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LEVERAGING MULTI-AGENT SYSTEM POWERED BY LARGE LANGUAGE MODEL TO IMPROVE TRANSPARENCY AND RELIABILITY IN AUTOMATED SUPPLY CHAIN COORDINATION

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ABSTRACT

Lack of transparency and information reliability in supply chain management have been persistent challenges. Based on the LangChain and LangGraph frameworks, this research proposed a Large Language Model (LLM)-based Multi-Agent System (MAS) specifically designed to enhance information reliability and transparency in construction supply chain coordination. A prototype system composed of multiple autonomous agents was designed and developed capable of working collaboratively, sharing information, and supporting decision-making. The system comprises Supplier Agents and General Contractor Agents capable of engaging in natural language interactions. These agents coordinate the supply chain by facilitating communication about material deliveries and project progress. The prototype demonstrated the potential of LLM-based MAS in improving supply chain transparency and reliability. This research not only validated the feasibility of applying large language models in automated supply chain coordination but also offered insights for the design and implementation of future systems.

KEYWORDS

Lean construction, Supply Chain Coordination, Large Language Model, Multi Agent System.

INTRODUCTION

The construction industry faces significant challenges in supply chain coordination due to project complexity, fragmented communication, and lack of real-time data sharing (Hamzeh et al., 2021; Osunsanmi et al., 2019). Information flow control and real-time adaptability are particularly critical, as on-site contractors struggle to coordinate with external fabricators compared to on-site subcontractors, and predicting supply chain workflows requires longer timeframes than the Last Planner System allows. Despite lean construction's contributions to workflow reliability, challenges persist when extending to external fabricators (Kim and Rhee, 2024). Traditional supply chain models often fail to adapt to rapid changes and uncertainties,

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resulting in delays, increased costs, and compromised outcomes (Berroir et al., 2021; Nugroho et al., 2021).

Recent advances in Large Language Models (LLMs) show potential for revolutionizing supply chain management, evolving from text generation to action-taking capabilities that align with lean thinking's progression from planning to implementation (Cattaneo, 2020; Srivastava et al., 2024). Multi-Agent Systems (MAS) represent a promising frontier, enabling LLMs to collaborate as autonomous agents with specialized tasks while maintaining sophisticated language understanding (Li et al., 2023). This breakthrough is particularly significant as it bridges the gap between theoretical AI capabilities and practical industry applications, offering new possibilities for complex coordination tasks that characterize modern supply chains.

Considering the challenges of rapid changes and uncertainties in construction supply chains, LLM-powered agents can transform how project information is processed and used, moving beyond simple information sharing to active decision-making (Luo, 2022). While these AI agents show promise in other fields, their use in construction remains largely unexplored. This paper proposes a system using multiple LLM agents that can understand construction contexts and take actions to improve supply chain coordination. Despite advances in lean construction, the industry still faces practical problems. Workers spend too much time reading emails, tracking issues, and updating plans, leading to miscommunication and delays. While AI has developed quickly, its application to construction supply chains is limited. This research addresses these challenges by creating an LLM-based system that works with existing communication methods while improving information reliability and transparency—key principles of lean construction.

The structure of this paper is as follows. First, a comprehensive review of the existing literature on supply chain coordination within the context of lean construction is provided. This is followed by an examination of LLMs and their emerging applications in construction management. The subsequent section details the design and implementation of the proposed prototype system, including the methodologies adopted and the expected outcomes. The paper concludes with a discussion of the theoretical and practical implications of the findings, along with recommendations for future research directions in this rapidly evolving domain.

LITERATURE REVIEW

CONSTRUCTION SUPPLY CHAIN COORDINATION

Research in lean construction has evolved significantly over the past decades, with particular emphasis on supply chain coordination and reliability challenges. Research by Reddy highlighted how communication barriers among stakeholders led to inefficiencies in construction projects, particularly in supplier-contractor relationships (Vidyasagar Reddy & Rao, 2022). These findings were further expanded by Boateng's research, which demonstrated that the complexity of construction projects often resulted in fragmented communication patterns, directly impacting project timelines and overall economic performance (Boateng, 2019).

