

Agentic AI for Real-Time Scheduling and Supply Chain Optimization:**An Adaptive Decision-Making Framework**¹Dr Bassey Essien Archibong²Mr. Mohammed Saeed Al Badawi³Sunil Kumar SahooExecutive Director, Agropedia Limited ¹Director, Zakat, Tax and Customs Authority ²Solutions Architect, Wipro ³**Abstract**

Supply chains increasingly operate under volatile demand, supplier uncertainty, transportation disruptions and rapidly changing production conditions. Conventional scheduling and optimization approach often rely on periodic planning, predefined rules or human intervention, which limits responsiveness when conditions change continuously. Agentic Artificial Intelligence (Agentic AI) offers an opportunity to move beyond prediction and recommendation toward autonomous, goal-directed decision-making. This conceptual paper develops an adaptive decision-making framework for applying Agentic AI to real-time scheduling and supply chain optimization. Through a structured literature analysis and thematic synthesis of research on artificial intelligence in supply chain management, dynamic scheduling, reinforcement learning, digital twins and multi-agent systems, the study identifies five interconnected capabilities: real-time supply chain sensing, agentic decision intelligence, multi-agent coordination and optimization, adaptive execution and feedback, and human oversight and governance. The framework explains how these capabilities operate within a continuous sensing, reasoning, coordination, execution and feedback loop, and seven propositions are formulated for future empirical validation. The paper contributes a decision-

oriented framework linking Agentic AI capabilities to supply chain responsiveness, efficiency and resilience, and offers guidance on allocating decision authority between autonomous agents and human decision-makers.

Keywords: Agentic AI; Supply Chain Optimization; Real-Time Scheduling; Autonomous Decision-Making; Adaptive AI; Digital Twins; Multi-Agent Systems

1. Introduction

1.1 Background of the Study

Modern supply chains operate in dynamic environments where demand fluctuations, supplier delays, transportation disruptions, and production constraints continuously influence operational decisions. Traditional scheduling approaches often rely on fixed rules, periodic planning cycles, and human intervention, limiting their ability to adapt rapidly. As supply chains become increasingly interconnected and data-driven, the ability to sense changes and revise decisions in real time have become essential. Artificial intelligence (AI) has been applied across supply chain activities, including demand forecasting, inventory management, procurement, production planning, and logistics. Existing reviews demonstrate that AI improves decision support, supply chain performance, resilience, and operational capabilities (Toorajipour et al., 2021; Younis et al., 2022; Kassa et al., 2023; Culot et al., 2024). However, many applications remain focused on prediction and recommendation,

with execution and coordination dependent on human planners or separate systems. Agentic AI extends these capabilities by enabling systems to interpret objectives, reason, plan actions, use digital tools, and learn through feedback. Building on intelligent agent concepts (Wooldridge & Jennings, 1995), recent research highlights autonomous supply chains as a progression toward higher levels of decision autonomy (Xu et al., 2024a). This study therefore proposes an adaptive framework integrating sensing, reasoning, multi-agent coordination, optimisation, execution, and continuous feedback for Agentic AI-enabled supply chain scheduling and optimisation.

1.2 Problem Statement

Supply chain scheduling requires continuous adjustment because demand, inventory levels, production capacity, supplier availability and transportation conditions can change rapidly. Many existing scheduling systems rely on predefined rules, periodic optimization or separate AI tools that address individual activities. Such tools

may provide useful recommendations, but they have limited ability to coordinate multiple decisions and respond autonomously to changing conditions.

Agentic AI creates an opportunity to address this limitation by enabling systems to sense operational changes, reason about alternatives, coordinate actions and adapt decisions continuously. Yet its application to real-time scheduling and supply chain optimization remains conceptually fragmented. The central problem addressed by this study is therefore the lack of an integrated framework explaining how Agentic AI can continuously sense supply chain conditions, coordinate distributed decisions and adapt scheduling and optimization decisions in real time. Without such a framework, organizations may struggle to translate emerging agentic capabilities into reliable and coordinated decision-making.

1.3 Research Aim

The aim is to develop an adaptive decision-making framework explaining how

Agentic AI can support real-time scheduling and optimization in dynamic supply chain environments.

1.4 Research objectives.

RO1: to examine the role of AI and Agentic AI in supply chain decision-making and scheduling.

RO2: to identify the key capabilities required for real-time and adaptive supply chain optimization.

RO3: to develop a conceptual framework integrating sensing, agentic reasoning, multi-agent coordination, optimization and continuous feedback.

RO4: to examine the potential contribution of Agentic AI to supply chain responsiveness, efficiency and resilience.

1.5 Research questions.

RQ1: How can Agentic AI support real-time supply chain scheduling and decision-making?

RQ2: What capabilities are required for adaptive Agentic AI-enabled supply chain optimization?

RQ3: How can multi-agent coordination and continuous feedback improve dynamic supply chain decisions?

