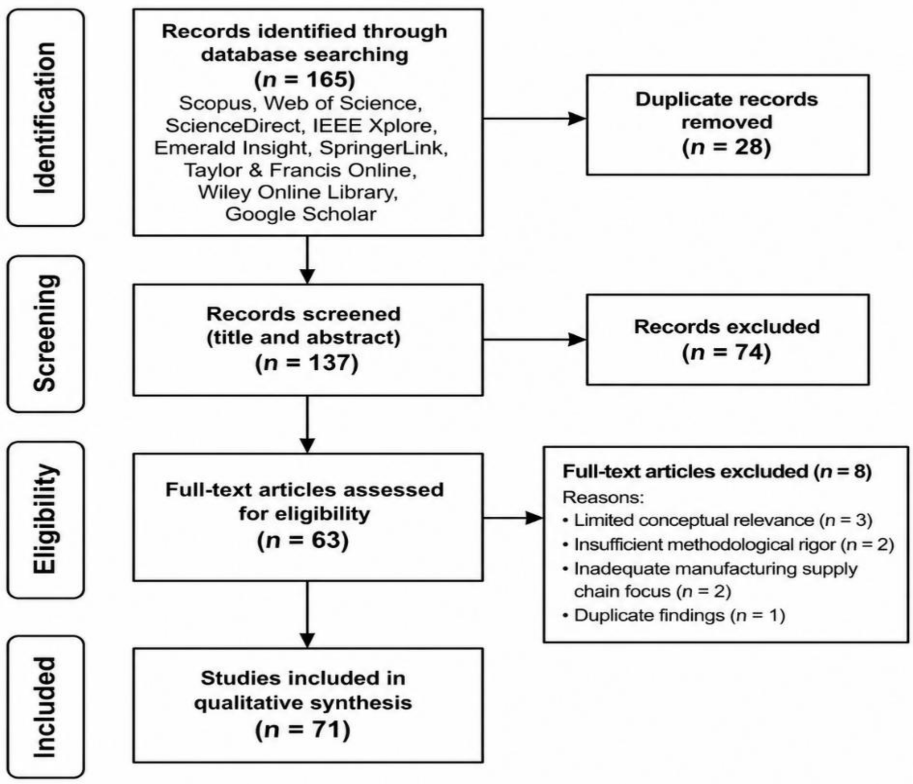

Figure 2. PRISMA flow diagram (2011–30 May 2026).

2.1. Evolution of Supply Chain Management and System Integration

SCM has evolved from isolated cost-minimization models toward integrated, system-wide coordination frameworks. Early EOQ models focused on deterministic inventory optimization but lacked system-level responsiveness. This was followed by MRP and ERP systems that enabled cross-functional integration across procurement, production, logistics, and finance, and later by JIT systems emphasizing lean, demand-driven operations. The SCOR framework standardized supply chain performance measurement and benchmarking and has since been enhanced with AI and ML to support predictive and prescriptive decision-making [34]. Consequently, SCM is increasingly viewed as a complex adaptive system where performance depends on real-time data integration, digital intelligence, and coordinated responsiveness rather than cost efficiency alone.

Supply chain performance measurement is commonly structured around quality and productivity. Quality reflects conformance to requirements, while productivity captures input–output efficiency [35], both essential for competitiveness. These are operationalized through metrics such as defect rates, service levels, inventory turnover, and labor utilization [36], while responsiveness indicators like cycle time and throughput gain importance under volatility. Standardization frameworks such as ISO 9001:2015 and ISO 14001:2015 formalize performance systems [37], complemented by KPIs including first-pass yield and customer satisfaction.

Despite these advancements, structural inefficiencies remain pervasive. Limited real-time visibility leads to delays and inventory imbalances [38], while fragmentation reduces coordination efficiency and forecasting accuracy. Major disruptions such as COVID-19 exposed systemic vulnerabilities, including demand shocks and supply shortages, alongside geopolitical and macroeconomic instability. Operational constraints such as labor shortages, automation costs, cybersecurity risks, and legacy IT systems further hinder efficiency and digital transformation.

2.2. Artificial Intelligence in Supply Chain Transformation

AI is transforming SCM from reactive systems into predictive, prescriptive, and increasingly autonomous networks. In logistics, AI enables real-time routing optimization using dynamic variables such as traffic and weather [39,40], while ML enhances transportation and pricing decisions under uncertainty [41]. This reflects a broader shift toward adaptive, data-driven supply chains under volatility [42].

Early AI systems relied on rule-based expert systems with limited adaptability [43]. Later, machine learning improved forecasting by capturing nonlinear demand patterns [44], enabling more proactive planning. AI further extended optimization through heuristics and metaheuristics for routing, scheduling, and facility location, integrating computational intelligence with operations research [45,46].

Advanced AI methods include neural networks, genetic algorithms, and swarm intelligence. Neural networks support nonlinear forecasting, anomaly detection, and risk assessment [47], genetic algorithms address combinatorial optimization, and swarm intelligence enables decentralized optimization for routing, inventory, and scheduling.

AI capabilities are significantly strengthened through integration with IoT, big data analytics, and blockchain. IoT enables real-time monitoring, big data supports large-scale analytics, and blockchain enhances transparency and traceability [18]. Integration with digital twins and multi-agent systems further enables autonomous supply chain ecosystems [19], although cost and complexity remain barriers.

At the operational level, AI improves robotics-based automation and logistics efficiency, enhances multi-echelon inventory optimization, and supports supplier evaluation, fraud detection, compliance, and risk management. It also strengthens resilience through disruption modeling, improves customer service via NLP, and supports sustainability through emissions reduction and predictive maintenance [39,48,49].

2.3 Machine Learning in Supply Chain Transformation

Machine learning is a core enabler of AI-driven supply chain transformation, supporting predictive and prescriptive decision-making through large-scale pattern recognition. By capturing nonlinear relationships in complex datasets, ML improves forecasting accuracy, inventory optimization, and risk detection beyond traditional statistical models. Techniques such as neural networks, clustering, and ensemble learning enhance demand planning, logistics optimization, and disruption management. Empirical studies show that SARIMA and Random Forest models improve forecasting using external variables such as weather and holidays, while hybrid LSTM–Q-learning–genetic algorithms strengthen adaptive forecasting and replenishment.

Demand forecasting remains the most studied ML application in SCM. [50] report increased adoption across forecasting, inventory, and transportation planning using the SCOR framework. [51] show improvements in sales forecasting and logistics efficiency, while [52] integrate ML with optimization for supplier selection and allocation. However, limitations persist in generalizability, scalability, and data quality.

Supplier management benefits from ML-based classification and evaluation methods such as Random Forest [53], ML–MARCOS hybrids [54], neural networks [55], decision trees [56], and SVMs [57]. Despite methodological diversity, interpretability and heterogeneous data integration remain key constraints.

In logistics and disruption management, ML enhances efficiency and resilience [58,59], including transportation cost reduction [53], risk prediction [60], and autonomous logistics systems [61]. However, real-time integration, cybersecurity, and interoperability issues remain significant barriers.

Hybrid ML–simulation approaches integrate discrete-event simulation with reinforcement learning to manage uncertainty and complexity [62,63], though scalability and real-world validation remain limited.

ML is increasingly embedded in digital and sustainability-oriented supply chains. SCM 4.0 integrates AI forecasting, blockchain, digital twins, and predictive maintenance [61], while cloud-based and smart manufacturing systems support sustainability [64,65]. Nevertheless, circular economy integration and real-time sustainability monitoring remain underdeveloped [66,67].

Across sectors, ML supports food safety and risk monitoring [68], agri-food optimization [69], and manufacturing applications such as fault detection and cost optimization [70]. However, applications remain fragmented and weakly transferable. Overall, ML improves forecasting, supplier evaluation, logistics, and decision-making, but remains fragmented and weakly integrated with broader digital ecosystems.

In conclusion, AI adoption in supply chain management (SCM) is constrained by structural, technological, and organizational barriers [48], including data fragmentation, weak governance mechanisms, talent shortages, legacy systems, and limited trust and explainability. In addition, AI effectiveness is inherently context-dependent and requires continuous adaptation across heterogeneous operational environments [71]. However, prevailing performance metrics—primarily focused on cost, quality, and productivity—are insufficient to capture AI-enabled capabilities such as autonomy, adaptability, and real-time intelligence. This underscores the need for dedicated AI-specific performance and evaluation frameworks. Against this backdrop, five key research gaps emerge: the lack of integrated frameworks linking AI capabilities, SCM strategy, and performance outcomes; limited understanding of AI maturity pathways toward autonomous supply chains; scarcity of longitudinal empirical evidence on resilience and sustainability impacts; absence of standardized AI-specific performance metrics and benchmarks; and underdeveloped socio-technical perspectives, particularly regarding governance, ethics, and human–AI collaboration.

3. Challenges and Research Gaps Analysis

The adoption of artificial intelligence (AI) and machine learning (ML) in supply chain management (SCM) has significantly advanced forecasting accuracy, operational efficiency, visibility, and resilience. Despite these gains, the transition toward fully autonomous, self-optimizing supply chains remains limited. As summarized in Table 1, this limitation is not attributable to a single factor but to a set of deeply interconnected structural, technological, organizational, and methodological constraints that collectively slow down AI maturity in SCM.

Referring to Table 1, these challenges and associated research gaps can be systematically organized into five interdependent dimensions: (i) data infrastructure and digital integration, (ii) security, trust, and ethical governance, (iii) organizational and human capability constraints, (iv) methodological, theoretical, and performance measurement limitations, and (v) maturity, scalability, and autonomous system development. Together, these dimensions explain why AI-enabled SCM remains in a transitional stage between augmentation and autonomy.

Overall, while AI-enabled SCM improves decision quality across forecasting, logistics, supplier management, and resilience planning, its deployment remains fragmented, uneven, and largely experimental at scale. The barriers identified in Table 1 are systemic in nature, requiring simultaneous advancement in technology, governance, organizational readiness, and theoretical integration.

1) Data Infrastructure and Digital Integration: The most fundamental constraint is fragmented and poorly governed data ecosystems. Supply chain data is dispersed across multiple independent actors, platforms, and legacy systems, resulting in silos that severely limit interoperability. Because AI and ML models depend on high-quality, integrated datasets, such fragmentation undermines predictive accuracy, robustness, and scalability [72]. This challenge is compounded by heterogeneous IT landscapes and legacy ERP infrastructures that were not designed for real-time analytics or autonomous decision-making. Consequently, integration with enabling technologies such as IoT, cloud computing, blockchain, and digital twins remains complex, costly, and often partial. The absence of standardized data architectures continues to prevent end-to-end digital continuity across supply chain networks. Addressing this gap requires interoperable, cloud-native, and governance-enabled data ecosystems capable of supporting real-time visibility, cross-organizational coordination, and scalable AI deployment.

2) Security, Trust, and Ethical Governance: Increasing digitalization amplifies cybersecurity exposure, data privacy risks, and system vulnerability. As supply chains become more interconnected through AI, IoT, and cloud infrastructures, the attack surface expands significantly, increasing operational and strategic risk [41]. Although blockchain enhances transparency and traceability, it introduces governance complexity in multi-stakeholder environments where accountability and control are distributed. More critically, the "black-box" nature of many AI systems limits explainability, reducing managerial trust and slowing adoption in high-stakes decision contexts [48]. This creates a pressing need for explainable AI (XAI), robust governance frameworks, and cybersecurity-by-design architectures that jointly ensure transparency, accountability, and operational resilience.

3) Organizational and Human Capability Constraints: Organizational readiness is a decisive factor in determining AI implementation success. Many firms continue to face low digital maturity, fragmented internal coordination, and weak alignment between analytics systems and decision-making structures [73]. Even when AI tools are available, their value is often underutilized due to insufficient process integration. A critical bottleneck is the shortage of interdisciplinary talent capable of bridging AI, data science, and SCM domain expertise. This capability gap leads to overdependence on external vendors and limits internal knowledge accumulation. Additionally, cultural resistance to algorithmic decision-making persists, particularly in environments where managerial judgment and experience remain dominant. This reinforces the need for structured transformation strategies that combine workforce upskilling, change management, and human–AI collaboration design.