The complexity and uncertainty of modern construction projects necessitates prudent supply chain management, as project performance heavily relies on coordination between contractor and module fabricator decisions (Kim et al., 2023; Kim et al., 2020; Kim & Kim, 2024). This issue becomes particularly evident in large-scale projects where both contractors and suppliers struggle to maintain reliability in their commitments.

A significant advancement in addressing construction supply chain coordination came through incentive-based approaches and technological solutions. Studies demonstrated that while independent contractors and fabricators made interdependent decisions, their conflicting interests often resulted in suboptimal economic outcomes (Kim and Rhee, 2024; Jiang et al., 2023). Recent research explored blockchain technology's potential in construction supply chain coordination, particularly for transparent communication and information sharing (Kim et al., 2023).

Despite technological advancements in construction management, recent research reveals a crucial gap: current supply chain coordination still heavily relies on traditional communication methods such as email and verbal exchanges, which can be inefficient and prone to misunderstanding (Lyu et al., 2023). This identifies a specific research opportunity: the need for intelligent systems capable of processing natural language communications through existing channels while providing structured information to support decision-making. There remains a need for approaches that can "drop in" to current work processes without disrupting established practices. Large language models present a promising direction for bridging this gap, offering the potential to enhance communication and coordination while maintaining familiarity with existing workflows.

ARTIFICIAL INTELLIGENCE AND MULTI AGENT LLM SYSTEM

The introduction of artificial intelligence (AI) into construction management presents new avenues for overcoming these challenges. Kazeem et al. have explored how AI systems can enhance communication among various stakeholders, thereby facilitating better coordination and decision-making (Kazeem et al., 2023). However, these early AI applications often necessitate structured data input and complex user interfaces, which can hinder their effectiveness in fast-paced construction environments (Kazeem et al., 2023). This gap indicates a need for more intuitive AI solutions that can seamlessly integrate into existing workflows without requiring extensive training or data structuring.

Recent advancements in Large Language Models (LLMs) have opened further possibilities for improving construction management processes. While the research by Kazeem et al. discusses AI's role in construction, it does not specifically address LLMs or their application in construction supply chain management (Kazeem et al., 2023). Additionally, while many research proposed a theoretical framework suggesting that natural language processing could enhance project management efficiency, they did not specifically address the reliability issues between suppliers and contractors in lean construction practices (He et al., 2024a; Jeong et al., 2024). This indicates a significant research gap in applying LLMs to enhance supplier-contractor reliability and streamline communication. Moreover, the integration of LLMs with existing supply chain coordination mechanisms remains largely unexplored.

RESEARCH GAP

Despite significant advancements in artificial intelligence for construction management, a critical research gap exists: no studies have developed or tested systems that leverage large language models to improve construction supply chain coordination. While existing AI applications have shown promise for improving stakeholder communication, they often require structured data input and complex interfaces that limit practical implementation (Kazeem et al., 2023). Although recent research has begun exploring LLMs for enhancing project management efficiency (He et al., 2024a; Jeong et al., 2024), no prior work has investigated the feasibility, limitations, and practical implementation of LLM-based multi-agent systems for improving supplier-contractor reliability and communication. This research addresses this gap by developing and testing a prototype system that can seamlessly integrate with existing construction workflows while maintaining accessibility for all stakeholders.

METHODOLOGY AND SYSTEM DESIGN

This research follows a design science research methodology (Hevner et al., 2004; Peffers et al., 2007) to develop and evaluate a novel LLM-based Multi-Agent System for construction supply chain coordination. Design science research is particularly appropriate for this study as it focuses on creating and evaluating innovative IT artifacts to solve identified organizational problems. The system design process presented in the following sections follows the design science research cycle of problem identification, artifact development, and evaluation through a structured architecture and implementation approach.