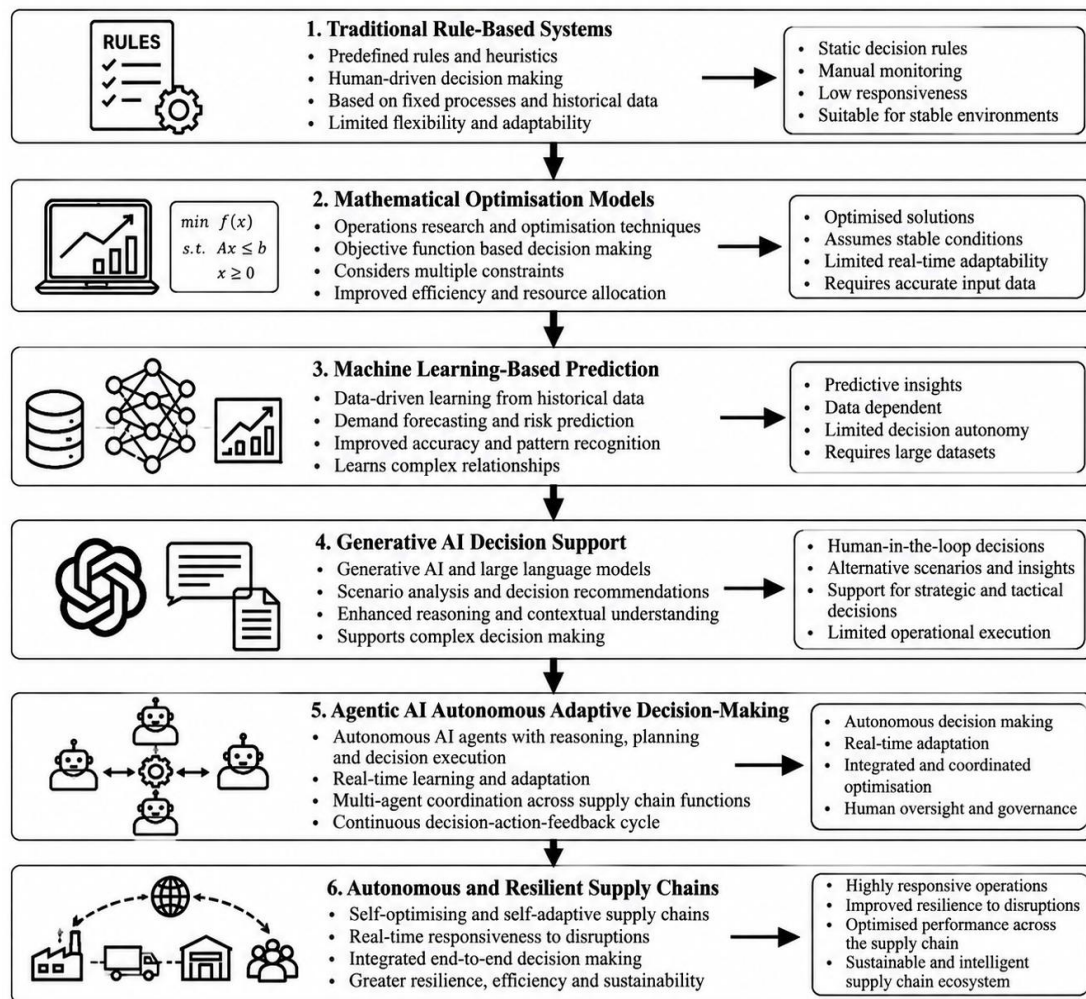
RQ4: What operational outcomes can result from Agentic AI-enabled adaptive decision-making?

1.6 Significance of the Study

The study provides a structured view of how Agentic AI can support continuous decision-making in dynamic supply chains. Rather than treating AI only as a forecasting or recommendation tool, the framework considers its role across the complete decision cycle, from real-time sensing to execution and feedback. The contribution is

threefold. It is conceptual, by connecting Agentic AI, real-time scheduling, multi-agent coordination and adaptive optimization within one framework. It is managerial, by identifying capabilities and governance requirements that organizations can consider when developing AI-enabled operations. It is also a research foundation for empirical studies of the relationship between agentic capabilities and supply chain performance. The remainder of the paper reviews the literature, presents the theoretical foundation and methodology, develops the framework and propositions, and discusses contributions, limitations and future research.

Figure 1. Evolution of AI-Based Supply Chain Decision-Making Towards Agentic AI



2. Literature Review

2.1 Agentic AI and Autonomous Decision-Making

Conventional AI systems typically generate predictions or recommendations that humans then interpret and implement. Agentic AI shifts this boundary by combining reasoning, planning, tool use and autonomous action in pursuit of defined goals. Its conceptual roots lie in agent theory,

in which an agent is characterized by autonomy, social ability, reactivity and proactiveness (Wooldridge & Jennings, 1995). In supply chain research, Xu et al. (2024a) define autonomous supply chains, describe their characteristics and propose levels of autonomy, providing a structured way to understand how far decision authority can be delegated to intelligent systems. Complementary work shows how multi-

agent systems can implement such autonomy in practice (Xu et al., 2024b) and how foundation models may extend agents' capabilities while raising new challenges (Xu et al., 2024c). Generative AI is also examined as a driver of supply chain transformation (Bahroun et al., 2026), although its role is

often confined to decision support and content generation. Figure 1 summarizes this progression of decision approaches. Despite this progress, the integration of Agentic AI with real-time scheduling and optimization remains limited.

