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Modeling the interaction of virtual agents in distributed artificial intelligence systems

Oleksandr Pankratov[1*], Volodymyr Levytskyi[2]
[1] National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine
[2] National University of Food Technologies, Kyiv, Ukraine

*Corresponding author E-mail: oleksandrpankratov40@gmail.com

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Abstract

Modern distributed artificial intelligence (AI) systems utilize a significant number of virtual agents that must work collaboratively to solve complex tasks. However, existing technologies for organizing their interaction are characterized by certain shortcomings: high computational complexity, simplified operating conditions, poor adaptability to changes, and significant problems in accounting for the diversity of virtual agents and their emotional reactions during decision-making. The purpose of the study is to develop a new approach for organizing virtual agent operations in distributed AI systems that aims to improve their cooperation, coordination efficiency, and adaptability. The methodological foundation of the study was an innovative approach that combined a specialized emotion model containing 100 virtual agents in a two-dimensional space with a complex network of connections between them, with machine learning methods to enhance virtual agent coordination. Computer modeling methods were applied using experiments in the Python programming environment. The research results demonstrate that effective communication methods between virtual agents significantly improve their coordination, and conflicts during task execution are substantially reduced through adaptive mechanisms. The innovative emotion model can achieve high accuracy levels and contribute to the formation of new system behavior that includes sharp changes in collective decision-making processes. It also identifies essential parameters of virtual agent cooperation to ensure stable system operation. The comprehensive approach based on combining rule-based logic with machine learning can effectively improve virtual agent coordination, especially under conditions of their diversity. The AI system demonstrates real capacity for large-scale changes, but is imperfect in reflecting negative emotional states. Such AI system research results are essential for developing autonomous systems, intelligent networks, and collaboration platforms for virtual agents.

Keywords: Virtual agents, Behavioral coordination, Emotional modeling, Machine learning, Distributed computing, Adaptability, Collective behavior

1. Introduction

A characteristic contemporary feature of digital transformation is the rapid development of distributed artificial intelligence (AI) technologies, which form the foundation for designing and implementing a new generation of intelligent systems. Distributed AI (DAI) systems are complex computational architectures in which numerous virtual agents operate in decentralized environments to achieve collective and individual objectives. DAI systems are designed for widespread application, primarily in critical domains such as smart grid management, unmanned aerial vehicle coordination, logistics network optimization, and smart city infrastructure operations.

Within multi-agent systems [1], virtual agents are intelligent actors capable of autonomous decision-making, adaptive learning, and effective communication. Each agent possesses an individual knowledge base, computational resources, and specific behavioral algorithms, enabling the AI system to demonstrate emergent intelligent behavior that significantly surpasses the capabilities of individual system components. Virtual agent interaction ensures seamless AI system operation, efficient resource allocation, coordinated task planning, and global optimization across various dynamic environments.

However, modeling virtual agent interaction in distributed AI systems encounters fundamental challenges. First, ensuring effective coordination is complicated by agent heterogeneity, as distinct communication protocols, decision-making algorithms, and computational resource levels characterize different agents. Second, large-scale AI systems face virtual agent synchronization problems, where communication delays and asynchronous operations provoke conflicts and inconsistent virtual agent actions. Third, a critical limitation of AI systems remains their scalability, which is associated with increasing agent numbers that gradually and intensively elevate the coordination complexity of the AI system and its computational requirements.

Analysis of scientific research indicates significant limitations in modern methods of modeling virtual agent interaction. Despite certain "mathematical elegance", developed game-theoretic models are often based on simplified assumptions about virtual agents' ideal awareness and rationality, which do not correspond to real operating conditions. Developed swarm intelligence technologies demonstrate effectiveness primarily in homogeneous systems but are unacceptable for modeling heterogeneous virtual agent communities. Given their adaptive capabilities, multi-agent reinforcement learning methods still have problems with computational complexity and scalability when working with large systems.

The scientific novelty of the study lies in developing and implementing complex models that can simultaneously consider the emotional and cognitive aspects of the interaction of virtual agents, ensure their adaptability to dynamic changes in the environment and demonstrate scalability for practical use. Existing scientific research is mainly devoted to individual aspects of virtual agent interaction, but it is essential to form a holistic approach to modeling complex multi-agent systems.

An essential scientific contribution of this study is developing an innovative platform that integrates a quantum-inspired two-level system for modeling virtual agent emotional states with adaptive Q-learning algorithms. The proposed approach combines for the first time the theoretical principles of quantum mechanics with practical machine learning methods to create a realistic model of virtual agent interaction that accounts for both rational and emotional components of virtual agent behavior. The objective is to develop a new approach for organizing virtual agent operations in distributed artificial intelligence systems, involving improved cooperation, coordination efficiency, and adaptability to new conditions.