SYSTEM ARCHITECTURE OVERVIEW

Construction projects often suffer from information fragmentation, particularly in supply chain communications. Daily emails between suppliers, contractors, and project managers contain critical information about potential constraints and their resolutions. However, manually tracking and updating project plans based on the communications is time-consuming and error prone. Drawing on lean construction principles, an LLM-enhanced system was developed that automatically processes these communications, identifies constraints, and maintains an up-to-date project production plan.

The system is primarily a multi-agent system powered by the GPT-4. The system tasks were specifically optimized for upstream and downstream construction supply chain communications. It consists of three main components: External Input Sources, MAS System, and the outputs.

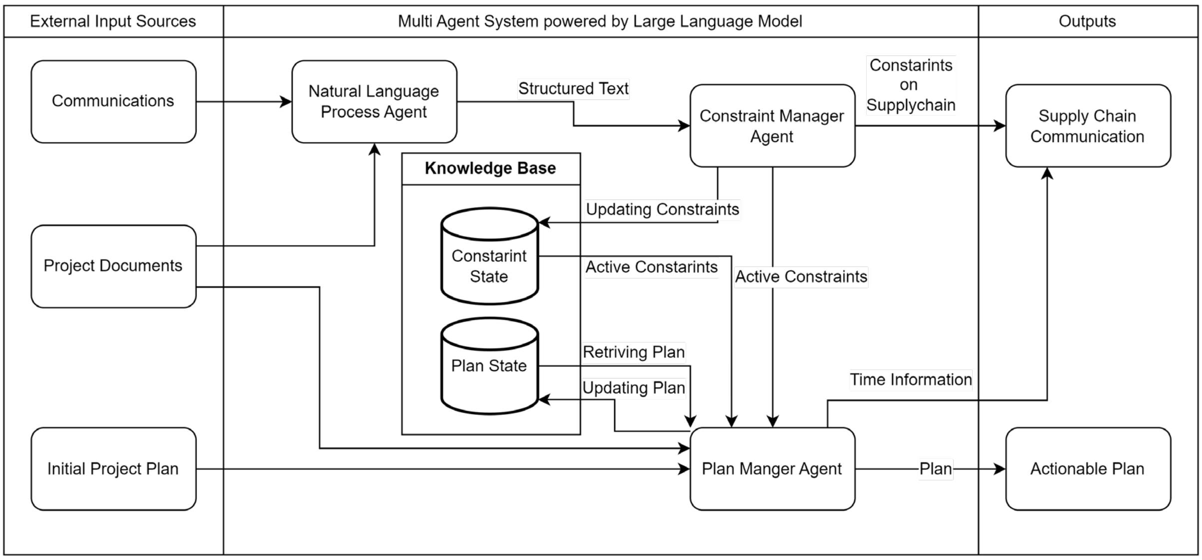

Figure 1: High-level Information Flow

The first component, External Input Sources, encompasses three key elements of construction project data. At its foundation is the 4-week look-ahead Project Plan shown in Figure 1, which serves as the baseline planning document. This plan follows the Last Planner System structure, capturing planned tasks, their dependencies, responsible parties, and scheduled timeframes. The system processes this structured plan to identify potential constraints and monitor progress. This is complemented by Stakeholder Communications, which includes all daily interactions through emails, phone calls, and text messages with construction suppliers. The third element consists of Construction Documentation, comprising Purchase Orders and Quality Control (QC) specifications that govern supply chain operations.

The second major component is our GPT-4-powered Multi-Agent System. This sophisticated processing layer analyzes and interprets all incoming data from the External Input Sources to identify constraints and potential issues in the construction workflow.

The third component delivers two crucial outputs: Supply Chain Communication, which synthesizes insights from all stakeholder interactions, and an Actionable Plan. This Actionable

Plan represents a thoroughly vetted execution strategy that incorporates all identified constraints and their resolutions, ensuring its feasibility within the project context. Together, these three components form a comprehensive system that integrates with existing construction processes while providing automated constraint management and planning capabilities.