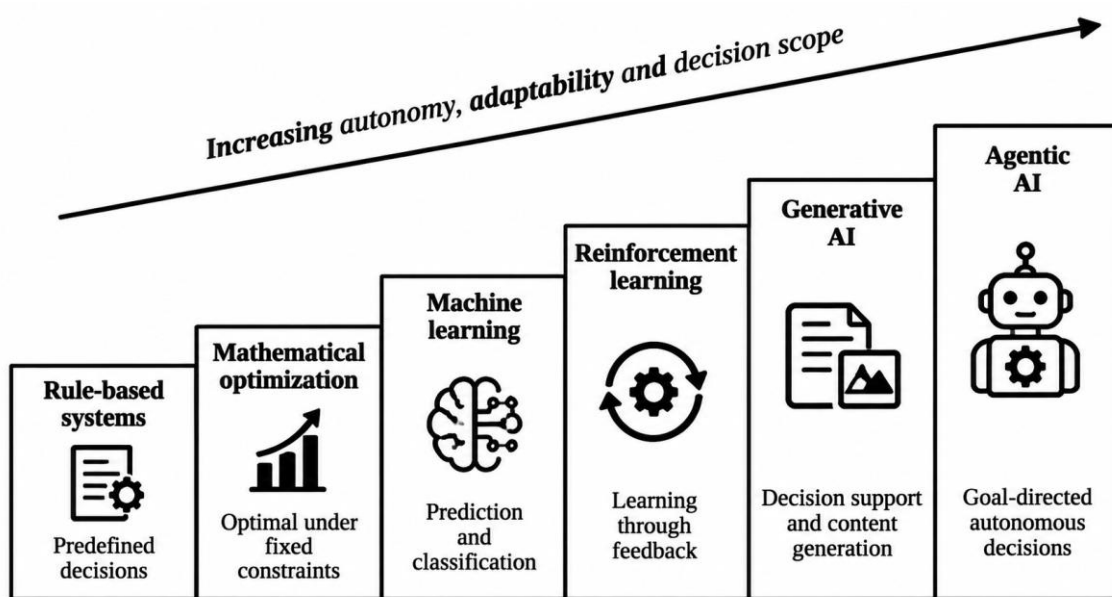


Figure 2. Progression of AI decision approaches in supply chains toward Agentic AI (authors' synthesis).

2.2 Artificial Intelligence in Supply Chain Management

AI is used for demand forecasting, inventory management, procurement, logistics and production planning. Systematic reviews consistently report that AI can improve decision support and performance (Toorajipour et al., 2021; Culot

et al., 2024), while providing broad overviews of applications and research directions (Younis et al., 2022). Studies of AI adoption synthesize evidence on how organizations implement these technologies (Shahzadi et al., 2024). AI has also been associated with supply chain resilience, where techniques support risk anticipation,

disruption response and recovery (Kassa et al., 2023), and with closed-loop supply chains, where reverse flows add planning complexity (Bhattacharya et al., 2024). A common limitation across these streams is that applications remain function-specific. Forecasting models, inventory optimizers and routing tools are often deployed separately, so decisions in one function may not be aligned with those in another. This creates a need for coordinated decision-making across supply chain activities, which is the focus of the proposed framework.

2.3 Real-Time Scheduling and Dynamic Optimization

Real-time scheduling requires continuous adjustment when demand, resources or operational conditions change. Early work applied reinforcement learning to agent-based production scheduling, showing that agents can learn scheduling policies through interaction rather than relying solely on fixed dispatching rules (Wang & Usher, 2005). Later studies developed deep

reinforcement learning approaches, such as actor-critic methods for job shop scheduling (Liu et al., 2020). More recent research combines reinforcement learning with digital twins to support live decision-making, including integrated process planning and scheduling (Müller-Zhang et al., 2023), real-time scheduling for flexible shop floors (Chang et al., 2023) and dynamic job shop scheduling (Zhang et al., 2026). At the supply chain level, digital twin-enhanced approaches address rescheduling under real-time order arrival and acceptance (Zhu et al., 2026). Bibliometric evidence also shows growing interest in combining machine learning with operations research for scheduling (Ouhadi et al., 2024). These approaches, however, typically address a specific scheduling problem and do not always integrate sensing, autonomous reasoning, coordination and execution within one decision process. Table 1 compares the main approaches.

Table 1. Comparison of AI Approaches in Supply Chain Decision-Making

AI Approach	Primary Decision Style	Adaptability Level	Main Limitation	Illustrative sources
Rule-Based Systems	Predefined decisions based on fixed rules	Low	Limited response to unexpected disruptions	General practice
Mathematical Optimisation	Generates optimal solutions under defined constraints	Moderate	Requires predefined objectives and updated information	Ouhadi et al. (2024)
Machine Learning	Prediction and classification based on historical data	Moderate	Limited autonomous execution	Toorajipour et al. (2021); Younis et al. (2022)
Reinforcement Learning	Learns through interaction and feedback	High	Requires training environments and continuous learning	Wang & Usher (2005); Liu et al. (2020)
Generative AI	Content generation and decision support	High	Limited operational autonomy	Bahroun et al. (2026)
Agentic AI	Goal-directed autonomous reasoning and action	Very High	Requires governance, coordination, and reliable data	Xu et al. (2024a, 2024b, 2024c)

2.4 Digital Twins, Multi-Agent Systems and Adaptive Supply Chains

Digital twins provide virtual representations of operations that can support real-time simulation and evaluation of alternative decisions before implementation. The studies discussed above show how they support dynamic scheduling when coupled with learning-based methods (Chang et al., 2023; Zhang et al., 2026; Zhu et al., 2026). Multi-agent systems, in contrast, enable distributed decision-making across functions, with agents that hold local information and

coordinate to achieve shared goals (Wooldridge & Jennings, 1995; Xu et al., 2024b). Guzmán-Ortiz et al. (2026) extend this logic with a cooperative digital twin and multi-agent reinforcement learning approach for circular supply chains that balances production, logistics and sustainability. Multi-agent systems combined with foundation models further suggest routes to autonomous supply chains, together with opportunities and challenges (Xu et al., 2024c). Taken together, the literature shows that digital twins, reinforcement learning and

multi-agent coordination are each maturing, yet their combined use within an Agentic AI decision cycle for real-time scheduling remains conceptually underdeveloped.

