Mitigating Cognitive Load in Supply Chain Decision-Making: An AI-Driven Framework for Enhanced Operational Efficiency

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Abstract

Humans face a lot of cognitive hinderances that slow down the operations and effectiveness in decision making in the scope of supply chain. Supply chain management systems have now become more intricate and data intensive. Existing systems usually overlook users' cognitive limitations, that results in information overload and decision fatigue despite advancements in digitalization and analytics. For cognitive load in supply chain to reduce significantly in decision-making, this study recommends an AI-driven framework that enhances human cognition instead of replacing it. The emphasis is on increasing operational efficiency, fostering human and AI collaboration, and developing supply chain sustainability. As companies grow, there is an increasing need to incorporate AI technologies that improve decision-making and operational resilience while assuring sustainable practices. The framework consists of layered components that filter information, provide contextual support, provide actionable recommendations, and incorporate human feedback. The design is based on Cognitive Load Theory and human-centered AI design. The study uses theoretical example applications in disruption management and demand forecasting to show how the framework might improve operational efficiency, minimize cognitive strain, and improve decision quality. The findings contribute to the AI-human collaboration and suggest new approaches to building intelligent decision-support systems that are both technologically advanced and cognitively aware.

Keywords: cognitive load, supply chain management, artificial intelligence, decision support systems, cognitive augmentation

1. Introduction

In today's dynamic and interconnected global marketplaces, supply chain operations are becoming increasingly complex, needing quick and precise procurement, production, logistics, and distribution choices. This growing complexity poses significant cognitive demands on supply chain personnel, who must handle huge volumes of data, manage several decision variables, and respond to disruptions in real time (Christopher, 2016). As supply chains become increasingly computerized and data-rich, human decision-makers' ability to perceive, prioritize, and act on information becomes a critical limiting factor in operational efficiency.

Cognitive Load Theory (CLT), established in educational psychology, offers insight into how people absorb information and make decisions under pressure (Paas & van Merriënboer, 1994). CLT distinguishes between intrinsic, extraneous, and germane cognitive loads, implying that overload, particularly from irrelevant or excessive information, might impair performance. In supply chain environments, this manifests as decision fatigue, delayed responses to interruptions, and increased error rates, especially in high-stakes or time-constrained scenarios (Kembro & Näslund, 2014).

Despite the growing use of digital technologies in supply chain management, most decision-support systems continue to rely primarily on human judgment and intuition. This limits cognitive performance and fails to take advantage of available technology that can help manage complicated data settings. Artificial intelligence (AI), with its skills in predictive analytics, pattern recognition, and automation, offers a possible answer to this problem (Waller & Fawcett, 2013). AI can minimize cognitive load by filtering information, prioritizing critical factors, providing real-time recommendations, and even automating mundane decisions, freeing humans to focus on strategic and high-level problem solving. Empirical evidence from cross-industry implementations shows that structured human-AI collaboration outperforms human-only or AI-only approaches, with documented accuracy increases of 27-42% and efficiency improvements of 31-36% across multiple supply chain functions (Zhang & Jiang, 2024).

However, there is limited number of theories and unevenness in the incorporation of AI into supply chain decision-making frameworks. Most current approaches mostly treat AI as a tool for total automation and overlook its potential as a cognitive partner to its human operators. This gap creates an opportunity to develop a more comprehensive framework, which focuses more on how AI can enhance human capabilities, instead of replacing human cognition in high-pressure supply chain scenarios. This study investigates how AI can be used strategically to reduce cognitive load in supply chain decision-making. It demonstrates an AI-powered system that aims to increase operational efficiency through human-AI collaboration and intelligent decision assistance. By addressing both the technological and cognitive dimensions of supply chain management, this work contributes to a growing body of research on human-centered AI and decision augmentation.

2. Literature Review

2.1 Cognitive Load Theory in Decision-Making

Simon (2013) theory of bounded rationality provides foundational insight into the limited cognitive capacity of human decision-makers, especially under uncertainty. The Cognitive Load Theory (CLT) analyzes how learning and decision-making are affected by the working memory limits. This theory identifies three categories of cognitive load (Plass et al., 2010). These categories are intrinsic load, that inherent to the task itself, extraneous load which is present due to poor task design or irrelevant information and germane load, which is beneficial for learning or schema formation.