DETAILS FOR EACH COMPONENT:

External Input Sources

In alignment with lean construction principles and the objective of developing a drop-in solution, existing email communications and related project information were identified as the most compatible with prevailing workflows. Based on insights gathered through industry interviews, a corresponding structure was formulated. A sample conversion from email communication to structured text is illustrated in Figure 2.

Figure 2 Communication Email to structured text for large language model

Such information extends beyond emails to include the Lookahead Plan and supply chain data, which undergoes structured processing to become comprehensible to the LLM system. In the system, the lookahead plan is primarily represented as textual descriptions within the language model, such as "Pour concrete foundation for columns A1-A5 on May 15th, contingent on weather conditions and reinforcement inspection approval." This text-based representation allows the system to process construction activities in a natural language format that mirrors how teams typically communicate. Similarly, constraints are extracted directly from email communications, where the system identifies statements like "Due to forecasted heavy rain, concrete pouring scheduled for May 15th will need to be postponed" and automatically registers this as a constraint affecting the corresponding task. This transformation of both planning documents and constraint information into structured text facilitates subsequent analysis by the Constraint Analysis Agent.

Multi-Agent System

The implementation leverages LangChain as the foundational infrastructure for the Multi-Agent System. LangChain is a Python-based framework that enables structured integration of large language models (LLMs) into complex applications, providing essential abstractions for prompt management, data ingestion, and multi-agent orchestration. This foundation was further enhanced using LangGraph to implement a graph-based workflow representation, which is essential for enabling cyclical interactions among agents. The combination allows agents to communicate through a shared state while maintaining the ability to dynamically update and adapt to changing project conditions (Mavroudis, 2024).

Core Agents and their responsibilities

The system operates through three interconnected processes that form the backbone of our constraint management approach, shown in Figure 3:

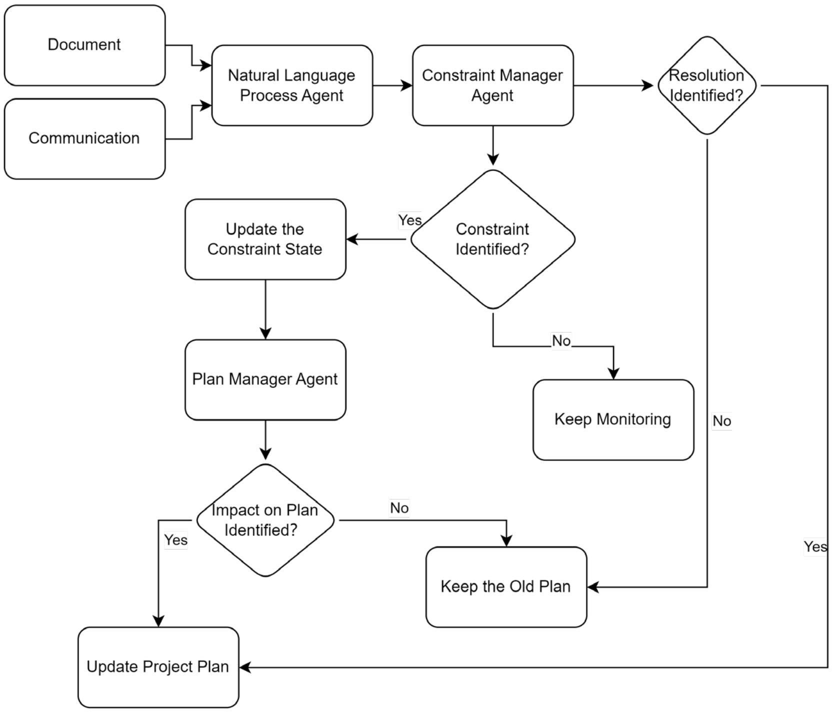

Figure 3 Simplified Multi Agent System Process Flow

The natural language process agent continuously monitors supply chain communications using GPT-4 to extract relevant information about potential constraints from emails and documents. For example, when an email communication indicates potential delivery delays (like Figure 2), the system automatically identifies and logs this as a constraint. As shown in Figure 3, the system similarly processes project documents containing weekly work plan updates or look-ahead plan updates from the Last Planner System, identifying potential delays and constraints with the same precision as it does with email communications. The constraint manager agent maintains the status of identified constraints by continuously monitoring communications from external suppliers for resolution information. Constraints remain active in the system, influencing the project plan's executable portions until explicit resolution information is received from suppliers.

The plan manager agent automatically adjusts the project plan based on active constraints and supplier communications. When suppliers provide updated lead times, the system recalculates the last responsible moment for releasing delivery orders and notifies contractors accordingly. This ensures the project plan reflects current reality and shows only truly executable tasks given known constraints and supplier conditions.

This structured approach enables just-in-time decision making in supplier coordination - for example, when a supplier communicates an updated lead time, the system automatically updates both the project status and delivery order schedules. The system then determines the optimal timing for order releases based on the latest supplier information. This automated supplier communication flow significantly reduces manual tracking effort while ensuring project plans remain current and executable throughout the project lifecycle.

State Structure Design

The project implements a state management system centered around a Project State typed dictionary that serves as the backbone for tracking and managing the entire construction project lifecycle. This state architecture maintains several key components: project specifications, current plan details, progress updates, supply chain information, and team configurations as shown in Figure 4.

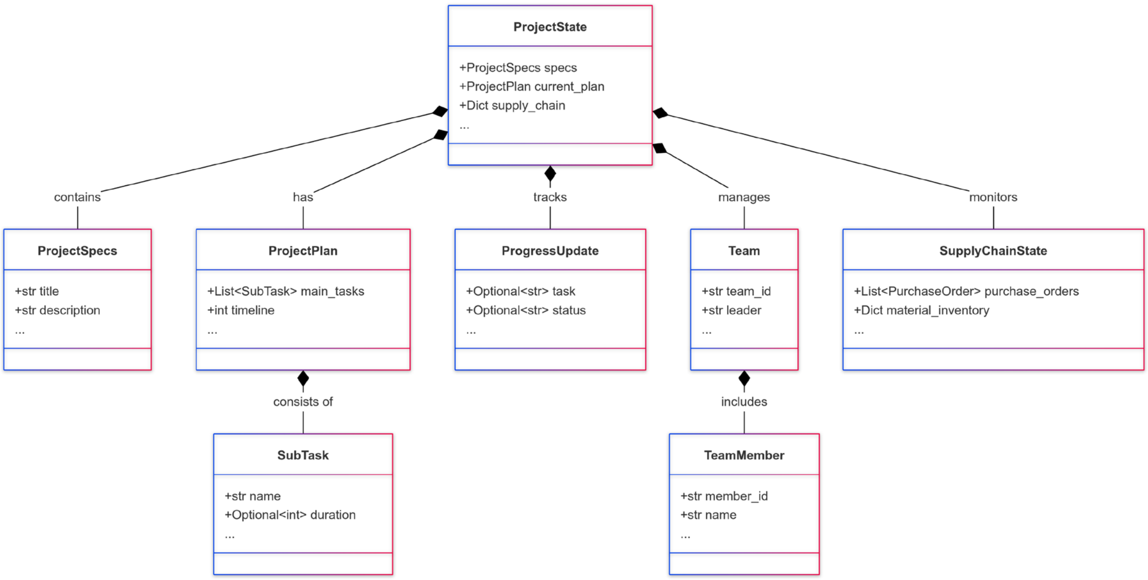

Figure 4 State design in our multiagent system

At the core of this state management system is a robust type system that ensures data integrity and facilitates efficient information flow throughout the construction project lifecycle. The state architecture is specifically designed to integrate constraint management functionality, enabling the system to track and respond to constraints identified through natural language processing of supplier communications.