2.5 Research Gaps

1. Integration Gap: Limited Understanding of Agentic AI as an Integrated Supply Chain Decision-Making Capability

2. Adaptive Optimisation Gap: Limited Integration of Real-Time Sensing, Dynamic Scheduling, and Autonomous Optimisation

3. Multi-Agent Coordination Gap: Limited Understanding of Autonomous Collaboration Across Supply Chain Functions

4. Governance and Outcome Gap: Limited Understanding of Human Oversight and Supply Chain Outcomes in Autonomous AI Systems

3. Theoretical Foundation

3.1 Dynamic Capabilities Perspective

Dynamic capabilities theory explains how organizations sustain performance in

changing environments through the capacity to sense opportunities and threats, seize opportunities and transform resources and routines (Teece, 2007). The perspective is relevant to real-time supply chain management, where the value of a decision depends on how quickly change is detected and acted upon. In the proposed framework, Agentic AI operationalizes sensing through continuous monitoring of operational data, supports seizing through reasoning, planning and optimization of responses, and enables transforming through adaptive execution and re-planning. Scheduling is therefore treated as a continuous organizational capability rather than a periodic planning task.

3.2 Sociotechnical Systems Perspective

The sociotechnical systems perspective emphasizes that system performance emerges from the interaction between technology, people and organizational processes rather than from technology alone (Baxter & Sommerville, 2011). This is important when autonomy is delegated to AI agents, because decisions

carry organizational consequences and require clear responsibilities. Accordingly, the framework incorporates human oversight and governance as a design element that defines objectives, boundaries, approval requirements and escalation conditions, so that autonomous decisions remain aligned with operational and organizational requirements.

3.3 Adaptive Decision-Making Perspective

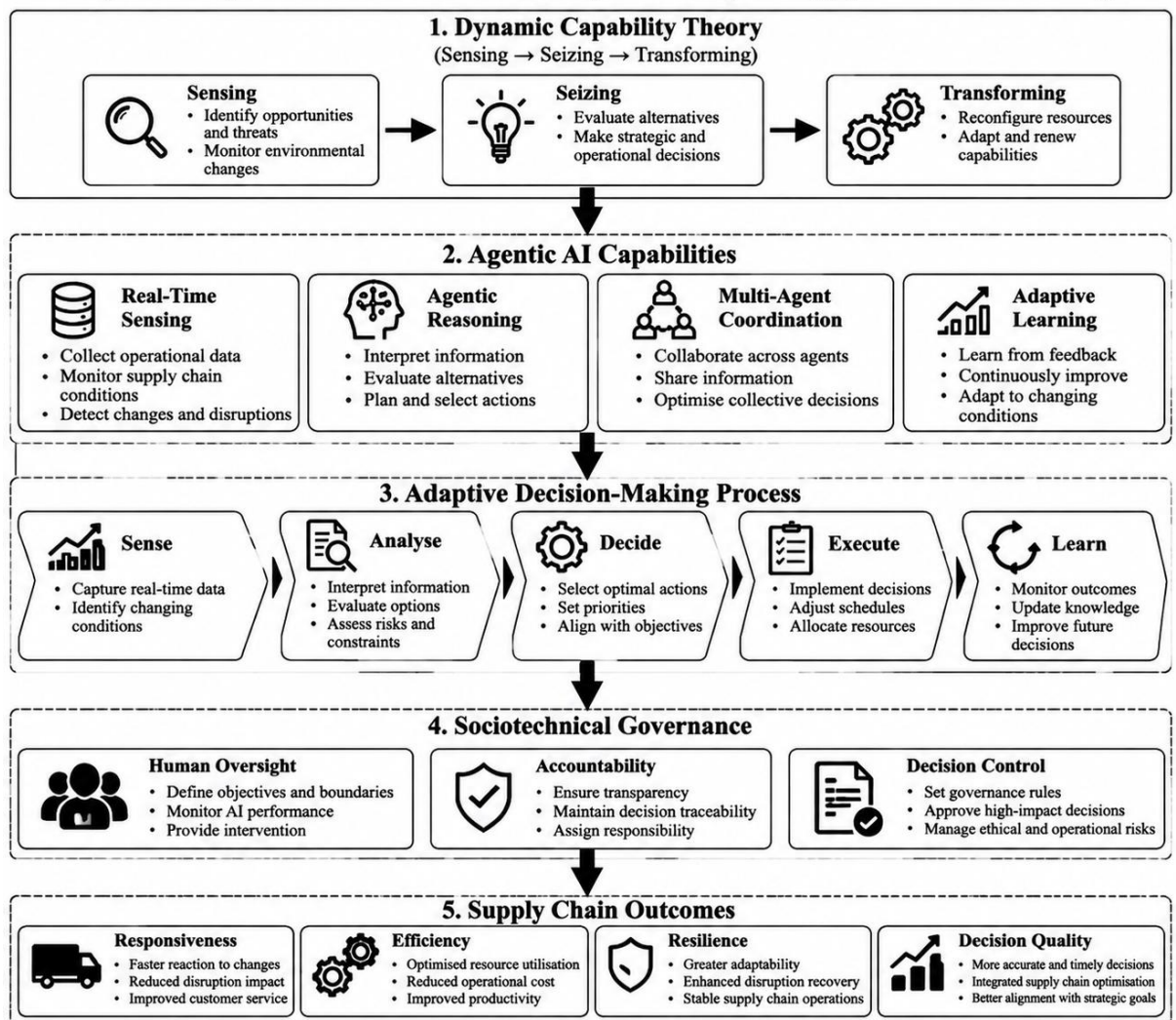
The adaptive decision-making perspective emphasizes continuous adjustment as new information and uncertainty emerge, rather than commitment to a single plan made in advance. It is consistent with agent-based and learning-based scheduling studies in which decisions improve through interaction with the environment and feedback (Wang & Usher, 2005; Liu et al., 2020). In the framework, Agentic AI supports this process by

evaluating current conditions, selecting actions and revising decisions using feedback from execution. The perspective explains why the decision–action–feedback cycle, rather than any single decision, is the primary unit of analysis.

