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Original Article

Autonomous Enterprise Intelligence Platforms Enabled by Collaborative Multi-Agent Large Language Models

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ABSTRACT: *Enterprise Intelligence provides decision-making assistance to all levels of managers throughout an organization, leveraging data, models, and computation. Enterprise Agility facilitates rapid self-diagnosis and reconfiguration of operations to align with constantly changing governing conditions. Self-Evolving Enterprise Intelligence Platforms are enabled through collaboration among several Multi-Agent LLM systems. Collaboration involves negotiation to resolve conflicts and make trade-offs, ultimately achieving a shared purpose. The Enterprise Intelligence and Enterprise Agility concepts serve as a foundation to explore Architectural Paradigms that enable Self-Evolving Platforms. Agent-based decomposition is proposed to delineate roles, interfaces, modular boundaries, and interaction protocols, thereby enhancing scalability and fault tolerance. The mechanisms for evolution in LLM-driven systems are outlined, followed by a description of collaboration frameworks among the agents. Self-evolution in self-evolving platforms is examined via three mechanisms: continuous learning and adaptation, negotiation and trade-offs, and Multi-Agent strategy. Data and experience ingress continuously, meeting the requirements of LLM systems. New training sets are formed, model updates undertaken, and permanent feedback loops instituted under neural architecture search and safe reinforcement learning principles. The drift inherent in LLM systems necessitates vigilant monitoring. Change is inevitable; adaptation can minimize harm and capitalise on opportunities. The foregoing mechanisms jointly impact all aspects of a platform, yet the implementation of Multi-Agent strategies is essential to acquire true Self-Evolution.*

KEYWORDS: *Multi-Agent Large Language Models, Self-Evolving Enterprise Intelligence, Enterprise Decision Intelligence, Collaborative AI Agents, Large Language Model Orchestration, Autonomous Enterprise Systems, Agentic Artificial Intelligence, Adaptive Knowledge Integration, Intelligent Workflow Automation, Human–AI Collaborative Decision-Making.*

1. INTRODUCTION

The increasing penetration of AI technologies, especially LLMs, leads to explosive innovations in human-computer cooperation and will drive a major change in enterprise information system architectures. Multi-agent collaboration of LLMs has the potential to establish self-evolving enterprise-intelligence platforms that continually adapt core enterprise capabilities to new internal and external requirements. Such platforms will accelerate the pace of enterprise decision-making cycles and adapt company governance mechanisms accordingly. To achieve this goal, special emphasis must be placed on collaborative negotiation mechanisms, trade-offs among conflicting objectives, and the introduction of intangible resources to provide incentives for multi-agent cooperation.

Enterprise Intelligence (EI) denotes the set of capabilities that each enterprise requires to achieve strategic objectives and that enable the enterprise to respond to external and internal changes by adapting goals and operations. These capabilities are expressed as flows of complex data among information systems that span all management functions.

Mathematical Formulas:
Eq. (1) Enterprise Intelligence

$$EI = D + K + DM$$

Where:
- D= Data
- K= Knowledge
- DM= Decision Making

Eq. (2) Enterprise Agility

$$EA = \frac{A}{T}$$

Where:
- A= Adaptation Capability
- T= Response Time

Eq. (3) Multi-Agent Collaboration

$$MAC = \sum_{i=1}^{n} A_i$$

Where:
- A_i= Individual Agent Contribution

Eq. (4) Decision Intelligence

$$DI = I \times C$$

Where:
- I= Information Quality
- C= Context Awareness

Eq. (5) Knowledge Evolution

$$K_{t+1} = K_t + \Delta K$$

Eq. (6) Continuous Learning

$$CL = D_{new} + F$$

Where:
- F= Feedback

Eq. (7) Agent Negotiation Score

$$NS = B - C$$

Where:
- B= Benefit
- C= Conflict Cost

Eq. (8) Collaboration Efficiency

$$CE = \frac{O}{H}$$

Where:
- O= Outcome
- H= Coordination Overhead

Eq. (9) Adaptation Rate

$$AR = \frac{\Delta P}{\Delta t}$$

Where:
- P= Platform Performance

Eq. (10) Resource Allocation

$$RA = \frac{R}{N}$$

Where:
- R= Total Resources
- N= Agents

Eq. (11) Agent Consensus

$$AC = \frac{A_g}{A_t}$$

Where:
- A_g= Agreeing Agents
- A_t= Total Agents

Eq. (12) Model Improvement

$$MI = P_{new} - P_{old}$$

Eq. (13) Feedback Optimization

$$FO = L + R$$

Where:
- L= Learning
- R= Reinforcement

Eq. (14) Self-Evolution Index

$$SEI = CL + AC + NT$$

Where:
- CL= Continuous Learning
- AC= Adaptation Capability
- NT= Negotiation Strength