4) Methodological, Theoretical, and Performance Measurement Limitations: Existing studies are typically domain-specific—focused on forecasting, logistics, supplier selection, or inventory optimization—without sufficient integration into holistic end-to-end decision systems. A major gap lies in performance measurement. Traditional KPIs such as cost, service level, and efficiency remain dominant, yet they are insufficient for capturing AI-enabled capabilities such as adaptability, autonomy, learning speed, and real-time responsiveness [35,36]. This misalignment limits both empirical comparability and managerial applicability. From a theoretical perspective, AI applications in SCM remain loosely connected to foundational frameworks such as the Resource-Based View (RBV), Organizational Information Processing Theory (OIPT), and dynamic capability theory. These frameworks are rarely integrated into a unified explanatory model of AI-driven supply chain transformation, resulting in theoretical fragmentation.

5) Maturity, Scalability, and Autonomous Systems Development: AI adoption in SCM is still in an early-to-intermediate maturity stage. Most implementations remain confined to pilot projects, proof-of-concept systems, or partially integrated solutions, rather than fully autonomous operational ecosystems. Scalability remains a major limitation. Many AI models demonstrate strong performance in controlled or narrow contexts but fail to generalize across industries, geographies, and disruption scenarios. This restricts their applicability in complex global supply chain networks characterized by uncertainty and heterogeneity. Furthermore, although Industry 4.0 technologies—including IoT, blockchain, robotics, cloud computing, and digital twins—offer complementary capabilities, their integration remains fragmented. The lack of unified architectural standards and high implementation costs continue to hinder the development of fully autonomous supply chain ecosystems. This underscores the necessity of staged maturity models and structured AI transformation roadmaps that progressively evolve from decision support to semi-autonomous and ultimately fully autonomous supply chain systems.

In conclusion, Table 1 demonstrates that the barriers to AI-enabled SCM transformation are multidimensional, interdependent, and systemic. They span data infrastructure fragmentation, cybersecurity and governance risks, organizational capability gaps, methodological and theoretical limitations, and insufficient system maturity. Overcoming these challenges requires not only technological advancement but also organizational transformation and theoretical integration, enabling the progression toward intelligent, resilient, and autonomous supply chain ecosystems.

Table 1. Challenges, research gaps, and strategic implications.

Group	Dimension	Key Challenges	Research Gaps	Strategic Implications
1. Data Infrastructure & Digital Integration	Data Governance	Fragmented, siloed data; weak standards and interoperability	Lack of end-to-end AI-ready data integration frameworks	Develop interoperable, federated data ecosystems for real-time analytics
	Digital Integration	Legacy systems; high integration complexity across ERP, IoT, cloud, blockchain	Lack of scalable Industry 4.0 SCM architectures	Adopt modular, API-driven, cloud-native architectures
2. Security, Trust & Ethical Governance	Cybersecurity & Trust	Cyber risks and vulnerabilities in interconnected systems	Limited SCM-specific AI cybersecurity frameworks	Implement zero-trust architectures with traceability
	Explainability & Ethics	Low transparency and accountability in AI systems	Underdeveloped explainable AI (XAI) for SCM contexts	Develop explainable and auditable AI for trustworthy decision-making
3. Organizational & Human Capability Constraints	Organizational Readiness	Low digital maturity; weak governance structures	Lack of SCM-specific AI maturity models	Develop AI readiness and maturity frameworks
	Human Capital	Shortage of AI–SCM expertise; reliance on external vendors	Limited research on human–AI collaboration	Strengthen interdisciplinary skills and hybrid capabilities
4. Methodological, Theoretical & Measurement Limitations	Methodological Fragmentation	Siloed AI applications across SCM functions	Lack of integrated end-to-end decision-support architectures	Develop multi-level SCM decision-support systems
	Theoretical Fragmentation	Fragmented SCM, RBV, OIPT, and dynamic capability perspectives	Absence of a unified theory of AI value creation in SCM	Build integrated AI–SCM theoretical frameworks
	Performance Measurement	Reliance on traditional KPIs (cost, efficiency, service)	Lack of AI-native performance metrics	Develop metrics capturing autonomy, adaptability, and resilience
5. Maturity, Scalability & Autonomous Systems	Maturity & Scalability	Early-stage, pilot-based adoption; limited scalability	Lack of validated AI maturity models	Establish staged AI maturity pathways for SCM transformation
	Autonomous Systems	AI supports decision-making rather than full autonomy	Limited evidence of autonomous SCM systems	Enable autonomous SCM via digital twins and multi-agent systems

4. Research Methodology

This study adopts an exploratory mixed-methods design to investigate AI adoption and its implications for AI-driven leadership in Egypt's manufacturing sector. While AI can enhance data-driven decision-making, operational efficiency, innovation, workforce productivity, and organizational responsiveness, realizing these benefits depends not only on technological adoption but also on organizational readiness, leadership capabilities, governance, data quality, and the effective orchestration of human and technological resources. In emerging economies such as Egypt, AI adoption remains uneven across firms and functions and is influenced by persistent challenges, including legacy systems, fragmented data infrastructures, limited digital capabilities, governance deficiencies, and workforce skill gaps. Accordingly, the study examines AI adoption and maturity, leadership practices, organizational readiness, implementation barriers, and their implications for AI-enabled manufacturing supply-chain transformation.

The methodological foundation of the empirical component is informed by the approach reported in [74]; however, the present study constitutes a distinct investigation with a different research focus, analytical framework, and theoretical contribution. Specifically, this study integrates the empirical investigation with a systematic literature review (SLR) to examine how leadership capabilities enable manufacturing firms to convert AI-related technological and organizational resources into sustained supply-chain value. Thus, the empirical analysis extends beyond measuring AI adoption to investigate the leadership, organizational, human, digital/data, and governance capabilities required to govern, integrate, and scale AI-enabled transformation. The present study therefore uses the empirical evidence to complement and contextualize the SLR findings rather than reproduce the analysis reported in [74]. Figure 3 presents the overall research methodology adopted in the present study.

(1) Population and Sample. The study focused on senior leaders and decision-makers across eight manufacturing sectors in Egypt: automotive, electronics, home appliances, glass and crystal, steel, chemicals, textiles, and food processing. These sectors were selected because of their economic importance and differences in technological use and digital maturity. The sample comprised 60 senior leaders from 15 manufacturing firms, representing variation in organizational size, operational scale, and digital maturity. Participants were involved in strategic planning, operations, information technology (IT), human resources (HR), research and development (R&D), or innovation. Their positions provided informed perspectives on AI adoption, organizational readiness, implementation barriers, leadership practices, and the development of AI-enabled capabilities.

(2) Sampling Procedure. A purposive sampling strategy was used to select firms and participants with direct knowledge of AI adoption and digital transformation. The selected firms represented different levels of AI adoption, technological readiness, organizational characteristics, and manufacturing activities. Participants were drawn from IT, operations, HR, and R&D to capture complementary functional perspectives on AI implementation and leadership. The sample also included multinational subsidiaries and medium-sized local manufacturers, providing variation in technological resources, organizational capabilities, implementation challenges, and leadership practices. Given the purposive sampling approach, the objective was to obtain information-rich and diverse perspectives rather than statistical representation of the wider Egyptian manufacturing sector.

(3) Data Collection and Instrumentation. Primary data were collected using a structured survey instrument based on validated measures of AI adoption and leadership effectiveness. The survey assessed AI integration across strategic, operational, and support functions, as well as organizational readiness, perceived leadership effectiveness, and barriers to AI implementation and scaling. Open-ended questions complemented the structured measures by capturing managers' perspectives on implementation challenges, strategic priorities, organizational responses, governance issues, and lessons learned from AI initiatives. Before administration, the instrument was reviewed by experts to assess its relevance, clarity, and content validity and was subsequently pretested to identify unclear items and improve the questionnaire. The revised instrument was then used for the final data collection.

(4) Data Analysis. Quantitative data were analyzed using descriptive statistics, including percentages, mean scores, standard deviations (SD), coefficients of variation (CV), and severity classifications. Leaders' Perception (%) represents the percentage of respondents who considered a particular factor or barrier

significant; the mean score, based on a five-point Likert scale, indicates the average level of agreement or perceived importance; the standard deviation (SD) measures variation in responses; and the coefficient of variation (CV) measures relative variation and is calculated as the standard deviation divided by the mean and expressed as a percentage. Barriers were classified as High when the mean score was ≥ 3.6, Moderate when the mean ranged from 3.3 to 3.5, and Low when the mean was ≤ 3.2. This classification was used to identify priority barriers and areas requiring managerial attention. Qualitative responses were analyzed through thematic analysis to identify recurring themes related to AI adoption, leadership practices, organizational readiness, implementation barriers, governance, workforce capabilities, and strategic priorities. The qualitative findings were then integrated with the quantitative results through triangulation, providing a more complete understanding of AI adoption and the organizational conditions that influence AI-driven leadership.

(5) Ethical Considerations. Participation was voluntary, and informed consent was obtained from all respondents before data collection. Participants were informed about the purpose of the study and the intended use of the information provided. The identities of participants and participating organizations were kept confidential, and identifying information was excluded from the analysis and reporting. Research data were securely stored and used solely for academic purposes. These procedures protected participants' rights, privacy, and confidentiality and encouraged candid responses concerning AI adoption, organizational challenges, governance, and leadership practices.

(6) Study Limitations and Mitigation. Several limitations should be considered when interpreting the findings. First, the cross-sectional design captures AI adoption and leadership perceptions at a specific point in time and therefore cannot fully explain how these factors develop as firms gain experience and AI maturity; future longitudinal studies could address this limitation. Second, the relatively small sample and purposive sampling strategy limit statistical generalizability, although the inclusion of eight manufacturing sectors, different organizational sizes, and multiple managerial functions provides broad contextual coverage. Third, self-reported data may introduce response or perceptual bias; this risk was reduced by obtaining perspectives from different organizational functions and integrating quantitative and qualitative evidence. Future research could strengthen the evidence through larger samples, probability-based sampling, longitudinal designs, and objective organizational and operational performance measures. Finally, although the empirical setting is manufacturing, the methodological framework may provide a useful basis for examining AI-driven leadership in other industrial sectors and emerging economies.

(7) Analytical Framework. The analytical framework comprises four interrelated dimensions: AI Adoption Across Business Functions, which examines the extent and maturity of AI use across strategic, operational, and support functions and its implications for decision-making, efficiency, workforce productivity, innovation, and supply-chain responsiveness; Barriers to AI-Enabled Leadership, which examines technological, organizational, human, ethical, and governance barriers that may constrain AI adoption and leadership effectiveness; Strategic Corrective Actions, which translate identified adoption gaps and barriers into practical interventions involving digital and data capabilities, workforce skills, organizational culture, human–AI collaboration, leadership development, and governance; and AI-Enabled Leadership Roadmap, which translates the empirical findings into a phased framework linking strategic priorities, implementation responsibilities, and measurable key performance indicators (KPIs), supporting progression from AI readiness and experimentation to functional integration, cross-functional scaling, strategic alignment, and sustainable value creation.

Overall, this methodology provides a structured, exploratory, and context-specific approach to examining AI adoption and AI-driven leadership in Egypt's manufacturing sector. The integration of quantitative evidence and qualitative managerial insights provides a more comprehensive understanding of the technological, organizational, human, and governance factors that influence AI implementation and leadership effectiveness. The findings provide an empirical basis for identifying critical barriers, developing targeted interventions, and designing an AI-enabled leadership roadmap to support organizational performance, innovation, resilience, and manufacturing supply-chain transformation [74].