3.4 Integrated Theoretical Perspective

The three perspectives are complementary. Dynamic capabilities explain organizational adaptation, sociotechnical systems explain human–AI coordination and accountability, and adaptive decision-making explains continuous decision revision. Together they support integrating sensing, reasoning, coordination, optimization, execution, feedback and governance in one framework. Section 5 shows how these logics are operationalized in the framework's five capabilities.

Figure 3. Integrated Theoretical Foundation of Agentic AI Adaptive Supply Chain Decision-Making



4. Research Methodology

4.1 Research Design

This study adopts a conceptual research design based on structured literature analysis and theoretical synthesis. The approach is appropriate because the objective is to develop an integrated framework and testable propositions rather than to empirically test a predefined model.

Literature concerning Agentic AI, AI in

supply chains, real-time scheduling, reinforcement learning, digital twins and multi-agent systems was examined to identify relevant concepts, capabilities and relationships. The paper is therefore theory-building in intent: it reports no primary data, and its claims are presented as propositions for later empirical testing.

4.2 Literature Search Strategy

The literature analysis focused on studies addressing AI-enabled supply chain decision-making, autonomous systems, real-time scheduling, adaptive optimization, reinforcement learning, digital twins and multi-agent coordination. Priority was given to peer-reviewed academic studies and recent research reflecting developments in AI-enabled supply chain transformation. Foundational studies were also considered where they provided theoretical or conceptual foundations for the framework. The analysis draws on twenty-one core sources spanning systematic reviews, research on autonomous supply chains, scheduling studies and foundational theory.

4.3 Inclusion and Exclusion Criteria

Studies were included when they directly addressed one or more of the following areas: Artificial Intelligence applications in supply chain management, Autonomous or intelligent supply chain systems, Real-time scheduling and optimisation, Digital twins

and reinforcement learning, Multi-agent systems, AI governance and human oversight. Studies unrelated to supply chain decision-making or focusing only on general AI applications without operational relevance were excluded. Recent studies were prioritised to capture emerging developments in Agentic AI and autonomous supply chains. However, established theoretical studies were retained where they provided important conceptual foundations.

4.4 Thematic Synthesis and Framework Development

The selected literature was thematically synthesized to identify recurring capabilities, decision mechanisms and operational outcomes. The synthesis compared how each stream described the detection of change, the selection of actions, the coordination of decisions and the evaluation of results, and grouped these into recurring themes. The analysis identified six interconnected decision activities: sensing, reasoning, planning, coordination, execution

and feedback. These were integrated with human oversight and governance, drawing on the theoretical perspectives in Section 3, to develop the proposed framework. The resulting relationships provide the conceptual foundation for the seven propositions in Section 6.

5. Proposed Agentic AI Adaptive Decision-Making Framework

The framework conceptualizes supply chain scheduling as a continuous

decision cycle rather than a periodic planning task. As Figure 4 shows, operational data feed a real-time sensing, whose outputs inform agentic decision intelligence, multi-agent coordination and optimization, and adaptive execution. Execution results return as feedback, and a governance layer spans the whole cycle. The following subsections describe each element.

Figure 4. Agentic AI Adaptive Decision-Making Framework for Real-Time Supply Chain Optimisation