Eq. (15) Enterprise Intelligence Platform Value

$$EIPV = EI + EA + MAC$$

1.1. MULTI-AGENT SYSTEMS IN AI

Artificial Intelligence (AI) addresses a wide range of problems; thus, the provision of its services is done by a multitude of (often conflicting) components. For example, hardware-and-software stacks of self-driving cars incorporate computer vision, natural language understanding, control, and path planning systems. Image synthesis is delivered via text-to-image generators and ongoing image generators. The necessity of cooperation and negotiation has led to the creation of probably the most important subset of AI: multi-agent systems (MAS), which is a subfield of AI concerned with problems solved by a collection of (often conflicting) components that have to find a solution.

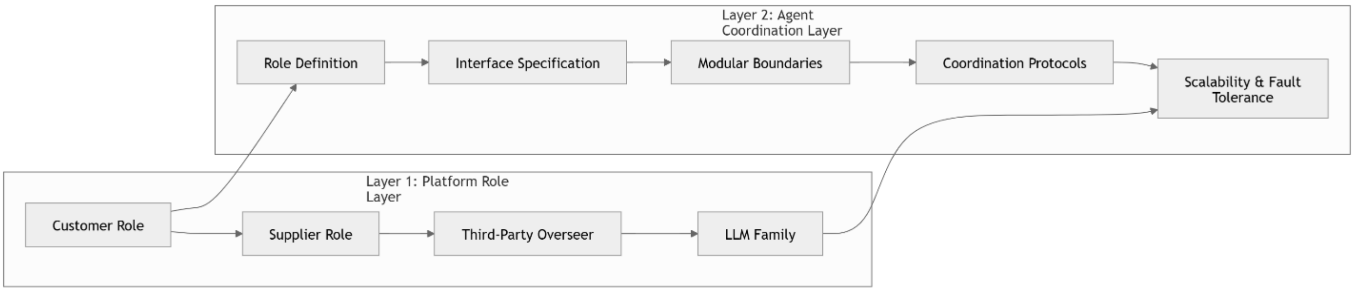

FIGURE 1 Agent-Based Decomposition

Agents are AI components that share a sub-objective and pursue it via cooperation, negotiation, or competition. Multi-agent collaboration is achieved through negotiation and trade-off mechanisms (e.g., trade-offs involving cost, efficiency, quality, speed) enabling conflict resolution, consensus discovery, and resource allocation. Moreover, cooperation usually generates overhead involved coordination and communication activities require time, energy, and money. Consequently, a crucial research question is how to minimize such overhead while maximizing the benefits of MAS.

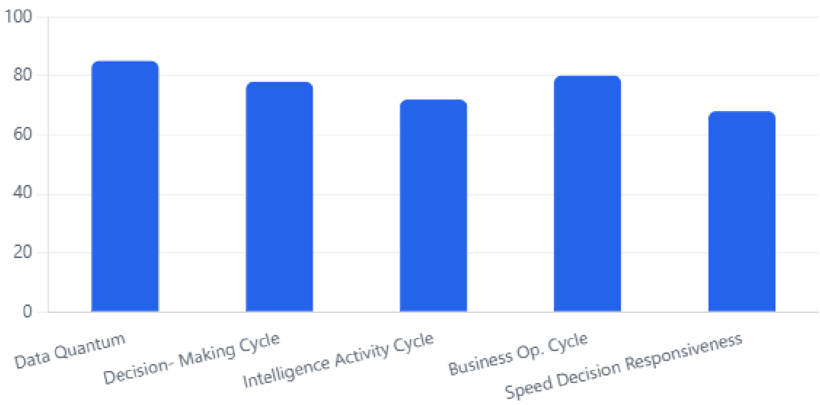

FIGURE 2 Business Decision-Making Performance Overview

Enterprise Intelligence Capability Classes (bar) the capability classes from Section 2 & 6 (Data Quantum, Decision-Making Cycle, Intelligence Activity Cycle, Business Operation Cycle, Speed Decision Responsiveness).