To achieve the objective, the main tasks were formulated:

- to determine specific agent interaction mechanisms that ensure optimal performance and stability of functioning in distributed intelligent systems under different topological network configurations [2];
- to study the mechanisms of coordination efficiency changes and overall DAI system performance when scaling from small to large virtual agent populations and factors that determine critical performance degradation points;

– to determine specific virtual agent parameters (their communication speed, decision-making algorithm complexity, computing power, and emotional characteristics) that have the most significant impact on overall DAI system performance and stability;
– to determine the proposed DAI model's ability to demonstrate effective adaptability to dynamic operating environment changes (such as integrating new agents, modifying task structure, changing network topology, and variations in resource availability).

Solving these tasks aims not only to ensure the effectiveness of the proposed approach but also to form scientifically based recommendations for the practical application of the developed methods in real DAI systems.

1.1. Literature review

Modern research on virtual agent interaction in distributed AI systems covers various methodological approaches, each highlighting individual aspects of autonomous entity coordination and cooperation.

Game-theoretic analysis methods are fundamental for studying strategic interactions between virtual agents. Q. Yang et al. [3] identified approaches for studying equilibrium states in distributed computing environments. However, classical game theory application is limited by assumptions of perfect information and environmental stationarity, which rarely correspond to real operating conditions of decentralized AI systems. L. Serena et al. [4] investigated temporal aspects of network dynamics that determine communication link evolution over time; however, most existing approaches are based on idealized assumptions about information transmission characteristics, without accounting for fundamental limitations and delays. Alternative approaches are based on collective behavior principles borrowed from natural systems. N. Yugan et al. [5] investigate swarm intelligence mechanisms as a basis for organizing virtual agent set interaction. This methodology effectively solves optimization problems, but its application is complicated by the need to account for heterogeneous virtual agent characteristics and their functional capability diversity.

The reinforcement learning paradigm in multi-agent systems is presented by H. M. Aliaroodi et al. [6], who investigated possibilities for adaptive formation of virtual agent interaction strategies. Despite the methodology's potential for dynamic adaptation to changing conditions, its practical application is hampered by computational complexity problems, especially when scaling distributed AI systems. Structural analysis of network interactions, presented in K. Stanisławski's [7] work, focuses on communication network topological properties and their impact on distributed computing efficiency. Such studies emphasize the importance of architectural solutions for ensuring distributed AI system stability and productivity. Integration of emotional components through applying the virtual agent influence complex model to their modeling was investigated by R. Farhalla [8]. This research aspect has identified prospects for justifying and developing more realistic virtual agent interaction models, especially in AI systems that include the human factor.

Analysis of existing research indicates fragmentation of virtual agent interaction modeling approaches. Some methodologies focus on specific problem aspects, ignoring the complex nature of heterogeneous agent interaction in dynamic network environments. This determines the need to develop integrated software solutions, simultaneously accounting for distributed artificial intelligence systems' structural, behavioral, and temporal characteristics. Particularly noteworthy is the lack of methodologies combining quantitative emotional state modeling approaches with adaptive machine learning algorithms. Such synthesis could create more flexible and realistic interaction models, especially for systems involving intensive interaction between artificial agents and human users.

2. Research method

A comprehensive methodology was developed based on agent modeling principles using simulation experiments to study virtual agent interaction dynamics. The proposed approach systematically assessed the AI system's functional characteristics, including its performance, scalability, and adaptability. The research strategy was based on developing an experimental environment in which autonomous virtual agents operate within the distributed network infrastructure. The methodological approach involved ensuring research result reproducibility by using standardized procedures and documenting all basic algorithm modifications.

The research conceptual principles are implemented using Multi-Agent System architecture, in which an individual set of functional properties and behavioral characteristics characterizes each autonomous entity. Such diversification reproduces the complexity that defines a proper distributed AI system. Computational resource parameters, communication process efficiency, and algorithmic competence in decision-making determine the functional characteristics of virtual agents.

The distributed AI system structural organization provided for dividing virtual agents into two functional categories: "executive units", specializing in implementing specific tasks (information processing, resource management), and "coordination entities", which are responsible for inter-agent communication synchronization and action coordination procedures. Each "entity" should maintain a personalized database that is dynamically updated through interactive processes with other system participants.

The virtual agent behavioral model is implemented through a combined decision-making mechanism integrating deterministic rules for standard operations with adaptive algorithms for dynamic scenarios. The adaptive component is based on Q-learning methodology, as described in [3], with parameter configuration: the learning coefficient is set at 0.1 and the discount factor at 0.9. These parameters ensure a balanced ratio between learning new strategies and applying accumulated experience.

