Multi-agent LLMs for Closed Loop Supply Chain Implementation (Extended Abstract)

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Abstract

This paper presents a multi -agent LLM system for closed-loop supply chain (CLSC) maturity assessment that transforms static capability evaluation into an interactive reasoning-based decision support process.

Introduction

Despite investments of approximately $164 billion in circular economy initiatives between 2018 and 2023, the global economy is only 6.9% circular, down from 9.1% in 2018 (Circle Economy 2026). The Circularity Gap report further stresses the persistent value losses across production, use, and end-of-life stages, underscoring the urgency for organisations to operationalise closed-loop supply chain strategies. However, while maturity models provide structured approaches to assessing organisational readiness to integrate circular economy principles within supply chains (Kayikci et al. 2022), they primarily diagnose capability gaps rather than explain how such gaps can be addressed under organisational constraints, competing stakeholder priorities, and limited resources.

Thanks to the recent advances in artificial intelligence, particularly large language models (LLMs), suggest new possibilities for supporting complex decision-making tasks through structured reasoning and planning capabilities (Guo et al. 2024). Leveraging these capabilities, this paper proposes a multi-agent LLM system that transforms closed-loop supply chain (CLSC) maturity assessment into a dynamic decision support tool. The system is designed to assist managers in diagnosing capability gaps and identifying actionable implementation pathways under real-world constraints.

System Architecture

We present a four-agent LLM system that converts maturity assessment into an interactive reasoning process, using a multi-agent architecture to diagnose and address capability gaps in closed-loop supply chain (CLSC) operations. Each agent is structured using the Cognitive Architectures for Language Agents (CoALA) framework (Sumers et al. 2023), implementing modular memory components (working, episodic, and semantic) and structured decision cycles to support reasoning and retrieval actions. An Assessment Agent elicits structured capability profiles through guided dialogue across key CLSC dimensions. A Critic Agent that employs a ReAct-based reasoning strategy (Yao et al. 2023) to challenge assumptions, identify incomplete or evasive responses, and trigger targeted follow-up queries. A Solution Designer then generates implementation pathways constrained by the organisation's operational context rather than generic best practice templates, and a Quality Guardrail monitors reasoning consistency across agent outputs. These agents are coordinated by a runtime orchestrator designed to dynamically route information among them based on emerging dialogue states rather than fixed interaction sequences.

Method

Grounded in design science research, we evaluate the system architecture through field sessions with 6- 8 supply chain managers using think-aloud protocols and semi-structured interviews to assess reasoning quality and actionable output generation. This exploratory approach allows us to assess the quality of the output and to capture both cognitive reasoning processes and the perceived usefulness of generated outputs, and observe actionability in realistic closed-loop supply chain (CLSC) decision scenarios. The system is benchmarked and evaluated against a baseline non-agentic LLM configuration to assess the added value of structured multi-agent orchestration.

Expected Contribution

This study contributes to AI literature by demonstrating how multi-agent LLM orchestration can support real-world managerial reasoning through integrated assessment, critique, and solution generation. For management research, this study examines how the use of the multi-agent system can help bridge the gap between sustainability knowledge and practical implementation in the supply chain.

References

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