TABLE 1 Enterprise Intelligence Capability Framework

Capability Layers	Primary Function	Input Sources	AI/LLM Role	Expected Outcome
Enterprise Data Quantum	Data acquisition and governance	Internal & external data streams	Data interpretation agents	Trusted knowledge base
Decision-Making Cycle	Strategic and operational decisions	Enterprise knowledge	Decision support agents	Faster decisions
Intelligence Activity Cycle	Knowledge generation and validation	Historical and real-time data	Reasoning agents	Actionable intelligence
Business Operation Cycle	Execution and monitoring	Operational events	Automation agents	Business optimization
Enterprise Agility Layer	Adaptation and response	Environmental changes	Adaptive orchestration agents	Continuous evolution

2. CONCEPTUAL FOUNDATIONS

Enterprise Intelligence and Enterprise Agility represent the ultimate objectives of self-evolving enterprise intelligence platforms. The Enterprise Intelligence concept diverges from the traditional perspectives that view intelligence solely as information access and knowledge repositories. Enterprise Intelligence refers to the ability of an enterprise to effectively create, manage, evolve, and utilize the dynamic and ever-growing body of data and knowledge needed for the daily execution of its business activities—guaranteeing the quality of knowledge when required, identifying knowledge gaps, and triggering knowledge creation processes whenever necessary. Enterprise Agility encompasses the capabilities of fast and effective enterprise assessment, direction-setting, and response to environmental changes, with reduced and predictable risk of unpredicted chaos.

Enterprise Data Quantum, Enterprise Decision-Making Cycle, Enterprise Intelligence Activity Cycle, and Business Operation Decision Cycle. Implemented properly, these four capabilities guarantee that the right data appear, in adequate quantity and quality, when required by the enterprise Decision-Making Cycle and the cycles of any other Intelligence Activity.

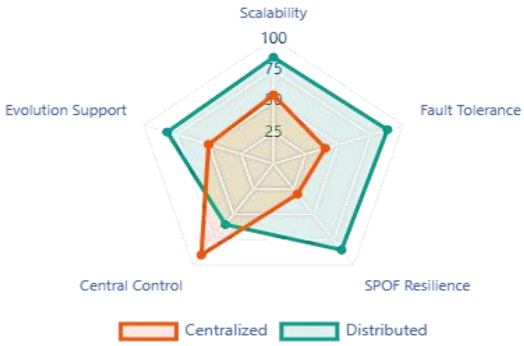

FIGURE 3 Comparative Analysis of Centralized and Distributed Systems

Centralized vs Distributed Control (radar): The architectural trade-off across scalability, fault tolerance, single-point-of-failure resilience, central control, and evolution support.

2.1. ENTERPRISE INTELLIGENCE AND AGILITY

Enterprise Intelligence and Agility cover enterprise information and decision-making capabilities in dynamic environments. Intelligence relies upon broad, accurate, and timely information flows; enterprise agility requires rigorous monitoring, adaptation, and planning capabilities for a changing environment. A model is proposed, defining data flows, decision cycles, governance structures, and tactical, operational, and strategic alignment with business objectives. Key considerations include the enrichment of operational data with external, non-mission-critical, or less trusted information, the distribution of decision-making and data-sourcing capabilities, and the balancing of agent fault tolerance against central control.

Enterprise Intelligence refers to the information management and decision-making capabilities of an organization in support of its mission. These capabilities are not static but evolve within dynamic environments. Intelligence is considered to depend on resource flows including Change, Production, Consumption, Delivery, Information, Knowledge, and Investment flows and beyond many Enterprise Knowledge Management Frameworks, Enterprise Agility is of particular interest. Enterprise Agility refers essentially to the organization's capacity to monitor its environment, detect changes, and quickly adapt its planning or decision-making and/or implementation processes in response. The model based upon this research therefore distinguishes between Enterprise Agility, the capacity to respond to changes, and the underlying Enterprise Intelligence capabilities, capabilities that make such detected changes known.