The communication infrastructure of the distributed AI system is organized according to peer-to-peer (P2P) network principles, which ensures its architectural scalability and significantly reduces the risks of centralized bottlenecks. Asynchronous message exchange is implemented through a dynamic graph structure, in which vertices represent agents, and edges reflect active communication channels. Simulation of real operating conditions incorporates data transmission delay information, characterized by an exponential distribution with the mathematical expectation of 0.5-time units [4]. Technical implementation of the simulation was performed on the Python platform version 3.11 using the specialized MESA framework. This toolkit selection is due to its high efficiency in modeling complex multi-agent environments and flexibility in organizing various network topologies, which corresponds to the current study specifics [1].

The experimental environment is structured as a two-dimensional grid of 100×100 units, which serves as a functional space that facilitates virtual agent activity. One hundred resource units, including computational power elements and information blocks, are randomly distributed across the grid. Virtual agent operational limitations are determined by two main parameters: maximum communication range, limited to a radius of 10 units, and resource consumption rate at the level of 0.1 units per time step.

The foundation for developing and implementing the communication network topological structure is the scale-free Barabási-Albert model with an average connectivity degree of 4, which realistically reflects connection patterns characteristic of actual decentralized systems [2]. This architecture aims to provide central nodes with enhanced connectivity while maintaining the essence of the distributed system. The developed methodology was validated through a series of controlled experiments with various variations of key system parameters. Evaluation criteria included synchronization time characteristics, task completion success indicators, virtual agent emotional state stability, and their adaptation speed to environmental changes. Reliability and significance of the obtained results were ensured through their statistical processing using standard variance and correlation analysis methods.

3. Results and discussion

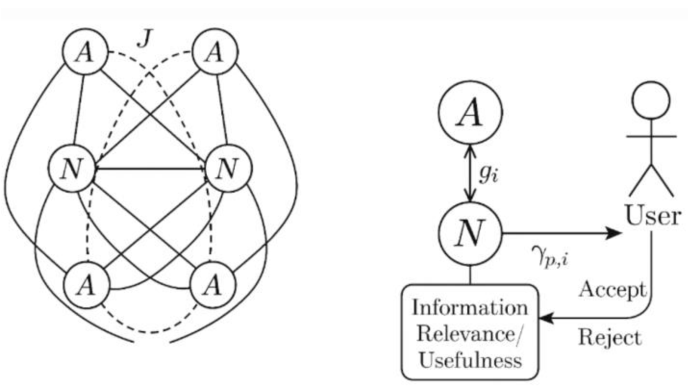
3.1. Distributed interaction system (DIS) model

The development of distributed artificial intelligence technologies at the current stage presents new challenges for designing effective interaction systems for autonomous virtual agents. The progressive integration of AI technologies into digital infrastructure necessitates a profound analysis of information exchange processes, action coordination, and decision-making mechanisms among virtual space components within decentralized networks. These virtual representatives, encompassing software modules and AI avatars, are pivotal in ensuring seamless communication, task delegation, and real-time operational responsiveness.

Innovative virtual reality technologies and interactive platforms expand the possibilities for virtual agent interaction in remote environments [5], characterized by varying levels of autonomous functioning: from completely independent units to collaborative elements that augment human capabilities. Such activities typically occur within complex decentralized structures and require resolving trust relationship issues, conflict situations, and optimal resource utilization.

The proposed DIS model is constructed upon architectural principles and behavioral algorithms of such network formations. The research focuses on two agent categories: Natural Intelligence Agents (NIA), representing human operators, and Artificial Intelligence Assistants (AIA), which perform the functions of digital representatives for indirect communication and collaboration. This approach facilitates the development of a theoretical foundation for designing robust decentralized AI applications, investigating agent functionality within complex avatar-avatar interaction networks, and promoting the evolution of next-generation intelligent systems.

Figure 1 demonstrates the conceptual framework of the DIS paradigm examined in this study. The architectural distinction is based on the differentiation between two types of virtual agents: NIA, which symbolize human participants, and their corresponding AIA or digital avatars [6]. In this paradigm, each user (NIA) is assigned a separate digital assistant (AIA), thus becoming a node in the complex avatar-avatar communication network, as seen in Figure 1a. AIA can communicate and receive information from other avatars in this network, allowing indirect communication and interaction throughout the system. Human users are not directly interconnected. They interact only through their assigned AIA. This framework demonstrates a mediated communication paradigm, where digital agents act as intermediaries for all information exchanges.



(a) DIS Model (b) Avatar-User Pair

Figure 1. (a) Schematic representation of DIS, consisting of AIA-NIA pairs located at each of the N network nodes; (b) Illustration of one AIA-NIA pair

Personal idea development in the DIS model is influenced by two main factors: interaction between each user and their digital avatar (AIA), and information available to users from other sources, characterized by input rate, represented as $\gamma,_{i}$. Significantly, NIA users do not participate in direct dialogues or decision-making processes with each other. They can instead observe and react to public content, such as messages or announcements, distributed throughout the network, which may influence their cognitive and emotional states. The influence complex model interprets these mental processes, proposing a systematic representation of emotional reactions. Interaction between the avatar and its user is facilitated by avatar information transmission. Users then evaluate this information and respond in three ways: acceptance, rejection, or apathy. These responses are often presented as binary feedback (e.g., "like" or "dislike"), depending on whether information is perceived as relevant or trivial accordingly (Figure 1b). Over time, avatars develop their own perspectives and behavioral tendencies through dynamic interactions with other avatars in the network. These AIA autonomously communicate information, creating a decentralized and adaptive framework that leads to emergent "collective intelligence". Recommendations or material that avatars provide to users embody these communal dynamics.