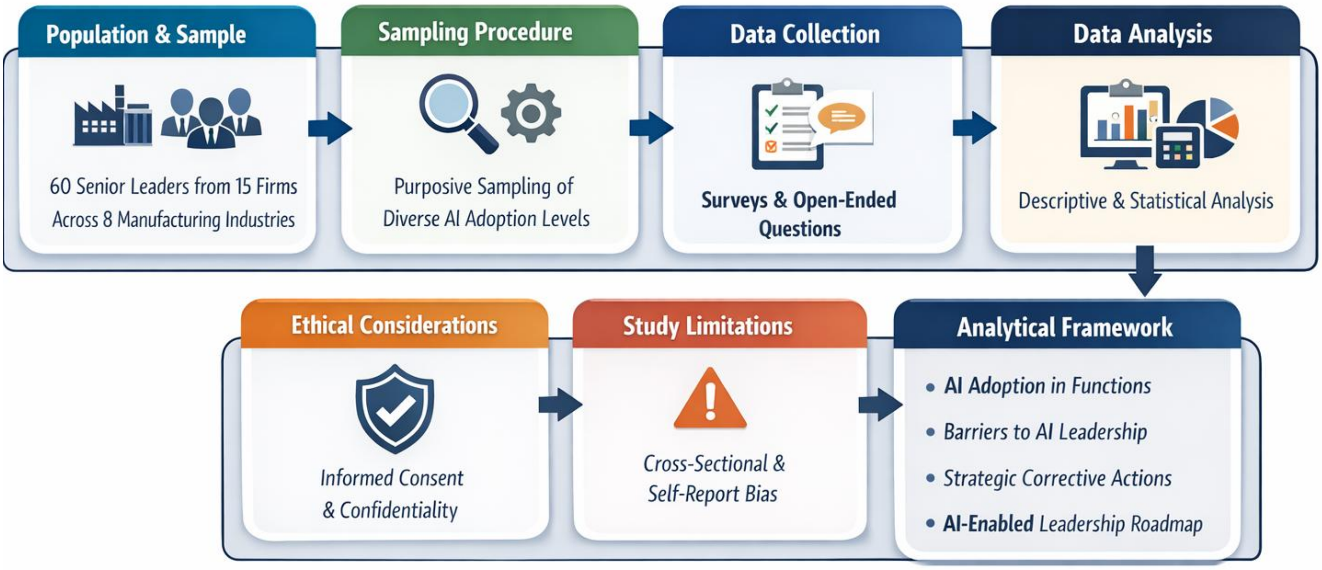

Figure 3. Research methodology framework for AI adoption and leadership effectiveness.

4.1. AI Adoption Across Business Functions

AI adoption in Egypt's manufacturing sector varies considerably across business functions. As shown in Table 2, adoption differs across the six main functional areas, reflecting differences in digital maturity, organizational readiness, available resources, and strategic priorities. Firms appear to adopt AI mainly for specific business needs rather than as an integrated organization-wide capability. Applications that provide clear and immediate benefits are more widely adopted, whereas those requiring stronger data infrastructure, cross-functional coordination, advanced skills, and organizational change remain limited. This pattern indicates that AI adoption is developing through individual applications rather than through a coordinated transformation strategy.

Strategic planning shows the highest level of AI adoption, with 21–25% of leaders reporting the use of predictive analytics, dashboards, and CRM systems. This suggests that firms are giving priority to AI applications that support planning, decision-making, performance monitoring, and customer management. These applications can provide visible benefits without major changes to existing processes. However, AI adoption for market intelligence is only 4%, indicating limited use of AI to monitor competitors, market trends, and external developments. This may weaken firms' ability to identify opportunities, anticipate threats, and respond quickly to changes in the business environment.

AI adoption in operations is moderate but uneven. Performance monitoring (18%) and production planning (11%) have relatively higher adoption, showing that firms are using AI to improve planning, monitoring, and operational efficiency. In contrast, process automation (7%) and energy optimization (8%) remain limited. This suggests that firms are mainly using AI to improve existing processes rather than to redesign production activities. Although this approach can generate short-term efficiency gains, greater use of automation, real-time data, and connected systems may be needed to achieve deeper operational transformation.

In quality and safety management, AI is used more for quality control and defect detection (14%) than for predictive safety (6%). This indicates that firms are more focused on identifying existing quality problems than on predicting and preventing safety risks. Expanding the use of predictive AI could help firms identify risks earlier, strengthen preventive action, and improve workplace safety and operational reliability.

AI adoption in supply chain and inventory management is also selective. AI is used for optimization (12%) and demand forecasting (10%), indicating growing use of AI to improve planning, inventory decisions, and resource allocation. However, only 4% of leaders report using AI for supplier performance evaluation. This low level of adoption may limit visibility into supplier performance and upstream risks. Greater use of AI-based supplier analysis could support better supplier decisions, earlier risk identification, stronger coordination, and greater supply chain resilience.

A significant gap is evident between customer analytics and workforce analytics. Customer analytics has an adoption rate of 16%, indicating that firms recognize the value of AI for understanding customers and supporting market-facing decisions. In contrast, workforce analytics is used by only 3% of respondents. This suggests that AI-enabled workforce management remains underdeveloped. Limited use of workforce analytics may restrict firms' ability to identify skills gaps, improve workforce planning, support employee development, and prepare employees for changing work requirements. This is particularly important because successful AI transformation requires organizations to develop human capabilities alongside technological capabilities.

The lowest adoption levels are found in innovation and product development. AI is used in product design by only 5% of respondents and in R&D by just 2%. These findings indicate that firms mainly use AI to improve existing activities rather than to support innovation, experimentation, and new product development. While this efficiency-focused approach can provide short-term benefits, limited AI use in innovation may reduce firms' ability to develop new products, improve processes, and create new sources of competitive advantage over the longer term.

Overall, the findings reveal a selective and uneven pattern of AI adoption across Egyptian manufacturing firms. Adoption is relatively stronger in strategic planning and customer-related activities, moderate in operations and supply chain management, and considerably lower in workforce management, market intelligence, predictive safety, innovation, and R&D. This pattern suggests that many firms are still developing their AI capabilities and are using AI mainly to address specific business problems rather than as part of an integrated transformation strategy. From an AI-driven leadership perspective, the key challenge is therefore not simply increasing AI adoption but developing the leadership, data, governance, technological, and human capabilities required to connect AI applications across functions. Greater attention to workforce analytics, market intelligence, supplier management, innovation, and cross-functional integration could help firms move from selective AI adoption toward an integrated and strategically managed AI capability, strengthening leadership effectiveness, supply chain resilience, innovation, adaptability, and long-term competitiveness.

Table 2. AI adoption across business functions in Egypt's manufacturing sector.

Category/function	AI application area	Strategic objective	% of leaders utilizing AI	Adoption level
Strategic Planning	Predictive analytics,	Facilitate data-driven decision-making	25%	High
	Strategic planning tools	Optimize resource allocation and support	21%	High
	Market trend & competitive	Monitor competitors and anticipate	4%	Low
Operations & Production	Operational performance	Improve efficiency and minimize	18%	Medium
	Production scheduling &	Maximize throughput and prevent	11%	Medium
	Energy management &	Reduce energy costs and improve	8%	Low
	Process automation &	Automate workflows and scale	7%	Low
Quality & Safety	Quality control & defect	Ensure consistent product quality and	14%	Medium
	Safety monitoring & hazard	Prevent workplace accidents and enhance	6%	Low
Supply Chain &	Supply chain optimization	Streamline logistics and improve	12%	Medium

	Inventory management &	Align supply with demand and reduce	10%	Medium
	Supplier performance	Strengthen supplier reliability and	4%	Low
Customer & HR Analytics	Customer insights	Personalize engagement and enhance	16%	Medium-
	Workforce productivity & HR	Optimize workforce performance and	3%	Low
Innovation & Design	Product design & simulation	Accelerate product development and	5%	Low
	Research & Development (R&D)	Drive innovation and shorten development cycles	2%	Very Low

4.2. Barriers to Effective AI-Enabled Leadership

Effective AI-enabled leadership in Egypt's manufacturing sector is constrained by interconnected digital, organizational, human, ethical, and strategic barriers. Although AI adoption is expanding across several business functions, technology adoption alone does not ensure that firms will realize meaningful organizational value. Leaders must align AI with business strategy, reliable data, operational processes, workforce capabilities, and governance systems. Weakness in any of these areas can limit the effective use of AI and reduce its contribution to decision-making, operational efficiency, workforce performance, innovation, and supply chain resilience. Identifying these barriers is therefore essential for understanding the uneven progress of AI adoption and the leadership capabilities required to support successful transformation.

The barriers were examined across six functional areas: Strategic & Planning, Operations & Production, Quality & Safety, Supply Chain & Inventory, Customer & HR Analytics, and Innovation & Design. This functional perspective shows how AI-related challenges differ across the organization. In Strategic & Planning, the use of predictive analytics, dashboards, and CRM tools is constrained by weak AI leadership, poor data quality, and limited executive support. In some firms, AI applications are not sufficiently aligned with strategic objectives, while the low use of market intelligence indicates limited attention to competitors and emerging market trends. As shown in Table 3, weak strategic alignment, resistance to AI, and limited integration of AI into strategic decisions reduce leaders' ability to use AI for effective planning and strategic foresight.

In Operations & Production, AI applications such as performance monitoring, production scheduling, energy management, and robotics are constrained by legacy systems, organizational silos, and inadequate digital infrastructure. Limited access to real-time information further reduces the speed and quality of operational decisions. These challenges show that AI value depends on the ability to connect data, systems, equipment, and managerial decisions. In Quality & Safety, the use of defect detection and hazard prediction is limited by weak human–AI collaboration, concerns about algorithmic bias, and employee concerns about job displacement. Such issues may reduce trust in AI and limit its effective use for quality improvement, risk prevention, and workplace safety.

In Supply Chain & Inventory, fragmented information, limited visibility, weak coordination, and an underdeveloped digital culture restrict the use of AI for demand forecasting, inventory management, and supplier monitoring. These limitations make it difficult for leaders to develop a timely and complete view of supply chain conditions and respond effectively to disruptions. In Customer & HR Analytics, low trust in AI, resistance to change, and concerns about job displacement limit the use of AI for customer engagement, workforce planning, productivity improvement, and skills management. This highlights the human side of AI transformation, as successful adoption requires leaders to manage changes in employee roles, skills, responsibilities, and expectations. In Innovation & Design, including AI-enabled product simulation and R&D, adoption is constrained by short-term investment priorities, weak digital culture, and inadequate infrastructure. These barriers limit the use of AI to support experimentation, product development, research, and long-term competitive differentiation.

The barriers identified across these functional areas were consolidated into four interrelated dimensions, as presented in Table 4: Digital & Data Capabilities, Cultural & Organizational Change, Human-Centric & Ethical Concerns, and Strategic Governance & Investment. Digital & Data Capabilities include poor data quality, weak data governance, insufficient AI and digital leadership skills, inadequate infrastructure, and limited access to real-time analytics. Cultural & Organizational Change includes resistance to AI-driven transformation, organizational silos, weak change-management capabilities, and limited digital learning. Human-Centric & Ethical Concerns include fairness, transparency, accountability, trust, and employee concerns about AI and job displacement. Strategic Governance & Investment includes the absence of a unified AI strategy, weak alignment with business priorities, regulatory uncertainty, financial concerns, and a short-term investment focus. These dimensions demonstrate that AI transformation requires coordinated changes in technology, leadership, organizational culture, workforce capabilities, and governance.

The perceived importance of these barriers is presented in Table 5 using five measures: Leaders' Perception (%), representing the proportion of respondents who identified a barrier as significant; Mean (1–5 Likert), representing the average level of agreement; Standard Deviation (SD), indicating variation in responses; Coefficient of Variation (CV, %), measuring relative dispersion; and Severity, classified as High (Mean ≥ 3.6), Moderate (3.3–3.5), or Low (≤3.2). Together, these measures provide a consistent basis for comparing barriers across firms and functional areas and identifying the areas requiring greater managerial attention.

The results identify Digital & Data Capabilities as the most critical barrier dimension. Poor data quality and weak governance (A1, 48%) and insufficient AI and digital leadership skills (A2, 46%) are the most frequently reported barriers. These findings indicate that firms face both a data challenge and a leadership capability challenge. Difficulties integrating AI with legacy systems (A3), underdeveloped infrastructure (A4), and limited access to real-time analytics (A5) further restrict leaders' ability to obtain reliable information and make timely decisions. The findings therefore suggest that the challenge is not simply whether firms have access to AI technologies, but whether they possess the data, systems, and leadership capabilities needed to use them effectively.

Cultural & Organizational Change represents another important barrier. Resistance to AI-driven transformation (B1, 36%) and limited executive sponsorship (B2, 31%) indicate that AI adoption depends strongly on leadership commitment and organizational readiness. Leaders need to communicate the purpose and value of AI, involve employees in the transformation process, and provide appropriate training and support. These actions can reduce resistance and improve employees' readiness to work with AI-enabled systems.