The state management system is organized in a hierarchical structure with ProjectState at the top level, containing various sub-states that manage specific aspects of the project. This composition allows for modular state management where each component handles its specific domain, while maintaining clear separation of concerns between different project aspects. Constraints identified by the constraint management system are contextually embedded within this state structure rather than maintained separately. For example, when a delivery delay constraint is identified in supplier communications, it is directly reflected in the relevant PurchaseOrder objects within the SupplyChainState component, affecting the associated timeline in ProjectPlan.

The supply chain state (Figure 5) represents a critical component of the overall state management system, specifically designed to support lean construction principles and supply chain coordination. This component serves as the primary interface between the constraint management system and project execution, as most supply chain constraints directly impact the information stored within this state. The Quality Purchase Order Management within this state tracks order quality through specific criteria validation, maintains approval status and schedule alignment, and monitors delivery timelines and potential impacts. The system ensures reliable information flow by verifying that orders are free from constraints and that delivery order information accurately reflects both the updated construction schedule and current supplier lead times. When the constraint management system identifies potential issues from communications, these are immediately reflected in the order status, enabling real-time constraint tracking throughout the supply chain.

Material Coordination within the supply chain state manages material specifications and inventory levels, verifies quantity requirements against site needs, and tracks material status throughout the supply chain. This systematic approach to material management helps prevent overordering and shortages while ensuring timely delivery of the right materials. Constraints related to material availability or specification changes are captured in the material_inventory dictionary, creating explicit linkages between identified constraints and affected project components. Supplier Coordination maintains detailed supplier information and capabilities, tracks lead times and capacity constraints, and facilitates communication protocols. This aspect of the state management system is crucial for maintaining clear communication channels and ensuring that supplier constraints and capabilities are properly considered in the planning process.

The supply chain state (Figure 5) represents a critical component of the overall state management system, with a particular emphasis on quality purchase orders to support lean construction principles and effective supply chain coordination. The quality purchase order mechanism serves as the foundation for ensuring reliable information flow and coordinated material delivery, incorporating key attributes that reflect both order quality and coordination requirements.

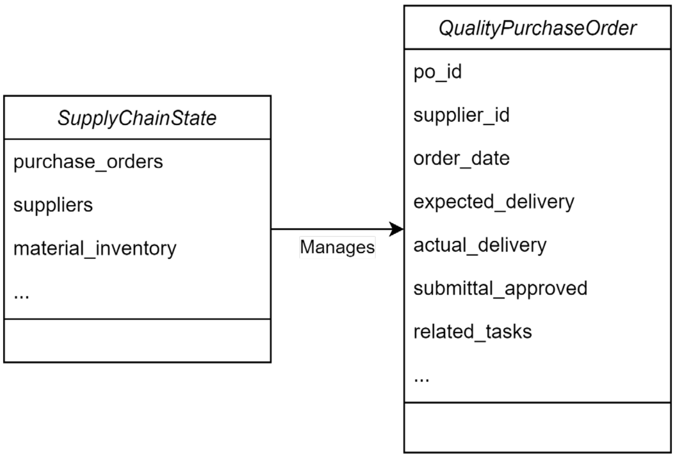

Figure 5 Supply Chain State

The quality purchase order management is designed to address the critical challenges identified in lean construction principles and practices, particularly the need for seamless coordination between external suppliers and on-site contractors. Each quality purchase order maintains essential quality characteristics including design submittal approval status, installation schedule alignment, and delivery timing requirements. This structured approach ensures that orders meet specific criteria necessary for improving the reliability of information flow and enabling suppliers to optimize their resources effectively to meet contractor requirements. Within the supply chain state, the quality purchase order system integrates with material specifications and supplier coordination information. Material specifications are directly linked to each order, ensuring precise tracking of quantities and requirements. The integration of supplier lead times and capacity information into the order system enables contractors to determine the "last responsible moment" for order releases, accounting for both installation schedules and supplier constraints.