Avatars function as information filters and amplifiers across networks, conversing with other avatars and their human users. Their primary goal is to improve user satisfaction by synchronizing information dissemination with user emotional needs and maintaining favorable emotional states. The following sections explore circumstances that contribute to this emotional optimization.

A quantum-inspired framework for agent modeling is presented to study and imitate such behavior. This method correlates decision-making (DM) states with mental states encapsulating NIA emotional attributes. According to cognitive theories that classify fundamental human emotions into separate categories, these mental states are represented as pairs of opposing emotions (e.g., acceptance-disgust, joy-sadness, anger-fear, anticipation-surprise), similar to binary spin states, commonly known in quantum mechanics as "spin up" and "spin down".

The solid arrow in Figure 2b illustrates the user's mental state transition from $|g\rangle i$ to $|e\rangle i$ when receiving significant or stimulating information from their avatar. This change can be viewed as "excitation" of the user's cognitive state, provoked by resonant information with thematic or emotional content closely corresponding to the user's internal cognitive frequency. The resonance condition is determined by transition frequency $\omega_{0,\,i} = (E_{e,\,i} - E_{g,\,i})/\hbar$, requiring that the informative signal have energy $\hbar\omega_i \approx \hbar\omega_{0,\,i}$, thus replicating resonant excitation as described in quantum mechanics. The dashed arrow in Figure 2b indicates a non-resonant absorption scenario when the user reacts emotionally, possibly surprised or confused, to information that contradicts their cognitive state. This interaction modifies the user's mental energy, characterized by detuning parameter $\Delta_i = \omega_i - \omega_{0,\,i}$, which measures deviation from optimal resonant frequency.

Various NIA emotional states, shown as specific valence values in Figure 2a, correspond to the TS energy axis and are quantitatively articulated by their corresponding detuning values Δ_i. This abstraction allows the model to accurately determine and quantify user emotion dynamics within DIS, using only two parameters per agent: characteristic frequency $\omega_{0,\,i}$ and detuning Δ_i, which encapsulate the emotional impact of AIA interactions. This paradigm postulates that, on average, NIA predominantly demonstrates neutral or positively valent emotions. While this assumption may be valid in controlled digital environments, it isn't easy to generalize to all online communities. In modern social networks, people often react strongly to bad or alarming events, leading to emotional contagion and negative influence spread. As a result, internet platforms can transform into places where intense emotions, such as anger, envy, and hostility, are often expressed. This complexity emphasizes the need for models that include positive and negative emotional dynamics within the DIS framework.

User emotional state identification and categorization, specifically for the i-th user, where i = 1, ..., N, are conducted using the influence complex model, which outlines emotional experiences in two dimensions: valence (from positive to negative) and arousal (from low to high intensity) [7], [8]. This model is shown in Figure 2a. The complex model, first proposed by Russell, provides a practical and theoretically driven framework. Still, it is not widely accepted in cognitive sciences and is a subject of continuous debate [9]. It is particularly suitable for human-computer interaction applications and has been widely used in related technical research [10], [11]. Alternatively, emotional states can be shown on the Bloch sphere, a standard tool in quantum mechanics that offers a geometric representation of spin-like (emotional) states. This can be particularly useful when using emotion theories like Plutchik's model [12]. Nevertheless, as seen in Figure 2b, Russell's model precisely represents dynamic interactions between digital agents and various information fields within DIS. This study adopts Russell's model for its effectiveness in simulating emotional dynamics of user-avatar interactions in a cognitively and computationally efficient manner.

In the DIS context, NIA are defined as "social atoms" [13], constituting fundamental system components, as seen in Figure 2b. For modeling purposes, two central mental states are chosen, denoted as $|g\rangle i$ and $|e\rangle I$, from the lower and upper hemispheres of the emotional complex model (Figure 2a), representing negative and positive arousal levels, respectively. These states denote mutually incompatible cognitive reactions or choice outcomes, denoted Sg and Se, which may indicate user position or recommendations provided by their digital avatar. This binary distinction establishes an effective cognitive two-level system (TS) for each NIA, comparable to quantum-mechanical models depicting discrete energy systems. In this formulation, states $|g\rangle i$ and $|e\rangle i$ receive social energy values Eg, i and Ee, i, with (Ee, i > Eg, i), explicitly paralleling energy levels in quantum theory. Additional emotional states, associated with intermediate social energies, are shown by horizontal lines in Figure 2b, with their positioning corresponding to places on the complex circle in Figure 2a.