TABLE 2 Multi-Agent LLM Role Decomposition

Agent Type	Core Responsibility	Collaboration Method	Key Output	Fault Tolerance Contribution
Coordinator Agent	Task orchestration	Workflow management	Execution plans	High
Knowledge Agent	Knowledge synthesis	Shared memory exchange	Knowledge graphs	Medium
Decision Agent	Alternative evaluation	Negotiation protocols	Recommendations	High
Monitoring Agent	Drift detection	Feedback integration	Performance alerts	High
Governance Agent	Compliance validation	Policy enforcement	Risk assessments	Very High
Learning Agent	Model adaptation	Reinforcement learning	Updated models	Medium

3. ARCHITECTURAL PARADIGMS FOR SELF-EVOLVING PLATFORMS

The development of self-evolving enterprise platforms via continuous collaboration among federated, multi-agent Large Language Models (LLMs) can be embedded in specific architectural paradigms that define the nature of the collaboration and their evolutionary mechanisms. Implementation inequities often make a platform neither scalable nor fault-tolerant at an expanding scale, let alone supporting continuous evolution on the same underlying basis. Accordingly, a decomposition strategy is proposed whereby distinct parts of the platform assume the respective roles of a customer, supplier, third-party overseer, and LLM family. Clear interface specifications, modular boundaries, and operational protocols enhance both the quality of internal collaboration and the stability of the growing platform, even when controlled centrally.

The quality of the ongoing collaboration between LLMs also deserves attention. Evolving self-improving systems are fragile because of limited feedback, yet high-leverage trade-offs among the LLMs concerned can strengthen evolution. For instance, negotiation mechanisms and simple models of their interactions can ensure all agents' long-term growth, together with formal models for other types of trade-offs, such as governing the consumption of scarce resources by a multitude of decision-makers and addressing alignment constraints. Extensions of LLM systems have also introduced further groups of specialized LLMs and re-groups of existing specialists under alternative concepts, usually external to the LLM family. Gradually merging these open frameworks will support a growing family of LLMs with adaptable characteristics for LLM-enhancing agency.

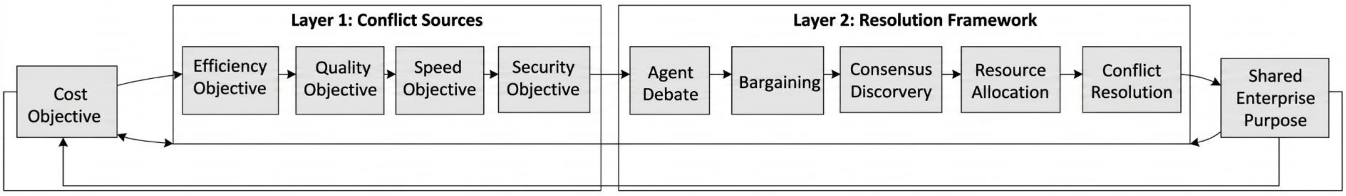

FIGURE 4 Negotiation and Trade-Off Framework

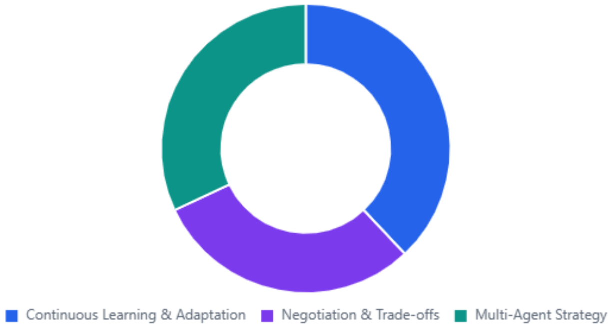

FIGURE 5 Key Components of Strategic Decision-Making in Multi-Agent Systems

Mechanisms of Self-Evolution (doughnut): The three mechanisms: continuous learning and adaptation, negotiation and trade-offs, and multi-agent strategy.