Human-Centric & Ethical Concerns (C1–C2) highlight the importance of trust, transparency, accountability, fairness, and effective human–AI collaboration. AI-supported decisions can affect employees, customers, suppliers, and other stakeholders. Leaders therefore need clear principles and responsibilities for the use of AI and should ensure that AI-supported decisions remain understandable, accountable, and appropriately supervised. Building trust is particularly important where employees associate AI with job displacement or reduced autonomy.

Strategic Governance & Investment presents a further challenge. The absence of a unified AI strategy (D1, 32%) and perceived financial risks (D2, 29%) suggest that some firms continue to manage AI as a set of separate technology projects rather than as a long-term organizational capability. Without clear priorities, governance structures, investment criteria, and accountability mechanisms, AI initiatives may remain fragmented and difficult to scale. Leaders therefore need to connect AI investments with business objectives, supply chain priorities, workforce development, risk management, and measurable performance outcomes.

The coefficients of variation, ranging from 19% to 25%, indicate differences in perceptions across firms and functional areas. These differences may reflect variation in digital maturity, AI readiness, organizational resources, and leadership preparedness. The findings therefore support a phased but integrated approach to addressing the barriers. First, firms should strengthen data quality, digital infrastructure, system integration, and AI leadership capabilities. Second, they should address resistance to change, develop workforce capabilities, build trust, and strengthen human-centered and ethical practices. Third, they should establish clear AI governance, strategic alignment, executive accountability, and long-term investment mechanisms. These actions should be coordinated because improvements in one area can strengthen capabilities in others.

Overall, the findings show that effective AI-enabled leadership depends on the ability to integrate technology, data, people, organizational change, and strategy. Weak digital foundations can limit AI performance, organizational resistance can slow implementation, low trust can reduce employee acceptance, and weak governance can prevent AI initiatives from supporting strategic objectives. The central leadership challenge is therefore not simply to increase AI adoption, but to create the conditions required to translate AI investments into sustained organizational and supply chain value. By identifying, measuring, and prioritizing these barriers, the study provides an evidence-based foundation for managers and policymakers to design targeted interventions and allocate resources more effectively. Addressing these barriers can help Egyptian manufacturing firms move from fragmented AI adoption toward integrated AI-enabled capabilities, strengthening decision quality, operational efficiency, workforce development, innovation, supply chain resilience, adaptability, and long-term competitiveness.

Table 3. Strategic gaps and key barriers for AI-enabled leadership.

Category	AI Application area	Strategic gaps	Key barriers
Strategic & Planning	Predictive analytics, dashboards, CRM	Limited use of data for informed decision-making	Weak AI leadership; poor data quality
	Strategic planning tools	Misalignment with organizational objectives	Lack of unified AI strategy; limited executive support
	Market trend & competitive intelligence	Low awareness of emerging trends and competitors	Resistance to AI adoption; fragmented initiatives
Operations & Production	Performance monitoring	Limited real-time visibility of production	Legacy systems; underdeveloped digital infrastructure
	Production scheduling & maintenance	Inefficient resource utilization	Limited access to real-time analytics
	Energy management & efficiency	Underutilized optimization opportunities	Perceived financial risk; low prioritization
	Process automation & robotics	Slow adoption and scaling	Siloed structures; insufficient digital capabilities
Quality & Safety	Quality control & defect detection	Inconsistent product quality monitoring	Limited human–AI collaboration; inadequate integration
	Safety monitoring & hazard prediction	Low adoption of predictive safety systems	Algorithmic bias; workforce anxiety
Supply Chain & Inventory	Supply chain optimization	Fragmented visibility and responsiveness	Misaligned initiatives; weak digital culture
	Inventory management & demand forecasting	Inaccurate demand planning	Poor data quality; limited real-time analytics
	Supplier performance evaluation	Limited oversight of suppliers	Siloed structures; regulatory ambiguity
Customer & HR Analytics	Customer insights	Weak personalization and engagement	Low trust in AI; resistance to change
	Workforce productivity & HR analytics	Suboptimal workforce alignment	Job displacement concerns; weak AI leadership
Innovation & Design	Product design & simulation	Slow product innovation	Short-term investment focus; weak digital culture
	Research & Development (R&D)	Limited AI-enabled R&D capacity	Absence of AI strategy; underdeveloped infrastructure

Table 4. Key barriers to effective AI-enabled leadership.

Barrier category	Code	Leadership constraint	Comments
	A1	Poor data quality & governance	Limits analytics reliability
	A2	Insufficient AI/digital leadership skills	Hinders adoption
Digital & Data Capabilities	A3	Difficulty integrating AI with legacy systems	Delays deployment
	A4	Underdeveloped digital/automation infrastructure	Reduces efficiency
	A5	Limited access to real-time analytics	Slows decision-making
	B1	Resistance to AI-driven transformation	Slows adoption
	B2	Lack of sustained executive sponsorship	Reduces prioritization
Cultural & Organizational Change	B3	Limited change management maturity	Hinders adaptation
	B4	Siloed structures restricting collaboration	Limits cross-functional work
	B5	Weak digital-learning culture	Reduces adaptability
	C1	Concerns over fairness, transparency, and bias	Reduces trust
	C2	Anxiety over job displacement	Lowers engagement
Human-Centric & Ethical Concerns	C3	Unclear accountability for responsible AI use	Limits ethical use
	C4	Limited human–AI collaboration	Reduces AI impact
	C5	Low organizational trust in AI	Slows adoption
	D1	Absence of a unified AI strategy	Limits long-term planning
	D2	High perceived financial risks	Reduces investment
Strategic Governance & Investment	D3	Misalignment with business priorities	Fragments adoption
	D4	Regulatory ambiguity	Creates uncertainty
	D5	Short-term focus limits long-term investments	Reduces sustainability

Table 5. Quantification of leadership barriers.

Code	Leaders' perception (%)	Mean (1–5)	SD	CV (%)	Severity
A1	48%	4.2	0.8	19.0	High
A2	46%	4.1	0.9	22.0	High
A3	34%	3.7	0.9	24.3	Moderate
A4	28%	3.4	0.8	23.5	Moderate
A5	27%	3.3	0.7	21.2	Moderate
B1	36%	3.7	0.9	24.3	Moderate
B2	31%	3.5	0.8	22.9	Moderate
B3	30%	3.4	0.7	20.6	Moderate
B4	24%	3.1	0.8	25.8	Low
B5	22%	3.0	0.7	23.3	Low
C1	35%	3.6	0.9	25.0	Moderate
C2	25%	3.2	0.8	25.0	Low
C3	27%	3.3	0.7	21.2	Low
C4	23%	3.1	0.7	22.6	Low
C5	21%	3.0	0.7	23.3	Low
D1	32%	3.5	0.8	22.9	Moderate
D2	29%	3.4	0.8	23.5	Moderate
D3	26%	3.2	0.7	21.9	Low
D4	27%	3.3	0.7	21.2	Low
D5	24%	3.1	0.7	22.6	Low

Severity classification: High (≥4.0), Moderate (3.3–3.9), Low (≤3.2).

4.3. Strategic Corrective Actions

Addressing the barriers to AI-driven leadership in Egypt’s manufacturing sector requires a coordinated and organization-wide approach rather than isolated technology investments. The strategic corrective actions proposed in this study were developed through a structured brainstorming process involving executives, managers, IT specialists, HR professionals, operational leaders, and AI experts. Participants identified key barriers, proposed potential responses, considered their feasibility, and refined the actions through collective discussion. The resulting recommendations are organized around the four dimensions identified in Section 4.2: Digital & Data Capabilities, Cultural & Organizational Change, Human-Centric & Ethical Concerns, and Strategic Governance & Investment. These dimensions are closely interconnected: reliable data enables effective AI use, organizational readiness supports adoption, human-centered practices build trust, and governance maintains strategic alignment. The corrective actions therefore aim to move manufacturing firms from fragmented AI applications toward an integrated capability that supports better decision-making, operational performance, workforce development, innovation, and supply chain resilience.

(1) Digital & Data Capabilities: Strong digital and data capabilities provide the foundation for AI-driven leadership. The findings identified poor data quality, outdated legacy systems, fragmented information, and limited access to real-time data as major constraints. To address these barriers, firms should establish clear data governance frameworks covering data ownership, responsibilities, quality standards, access, security, and continuous monitoring. Legacy systems should be progressively modernized, supported by AI-ready integration solutions that connect data and AI applications across production, operations, and supply chain processes. Firms should also expand the use of IoT, advanced analytics, predictive dashboards, and automation to improve real-time visibility and support proactive decision-making. These investments should be accompanied by executive and managerial AI development programs that strengthen leaders’ ability to interpret AI outputs, assess their reliability, recognize their limitations, and translate insights into appropriate strategic and operational decisions. Together, these measures provide the digital and managerial foundation required for reliable and scalable AI adoption.

(2) Cultural & Organizational Change: Effective AI transformation requires organizational readiness as well as technological capability. The findings identified resistance to change, organizational silos, weak learning cultures, and limited cross-functional cooperation as important barriers. Firms should therefore establish structured change-management programs that combine communication, training, practical support, and continuous feedback. Executive sponsorship and designated AI champions can reinforce commitment, clarify responsibilities, and maintain implementation momentum. Cross-functional teams involving IT, operations, HR, R&D, and other relevant functions can improve coordination and facilitate the sharing of AI-related knowledge and insights. Continuous learning and controlled experimentation should also be encouraged to strengthen employees’ skills, confidence, and adaptability. These measures can help shift AI adoption from a technology-centered initiative toward an organization-wide transformation supported by leadership commitment and employee participation.

(3) Human-Centric & Ethical Concerns: Sustainable AI adoption depends on employee trust, transparency, fairness, and accountability. The findings highlighted concerns related to job displacement, algorithmic bias, unclear AI-supported decisions, and limited human–AI collaboration. Firms should therefore establish human-centered AI governance that incorporates bias assessment, explainability, human oversight, and clear accountability. Reskilling and upskilling programs should prepare employees for changing work requirements and enable them to use AI to complement human knowledge, experience, and judgment. Clear communication should explain the purpose of AI, how AI supports decision-making, and how implementation may affect employees. Regular monitoring should identify ethical, operational, and workforce risks and enable timely corrective action. These measures can strengthen trust, reduce resistance, and support effective human–AI collaboration while maintaining appropriate human oversight of critical decisions.

(4) Strategic Governance & Investment: Effective AI-driven leadership requires clear strategic direction, disciplined investment, and appropriate governance. The findings identified fragmented initiatives, weak strategic alignment, limited investment planning, unclear accountability, and regulatory concerns as important challenges. Firms should develop a unified AI roadmap that links AI initiatives to business objectives, supply chain priorities, implementation milestones, and measurable outcomes. AI steering committees and periodic strategic reviews can strengthen executive oversight and coordination across functions. ROI-based project prioritization should guide investment toward initiatives with clear strategic, operational, or financial value, while regular regulatory and compliance reviews can reduce legal, ethical, and reputational risks. Clear decision rights and accountability should also be established to ensure that responsibility for AI-related decisions is well defined. These mechanisms can help firms manage AI as a long-term strategic capability rather than as a collection of disconnected technology projects.

(5) Integrated Implementation and Strategic Impact: The four dimensions should be implemented as a mutually reinforcing system rather than as independent initiatives. Digital infrastructure and data governance provide the foundation for reliable AI applications; leadership development enables managers to interpret and apply AI insights; change management and cross-functional collaboration support organizational adoption; human-centered governance and workforce development strengthen trust and acceptance; and strategic governance ensures that AI investments remain aligned with organizational priorities. Table 6 summarizes the Strategic Corrective Actions by linking each action to its priority, expected impact, and responsible organizational units. High-priority actions, including data governance, executive AI development, and ethical AI frameworks, directly address the most critical barriers identified in the empirical findings. Medium-priority actions, including cross-functional integration, advanced analytics, workforce development, and experimentation, support broader adoption and organizational scalability.