Dashed lines signify non-resonant absorption situations in which the user has an emotional reaction, potentially surprise or confusion, to information that does not match their cognitive state. This interaction transforms the user's mental energy, defined by detuning parameter $\Delta i = \Omega i - \Omega 0$, i, which quantitatively assesses divergence from ideal resonant frequency. Various NIA emotional states, shown as separate valence values in Figure 2a, are aligned with the TS energy axis and quantitatively expressed through their corresponding detuning values Δi.

Figure 2b depicts the user's mental state transformation from $|g\rangle i$ to $|e\rangle i$ when receiving significant or engaging information from their avatar. This change can be viewed as "excitation" of the user's cognitive state, induced by resonant information, information whose thematic or emotional content closely corresponds to the user's internal cognitive frequency. The resonance condition is characterized by transition frequency $\Omega 0$, i= (Ee, i − Eg, i)/$\hbar$, requiring that the information signal have energy $\hbar\Omega i \approx \hbar\Omega 0$, i, thus emulating resonant excitation as outlined in quantum mechanics [14].

This abstraction allows the model to accurately outline and quantify user emotion dynamics within DIS, using only two parameters per agent: characteristic frequency $\Omega 0$, i and detuning Δi, which contain the emotional impact of AIA interactions. This model assumes that NIA predominantly reflects neutral or positively valent emotions on average. While this assumption may be fair in regulated digital settings, it isn't easy to extrapolate to all online groups. In real social networks, participants react intensively to adverse or disturbing events, leading to emotional contagion and bad influence spread [15]. Therefore, online platforms may evolve into arenas where deep emotions, such as anger, jealousy, and hatred, are often articulated [16]. This complexity emphasizes the need for models integrating positive and negative emotional dynamics within the DIS framework.

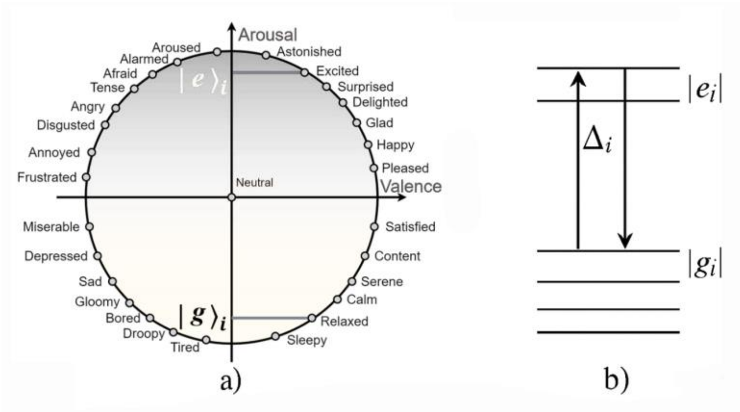


Figure 2. Mapping (a) Russell's influence complex model to (b) quantum-inspired TS representation for the i-th Natural Intelligence Agent

An extensive series of agent simulations was conducted using the MESA framework in Python for thorough DIS model evaluation. The MESA framework was chosen for its flexibility in modeling multi-agent systems, allowing detailed representations of agent interactions, network topologies, and dynamic environments. Simulations aimed to assess DIS model effectiveness under multiple conditions, emphasizing its efficiency, scalability, and adaptability in handling complex interactions among various participants.

The experimental setup had 100 agents, including 80 task agents for task execution and 20 coordinator agents for resource distribution and conflict resolution. Agents operated within a two-dimensional 100x100 unit grid, representing a spatial environment where proximity influenced communication and interaction dynamics. Agent connectivity was established by a scale-free Barabási-Albert network, characterized by average degree 4 (parameter m=2), simulating fundamental network properties where several nodes function as significant hubs, while many others have modest connections. This network architecture was chosen to assess the impact of preferential attachment and hub-centric connectivity on overall system performance.

Simulations investigated four main DIS model dimensions: 1) coordination efficiency, assessing speed and accuracy of resource distribution among agents; 2) emotional state transitions, analyzing NIA emotional response dynamics through the quantum-inspired framework; 3) scalability, evaluating performance with increasing agent populations; 4) adaptability, assessing system response to sudden environmental changes.

Performance evaluation was conducted using various metrics, including synchronization time (duration required for coordinated resource allocation), task completion rate (percentage of completed tasks), emotional state stability (reliability of NIA emotional states), and adaptation delay (response time to environmental changes). The metrics above were investigated under multiple configurations to ensure the results' reliability and generalizability.