3.1. AGENT-BASED DECOMPOSITION

An agent-based decomposition is proposed to facilitate self-evolving enterprise-intelligence platforms that leverage multi-agent collaboration among large-language models. The decomposition delineates the different roles to be assumed by the collaborating LLM agents, describes the required interfaces through which each agent interacts with others, defines the modular boundaries of each role, and specifies the coordination protocols across agents. The decomposition is further justified in terms of properties such as scalability and fault tolerance. A high-level comparison between centralized and distributed control is also discussed.

Self-evolving enterprise-intelligence platforms are complex systems whose behavior is intended to change over time in a purposeful way. Such systems are composed of elements that continuously learn from their environment and update their internal models in a way that enhances decision-making and execution capabilities, without explicit training from external agents. The structures of such systems are modified to aggregate features in an intelligent way, facilitating the resolution of new tasks, while their operation is tuned to continually improve performance over time.

TABLE 3 Architectural Paradigms for Self-Evolving Platforms

Architecture Pattern	Characteristics	Advantages	Challenges	Recommended Usage
Centralized MAS	Single controller	Simpler governance	Single point of failure	Small enterprises
Distributed MAS	Autonomous agents	Scalability	Coordination complexity	Large enterprises
Federated LLM Architecture	Independent agent groups	Privacy preservation	Synchronization overhead	Multi-domain enterprises
Hybrid Agent Ecosystem	Central oversight + autonomy	Balanced control	Design complexity	Enterprise intelligence platforms

4. MECHANISMS OF EVOLUTION IN LLM-DRIVEN SYSTEMS

Self-evolving platforms using multi-agent collaboration among Large Language Models (LLMs) evolve through continuous learning and adaptation, requiring management of data ingress, model updates, feedback loops, safety constraints, and performance monitoring. Dedicated agents handle new information from the business environment and the public domain. External inputs such as social media reactions, competitor actions, or changes in other companies drive updates to the current backbone business model. Safeguarded operational exposure to end users ensures user experiences inform model tuning and retraining. Backtesting and comparison against earlier behavioral versions validate model drift and versioning.

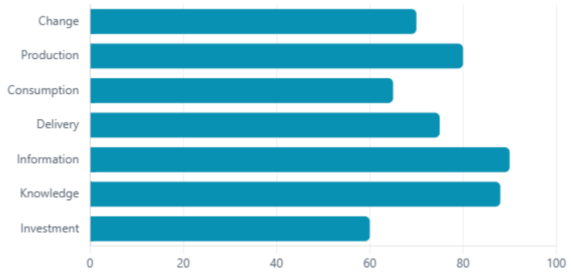

FIGURE 6 Relative Importance of Key Factors in the Digital Economy

Enterprise Resource & Knowledge Flows (horizontal bar): Change, Production, Consumption, Delivery, Information, Knowledge, Investment.

Self-evolving platforms using multi-agent collaboration among LLMs evolve through continuous learning and adaptation, requiring management of data ingress, model updates, feedback loops, safety constraints, and performance monitoring. Continuous emergence analyses confirm natural language processing (NLP)-based chatbots like ChatGPT as disruptive technologies. Platforms like ChatGPT are extremely limited but disruptive due to ease of use, rapid application development, and imminent affordances for enterprise users. A strategy with these attractors accords with mainstream disruptive innovation theory. Advanced adoption embraces self-evolving enterprise intelligence platforms based on multi-agent LLM collaboration.

4.1. CONTINUOUS LEARNING AND ADAPTATION

Continuous learning enables data-related services to acquire new knowledge: feeding these services with production data allows them to adjust their outputs to changing requirements. Two aspects merit attention: the data flows that introduce new information into the models and the particular mechanisms that use these data to update the models themselves.

In enterprise environments, LLMs operate in tactical and operational roles. Tactical roles are responsible for producing knowledge that is periodically used in operations, typically during shorter tactical cycles. Production data produced in these roles are natural candidates for continuous learning for tactical agents. Tactical agents can be supplied with both quality validation labels generated by the party consuming their results and explicitly rejected proposals to build a validation set, or they may receive quality labels volunteered by the user interacting with them. The resulting data flows fulfil the data ingress definition for supervision and reinforcement learning. The modified knowledge can be propagated to production upon validation, through a reinforcement learning mechanism that attempts to mimic human acceptance in a more consistent way.

