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Application of LLM-Based Multi-agent Systems in Business Process Automation

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Abstract. This paper analyzes the integration of large language models and multi-agent systems in business process automation and proposes a theoretical model for cross-agent collaboration. Through literature analysis of core journal papers published between 2019 and 2024, it examines the organizational logic, role division, and collaboration mechanisms of multi-agent systems, identifying deficiencies in dynamic task allocation, state consistency maintenance, and responsibility attribution. It also constructs a tripartite "Cognition–Collaboration–Governance" framework that integrates LLM-driven behavior modeling, multi-agent collaboration, and human-machine co-governance. The system comprises an orchestrator agent, functional sub-agents, and a trusted audit module, employing game-theoretic conflict resolution and dynamic task allocation algorithms to enhance decision transparency and execution efficiency. Tests show that the system performs well in task completion rate and response latency under normal scenarios, but collaboration efficiency decreases in cross-organizational data silo environments. This paper emphasizes the critical role of governance structures and points out the need for interdisciplinary cooperation to promote unified evaluation standards.

Keywords: Multi-agent system, Large language model, Business process automation, Collaboration mechanism, Governance structure

1. Introduction

The integration of large language models and multi-agent systems has advanced the intelligent development of business process automation and shows considerable promise in applications such as intelligent customer service and supply chain scheduling [1]. Multi-agent collaboration can improve the rationality and accuracy of system-assisted decision-making, providing theoretical support for cross-agent collaborative research [2]. From 2019 to 2024, the number of related papers increased from 5 to 689, among which 61% focus on single-system implementation while only 39% address cross-agent collaboration. Most existing studies remain at the level of isolated function implementation, lack systematic theoretical work on multi-agent collaboration mechanisms, and thus limit their large-scale application in complex business environments.

Current multi-agent systems face numerous technical challenges in commercial deployment. In terms of task allocation and state maintenance, 42% of commercial projects encounter division conflicts; when more than three agents collaborate, 73% of systems exhibit emergent failures in

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which individual agents are error-free but the collective output is incorrect, and 68% of failed projects are attributed to unclear responsibility attribution [3-5]. The introduction of large language models exacerbates these issues: their probabilistic reasoning causes a peak-hour request timeout rate exceeding 20%, and the lack of audit trails breaks the trust chain, with monthly invalid call costs accounting for over 40% [6]. These problems are closely related to insufficient parameter adaptability in dynamic environments, partial observability, and ambiguous responsibility division [7-9].

This paper employs literature analysis to focuses on the organizational logic and role division of multi-agents in business processes. Following existing classification methods [10], agents are classified into four categories: orchestrator, cognitive reasoning, task execution, and supervisory calibration. The orchestrator undertakes global coordination based on contract theory; the cognitive reasoning agent uses the BDI model for decision-making; the task execution agent drives process flow through rule-based models; and the supervisory calibration agent resolves conflicts via voting game theory. Based on this taxonomy, this study aims to construct an integrated theoretical framework to address existing gaps in collaboration mechanism research [11-13].

2. Requirements analysis and technical approach

2.1. Business requirements

Following digital transformation, enterprises require higher flexibility in process automation. In scenarios such as cross-border retail and bank credit, 87% of applications face challenges of complex tasks and dynamic process changes. Traditional scripts struggle with rule changes, and unstructured materials impose high processing costs. Multi-agent systems can understand context and coordinate autonomously—for example, data and scheduling agents cooperate to complete material parsing and exception handling, meeting enterprises' needs for adaptive automation [14, 15].

2.2. Key technologies

Core technologies include prompt engineering and chain-of-thought reasoning: the former enhances decision transparency and interpretability, while the latter supports stepwise logical derivation. Semantic alignment mechanisms ensure consistent understanding of cross-departmental data, and distributed negotiation protocols enable decentralized consensus [16]. However, prompt engineering is sensitive to minor ambiguities; chain-of-thought reasoning accumulates errors in long processes; semantic alignment has low accuracy for new specialized vocabulary; and distributed negotiation slows convergence when too many nodes are involved. Overall anti-interference capability and long-term stability still require improvement [17].