This state management approach for quality purchase orders facilitates the two-way exchange of information between suppliers and contractors, enhancing predictability and reducing misalignments in the construction supply chain. By maintaining this structured state information, the system supports informed decision-making in order releases while ensuring consistency and reliability across the supply chain coordination process.

SYSTEM IMPLEMENTATION

To validate the multi-agent system's capabilities, this research implemented and tested a prototype focused on a critical steel column installation process. This implementation included the core components of the architecture: the natural language processing agent, constraint manager agent, and plan manager agent, all powered by GPT-4. The scenario centered around a construction project where prefabricated steel columns were scheduled to be installed on a concrete foundation. The test case captured a series of events beginning with an unexpected weather disruption that prevented concrete pouring, followed by an engineering solution that modified the installation method. The communication occurred primarily through email exchanges between the project engineer and the steel column supplier, documenting both the initial delay notification and the subsequent technical solution. This scenario was particularly valuable for testing as it incorporated multiple aspects of construction supply chain management: schedule adjustments, technical modifications, supplier coordination, and engineering constraints.

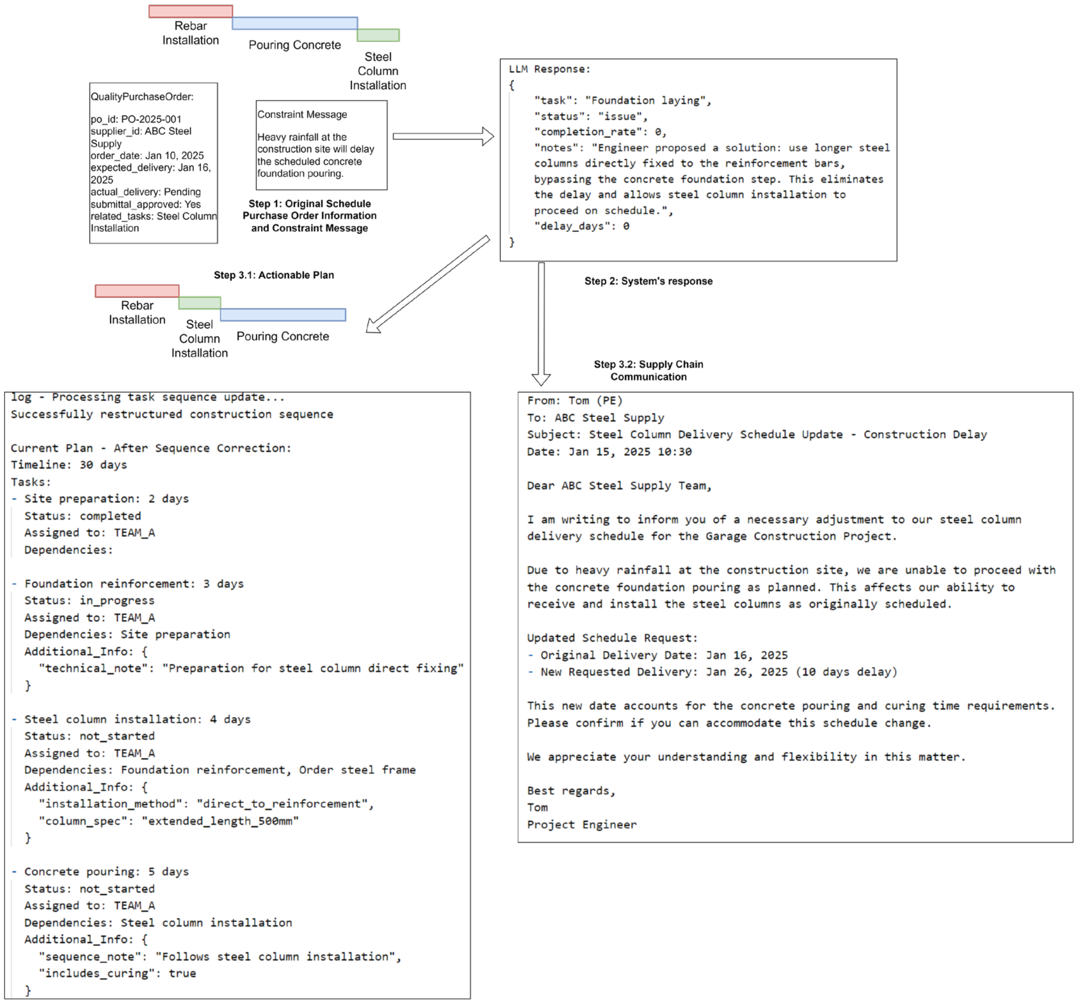

Figure 6 Validation of the proposed multi agent system

Test for Validation

The testing provided the system with three types of text inputs: (1) sample email communications between the project engineer and steel supplier regarding weather delays and engineering solutions, (2) a four-week look-ahead schedule for the construction project, and (3) purchase order information for the steel columns. The system processed these text-based inputs and produced two key outputs: (1) an updated constraint log that identified the concrete pouring delay and the engineering solution as a constraint and resolution, respectively, and (2) an updated executable plan that reflected the revised installation method. To clearly demonstrate these changes and how information flows through the system, a graphical representation was created in Figure 6 that visually maps the transformation from inputs to outputs. This visual workflow diagram helps illustrate how the system processes textual information and adapts to changing conditions. The complexity of the scenario, involving weather delays, engineering solutions, and supplier coordination, created an ideal environment for testing the system's adaptive capabilities.

DISCUSSION