Continuous adaptation of operational agents is more complex: their data ingress must be blind to the operations in order to avoid the introduction of spurious information and model drift. The correct data resources must therefore be determined externally, as an additional orthogonal task. Three orthogonal strategies can be defined here for continuous adaptation. The first one gathers two classes of feedback. The first class, public error feedback, captures contrastive pairs in output data of LLMs produced by and for the same operational agent. These contrastive examples are used to define fault detection methodologies, enabling detection of status drift conditions. The second class, private positive feedback, identifies the most useful answers posted by operational agents, creating a positive reinforcement source.

TABLE 4 Continuous Learning and Adaptation Mechanisms

Learning Mechanism	Data Source	Adaptation Method	Validation Approach	Business Impact
Supervised Learning	Labeled enterprise data	Fine-tuning	Accuracy testing	Improved predictions
Reinforcement Learning	User feedback	Reward optimization	Policy evaluation	Better decision quality
Neural Architecture Search	Performance metrics	Model redesign	Benchmark testing	Enhanced efficiency
Feedback Loops	Operational outcomes	Continuous updates	Drift monitoring	Sustained relevance
Backtesting	Historical records	Comparative evaluation	Version comparison	Reduced deployment risk

5. COLLABORATION FRAMEWORKS AMONG AGENTS

Negotiation and trade-offs pose additional challenges for an agent-driven self-evolving platform. The underlying intelligent agents not only generate competing views about certain issues but may also pursue conflicting goals. Consequently, processes for facilitating negotiation, conflict resolution, and trade-offs among agents become imperative. Trade-offs among different aspects of service quality, such as completeness, precision, and freshness that an agent offers constitute another important consideration. In fact, negotiation and trade-offs are likely to be recurring themes in a self-evolving enterprise intelligence platform.

Collaboration among agents may be modelled as a market, where agents competitively supply resources and demand services. Even an “invisible hand” of market equilibrium cannot guarantee that service demands will exactly match service offers. Therefore, problems of resource allocation and service provision must also be addressed. Incentives may sometimes ease the self-sacrificing burden on an agent taking on resources. Finally, high overhead associated with negotiation, coordination, and cooperation may hamper detection and resolution of trade-offs, conflicts, and competition between services. Negotiation is also influenced by the existence of interoperability standards, which, when properly designed, balance the need for flexibility in interactions among agents and the required conformance degree. Moreover, debate is a natural mode of communication for intelligent agents engaged in autonomous and self-organizing processes. It is a persuasion-based mechanism offering intelligent agents the opportunity to construct or revise their knowledge bases by listening or participating in group discussions.

In multi-agent systems, collaboration among agents can be conceptualized as a market-driven process in which autonomous agents competitively supply resources while simultaneously demanding services from one another. Although market mechanisms and the notion of an "invisible hand" facilitate decentralized coordination, equilibrium alone cannot guarantee that service demands precisely align with available service offerings. Consequently, effective resource allocation and service provisioning strategies remain essential to ensure system stability and operational efficiency. Incentive mechanisms can further encourage agents to assume resource-intensive responsibilities by mitigating the self-sacrificing burden associated with cooperative behavior. However, the benefits of collaboration may be constrained by the substantial overhead introduced through negotiation, coordination, and cooperation processes, which can impede the timely identification and resolution of trade-offs, conflicts, and competitive interests among services. The success of negotiation is also influenced by the presence of interoperability standards that appropriately balance interaction flexibility with the degree of conformance required among heterogeneous agents. Furthermore, debate represents a natural and powerful mode of communication within intelligent multi-agent environments. As a persuasion-based mechanism, debate enables agents to exchange viewpoints, challenge assumptions, and collaboratively refine their reasoning, thereby allowing them to construct new knowledge or revise existing knowledge bases through active participation in collective discussions. Such capabilities enhance adaptability, support self-organization, and contribute to more informed and robust decision-making in autonomous agent ecosystems.