The combined implementation of these actions can strengthen several organizational and supply chain outcomes. Operational efficiency can improve through automation, predictive analytics, and more effective resource allocation. Leadership effectiveness can increase as managers develop stronger AI capabilities and gain access to reliable and timely information. Workforce capability and engagement can be strengthened through reskilling, participation, and transparent communication. Innovation capability can benefit from experimentation, AI-supported R&D, and cross-functional knowledge sharing. Supply chain resilience and strategic agility can also improve through greater visibility, faster decision-making, stronger coordination, and more effective responses to disruption. The purpose of these actions is therefore not simply to increase AI adoption, but to strengthen the organizational capabilities required to convert AI investments into sustained strategic and operational value.

Overall, the strategic corrective actions translate the barriers identified in Section 4.2 into a practical framework for AI-driven leadership. The findings indicate that successful AI transformation depends on five closely connected conditions: strong digital and data foundations, organizational readiness, capable and trusted employees, responsible governance, and strategically aligned investment. The structured brainstorming process helped translate these requirements into practical actions suited to the Egyptian manufacturing context. As summarized in Table 6, the proposed framework provides a pathway from fragmented AI adoption toward coordinated and sustainable AI-driven transformation. By strengthening leaders' ability to integrate technology, data, people, processes, and strategy, the framework provides a practical basis for improving decision quality, operational performance, workforce development, innovation, supply chain resilience, and long-term competitiveness.

Table 6. Strategic corrective actions for overcoming AI-enabled leadership barriers.

Code	Corrective actions	Priority	Expected impact	Implementation focus

A1	Establish robust data governance, assign stewardship	High	Improved decision-making, reduced errors	IT & Data Management
A2	Executive AI upskilling programs and workshops	High	Stronger AI-driven decision-making	HR & Leadership
A3	Modernize systems, implement middleware	Medium	Streamlined operations	IT Infrastructure
A4	Expand IoT and automation	Medium	Operational scalability	Operations & IT
A5	Deploy dashboards and predictive analytics	High	Faster, accurate decisions	IT & Business Intelligence
B1	Structured change management, employee involvement	High	Higher AI adoption	Change Management
B2	Secure executive commitment, appoint AI champions	High	Sustained AI initiatives	Executive Management
B3	Train managers, standardize processes	Medium	Consistent adoption	Leadership & HR
B4	Promote cross-functional teams, collaborative tools	Medium	Knowledge sharing, accelerated AI adoption	Operations & IT
B5	Continuous learning programs, reward experimentation	Medium	Enhanced adaptability	HR & Innovation
C1	Ethical AI governance, bias audits, explainable AI	High	Increased trust	Governance & AI Teams
C2	Communicate AI augmentation, reskilling programs	High	Reduced resistance, workforce engagement	HR & Change Management
C3	Define accountability structures, monitoring	Medium	Responsible AI use	Governance & Risk
C4	Train employees, integrate AI support	Medium	Improved productivity	HR & Operations
C5	Promote transparency, share success stories	Medium	Smoother adoption	Change Management & IT
D1	Develop AI roadmap, align initiatives	High	Cohesive adoption, long-term competitiveness	Executive Management
D2	Conduct ROI analysis, prioritize high-impact projects	High	Cost-effective deployment	Finance & Strategy
D3	Establish AI steering committees, review alignment	Medium	Optimized strategic impact	Executive Management
D4	Monitor regulations, compliance frameworks	Medium	Reduced compliance risk	Legal & Governance
D5	Develop multi-year AI plans, balance short-term wins	Medium	Sustainable transformation	Strategy & Finance

4.4. AI-Driven Leadership Roadmap

AI-driven leadership in Egypt's manufacturing sector extends beyond the implementation of AI technologies. It represents a strategic organizational capability through which leaders align technology, data, people, processes, governance, and investment to convert AI potential into sustainable business and supply chain value. The effectiveness of AI adoption therefore depends not only on technological readiness but also on leaders' ability to establish strategic direction, coordinate resources, develop workforce capabilities, manage organizational change, and ensure responsible AI use. Building on the barriers identified in Section 4.2 and the corrective actions developed in Section 4.3, this roadmap provides a structured pathway for moving from fragmented AI applications toward integrated, responsible, and strategically aligned AI-driven transformation. It is also consistent with the priorities of Egypt Vision 2030, particularly digital transformation, innovation, human capital development, and sustainable economic growth.

The roadmap was developed through a structured brainstorming process involving executives, managers, IT specialists, HR professionals, operational leaders, and AI experts. The process brought together complementary perspectives on technology, operations, workforce readiness, organizational change, ethics, and governance. IT specialists highlighted legacy systems, data quality, and integration challenges; HR professionals emphasized workforce capabilities and organizational readiness; operational leaders identified process and performance requirements; and AI experts contributed perspectives on emerging technologies and responsible AI. These inputs were consolidated into Table 7, which links each initiative to a specific action code, responsible unit, implementation phase, and measurable target. The roadmap is structured around four interdependent dimensions and implemented through three progressive phases.

(1) Digital & Data Capabilities (Table 7: Codes A1–A5). Digital and data capabilities constitute the foundation of AI-driven leadership because effective AI applications depend on reliable data, connected systems, and timely access to information. During the foundation phase (0–6 months), IT and Data Management should implement A1: comprehensive data governance, with the target of governing 100% of critical data assets. At the same time, HR and Leadership should implement A2: executive AI upskilling, targeting 90% of executives trained and certified to interpret and apply AI insights. During the integration and scaling phase (6–18 months), IT Infrastructure should implement A3: legacy-system modernization and integration, targeting 80% system coverage, while IT and Business Intelligence deploy A5: predictive analytics dashboards, targeting 95% adoption across key business units. During the optimization and strategic alignment phase (18–24 months), Operations and IT should expand A4: IoT infrastructure and automation, targeting 70% of production lines to become IoT-enabled and AI-integrated. Collectively, these initiatives establish the data quality, interoperability, real-time visibility, and analytical capacity required for effective AI-supported decisions across manufacturing and supply chain operations.

(2) Cultural & Organizational Change (Table 7: Codes B1–B5). AI transformation requires organizational conditions that support experimentation, learning, collaboration, and adaptation. Resistance to change, functional silos, weak learning cultures, and limited cross-functional coordination can prevent firms from converting technological investment into organizational value. During the foundation phase, Change Management should implement B1: structured change-management and employee-engagement programs, targeting 80% workforce participation. Executive Management should establish B2: executive sponsors and AI champions across business units to provide visible leadership commitment and accountability. During the integration and scaling phase, Leadership and HR should implement B3: managerial AI training and standardized adoption processes, targeting 90% of managers trained, while Operations and IT establish B4: cross-functional AI teams, with 75% of AI-related projects implemented through integrated teams. During the optimization phase, HR and Innovation should implement B5: continuous learning, innovation, and experimentation programs, targeting 80% workforce engagement. Together, these initiatives are intended to reduce resistance, strengthen cross-functional integration, and develop an adaptive organizational culture capable of sustaining AI-enabled transformation.

(3) Human-Centric & Ethical Leadership (Table 7: Codes C1–C5). Sustainable AI adoption requires leaders to address the human and ethical implications of AI alongside its technical and economic benefits. Key concerns include workforce uncertainty, potential job displacement, algorithmic bias, limited transparency, and unclear accountability. During the foundation phase, Governance and AI Teams should implement C1: ethical AI governance, including bias assessment and explainability, with 100% of AI projects subject to ethical review. HR and Change Management should implement C2: workforce communication and reskilling, targeting 85% employee awareness and participation. Governance and Risk should establish C3: accountability and monitoring mechanisms covering all AI initiatives. During the integration and scaling phase, HR and Operations should implement C4: employee training and AI integration into workflows, targeting 90% workforce coverage. Change Management and IT should implement C5: transparency and knowledge-sharing mechanisms, with 70% of teams sharing AI-related lessons and practices. These initiatives position trust, human oversight, transparency, and continuous capability development as core elements of AI-driven leadership.

(4) Strategic Governance & Investment (Table 7: Codes D1–D5). Strategic governance ensures that AI initiatives are not developed as isolated projects but are prioritized and coordinated according to organizational objectives. During the foundation phase, Executive Management should establish D1: a unified AI roadmap linking AI initiatives to organizational strategy. During the integration and scaling phase, Finance and Strategy should implement D2: ROI-based project prioritization, with 80% of high-impact projects subject to formal evaluation. Executive Management should establish D3: AI steering committees and regular alignment reviews to provide quarterly oversight, while Legal and Governance implement D4: regulatory and compliance monitoring to ensure adherence to applicable requirements. During the optimization phase, Strategy and Finance should implement D5: multi-year AI planning, supported by annual reviews. These mechanisms provide the strategic coordination, investment discipline, accountability, and continuity required to scale AI beyond individual functions.

The roadmap follows three progressive phases that reflect the development of AI capabilities from organizational readiness to integration and strategic optimization. The foundation phase (0–6 months) establishes the conditions required for responsible AI adoption, including data governance, executive AI literacy, workforce engagement, ethical oversight, and strategic direction. Its principal targets include governance of 100% of critical data assets, training 90% of executives, 80% workforce participation, and ethical review of all AI projects. The integration and scaling phase (6–18 months) embeds AI into operational processes, management practices, and cross-functional workflows. Its principal targets include 80% legacy-system coverage, 95% predictive-dashboard adoption, 90% of managers trained, and 75% of AI projects implemented through cross-functional teams. The optimization and strategic alignment phase (18–24 months) focuses on expanding IoT and automation, strengthening innovation and organizational learning, increasing knowledge sharing, and embedding AI within long-term strategic planning. Its principal targets include 70% of production lines becoming IoT-enabled and AI-integrated, 80% workforce engagement in learning and innovation, and full implementation of multi-year AI planning with annual reviews.

A KPI-based monitoring system is incorporated to support implementation, evaluation, and continuous adjustment. The targets presented in Table 7 include a proposed 20–30% improvement in operational efficiency, approximately 25% improvement in leadership effectiveness, workforce trust and engagement above 80%, and more than 95% alignment of AI initiatives with organizational and national priorities. These values are proposed implementation targets rather than empirical outcomes observed in the present study. Accordingly, they should be interpreted as performance benchmarks that organizations can use to monitor progress and evaluate the effectiveness of their transformation initiatives. Periodic KPI reviews can identify capability gaps, reveal implementation problems, and support evidence-based adjustments to priorities and resource allocation.

The sequencing of the roadmap reflects a capability-building logic. The foundation phase develops the technological, managerial, human, and governance conditions required for AI adoption. The integration phase extends AI across organizational functions while strengthening collaboration and workforce capabilities. The optimization phase advances automation, analytics, innovation, organizational learning, and strategic integration. This sequence reduces the risk of pursuing advanced AI applications without first establishing the data, skills, governance, and organizational readiness required for effective implementation.

The four dimensions are interdependent and mutually reinforcing. Digital and data capabilities provide the technological foundation, but their value depends on workforce capability and organizational readiness. Cultural and organizational change facilitates adoption, but sustained adoption requires trust, ethical safeguards, and effective governance. Strategic governance establishes direction and investment discipline, while human capabilities determine whether AI-generated insights can be translated into sound managerial and operational decisions. Consequently, AI-driven leadership should be viewed as an integrated dynamic capability rather than a set of independent technological initiatives.

This integrated perspective is particularly important for manufacturing supply chains, where value is created through the coordination of multiple interdependent functions. Improved data capabilities can strengthen demand forecasting, inventory management, supplier monitoring, production planning, and logistics visibility. Cross-functional AI teams can connect previously fragmented decisions across procurement, production, inventory, logistics, and customer-facing activities. Human–AI collaboration can improve decision quality and accountability, while strategic governance can ensure that AI investments support broader supply chain objectives. The roadmap therefore provides a pathway from functional AI adoption toward more connected, responsive, resilient, and adaptive manufacturing supply chains.

Overall, Table 7 and Figure 4 translate the study's empirical findings into an integrated framework for AI-driven leadership in Egyptian manufacturing firms. The roadmap connects identified barriers, strategic corrective actions, implementation phases, responsible units, KPIs, and expected outcomes within a coherent implementation architecture. Its central proposition is that the value of AI is determined not solely by technological adoption but by leaders' ability to orchestrate technology, data, people, processes, and strategy as an integrated organizational capability. By following this pathway, Egyptian manufacturing firms can progress from fragmented AI initiatives toward coordinated and sustainable transformation, strengthening decision quality, operational efficiency, workforce capabilities, innovation, supply chain resilience, and long-term competitive advantage.