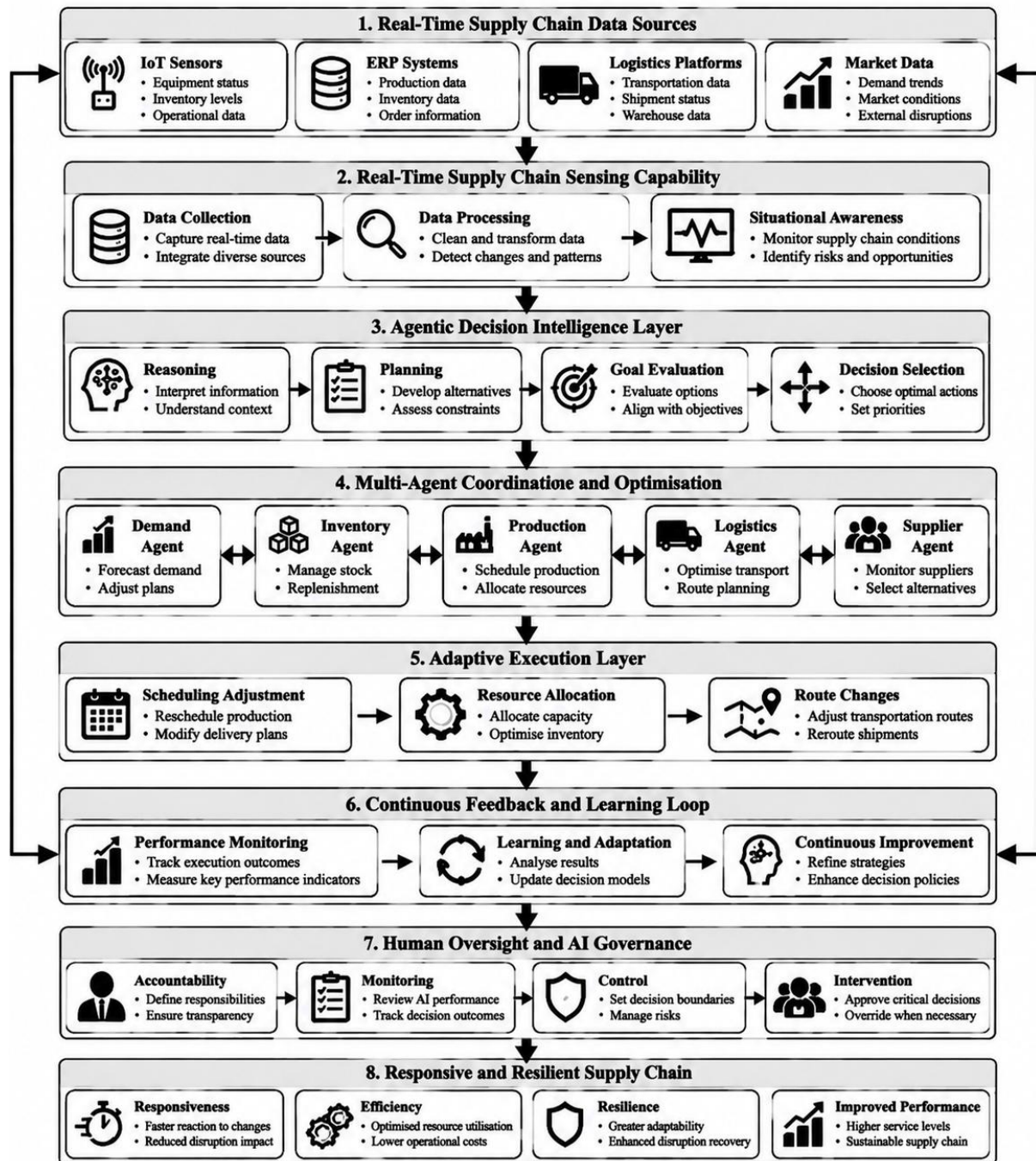


Figure 4. The Agentic AI adaptive decision-making framework for real-time scheduling and supply chain optimization.

5.1 Real-Time Supply Chain Sensing

Real-time sensing forms the first layer of the framework. Agentic AI systems require continuous information about demand, inventory, production capacity, supplier status, transportation and external disruptions. Data can be collected from enterprise systems, IoT devices, logistics

platforms and other operational sources. Sensing enables the system to identify changes in supply chain conditions rather than relying only on periodic planning cycles. When a significant change is detected, such as a machine stoppage, a delayed shipment or a sudden order, the relevant agent can trigger further analysis and decision-making. Digital twin research shows that virtual representations of operations can support live decision-making when connected to real-time data (Müller-Zhang et al., 2023; Chang et al., 2023). Real-time sensing therefore provides the information foundation for adaptive scheduling and optimization, and reflects the sensing capability described in dynamic capabilities theory (Teece, 2007).

5.2 Agentic Decision Intelligence

Agentic decision intelligence forms the core decision-making layer. It enables AI agents to interpret real-time information, identify operational problems and evaluate possible responses according to defined objectives. Consistent with agent theory, such agents combine autonomy with

reactivity to their environment and proactive, goal-directed behavior (Wooldridge & Jennings, 1995). The system can use specialized agents for demand, inventory, production and logistics activities. Each agent analyzes relevant information while contributing to broader supply chain objectives. Unlike conventional recommendation systems, Agentic AI can combine reasoning, planning and tool interaction to develop and revise decisions as conditions change. Learning-based methods such as reinforcement learning can supply decision policies within this layer (Wang & Usher, 2005; Liu et al., 2020), while foundation models may extend agents' reasoning and interaction capabilities (Xu et al., 2024c). The objective is not simply to automate individual decisions but to create a continuous process in which agents evaluate alternatives, identify constraints and initiate appropriate actions.

5.3 Multi-Agent Coordination and Optimization

Multi-agent coordination enables different agents to work together across supply chain functions. Specialized agents, namely demand, inventory, production, logistics and supplier agents, analyze their respective conditions independently while sharing information, and a coordination agent aligns their decisions with overall objectives (Table 2). Multi-agent approaches have been proposed as a practical route to autonomous supply chains (Xu et al., 2024b) and have been combined with digital twins and reinforcement learning to balance production, logistics and sustainability objectives (Guzmán-Ortiz et al., 2026).

Coordination reduces the risk of isolated

decisions that optimize one function while creating problems elsewhere. For example, a production agent may adjust a schedule based on inventory information, while a logistics agent considers transport capacity and delivery requirements. The framework combines coordination with optimization techniques to evaluate constraints, compare alternatives and select feasible actions, an integration also reflected in work combining machine learning with operations research (Ouhadi et al., 2024). As new information arrives, agents revise their decisions and coordinate again, so decisions are distributed, coordinated and continuously adaptable rather than fixed at the start of a planning cycle.