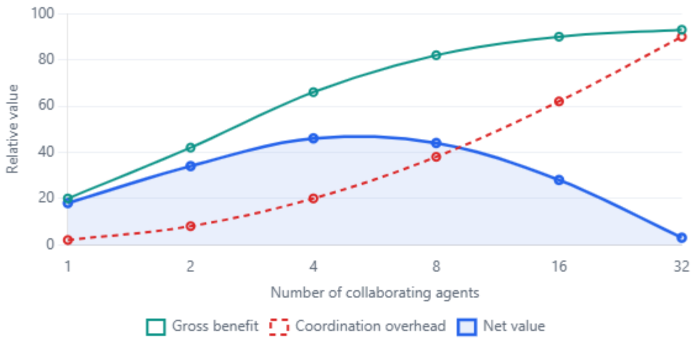

FIGURE 7 Relationship Between Number of Collaborating Agents, Gross Benefit, Coordination Overhead, and Net Value

Negotiation: Before vs After Consensus (radar) service-quality and resource trade-off dimensions improving through negotiation.

5.1. NEGOTIATION AND TRADE-OFFS

Collaboration among multiple agents can take many forms, ranging from competitive to cooperative behaviour. Though competition is usually viewed in negative terms, it can increase performance, as has been observed in various biological systems. Conflicts among agents in a self-evolving enterprise intelligence platform must thus be managed optimally rather than eliminated. Trade-offs can also arise in resource-constrained operational environments, where agents may need to share processing power, data bandwidth, or support for other agents. Such trade-offs can also be managed effectively, and formal methods exist that provide a solid foundation for implementation.

Conflicts among agents can occur at various levels. At the highest level of representation, agents can work towards different business objectives that can conflict with each other. For instance, an analyst may create a helpful business model recommending an organisational change in operations to lower costs, while a different analyst identifies a new direction for the company that may require more frequent project changes. Lower-level conflicts can also occur. Suppose that Team A is working on an enterprise project at T0. The COE agent has requested the application of a corporate security model and identified a recombinant agent that can apply the model in a reasonable time. However, Team A cannot accept the delay at T0, and Team A's risks associated with corporate security are still reportable and acceptable. In this case, the two agents should negotiate, perhaps through a simple bargaining method to determine whether or not the model can be applied at T0. A timely reply from Team A can help make such negotiation efficient.

TABLE 5 Agent Negotiation and Trade-Off Framework

Trade-Off Category	Competing Objectives	Negotiation Strategy	Resolution Method	Success Metric
Cost vs Quality	Efficiency vs Accuracy	Utility optimization	Consensus scoring	Cost-benefit ratio
Speed vs Precision	Response time vs Reliability	Priority weighting	Dynamic balancing	SLA compliance
Security vs Accessibility	Protection vs Availability	Risk assessment	Policy-driven control	Risk score
Resource Allocation	Agent competition	Market-based negotiation	Resource scheduling	Utilization rate
Innovation vs Stability	Change vs Consistency	Governance review	Controlled deployment	Adoption success

6. CONCLUSION

Enterprise Intelligence (EI) has emerged as a critical business competence addressing continual uncertainty and high entropy. Yet, the collection of capabilities constituting EI remain abstract. Thus, a generic conceptual model of EI is proposed, identifying five capability classes that support data flows throughout the entire enterprise Intelligence Cycle. Within this model, the flow-based interactions of the governance nodes that architect, govern, and control enterprise decisions, particularly the Speed Decision Responsiveness Capability are detailed. Using this model as a foundation, the idea of self-evolving platforms that accommodate adaptive negotiation and co-specialization among modular agents is explored. This is achieved through a combination of two established ideas: the intelligent-agent decomposition of complex systems, and the agent-based decomposition of multi-agent systems capable of evolving in real time through feedback from their environment. The resulting concepts represent an avenue for advancing the level of enterprise agility required for the increasingly challenging business environment.

By sustaining business-level alignment while adopting a distributed-control architecture, such self-evolving platforms offer an interesting alternative to Enterprise Intelligence Platforms and Business Decision Support Systems, especially for intranets with the self-evolving-archetype governance mode. The discussion presented here contributes to the ongoing research efforts aiming to establish a scientific foundation for enterprise intelligence by defining the concept of Enterprise Intelligence Agility, outlining its decision-environment flows, and representing the foundational layer of self-evolving Enterprise Intelligence Platforms based on the distribution of a Decision Responsiveness Capability metamodel across the possible Supply, Negotiation, or Customer Solving Modes.

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