Table 7. AI-enabled leadership roadmap.

Dimension	Code	Initiative	Phase	Responsible unit	Target
Digital & Data Capabilities	A1	Establish comprehensive data governance	Short-term	IT & Data Management	100% of critical data assets are governed
	A2	Deliver AI upskilling for executives	Short-term	HR & Leadership	90% of executives trained & certified
	A3	Modernize legacy systems & deploy AI-ready middleware	Medium-term	IT Infrastructure	80% of legacy systems upgraded & integrated
	A4	Expand IoT infrastructure & automate operations	Long-term	Operations & IT	70% of production lines are IoT-enabled & automated
	A5	Deploy predictive analytics dashboards	Medium-term	IT & Business Intelligence	95% adoption in key business units
Cultural & Organizational Change	B1	Implement structured change management & engagement	Short-term	Change Management	80% workforce participation
	B2	Appoint executive sponsors & AI champions	Short-term	Executive Management	Sponsors assigned to 100% of key units
	B3	Train managers & standardize AI adoption processes	Medium-term	Leadership & HR	90% of managers trained & certified
	B4	Foster cross-functional collaboration & AI-driven teams	Medium-term	Operations & IT	75% of projects executed cross-functionally
	B5	Promote continuous learning, innovation & experimentation	Long-term	HR & Innovation	80% workforce is engaged in learning programs
Human-Centric & Ethical Leadership	C1	Establish ethical AI governance & conduct bias audits	Short-term	Governance & AI Teams	100% of AI projects are ethically reviewed
	C2	Communicate AI augmentation & reskilling initiatives	Short-term	HR & Change Management	85% employee awareness & participation
	C3	Define accountability structures & monitoring	Short-term	Governance & Risk	100% of AI initiatives with clear accountability
	C4	Train employees & integrate AI	Medium-	HR & Operations	90% of the relevant

		into workflows	term		workforce trained & AI-enabled
	C5	Promote transparency through success stories & knowledge sharing	Medium-term	Change Management & IT	70% of teams share AI success stories
Strategic Governance & Investment	D1	Develop unified AI roadmap aligned with strategy	Short-term	Executive Management	100% initiatives aligned with strategy
	D2	Conduct ROI analysis & prioritize high-impact projects	Medium-term	Finance & Strategy	80% of projects prioritized by ROI
	D3	Operationalize AI steering committees & alignment reviews	Medium-term	Executive Management	Quarterly reviews for all initiatives
	D4	Monitor regulations & enforce compliance	Medium-term	Legal & Governance	100% compliance with legal & ethical standards
	D5	Develop multi-year AI plans balancing short- & long-term goals	Long-term	Strategy & Finance	Multi-year AI roadmap implemented & reviewed annually

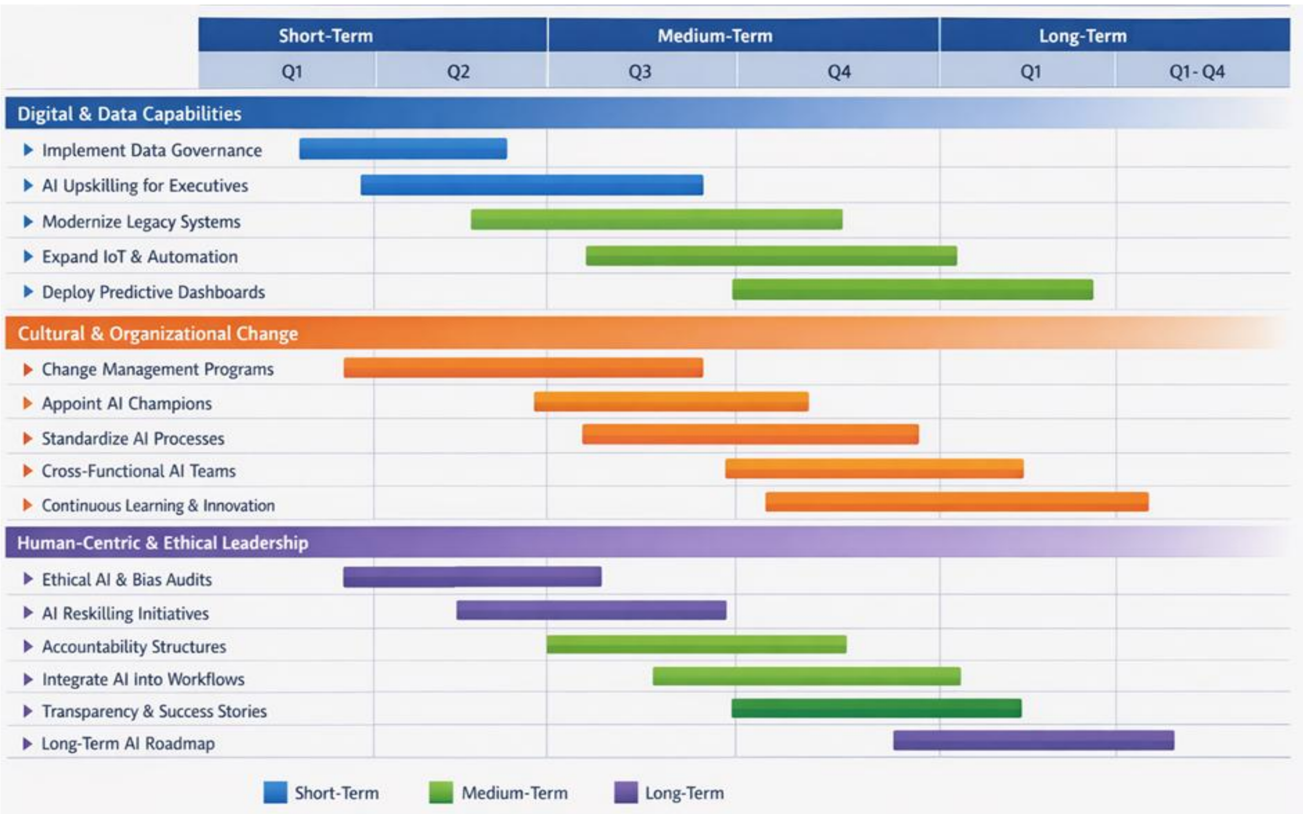

Figure 5. AI-enabled leadership roadmap Gantt chart.

5. Conceptual Roadmap for AI-Driven Leadership in Supply Chain Management

Artificial intelligence is fundamentally reshaping supply chain systems by shifting them from linear, forecast-driven structures to interconnected, data-intensive ecosystems capable of real-time sensing, learning, and adaptive decision-making. Within this context, AI adoption should not be interpreted as a standalone technological upgrade, but as a systemic transformation in which data infrastructures, algorithms, organizational capabilities, and governance mechanisms evolve in parallel. This section develops a conceptual roadmap that explains how AI capabilities accumulate across maturity stages and how they are embedded across supply chain functions to enable progressively higher levels of intelligence, adaptability, and autonomy.

5.1. Conceptual Roadmap for AI-Driven Transformation

The proposed conceptual roadmap synthesizes extant literature into a structured, multi-stage transformation framework explaining how traditional supply chains evolve into intelligent, adaptive, and ultimately autonomous ecosystems. Rather than treating artificial intelligence (AI) as a discrete technological intervention, the roadmap conceptualizes it as a cumulative, path-dependent socio-technical transformation in which technological capabilities co-evolve with organizational routines, data governance structures, human expertise, and institutional constraints.

This perspective reflects the systemic limitations of contemporary supply chains, including fragmented data environments, limited end-to-end visibility, weak interoperability, and persistent misalignment between digital investments and operational value creation. Accordingly, AI is positioned not merely as an efficiency-enhancing tool but as a catalyst for reconfiguring decision rights, coordination mechanisms, and value creation logic across the supply chain.

Departing from deterministic maturity models, the roadmap adopts a non-linear, multi-speed progression logic, recognizing that organizations evolve unevenly across functions and capabilities. Firms may operate simultaneously across multiple stages depending on differences in digital maturity, data availability, organizational readiness, and strategic intent, reflecting iterative transformation characterized by experimentation, partial deployment, and legacy constraints.

Each stage represents a distinct configuration of capabilities and coordination structures, characterized by increasing levels of data integration, analytical sophistication, decision autonomy, and systemic complexity. Progression depends on overcoming transition barriers such as data readiness thresholds, integration constraints, capability gaps, and governance misalignment. If unaddressed, these barriers may lead to stalled transformation, fragmented optimization, or systemic inefficiencies.

Table 8 summarizes the stages in terms of focus areas, challenges, and strategic actions, while Table 9 operationalizes them through KPIs and expected outcomes. Together with Figure 5, the framework provides an integrated strategic–operational architecture linking capability development to measurable performance realization.

Stage 1: Digital Foundation and Data Enablement

1) Description: Establishes the digital backbone through digitization, integration, and standardization of supply chain data and processes, enabling end-to-end visibility.
2) Objective: Build a unified, interoperable, and high-integrity data environment for reliable capture, exchange, and access.
3) Key Challenges: Data silos, legacy fragmentation, inconsistent semantics, poor data quality, limited interoperability, immature governance.
4) Key Activities: ERP, WMS, TMS integration; IoT data capture; cloud infrastructure; master data management; process standardization; data governance frameworks.
5) KPIs: Data accuracy, integration coverage, latency, completeness, digitization rate, visibility index, interoperability level.
6) Implementation Logic: Establish data integrity and architectural coherence as prerequisites for all advanced analytics and AI applications.
7) Outcome: A digitally integrated supply chain with standardized data structures and end-to-end visibility.

Stage 2: Predictive Intelligence and Analytical Maturity

1) Description: Introduces predictive capabilities that transform integrated data into forward-looking intelligence using machine learning and statistical methods.
2) Objective: Enable anticipatory decision-making through forecasting, risk sensing, and proactive planning.
3) Key Challenges: Limited analytical maturity, skill gaps, fragmented or biased data, interpretability constraints, weak integration into operations.
4) Key Activities: Demand forecasting, demand sensing, predictive inventory optimization, supplier risk analytics, anomaly detection, model monitoring and validation.
5) KPIs: Forecast accuracy, demand error rate, inventory turnover, stockout rate, supplier risk accuracy, model robustness.
6) Implementation Logic: Translate data into predictive intelligence while maintaining human-in-the-loop oversight to ensure trust, interpretability, and contextual grounding.
7) Outcome: A predictive supply chain capable of reducing uncertainty and improving forward visibility.

Stage 3: Prescriptive Optimization and Embedded Intelligence

1) Description: Extends predictive capabilities with optimization and simulation to generate actionable, constraint-aware decision recommendations.
2) Objective: Improve decision quality and operational efficiency through embedded decision intelligence.
3) Key Challenges: High integration complexity, computational intensity, workflow embedding difficulties, resistance to reduced human decision authority.
4) Key Activities: Optimization models, digital twins, simulation systems, prescriptive analytics, enterprise system integration.
5) KPIs: Cost-to-serve, service level, cycle time, utilization, logistics efficiency, execution speed.
6) Implementation Logic: Integrate prediction and optimization into scalable decision systems that operate under real-world constraints.
7) Outcome: A semi-automated supply chain with embedded decision intelligence.

Stage 4: Semi-Autonomous and Adaptive Supply Networks

1) Description: Evolves into decentralized networks where decision-making becomes partially autonomous and distributed across nodes.
2) Objective: Enable real-time responsiveness, distributed coordination, and systemic resilience.
3) Key Challenges: Coordination complexity, interoperability gaps, cybersecurity risks, governance and accountability concerns.
4) Key Activities: Reinforcement learning, multi-agent systems, IoT monitoring, blockchain traceability, adaptive planning mechanisms.
5) KPIs: Disruption response time, resilience index, adaptation speed, uptime, coordination efficiency, network stability.
6) Implementation Logic: Distribute intelligence while maintaining system-wide coherence through coordination protocols and governance mechanisms.
7) Outcome: A self-adaptive supply network capable of decentralized optimization and rapid response.