Table 2. Agent Types and Supply Chain Responsibilities

Agent Type	Primary Responsibility	Key Decisions	Typical inputs
Demand Agent	Monitor demand patterns and market changes	Forecast updates, demand adjustments	Order history, market signals
Inventory Agent	Manage inventory visibility and availability	Stock allocation, replenishment decisions	Stock levels, replenishment lead times
Production Agent	Manage manufacturing activities	Scheduling, sequencing, resource allocation	Capacity, machine status, work orders

Logistics Agent	Coordinate transportation activities	Routing, shipment timing, carrier decisions	Transport capacity, shipment status, delivery windows
Supplier Agent	Monitor supplier conditions	Supplier selection, order modification	Supplier performance, lead-time and risk signals
Coordination Agent	Integrate decisions across agents	Conflict resolution, overall optimisation	Agent proposals, constraints, priority rules

5.4 Adaptive Execution and Feedback

Adaptive execution connects AI-generated decisions with actual operations. After an optimized decision is selected, the system can trigger or recommend actions such as rescheduling production, reallocating inventory, changing transportation plans or adjusting procurement. Digital twins can be used to evaluate such actions before implementation, and dynamic rescheduling research shows how real-time order arrival and acceptance can be handled within a twin-enhanced approach (Zhu et al., 2026). The framework includes continuous monitoring of execution results against expected outcomes. Performance deviations, new disruptions and changes in operating conditions return to the system as feedback, allowing agents to reassess the current plan

and generate revised decisions. This creates a continuous decision–action–feedback cycle in which scheduling is not a one-time activity. Such adaptation can support faster responses to disruptions while maintaining alignment with operational constraints, consistent with the role of AI in supporting resilience (Kassa et al., 2023).

5.5 Human Oversight and Decision Governance

Human oversight provides a governance layer for Agentic AI-enabled decisions. Although agents may perform planning and execution autonomously, human decision-makers should define objectives, operational boundaries, approval requirements and escalation conditions. The sociotechnical perspective supports this design, since reliable performance depends

on the fit between technology, people and organizational processes (Baxter & Sommerville, 2011). The framework proposes different levels of human involvement according to decision risk and operational impact. Routine decisions may be executed automatically within predefined limits, whereas significant decisions, such as major production changes, supplier switches or high-cost logistics adjustments, can require human approval. This graduated logic resembles the levels of autonomy discussed in research on autonomous supply chains (Xu et al., 2024a). Governance should also include decision traceability, performance

monitoring, exception handling and the ability to override or suspend automated actions. Human oversight therefore does not replace Agentic AI autonomy; it establishes the boundaries within which autonomous decisions can operate safely and consistently.

6. Conceptual Propositions

Based on the framework, seven propositions describe how Agentic AI capabilities may influence real-time scheduling, supply chain optimization and performance. Figure 4 shows the proposed relationships, and Table 3 summarizes the capabilities, mechanisms and expected outcomes.

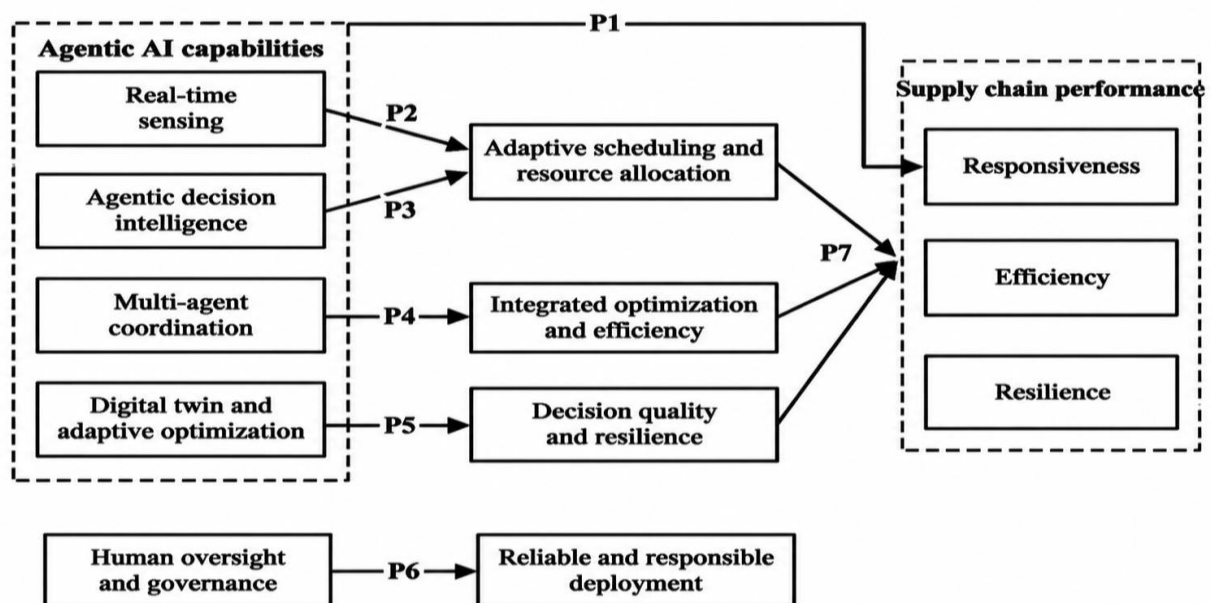


Figure 5. Conceptual model of the proposed relationships (P1–P7).

6.1 Sensing, Reasoning and Responsiveness

P1: Stronger Agentic AI capabilities are positively associated with real-time supply chain responsiveness. Agentic AI allows decisions to be revised as conditions change rather than at fixed planning intervals, shortening the time between a disturbance and an organizational response (Teece, 2007; Xu et al., 2024a).

P2: Stronger real-time sensing capabilities are positively associated with adaptive supply chain scheduling under changing operational conditions. Continuous data and event detection allow schedules to be revised when disruptions occur, as digital twin-based scheduling studies suggest (Chang et al., 2023; Zhu et al., 2026).