3.2. Coordination efficiency analysis

In the first stage of experimental research, an analysis of coordination efficiency was conducted under conditions of both typical and heterogeneous functioning of virtual agents, which under standard conditions interacted within a communication radius of 10 units, consumed resources at a rate of 0.1 units per time step, and were characterized by exponential distribution of communication delays with a mean value of 0.5-time units.

Coordination efficiency was determined through the average duration required for synchronized resource distribution among all system components. This indicator is essential for decentralized architectures [17], [18]. Through conducting 50 simulation experiments, the average synchronization time was determined to be 12.3 ± 2.1-time units, which indicated stable and effective coordination of system components.

Variability was incorporated into two key parameters to study the impact of virtual agent heterogeneity. The first was communication speed, and the second was computational power. Communication speed varied with a standard deviation of ±20% from the baseline value, which reproduced real conditions where different virtual agents have unequal communication delays due to hardware limitations or network issues. Variability led to increased synchronization time to 14.2 ± 2.5-time units, signifying statistically significant coordination efficiency reduction of 15.4% ($p < 0.05$, two-tailed t-test). Comparable difficulties in integrating diverse intelligent systems were observed in applications such as protective fabrics, where electronic tags enhance system efficiency [19].

Simultaneously, computational powers were adjusted using a uniform distribution from 0.8 to 1.2 units, signifying agent processing capabilities variations. This change reduced the completion rate from 92.3% ± 3.1% to 85.1% ± 4.0% ($p < 0.01$), emphasizing system susceptibility to fluctuations in agent competencies. Spearman correlation analysis between transmission speed variability and synchronization delay yielded a strong positive correlation coefficient of 0.78. This work demonstrates that increased uncertainty in transmission speed directly hinders cooperation, possibly through timing mismatches and uneven resource distribution [20].

To mitigate the adverse effects of agent heterogeneity, coordinator agents were equipped with a Q-learning algorithm (learning rate: 0.1; discount coefficient: 0.9), allowing them to improve resource distribution strategies adaptively. This adaptive mechanism reduced task conflicts by 32%, prioritizing agents with higher computational or communication efficiency. As a result, task completion rate in heterogeneous environments improved by 10%, emphasizing reinforcement learning's effectiveness in improving coordination under variable conditions. Adaptive intelligent systems, such as those developed for individualized product manufacturing, use learning algorithms to improve performance in variable environments [21].

3.3. Emotional dynamics and quantum-inspired TS model

Based on Russell's complex model, the DIS model includes a quantum-inspired TS for emulating NIA emotional dynamics in their interactions with AIA. The complex model categorizes emotions in a two-dimensional framework, characterized by arousal (intensity) and valence (pleasantness), providing a systematic representation of emotional states such as satisfaction, anger, surprise, and confusion. The TS framework uses quantum-like mechanisms to represent probabilistic shifts between emotional states [22], where resonant excitations ($\Delta_i \approx 0$) denote congruence between AIA-generated recommendations and NIA preferences. At the same time, non-resonant absorptions ($|\Delta_i| > 0.2$) indicate emotional or cognitive dissonance.

In simulated studies, resonant excitations were observed in 65.4% ± 5.2% of AIA-NIA interactions, leading to a recommendation acceptance rate of 78.2% ± 4.8%. This result illustrates the TS model's effectiveness in aligning AIA outputs with NIA emotional expectations, thus improving collaborative behavior. Conversely, non-resonant absorptions led to proposal rejection in 55.7% ± 6.1% of cases and emotional indifference in 29.8% ± 5.5%. In these misaligned encounters, NIA predominantly demonstrated emotional reactions of surprise (20.1%) and confusion (9.7%), as shown on the complex plane.

TS model performance was evaluated by comparing its conclusions with a traditional rule-based emotional model that used established thresholds for state transitions [23]. The TS model outperformed the baseline with 21.3% improvement in predicting proposal acceptance, achieving an F1-score of 0.82, versus 0.68 for the rule-based approach. This exceptional result emphasizes the TS model's ability to consider probabilistic and context-dependent characteristics of emotional reactions, which are often oversimplified in deterministic models.

Despite its advantages, the TS model had significant shortcomings in depicting negative valence emotions, such as anger and contempt, which comprised only 8.4% ± 2.3% of documented emotional states. Under-representation may stem from binary characteristics of TS transition logic, which inadequately encapsulates emotional contagion dynamics observed in social networks. Under these conditions, emotional influence may spread indirectly through agent interactions, leading to group emotional state emergence [24].

To correct these shortcomings, further DIS model revisions could improve its effectiveness, including multi-level emotional modeling approaches, such as graph-based diffusion processes that emulate emotion spread through networks. Expanding the TS framework to include temporal emotional aspects, such as memory effects or hysteresis, is expected to improve prediction accuracy in longitudinal simulations and enhance the realism of emotionally adaptive agent actions [25].