Stage 5: Fully Autonomous and Self-Optimizing Ecosystems

1) Description: Represents fully autonomous supply chain ecosystems characterized by continuous learning and self-optimization.
2) Objective: Achieve autonomous operations aligned with strategic, ethical, and regulatory constraints under volatility.
3) Key Challenges: Trust in autonomy, ethical and regulatory compliance, system complexity, explainability, accountability.

4) Key Activities: Generative AI orchestration, ecosystem digital twins, multi-agent coordination, autonomous execution, continuous learning loops.
5) KPIs: Autonomy index, efficiency, resilience, sustainability, decision latency, adaptability.
6) Implementation Logic: Enable self-regulating systems governed by embedded constraints and continuous feedback learning.
7) Outcome: A self-optimizing ecosystem capable of sustained performance under uncertainty.

Across all stages, transformation is enabled by cross-cutting foundations, including interoperable data infrastructures, workforce capability development, and AI governance frameworks (ethics, transparency, accountability, trust). These elements evolve in parallel with technological maturity and jointly determine transformation speed and sustainability.

Overall, the roadmap conceptualizes AI-driven transformation as iterative, non-linear, and capability-dependent. Organizations may operate across multiple stages simultaneously, reflecting heterogeneous maturity paths and contextual constraints. By linking capabilities to performance outcomes and explicitly incorporating transition barriers, the framework advances beyond maturity models toward a mechanism-based understanding of AI-enabled transformation.

Table 8. Strategic Roadmap for AI-Driven SCM.

Step	Stage	Focus Area	Key Challenges / Gaps	Strategic Actions
1	Digital Foundation & Data Enablement	Data integration and supply chain visibility	Data silos, legacy systems, poor data quality, and weak governance	Integrate ERP–WMS–TMS systems; deploy IoT and cloud; establish master data management and data standards
2	Predictive Intelligence & Analytical Maturity	Forecasting and predictive decision support	Limited analytics capability, fragmented data, skill gaps, and model reliability issues	Apply ML for forecasting, demand sensing, inventory, and supplier risk prediction; build analytics capability and governance
3	Prescriptive Optimization & Embedded Intelligence	Optimization and semi-automated decision-making	Integration complexity, high computational cost, legacy constraints, and resistance to automation	Deploy optimization models, simulation, and digital twins; embed prescriptive analytics into enterprise systems
4	Semi-Autonomous & Adaptive Supply Networks	Decentralized and adaptive coordination	Coordination complexity, cybersecurity risks, interoperability, and accountability issues	Implement reinforcement learning and multi-agent systems; integrate IoT and blockchain for real-time coordination
5	Fully Autonomous & Self -Optimizing Ecosystems	End-to-end autonomous orchestration	Trust, ethics, regulation, system complexity, and accountability of AI decisions	Use generative AI, ecosystem digital twins, and autonomous planning and execution systems
6	Cross-Cutting Enablers	Data, people, and governance foundations	Skill gaps, weak digital maturity, lack of trust, and fragmented governance	Develop interoperable data infrastructure, enhance workforce capabilities, and establish AI governance and ethics frameworks

Table 9. KPI framework for AI-driven SCM.

Step	Focus Area	Strategic Objective	Key KPIs	Expected Outcomes
1	Digital Foundation & Data Enablement	Build integrated, high-quality data infrastructure	Data accuracy, integration coverage, data latency, visibility index	Reliable and transparent data ecosystem
2	Predictive Intelligence & Analytical Maturity	Enable forecasting and proactive decision support	Forecast accuracy, demand error rate, inventory turnover, stockout rate, supplier risk accuracy	Improved forecasting and reduced uncertainty
3	Prescriptive Optimization & Embedded Intelligence	Optimize decisions through AI-driven	Cost-to-serve, cycle time, service level, resource utilization, logistics	Higher efficiency and optimized operations

		recommendations	efficiency	
4	Semi-Autonomous & Adaptive Networks	Enable decentralized, adaptive decision-making	Disruption response time, resilience index, adaptation speed, system uptime	Faster response and stronger resilience
5	Fully Autonomous Ecosystems	Achieve end-to-end autonomous orchestration	Autonomy level, total efficiency, sustainability score, decision latency	Self-optimizing supply chain performance
6	Cross-Cutting Enablers	Strengthen enabling capabilities across all stages	Data maturity, workforce capability, AI governance maturity, trust index	Scalable and sustainable AI transformation

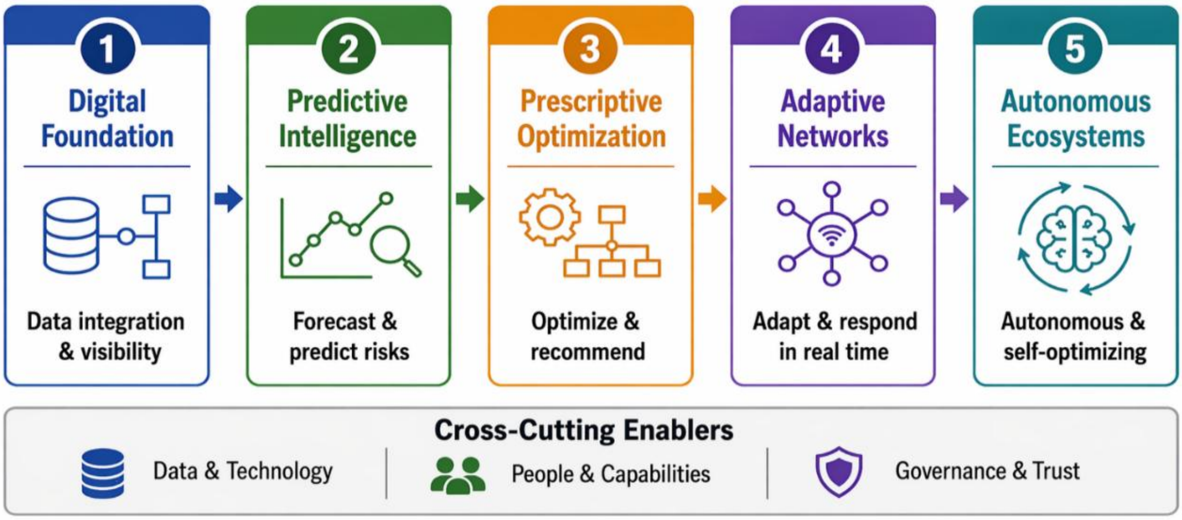

Figure 5. Conceptual roadmap for AI-driven SCM.

5.2. AI-Driven Supply Chain Management Functional Mapping

Table 10 translates the conceptual roadmap into a functional-level AI transformation framework for supply chain management. It maps SCM functions, operational domains, managerial objectives, and AI capabilities within a unified decision architecture. Rather than treating SCM functions as isolated units, the framework positions them as interconnected decision domains that jointly drive system-level outcomes such as efficiency, resilience, responsiveness, cost optimization, and customer-centricity. This reflects a shift from activity-based execution toward outcome-oriented supply chain design.

Across functions, AI operates as a layered intelligence system: predictive analytics enables forecasting and risk sensing, prescriptive optimization supports constrained decision-making, and autonomous systems enable real-time execution. Cognitive technologies such as NLP, computer vision, and conversational AI extend intelligence into unstructured and human-facing processes.

Structurally, the framework distinguishes strategic (planning, performance management), coordination (procurement, risk & compliance, customer management), and execution (production, inventory, logistics, warehousing, fulfillment) functions, highlighting that AI transformation occurs both within and across functional layers.

Overall, Table 10 captures the transition from fragmented operational execution to an integrated, intelligence-driven architecture enabling adaptive, resilient, and increasingly autonomous supply chains.

1) Supply Chain Planning: Supply Chain Planning functions as the central orchestration layer integrating S&OP, demand–supply balancing, capacity planning, and network design. Its objective is end-to-end alignment of operational, financial, and service objectives under uncertainty. AI enables stochastic

optimization, scenario simulation, digital twins, and prescriptive planning systems that continuously recalibrate decisions based on real-time signals.

2) Procurement & Sourcing: Procurement & Sourcing manages supplier selection, contracting, lifecycle management, and strategic sourcing. Its objective is resilient, cost-efficient, and risk-aware supplier ecosystems. AI enables supplier intelligence, predictive risk scoring, contract analytics, and sourcing optimization to improve transparency and supplier performance.
3) Production & Manufacturing: Production & Manufacturing includes scheduling, shop-floor control, quality assurance, and maintenance planning. Its objective is adaptive, high-quality, low-downtime production. AI enables predictive maintenance, reinforcement learning scheduling, computer vision inspection, and digital twin-based process optimization.
4) Inventory Management: Inventory Management covers multi-echelon planning, replenishment, allocation, and safety stock optimization. Its objective is cost-efficient inventory positioning while maintaining service levels. AI enables probabilistic forecasting, adaptive replenishment, and autonomous inventory control across multi-echelon networks.
5) Logistics & Transportation: Logistics & Transportation includes routing, fleet optimization, last-mile delivery, and visibility management. Its objective is fast, reliable, and cost-efficient physical flow execution. AI enables real-time routing, dynamic dispatching, predictive ETAs, and autonomous coordination systems.
6) Warehousing & Storage: Warehousing & Storage includes layout design, storage optimization, picking, and automation integration. Its objective is high throughput, spatial efficiency, and operational accuracy. AI enables robotics automation, computer vision tracking, intelligent picking, and layout optimization.
7) Order Management & Fulfillment: Order Management & Fulfillment covers orchestration, execution, returns, and customer experience. Its objective is seamless, accurate, and timely fulfillment. AI enables intelligent order routing, automated orchestration, predictive delivery, and conversational interfaces.
8) Supply Chain Risk & Compliance: Supply Chain Risk & Compliance includes disruption monitoring, risk analytics, regulatory compliance, and ESG governance. Its objective is resilience and compliance assurance. AI enables predictive risk analytics, anomaly detection, resilience modeling, and automated compliance monitoring across regulatory and sustainability domains.
9) Performance Management & Analytics: Performance Management & Analytics includes KPI monitoring, benchmarking, and decision intelligence. Its objective is continuous optimization across all supply chain functions. AI enables control towers, predictive KPIs, prescriptive dashboards, and closed-loop decision systems.
10) Customer Relationship Management: Customer Relationship Management integrates demand sensing, personalization, interaction, and feedback analytics. Its objective is aligning supply chain decisions with real-time customer demand signals. AI enables NLP agents, sentiment analysis, recommendation systems, and demand sensing engines.

In conclusion, the roadmap and functional mapping jointly provide a unified framework for understanding AI-driven transformation in supply chains. The roadmap explains the temporal evolution of capability maturity, while Table 10 explains how these capabilities are embedded across functional domains. Together, they demonstrate that AI is not a standalone tool but a systemic enabler of coordination, optimization, and autonomy across supply chain structures. Successful transformation, therefore, depends on the co-evolution of technology, data infrastructure, organizational capability, and governance maturity toward resilient and self-optimizing supply chain systems.

Table 10. AI-driven supply chain management functional mapping.