In supply chain situations where choices are time-sensitive and data-intensive, extraneous and intrinsic loads usually meet at high-stakes. According to Paas and van Merriënboer (1994), decreasing cognitive strain helps improve task performance and learning outcomes. Supply chain decision-making entails creating systems and interfaces that promote clarity, relevance, and actionable information.

2.2 Cognitive Complexity in Supply Chain Decision-Making

Supply chains are multidimensional, distributed decision environments without stable priorities. Priorities among supply chain factors are always changing, some of which are cost, time, risk, sustainability, etc. Kembro and Näslund (2014) discovered that supply chain managers usually experience an overload of information, especially when data sharing channels are poorly integrated. This can strain cognitive functions that consequently results in decision fatigue, mistakes, or overly dependence on shortcuts, hence compromising ideal performance.

Christopher (2016) found that, while digitizing supply chain enhances visibility, it similarly increases the volume and velocity of information, hence increasing mental stress. This could be managed by designing technologies that assist cognitive processing instead of solely collecting data. The transition to Industry 5.0 prioritizes cognitive support, well-being, and long-term augmentation of human labor.

2.3 AI as a Cognitive Partner, Not Just a Tool for Automation

AI has emerged as a sustainable decision-making tool which is capable of digesting massive data streams, finding patterns, and making suggestions (Waller & Fawcett, 2013). However, most solutions still prioritize automation over augmentation. Shahzadi et al., (2024) have mapped recent AI trends in supply chains but what this mapping lacks is alignment with human cognition. AI should be viewed as a tool that enhances capability, not a tool that replaces human capabilities (Hendriksen, 2023). Genetti et al (2020) advocate for a human-centered AI model, in which technologies like AI and machine learning balances human cognition instead of replacing it. The framework emphasizes cognitive alignment which ensures AI outputs match human mental models, it also highlights transparency and adaptivity which makes AI decisions understandable and adjusts AI support based on user expertise or workload.

AI improves visibility, resilience, and efficiency, but for it to provide any cognitive benefits it must be incorporated into decision-making workflows (Daios et al., 2025). This human-AI collaboration is consistent with recent research on decision support systems (DSS) and cognitive augmentation. They both aim to help people manage uncertainty, reduce mental strain, and boost their confidence when it comes to judgments that are challenging.

2.4 Identified Research Gaps

Besides all this, existing research doesn't outline any integrated framework that clearly models cognitive load reduction as a design goal for AI systems in supply chains. Neither does it have any integrated framework that creates a bridge between CLT principles and AI abilities in operational decision-making. And in all, they do not provides empirical validation or simulation-based evidence of such frameworks in action.

This gap emphasizes the necessity for an AI-driven, cognition-aware decision-support framework that improves operational efficiency while respecting human limits.

2.5 Key Takeaways from Existing Work

After reviewing past work on cognitive load in supply chain decision making and AI integration, the table below highlights the summary of the key observations:

Table 1: Summary of reviewed literature

Theme	Insights	Gaps
Cognitive Load Theory	Decision is impaired when the working memory is overloaded due to the limited human memory capabilities	Little applications in SCM or DSS

Supply Chain Complexity	Decisions come in multiple layers, and they involve high-pressure	The tools implemented increase data, mostly negleting insight
AI Integration	AI can support or automate decisions	It lacks human-focused design
Research Need	Frameworks must integrate AI and CLT	Few conceptual models exist

3. Conceptual Research Design

This study employs a qualitative, conceptual research design to provide an AI-driven framework for reducing cognitive strain during supply chain decision-making. The technique uses elements from Cognitive Load Theory (CLT), supply chain management (SCM) literature, and AI-based decision support systems to generate a theoretically grounded model.

The methodology takes a design science approach, which is appropriate for developing theoretically sound practical solutions (Van Aken & Berends, 2018).