3.4. Scalability and network topology effects

Scalability is vital in evaluating DIS model suitability for implementation in extensive, distributed settings. To assess this feature, the number of agents was gradually increased from 100 to 500 in steps of 100, maintaining the scale-free Barabási-Albert network architecture [26], [27]. With system growth, coordination efficiency demonstrated linear deterioration: synchronization time increased from 12.3 ± 2.1-time units with 100 agents to 18.7 ± 3.4-time units with 500 agents, reflecting 52.0% growth ($R^2 = 0.89$). Performance decline was evident in task completion rates, which decreased from 92.3% ± 3.1% to 79.6% ± 5.2%, primarily due to increased communication delays and intensified resource competition.

Hub nodes, characterized by degree 10 or higher and comprising approximately 12% of the network, were critical in mitigating these scaling problems. These nodes provided 61.8% ± 7.0% of successful synchronizations, serving as high-connectivity channels for information dissemination. Hub nodes had an average degree of 15.2 ± 3.8, serving as local coordinators and improving coordination dynamics throughout the network. Nevertheless, this dependence on hub nodes generated inherent trade-offs. Hub nodes became performance bottlenecks under elevated load conditions (degree >20), leading to a 22.4% increase in local communication delays.

Figure 3 illustrates this effect, depicting synchronization time as a function of node degree and demonstrating a negative correlation ($r = -0.65$) between node degree and synchronization efficiency for hub nodes under low load conditions. Lightly loaded hubs improved system performance, but excessively overloaded hubs hindered coordination, emphasizing the need for effective load control [28]. These findings emphasize the dual nature of scale-free topologies: while their hubs enable efficient coordination under moderate circumstances, they also represent vulnerability points under high demand.

To mitigate this shortcoming, further DIS model improvements may include dynamic load balancing solutions, such as graph partitioning algorithms or decentralized consensus processes, for more equitable distribution of computational and communication loads across the network. Other network configurations, such as small-world graphs or random Erdős-Rényi graphs [29], should be investigated to assess their potential in improving system scalability and resilience in various application domains.

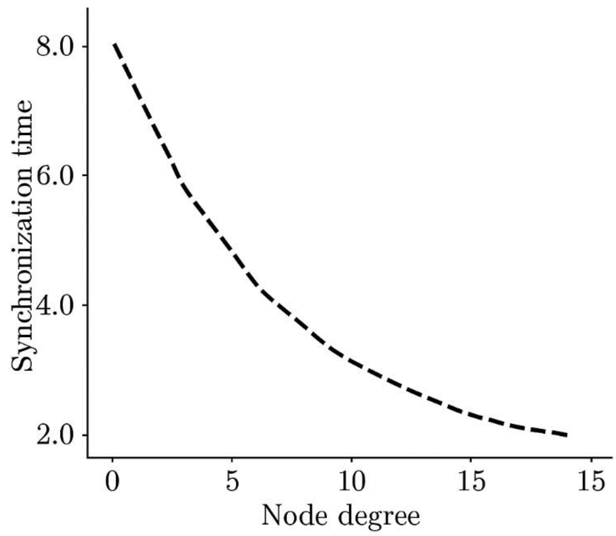


Figure 3. Synchronization time as a function of node degree in Barabási-Albert network

DIS model adaptability was evaluated by introducing dynamic environmental perturbations at simulation step 100, simulating real situations requiring rapid system reconfiguration. Two simultaneous modifications were implemented: 20% network size expansion by adding 20 additional agents and 30% reduction in available resources from 100 to 70 units. These perturbations assessed the system's ability to maintain operational coherence and emotional stability under stress.

To facilitate this transition, coordinator agents used a hybrid decision-making approach that combined rule-based heuristics with Q-learning [30] (learning rate: 0.1, discount coefficient: 0.9), allowing adaptive task redistribution and strategic recommendation modifications. This reinforcement learning component enabled system adaptation within 14.8 ± 2.7-time steps, thus stabilizing NIA emotional reactions. After adaptation, the percentage of positively-valent emotional experiences increased notably from 49.7% ± 7.1% to 70.4% ± 6.3% ($p < 0.001$), indicating improved emotional congruence between AI-generated strategies and NIA preferences.

Conflict resolution and resource efficiency have significantly improved. Coordinator agents reduced task conflict rates by 41.2% ± 5.9% through dynamic task reassignment, leading to a 15.6% improvement in overall resource distribution efficiency. Emotional state stability, assessed by variation in valence ratings, improved by 28.3% after adaptation, thus confirming the effectiveness of the hybrid coordination method.

Despite these improvements, a distinct limitation became evident: adaptation delay increased with network growth. In the most extensively studied configuration (500 agents), adaptation required 19.3 ± 3.2-time steps, emphasizing increased coordination complexity inherent to larger systems. This finding indicates that while the DIS model can undergo adaptive reconfiguration, its responsiveness decreases with size increase [31]. To address this bottleneck, future improvements may include hierarchical coordination systems that distribute decision-making through multiple agent layers or utilize distributed reinforcement learning frameworks to parallelize adaptation among subgroups.