#	SCM Function	Key Activities	Objective	AI-Driven Capabilities

1	Supply Chain Planning	S&OP, demand–supply balancing, capacity planning, network design, scenario modeling	Align demand, supply, capacity, and financial objectives under uncertainty	Prescriptive analytics, scenario generation, stochastic optimization, digital twins, autonomous planning
2	Procurement & Sourcing	Supplier management, sourcing, contracting, and evaluation	Build resilient and cost-efficient supplier networks	Supplier intelligence, predictive risk analytics, sourcing optimization, contract intelligence
3	Production & Manufacturing	Scheduling, shop-floor control, quality, maintenance	Enable adaptive and efficient production systems	Predictive maintenance, reinforcement learning, computer vision, digital twins
4	Inventory Management	Multi-echelon planning, replenishment, allocation	Optimize inventory across networks with minimal cost and risk	Probabilistic forecasting, optimization, adaptive replenishment, autonomous control
5	Logistics & Transportation	Routing, fleet optimization, delivery, tracking	Ensure efficient and reliable physical flows	Dynamic routing, real-time optimization, predictive ETA, autonomous dispatching
6	Warehousing & Storage	Storage, picking, automation, layout design	Improve throughput and operational accuracy	Robotics, computer vision, intelligent picking, layout optimization
7	Order & Fulfillment	Order processing, returns, customer service	Ensure seamless end-to-end fulfillment	Intelligent routing, automated orchestration, predictive delivery, conversational AI
8	Risk & Compliance	Risk monitoring, disruption tracking, ESG compliance	Strengthen resilience and regulatory compliance	Risk analytics, anomaly detection, resilience modeling, ESG monitoring
9	Performance & Analytics	KPI tracking, benchmarking, diagnostics	Enable real-time performance optimization	Control towers, predictive KPIs, prescriptive dashboards, decision intelligence
10	Customer Management	Demand sensing, interaction, personalization	Enhance customer responsiveness and insight	NLP, sentiment analysis, recommendation systems, demand sensing

6. Conclusion and Future Research

This study provides an integrated examination of AI-driven leadership in manufacturing supply chains by combining a systematic literature review of studies published between 2011 and 30 May 2026 with exploratory empirical evidence from 60 senior leaders across 15 Egyptian manufacturing firms. The review covers major AI applications in demand forecasting, inventory management, procurement, production planning, logistics, customer management, and risk management, while highlighting the growing role of machine learning, deep learning, reinforcement learning, predictive analytics, and digital twins. The findings indicate that AI is evolving from a collection of functional technologies into a strategic capability that can enhance supply chain efficiency, visibility, responsiveness, resilience, and adaptability.

Despite this progress, the literature remains fragmented and predominantly technology-oriented. Existing research has extensively examined AI applications and technical capabilities, but comparatively less attention has been given to the leadership and organizational conditions required to convert these capabilities into sustained value. The review identifies five major gaps: limited strategic alignment between AI and supply chain objectives; insufficient understanding of AI maturity and progression toward autonomous decision-making; limited longitudinal evidence on resilience and sustainability outcomes; a lack of standardized measures for AI-enabled supply chain performance; and insufficient integration of governance, ethics, workforce readiness, accountability, and human–AI collaboration. These gaps suggest that future research should move beyond AI adoption as an outcome toward understanding AI orchestration as an organizational capability.

The empirical findings from Egypt provide additional evidence of this challenge. AI adoption is relatively stronger in strategic planning and customer analytics, moderate across operations, production, quality, and supply chain activities, and limited in workforce analytics and innovation/R&D. This pattern indicates that adoption among the participating firms remains selective, function-specific, and primarily efficiency-oriented, rather than enterprise-wide. The analysis further identifies legacy systems, weak data infrastructure, fragmented governance, limited AI leadership capabilities, organizational resistance, and workforce concerns as important constraints. These findings reinforce the argument that successful AI transformation requires coordinated technological, organizational, human, and governance capabilities.

To address these gaps, the study develops an AI-driven leadership and supply chain transformation framework that conceptualizes AI adoption as a path-dependent and socio-technical process. The proposed five -stage maturity pathway progresses from digital foundations and data readiness toward predictive, prescriptive, coordinated, and potentially autonomous decision-making. A complementary functional mapping framework covers ten core supply chain domains and illustrates how AI capabilities can develop across strategic and operational activities. Together, these frameworks provide a structured basis for understanding the transition from basic analytics to advanced decision intelligence and for identifying the capabilities required at different stages of AI maturity.

6.1. Theoretical Contribution

The principal theoretical contribution of this study is conceptualizing AI-driven leadership as a socio-technical organizational capability. Conventional leadership perspectives generally emphasize human behavior, interpersonal influence, and managerial decision-making. In AI-enabled supply chains, however, decision processes increasingly involve managers, algorithms, data infrastructures, and digital platforms. Leadership must therefore extend beyond directing people to include the ability to orchestrate, interpret, evaluate, govern, and strategically deploy AI-generated intelligence.

This conceptualization shifts the analytical focus from the individual leader to the human–AI decision system. AI-driven leadership does not imply replacing human judgment with machine intelligence. Rather, it concerns the effective distribution and coordination of decision responsibilities between humans and AI. Leaders must determine which decisions should remain human-led, which should be AI-supported, and which can be automated. They must also establish decision rights, evaluate algorithmic recommendations, monitor system performance, manage exceptions, maintain appropriate human oversight, and ensure accountability.

The study further develops a maturity-based view of AI-driven leadership. At lower maturity levels, AI primarily provides information, predictions, and recommendations to support managerial decisions. As maturity increases, leadership responsibilities expand toward cross-functional coordination, human–AI collaboration, system supervision, and AI governance. At advanced stages, leaders increasingly focus on strategic direction, decision architecture, autonomous-system oversight, exception management, and governance rather than routine operational decisions. Thus, greater AI maturity does not diminish the importance of leadership; it reconfigures leadership roles, decision rights, and organizational responsibilities.

The study also extends the socio-technical perspective by identifying four interdependent capability domains underlying effective AI-driven leadership: digital and data capabilities, organizational capabilities, human capabilities, and strategic governance. These domains are mutually reinforcing. Advanced technology without reliable data, organizational readiness, skilled employees, ethical safeguards, and effective governance is unlikely to generate sustained value. This integrated view provides a stronger explanation of why similar AI technologies can produce different outcomes across firms and contexts.

6.2. Practical and Managerial Implications

The findings provide managers with a structured basis for moving from isolated AI applications toward integrated and strategically governed AI transformation. AI readiness should be assessed across technology, data, leadership, workforce capabilities, organizational culture, and governance rather than being measured by technology deployment alone.

The findings also highlight the need to broaden AI applications beyond areas that generate immediate efficiency gains. Greater attention should be directed toward workforce analytics, innovation, R&D, external market intelligence, and cross-functional decision-making. Developing these capabilities can help organizations move from short-term process optimization toward innovation, workforce development, strategic responsiveness, and supply chain resilience.

Leadership development should form an integral part of AI transformation. Senior executives require sufficient AI literacy to understand technological capabilities and limitations, evaluate AI-generated recommendations, identify risks, and make informed strategic decisions. Middle managers require capabilities in AI-enabled process management, human–AI collaboration, and organizational change. Workforce reskilling and continuous learning should therefore progress alongside AI implementation.

The proposed transformation roadmap supports a phased implementation strategy. Organizations should first establish reliable data, digital infrastructure, governance, and leadership capabilities. They can then expand AI across business functions, strengthen cross-functional integration, and progressively introduce advanced automation and autonomous decision support. Such sequencing can reduce implementation risk while improving alignment between technological maturity and organizational readiness.

6.3. Study Limitations

Several limitations should be considered when interpreting the findings. First, the empirical analysis is based on 60 senior leaders from 15 Egyptian manufacturing firms. Although the sample covers eight industries and multiple functional areas, its relatively small size and country-specific context limit the generalizability of the findings to other industries and national settings.

Second, the cross-sectional design captures AI adoption and leadership perceptions at a single point in time. Consequently, the study cannot establish causal relationships or fully explain how AI maturity, leadership capabilities, organizational performance, and supply chain resilience evolve over time.

Third, reliance partly on self-reported data may introduce response and perception bias. Future research could strengthen empirical validity by combining managerial assessments with objective indicators such as forecast accuracy, inventory turnover, production efficiency, delivery reliability, productivity, innovation outcomes, and AI-related investment.

Fourth, the systematic literature review is shaped by the databases, search strategy, inclusion criteria, and analytical procedures employed. Consequently, some emerging, non-indexed, or rapidly developing studies may not have been included.

Finally, the proposed AI maturity pathway, KPI framework, and transformation roadmap have not yet been empirically validated across diverse organizational contexts. Accordingly, the proposed targets should be regarded as conceptual or managerial benchmarks rather than established causal performance effects.

6.4. Future Research Directions

Future research should empirically validate the proposed AI-driven leadership framework across different manufacturing industries, supply chain configurations, organizational sizes, and levels of digital maturity. Cross -country research involving emerging and developed economies could further clarify which AI leadership capabilities are context-dependent and which have broader applicability.

Longitudinal studies should investigate how firms progress across AI maturity stages and how this progression affects leadership roles, decision rights, organizational capabilities, and supply chain outcomes. Such studies could provide stronger evidence regarding the effects of AI maturity on operational performance, resilience, sustainability, innovation, and competitive advantage.

Future research should also develop and validate quantitative measures of AI-driven leadership and AI maturity. Potential dimensions include AI strategic orientation, data capability, technological integration, leadership competence, human–AI collaboration, governance maturity, organizational readiness, and supply chain integration. Such measures would support benchmarking and enable more rigorous testing of the relationships among AI capabilities, leadership, and organizational performance.

Further research should examine the human, ethical, and governance implications of increasingly autonomous supply chains, particularly algorithmic accountability, explainability, fairness, transparency, cybersecurity, employee trust, human oversight, decision-right allocation, and responsibility for AI-supported decisions. Research should also examine how organizations determine appropriate levels of automation and when human intervention remains essential.

Finally, future studies should investigate the organizational mechanisms through which firms overcome legacy systems, interoperability constraints, poor data quality, cybersecurity risks, workforce skill gaps, organizational inertia, financial constraints, and regulatory uncertainty. Longitudinal, multi-case, and comparative studies would be particularly valuable for identifying the conditions that enable successful movement from one AI maturity stage to another.

6.5. Final Conclusion

The central conclusion of this study is that AI creates technological potential, but AI-driven leadership determines how effectively that potential is converted into organizational and supply chain value. The findings demonstrate that technological adoption alone is insufficient to achieve meaningful transformation. Sustainable value depends on the alignment of AI capabilities with strategy, data, people, processes, governance, and decision-making structures.

Accordingly, this study positions AI-driven leadership as a strategic organizational capability that connects AI intelligence with organizational action. Its theoretical contribution lies in shifting the focus from leadership as an exclusively human managerial activity toward leadership as the design, coordination, and governance of human–AI decision systems. Within this perspective, increasing AI capability does not make leadership less important; rather, it changes where leadership effort is directed—from routine decisions toward orchestration, strategic alignment, oversight, exception management, and governance.

The proposed maturity pathway and functional mapping framework provide a conceptual structure for understanding this transition, while the transformation roadmap translates the framework into a phased approach for implementation. These contributions should be regarded as a foundation for future empirical testing rather than as fully validated causal models.

The broader implication is that the transition toward intelligent manufacturing supply chains requires a shift from technology adoption to strategic AI orchestration. Organizations that successfully align AI with leadership, data, people, governance, and supply chain strategy will be better positioned to develop intelligent, resilient, adaptive, and human-centered supply chains. Future research should therefore move beyond measuring AI adoption and examine the leadership capabilities, organizational mechanisms, and governance conditions that determine whether AI generates sustained and measurable supply chain value.

Ultimately, the effectiveness of AI-enabled supply chains will depend not simply on the sophistication of the technologies deployed, but on the organization's ability to integrate AI into its strategic architecture, distribute decision rights effectively, maintain human accountability, and continuously develop the capabilities required for higher levels of autonomy. This study provides a foundation for advancing AI-driven leadership as a measurable and strategically important capability in the emerging era of intelligent manufacturing.

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Generative AI Statement

The authors used ChatGPT (OpenAI) solely for language editing and stylistic refinement of the manuscript, including improvements in grammar, clarity, readability, and academic expression. ChatGPT was not used to generate original research content, data, analyses, interpretations, or references. The authors reviewed and verified all AI-assisted revisions and take full responsibility for the accuracy, integrity, and final content of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data supporting the findings of this study are available within the article.

Abbreviations

Abbreviation	Full Term	Short Definition
AI	Artificial Intelligence	Systems that learn, reason, and support decision-making
BDA	Big Data Analytics	Techniques for analyzing large-scale and complex datasets
DL	Deep Learning	Neural network methods for complex pattern recognition
DSS	Decision Support System	Computer-based systems supporting decision-making
DT	Digital Twin	Virtual representation of physical systems for simulation and analysis
ERP	Enterprise Resource Planning	Integrated systems for managing core business processes
IoT	Internet of Things	Network of connected devices enabling real-time data exchange
KPI	Key Performance Indicator	Quantitative measure of performance outcomes
ML	Machine Learning	Data-driven algorithms that improve prediction and decision-making
RL	Reinforcement Learning	Sequential decision optimization through reward-based learning
SCM	Supply Chain Management	Coordination of end-to-end flows of materials, information, and finances

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