The processes involved in this approach may begin with identifying a real-world problem that we have made out to be cognitive overload in supply chains. Then proceed with drawing from relevant academic disciplines and proposing a novel framework. Conclusively, validate it conceptually or through illustrative case studies.

3.1 Data Sources

There was no empirical data collected in this study; hence, future research is needed for validation**.** The framework is developed using secondary data obtained from academic literature, which includes journals in SCM, AI, and cognitive science, that are mostly peer-reviewed**.** Some other sources also include white papers and some industry reports on AI applications in logistics and operations and case examples of AI-driven decision-support systems (DSS) used by companies like Amazon, Maersk, DHL, or other recognized logistics companies. The sources were selected based on relevance, recency, and academic accuracy.

3.2 Framework Development Process

The proposed framework was developed in the stages. The first is to determine or properly structure the problem at hand. Cognitive demands in supply chain decision contexts (e.g., demand forecasting, disruption reaction, inventory planning) were examined to identify important sources of cognitive burden. Cognitive Load Theory principles have been represented to supply chain decision situations. Then we evaluate the reviewed AI skills (machine learning, natural language processing, recommender systems) that facilitate cognitive reduction. This constitutes the synthesis of literature stage in the development process.

Integrating findings to design a modular framework begins the framework construction stage. These layers of the framework consist of the perception layer which functions as a filter of raw supply chain data, the cognition support layer that interprets and prioritizes information, decision augmentation layer which suggests actions or automates low-risk decisions, and finally the human feedback loop that allows user control and learning.

Finally in the conceptual validation stage, the framework is validated conceptually through alignment with human-centered AI best practices, the design principles from Cognitive Load Theory (e.g., minimizing extraneous load) and known success factors in AI-assisted SCM.

3.3 Simulation and Validation

The effectiveness of the suggested AI-based framework is explored by using digital supply chain twins (DSCTs) that offer a realistic and flexible testbed. DSCTs are virtual models of physical supply chain operations and enable real-time disruption, demand variation, and AI-aided decision simulation (Ivanov and Dolgui, 2020). The framework can be embedded in a DSCT and thus each component can be questioned.

The correctness of the data filtering and the quality of the contextual summaries created is checked at the Perception and Cognitive Support layers.

The Decision Augmentation component is evaluated through a simulation of disruptions and the comparison of the AI-assisted and manual decision in terms of speed, cost, and risk.

The Human Feedback and Monitoring layers are validated through the implementation of NASA-TLX cognitive workload tests (Fragiadakis et al., 2024) to measure the level of trust, confidence in decision-making, and mental effort during the AI-assisted activities.

The given methodology allows measuring not only operational performance indicators (e.g., efficiency, resilience, service level) but also cognitive outcomes (e.g., reduced workload, improved trust), thus, proving the practical influence of the given framework.

3.4 AI Techniques Used and Their Role in Mitigating Different Types of Cognitive Load

Table 2 shows a summary of how several artificial intelligence (AI) methods align with Cognitive Load Theory by reducing extraneous, intrinsic, and germane cognitive load in supply chain decision-making.

Table 2:How AI techniques affect cognitive load types

Cognitive Load Type	AI Techniques	Effects	References
Extraneous Load	NLP, anomaly detection, data mining	Filters are the tools that help to get rid of irrelevant data, thereby decreasing information overload.	Daios et al. (2025); Waller & Fawcett (2013)
Intrinsic Load	Machine learning clustering, knowledge graphs, dashboards	They interpret important relationships through simplification of complex variables	Choi et al. (2018); Kembro & Näslund (2014)
Germane Load	Reinforcement learning, explainable AI, adaptive learning	This process leads to the building of cognitive schemas, thus, increasing trust and understanding.	Genetti et al. (2025); Vann Yaroson et al. (2025)

3.5 Limitations

This conceptual approach does not involve empirical testing and simulation data. The framework's effectiveness is based on theory and illustrative data, but it will require more empirical validation to assess real-world applicability, scalability, and ROI in operational contexts. User trust, task alignment, cognitive burden, and override behavior measures should all be considered during the evaluation process. Furthermore, of the primary challenges is the digital divide, which affects the implementation of advanced technologies in less developed regions that may lack the necessary infrastructure and technical know-how (Riad et al., 2024).