This research demonstrated both the potential and limitations of using Large Language Models (LLM) in construction supply chain management. Through a steel column installation test case, the system showed promising capabilities in processing natural language communications and adapting to changing conditions through automated constraint updates. Notably, it successfully managed technical communications and identified relationships between construction activities, such as recognizing the impact of concrete pouring delays on steel column installation. These findings align with recent research (He et al., 2024b), which demonstrates that LLMs can effectively parse construction-related communications and extract relevant project information.

However, several limitations emerged in practical implementation that need to be considered. First, while the system effectively processes individual emails, it currently lacks the ability to extract and analyze data from attachments such as drawings or spreadsheets, which often contain critical information in construction communications. Second, the system's logging of all communications presents a risk of information overload, potentially creating noise in large projects with thousands of messages. Third, the system's ability to accurately assess supplier inventories is entirely dependent on information shared by suppliers in communications, which may not always be complete or accurate.

The system's construction sequence recognition, while effective for simple dependencies, may struggle with more complex scenarios. Based on the analysis, commercial closed-source models, driven by business considerations, tend to offer limited context windows for information processing. Within the system's current implementation using GPT-4 (with an 8,000 token limit), the capability to simultaneously process approximately 20 subtasks and their corresponding suppliers, which is consistent with the processing limitations observed by LLM researchers (An et al., 2024).

CONCLUSION

This paper makes two primary contributions to the field of lean construction: (1) demonstrating the technical feasibility of using LLM-based multi-agent systems to process natural language communications in construction supply chains, and (2) proposing a framework for integrating these technologies with existing communication workflows. The prototype implementation validated the core concepts while revealing important limitations that should be addressed in future research. Based on these findings, three primary directions for future research are recommended:

1. Enhancing domain-specific capabilities through construction-specific datasets and specialized RAG systems
2. Optimizing the framework through robust sequence validation and structured database implementation
3. Integrating expert systems, particularly exploring Mixture of Experts (MoE) approaches for complex engineering decisions

While the implementation using GPT-4 proved the concept's viability, future development should focus on creating more specialized systems that can fully address construction supply chain complexity while exploring both open-source alternatives and advanced planning methodologies.

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