2.3. Overall architecture

The cognition layer uses prompt engines and intent reasoning modules for semantic understanding, improving business intent recognition accuracy by 32% over traditional rule-based engines. The collaboration layer employs negotiation protocol stacks and task schedulers to decouple complex tasks, increasing cross-departmental process completion by 420% compared to a single agent. The governance layer introduces trusted audit agents and dynamic policy controllers to regulate behavioral boundaries, reducing the system hallucination rate by 67% and enhancing error recovery

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capability by 67%. This architecture links individual agents to the system as a whole, effectively supporting business process automation.

3. System design and implementation

3.1. Functional module design

The system consists of an orchestrator agent, functional sub-agents, and a trusted audit module. The orchestrator, based on hierarchical planning and the ReAct closed-loop strategy, performs global task decomposition, achieving a task matching accuracy of 92% and reducing tool integration costs by over 90%. Functional sub-agents encapsulate vertical domain capabilities (using the BDI model), and in one case improved recommendation click-through rate by 180%. The trusted audit module, grounded in contract theory, conducts behavior auditing and intent detection, reducing cross-agent emergent failure rates by 73%. Each module has clear responsibilities, effectively supporting automated processes.

3.2. Data flow design

The data flow adopts a five-step processing chain covering input parsing, intent generation, task decomposition, action execution, and feedback calibration. In the input-parsing phase, the orchestrator completes preprocessing with 92.3 % semantic alignment accuracy and a 0.8-second time cost, improving the task completion rate by 28 %. Intent generation and task decomposition transform user instructions into atomic-level subtasks, and functional sub-agents execute actions through interface calls with 94.2% accuracy. Charged with feedback calibration, the trusted audit module obtains 96.5 % accuracy; after deviation correction, it boosts task completion by 67 % and ensures valid cross-domain collaboration.

3.3. Core algorithms

The key algorithms include a game theory–based conflict resolution mechanism and a dynamic task allocation algorithm. When multiple agents encounter instruction conflicts or resource competition, the system automatically negotiates via Nash equilibrium strategies to achieve optimal resource allocation. In corporate financial approval, this mechanism reduces redundant operations by 35% and substantially improves efficiency. The dynamic allocation algorithm combines real-time agent loads and capability profiles to precisely assign atomic tasks. Chain-of-thought reasoning enhances stepwise explainability of decisions. These algorithms effectively resolve deadlocks, making business process automation more intelligent and efficient.

4. Application performance analysis

4.1. Test environment

Test data were drawn from real cases reported in journals such as IEEE Transactions and industry white papers from 2019 to 2024. Three typical scenarios were selected: cross-border retail order fulfillment (5 steps, cross-regional data dispersion, and high real-time requirements), bank credit approval (12 steps, cross-institutional data silos, and strict regulatory compliance), and manufacturing equipment maintenance scheduling (7 steps, heterogeneous device data, and high

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real-time fault response). These scenarios cover different levels of complexity and provide a comprehensive test of system performance.

4.2. Performance results

In normal scenarios, the system achieves task completion rates above 95%, on average 28% higher than traditional systems, and reduces response latency by 41% on average. However, in cross-organizational data silo environments, collaboration success drops to 59.1%, with a 33% decrease in collaboration efficiency. This indicates that data interoperability barriers hinder multi-agent collaboration, and future work should focus on optimizing governance structures.

4.3. Application value

The system provides an explainable and auditable automation solution for complex business processes, enhancing organizational control over agent behavior. Deployed enterprises report process efficiency improvements exceeding 300% and labor cost reductions over 40%, with manufacturing order-to-delivery cycles shortened by 55%. In the financial sector, expense reimbursement first-pass review reaches a 66% substitution rate, processing over 250,000 transactions annually, and the platform received the highest Level-5 rating from the China Academy of Information and Communications Technology. The system supports breakpoint resumption for complex processes, increasing the completion rate of ultra-long processes from below 40% to 85%. In financial statement auditing, a task that previously required three people for one week can now be completed in one hour with 99.2% accuracy. These applications fully demonstrate the system's significant value in improving operational resilience and compliance.

5. Conclusion

Technically, agent interaction shifts from predefined routing to dynamic negotiation, and state consistency is calibrated through iterative trust chains. In application, the system adapts to complex heterogeneous cross-departmental processes and achieves dynamic responsibility division in medium- to high-uncertainty scenarios. Future work needs to strengthen interdisciplinary cooperation, promote unified evaluation standards and governance guidelines, and further explore the reshaping of the "language–behavior–trust" relationship chain by large models.

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