3.6 Ethical Considerations

Because this study relied entirely on secondary data and conceptual modeling, no ethical approval or human subject interaction was needed. However, any extensions, including practitioners or organizations, would require appropriate ethical clearances.

4. Proposed Framework

4.1 Goal of the Framework

According to Genetti, Longobardi, and Iacca (2025), reinforcement learning combined with decision-tree-based policies improves both performance and interpretability therefore, the framework aims to reduce the cognitive burden on human decision-makers in complex supply chain environments by using AI tools that filter and simplify information, provide intelligent recommendations, automate routine decisions, and support user knowledge and control.

4.2 Framework Components

The first component of the framework evidently is the perception layer that involves data filtering and preprocessing. This layer provides cognitive benefits by reducing extraneous cognitive load by eliminating noise and irrelevant data. Its function is to ingest and filter raw supply chain data (from sensors, ERPs, CRMs, and external data sources) using AI tools suitable for natural language processing, data mining, and anomaly detection.

The next component is the cognitive support layer that deals with contextual understanding. It converts filtered data into understandable outlines and infographics. Prioritizes key variables based on their context. This decreases the fundamental burden by highlighting what is most important. This layer needs the usage of machine learning, clustering, dashboards, and knowledge graphs.

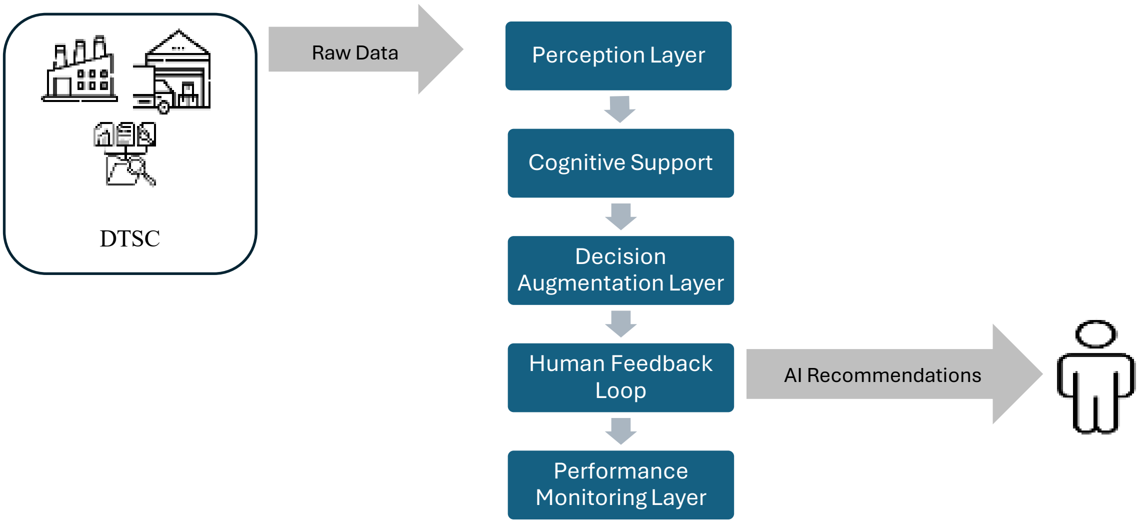
This component handles recommendations and automation and its characterized by the decision augmentation layer. This layer uses AI techniques such as prescriptive analytics, reinforcement learning, and decision trees to present decision possibilities ranked by cost, speed, or risk, as well as to automate low-risk routine choices. Its goal is to reduce overload by offloading repeated or low-stakes jobs. (Genetti et al., 2025).

This component ultimately defines human involvement. It is the human feedback loop which provides ability for seamless control, override and constant learning. This layer enables users to examine, alter, or override AI ideas. Tracks user behavior to tailor future help. It employs explainable AI (XAI), user profiling, and adaptive learning algorithms (Vann Yaroson et al.2025). One cognitive benefit of this layer is that it enables relevant load, which increases trust and decision confidence.