P3: Stronger agentic reasoning, planning and decision-making capabilities are positively associated with effective real-time scheduling and resource allocation. Learning-based scheduling studies show that policies can improve through interaction and

feedback (Wang & Usher, 2005; Liu et al., 2020; Müller-Zhang et al., 2023).

6.2 Coordination and Digital Twin Integration

P4: Effective multi-agent coordination is positively associated with integrated supply chain optimization and operational efficiency. Coordination aligns distributed decisions across functions and reduces isolated optimization (Xu et al., 2024b; Guzmán-Ortiz et al., 2026).

P5: Stronger integration of digital twins and adaptive optimization is positively associated with supply chain decision quality and resilience. Twins allow alternatives to be evaluated before execution, which may improve decision quality and support resilience (Zhang et al., 2026; Zhu et al., 2026; Kassa et al., 2023).

6.3 Governance and Overall Performance

P6: Effective human oversight, governance and accountability are positively associated with the reliable and responsible deployment of Agentic AI in supply chain operations. Sociotechnical theory associates

clear boundaries and accountability with responsiveness, efficiency and resilience. AI reliable system performance (Baxter & in supply chain management has been linked Sommerville, 2011). to improved decision support and

P7: Adaptive Agentic AI decision-making is positively associated with supply performance (Toorajipour et al., 2021; Culot et al., 2024). chain performance through improved

Table 3. Proposed Framework Capabilities and Expected Outcomes

Framework Capability	Key Mechanism	Decision Focus	Expected Outcome	Linked propositions
Real-Time Supply Chain Sensing	Continuous data collection and disruption detection	Identifying changing operational conditions	Faster responsiveness	P1, P2
Agentic Decision Intelligence	Reasoning, planning, and autonomous evaluation	Selecting appropriate actions	Improved decision quality	P1, P3
Multi-Agent Coordination	Information sharing and collaborative decisions	Aligning supply chain functions	Greater efficiency and coordination	P4
Adaptive Execution and Feedback	Monitoring outcomes and revising decisions	Continuous improvement	Flexibility and resilience	P5, P7
Human Oversight and Governance	Control mechanisms, monitoring, and intervention	Responsible AI operation	Reliable autonomous decision-making	P6

7. Discussion and Contributions

7.1 Theoretical Contributions

The framework contributes to supply chain literature by integrating Agentic AI, dynamic capabilities and adaptive decision-making in one decision framework. It extends also incorporates the sociotechnical AI-based decision support, which is often function-specific (Toorajipour et al., 2021; Culot et al., 2024), by connecting sensing, reasoning, coordination, optimization and adaptation within a continuous process. It

perspective by positioning human oversight alongside autonomous capabilities, highlighting the balance between technological autonomy and organizational control. The novelty of the framework lies not in introducing individual AI technologies but in integrating real-time sensing, agentic reasoning, multi-agent coordination, optimization, adaptive execution and human governance into a continuous supply chain decision cycle.

7.2 Managerial Implications

The framework gives managers a structured approach for applying Agentic AI across demand, inventory, production, logistics and supplier activities. Decision boundaries, approval thresholds and escalation mechanisms can be defined according to operational risk, following the logic of graduated autonomy (Xu et al., 2024a). Organizations can thereby combine autonomous routine decisions with human involvement in high-impact decisions.

7.3 Practical Contributions

The framework connects real-time operational data with adaptive scheduling and optimization through a continuous feedback cycle. Organizations can initially implement Agentic AI within individual supply chain functions, such as production scheduling, and gradually extend coordination across the wider supply chain. Reliable real-time data and clear governance arrangements are prerequisites for such extension.

7.4 Research Contributions

The seven propositions provide a basis for future empirical research on Agentic AI and supply chain performance. Future studies can examine relationships between agentic capabilities, scheduling responsiveness, optimization effectiveness, decision quality and resilience. The framework also provides measurable dimensions that can be investigated through case studies, surveys, simulation experiments and longitudinal research.

8. Limitations and Future Research

8.1 Limitations

This study is conceptual and therefore does not empirically validate the framework or propositions. The effectiveness of Agentic AI may also vary across industries because supply chain structures, data availability, operational constraints and levels of automation differ. A further limitation concerns the reliability and governance of autonomous decisions. Agentic systems may face challenges related to data quality, model reliability, cybersecurity, coordination between agents and appropriate levels of human intervention, and these require investigation before large-scale autonomous deployment.

8.2 Future Research Directions

Future research should empirically test the propositions using case studies, surveys, simulation and real-time supply chain experiments. Studies can also examine how digital twins, reinforcement learning and multi-agent architectures influence scheduling performance under different

disruption scenarios. Longitudinal research could investigate whether Agentic AI improves supply chain responsiveness, efficiency and resilience over time, and how governance arrangements evolve as autonomy increases.

9. Conclusion

Agentic AI provides an emerging approach for addressing the growing complexity and uncertainty of modern supply chains. Unlike conventional AI applications that primarily support prediction or recommendation, Agentic AI can integrate sensing, reasoning, planning, coordination, execution and continuous feedback within an adaptive decision-making process.

This paper proposed a conceptual framework connecting real-time supply chain sensing, agentic decision intelligence, multi-agent coordination, optimization, adaptive execution and human governance. The framework proposes that Agentic AI can improve supply chain performance through more responsive scheduling, adaptive optimization, better decision quality and

resilience. The seven propositions provide a management from periodic and reactive foundation for future empirical investigation. planning toward continuous, coordinated and Overall, the framework positions Agentic AI adaptive decision-making. as a mechanism for moving supply chain

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