The performance monitoring layer is only projected for future work and development. This layer is optional, incorporated for probable future work. It allows for ongoing enhancement of the AI-human interface. Assesses cognitive effect (using performance measurements, cognitive workload assessments, or user input). It requires task completion time, accuracy, NASA-TLX, or subjective measurements (Fragiadakis et al., 2024).

4.3 Integration of Framework Layers with a Digital Supply Chain Twin

Figure 1:Conceptual Diagram of the AI Framework Embedded in a Digital Supply Chain Twin (DSCT).



Figures 1 shows the operational architecture of an AI-based framework in a Digital Supply Chain Twin (DSCT). The layered diagram explains the internal logic of the system and shows how it can be practically implemented in a simulated supply-chain scenario.

The framework begins with the Perception Layer which takes in and sifts through raw DSCT data in order to reduce cognitive overload. The Cognitive Support Layer then transforms these processed inputs into contextually enriched insights, dashboards and summaries, thus reducing the complexity of the decision-making process itself. The Decision Augmentation Layer is a reinforcement learning, decision tree, prescriptive analytics and provides actionable recommendations or automates repetitive tasks.

A Human Feedback Loop ensures managerial control by letting courses of action proposed by AI be confirmed, modified, or rejected, thus making learning and trust possible. The Performance Monitoring Layer evaluates not only the operational performance of the DSCT including cost efficiency, resilience, and lead-time stability but also the cognitive experience of decision-makers including, e.g., workload reduction through NASA-TLX, accuracy, and decision confidence.

Therefore, figure 1 show that the framework is not just a theoretical construct; it is an empirically accessible system. The flowchart defines the connections between AI layers, but the DSCT model shows the connection between the layers and a simulated supply chain, forming a closed-loop interaction between data, AI, and human decision-making.

5. Case Applications

In this section, we present two fictional but realistic case studies to demonstrate the practical relevance and adaptability of the proposed AI-driven architecture. These scenarios show how the framework may be applied in real-world supply chain settings to reduce cognitive strain and improve decision quality.

5.1 Case Study 1

In this scenario, ElectroNova, a multinational electronics firm, suffers a sudden supply disruption caused by a geopolitical crisis that prevents semiconductor exports from a key Southeast Asian supplier. This leaves the corporation the only option to quickly figure out how to reroute supply chains, utilize available resources, and maintain service levels across various geographies. This disruption scenario is like prior global events, such as the 2021 semiconductor shortage, in which enterprises suffered major failures due to unexpected supply shocks (Ivanov & Dolgui, 2020). So, in this case the framework is applicable as an AI supported disruption management in this supply chain scenario.

This is how the proposed framework deployed in this case works. The perception layer detects the event by automatically analyzing worldwide news and supplier notifications, filtering out unrelated disturbances. The cognition support layer visualizes the financial and operational implications of critical supply chain factors, including impacted SKUs, lead times, and supplier risk scores. The decision augmentation layer simulates various sourcing methods and offers a rerouting strategy with a European source for greater costs but immediate availability. The human feedback loop enables analysts to change scenario assumptions (e.g., prioritize cost to service level) before approving recommended actions.

This case demonstrates how the framework reduces both extraneous and intrinsic cognitive load during high-pressure disruptions. Analysts report reduced cognitive stress, and the company by implementing a timely response that helps avoid significant revenue loss. This would have taken a typical manual decision cycle of about 2 to 3 hours, but the framework completes this cycle in less than 30 minutes.

5.2 Case Study 2

AI-based demand forecasting systems have demonstrated significant potential in retail environments for managing high SKU complexity while minimizing forecast mistakes (Choi et al., 2018). QuickMart, is major fast-moving consumer goods (FMCG) retailer, and they must anticipate demand for more than 1,000 SKUs across over 300 retail locations during the peak Christmas season. There were challenges like widespread overstocking and stockouts, and putting strain on regional managers' cognitive abilities due to inaccurate demand planning in previous years,

In using the proposed AI-driven framework for this case, the perception layer filters and integrates data from multiple sources, such as POS, weather, social media, and previous holiday performance. The cognition support layer recognizes the demand of hotspots and variability clusters, providing a prioritized SKU-location matrix with embedded recommendations. The decision augmentation layer automates replenishment plans for stable SKUs and provides scenario-based forecasts for volatile categories. The human feedback loop allows regional managers to fine-tune AI-generated plans based on local knowledge, which is then logged to improve future system accuracy.

QuickMart reduces stockouts while decreasing surplus inventory. Managers' report increased confidence and reduced workload, especially during high-pressure planning periods. This scenario highlights the framework's ability to increase germane cognitive burden, allowing decision-makers to focus on tasks that are valuable while reducing routine cognitive strain. Therefore, it has optimized the demand forecasting system in this organization's supply chain

5.3 Summary of Applications

The two case studies show how the AI-driven methodology could be applied in different supply chain challenges, that is, disruption management and demand planning while still maintaining human control. The system has proven to improve decision-making by outsourcing routine data processing and providing recommendations that are context aware. Therefore, the main assumption of this paper, which is AI acting as a cognitive partner, not just a tool, in complex supply chain systems is confirmed by these examples.

6. Discussion

This paper draws on Cognitive Load Theory, AI decision-support systems, and human-centered design to provide a novel AI-driven approach for decreasing cognitive loads in supply chain decision-making. The concept addresses a very important but understudied issue which is, the mental strain that supply chain professionals face while navigating complex, data-intensive environments. Responsible AI improves trust and cognitive alignment by acting as a moderator in human-machine decision-making.

The framework aims to segment the process into organized layers, from perception and filtering to decision augmentation and feedback. By doing so, it reduces superfluous and intrinsic cognitive load while increasing relevant cognitive burden that is associated with learning and confidence building. The applicability of a variety of operational situations is demonstrated in the case studies. This ranging from disruption management to demand forecasting which highlights its cross-functional value. When end users lack the explainability and seeming control because of cognitive resistance, the adoption of this framework becomes major adoption problem.

From a theoretical standpoint, this study expands the application of Cognitive Load Theory to operational decision support, bridging the gap between cognitive psychology and supply chain management. It also adds to the narrative on human-AI collaboration. It does so by portraying AI as a cognitive partner who improves decision-making through alignment, adaptivity, and transparency.

Practically, the framework provides enterprises with a disciplined way to develop AI tools that does not only handle data but are also cognitively aware and support human users without overwhelming them. Recent work by Vann Yaroson et al. (2025) sheds light on how responsible AI mediates successful collaboration that aligns with our trust-building mechanisms. In contexts like just-in-time logistics, risk mitigation, and global sourcing, that involves high pressure where incorrect decisions can have rapid and costly effects, this trust comes in handy.

However, the proposed framework remains conceptual. Literature-informed and anchored in actual use cases, empirical validation is required to measure real-world efficacy. Future research should consider metrics such as decision correctness, task completion time, error reduction, and user cognitive burden (for example, NASA-TLX assessments). Emerging paradigms from Industry 4.0 to 6.0 (Samuels, 2025) highlights intelligent adaptation, that aligns with our framework's future scalability.

7. Conclusion

The cognitive demands on human decision-makers are increasing, so is the complexity and uncertainty of supply chains. Usually, traditional methods to decision support disregard this human constraint, which results in inefficiencies, errors, and missed opportunities. This research helps to close that gap by offering an AI-driven framework that is designed to reduce the cognitive strain and still maintaining human oversight and judgment.

The framework presents a layered structure that filters information, contextualizes decision options, and augments human thinking with adaptive support. This is based on Cognitive Load Theory and current AI capabilities. Its potential in both strategic and operational situations is demonstrated in the hypothetical case scenarios.

Although the framework is conceptually solid, the implementation and the performance in real-world circumstances must be examined using simulations, field trials, or longitudinal studies. The concentration of future research should be on discovering the measurable cognitive and operational benefits of such systems, as well as refining their design in response to user feedback and contextual factors.

In conclusion, this study highlights the necessity of creating AI systems that are not only clever but also helpful in reducing cognitive stress, allowing supply chain professionals to make faster, wiser, and more confident decisions.

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