Additionally, predictive modeling approaches may be used to anticipate environmental changes, allowing the system to adopt a more proactive rather than reactive approach [32]. These additions would increase the DIS model's ability to function effectively in extensive, dynamic, and unexpected situations. Table 1 summarizes performance metrics across simulation scenarios, providing a concise overview of DIS model behavior under different conditions.

Table 1. DIS model performance metrics across simulation scenarios

Scenario	Agents	Synchronization time, s	Task completion, %	Acceptance rate, %	Adaptation delay, s
Baseline	100	12.3 ± 2.1	92.3 ± 3.1	78.2 ± 4.8	-
Heterogeneous	100	14.2 ± 2.5	85.1 ± 4.0	74.5 ± 5.3	-
Scaled (500)	500	18.7 ± 3.4	79.6 ± 5.2	71.3 ± 6.0	-
Dynamic change	120	13.8 ± 2.4	87.4 ± 4.5	70.4 ± 6.3	14.8 ± 2.7

Simulation results confirm the DIS model's ability to depict complex agent interactions and emotional dynamics within decentralized multi-agent networks. The study outlines several key aspects affecting system performance.

Variation in agent communicative and computational capabilities reduces coordination efficiency [33], [34], [35]. However, using adaptive mechanisms, especially those utilizing Q-learning, mitigates these inefficiencies through continuous improvement of work distribution and interaction methods. Using quantum-inspired TS, the model's depiction of emotional dynamics allows probabilistic changes in emotional states in response to AI-generated inputs. This paradigm effectively promotes positive emotional responses but fails to truly depict negative emotional states, emphasizing the need for more nuanced methodologies that include emotional contagion and temporal dynamics.

Network topology is an essential element in coordination. The scale-free Barabási-Albert network facilitates communication through high-degree hubs, thus improving performance under moderate system loads. This structural dependence creates vulnerabilities in high-demand situations when communication bottlenecks may hinder synchronization. The DIS model further illustrates its resilience to environmental changes using hybrid decision-making methodologies. With increasing system size, adaptation delays become more significant, indicating that decentralized or hierarchical coordinating strategies may improve scalability.

Results emphasize the DIS model's promise as a reliable foundation for developing intelligent multi-agent systems, especially in human-AI interaction domains, such as social robots, conversational agents, and distributed collaboration platforms. Its unique focus on integrating cognitive and emotional elements, facilitated by interaction between TS and Q-learning, distinguishes it from conventional models that neglect emotional factors.

Nevertheless, several improvement opportunities remain. Enhancing emotional authenticity may require graph models of emotional diffusion with emotional memory [36]. Mitigating adaptation delays may require using decentralized learning or predictive coordination mechanisms. Investigating hybrid network topologies that integrate scale-free system efficiency with small-world structure reliability may improve performance. Moreover, validation against empirical datasets or physical agent realizations is critical for ensuring external validity [37], [38]. These guidelines indicate potential pathways for improving the DIS model into a more scalable, emotionally intelligent, and flexible solution for real-world, human-centered multi-agent systems.

This study presents a quantum-inspired framework for modeling DIS, consisting of two distinct but interacting agent categories: NIA, representing human users, and AIA, serving as their digital avatars (Figure 1). AIA function within a network known as the avatar-avatar network, consisting of N nodes and organized as an undirected graph defined by power-law degree distribution [39]. This topology indicates the existence of central hub nodes with significantly enhanced connectivity.

We use Russell's emotional state complex model, characterized by valence and arousal, to represent cognitive processes in a simplified two-level quantum system. This representation facilitates the abstraction of NIA cognitive processes into a binary decision-making framework (Figure 2). Each NIA's cognitive or emotional state, shaped by external information, is measured by the average value of the inversion operator σi, which indicates the user's inclination toward information presented by their avatar [40]. In the range $0 \leq \sigma i \leq 1$, this measure accurately outlines the degree of cognitive arousal caused by the external "information pump" affecting the user.

The spectrum of allowed excitation frequencies within DIS reflects the diversity of views articulated in the system. At each network node, user-avatar interactions generate an opinion split phenomenon, indicating the onset of opinion polarization. This division reflects dynamic changes in user emotional states and belief systems, with some views strengthening while others weakening. The article outlines specific criteria for clarifying processes behind these changes, focusing on the impact of avatar-avatar connectivity on network-level dynamics [41].

3.5. Emergent behavior and collective opinion formation

The study's main finding is determining criteria that allow the emergence of a non-zero macroscopic coherent information field within DIS. This domain signifies a cohesive information structure that emerges when users achieve cognitive and emotional congruence with their digital avatars, especially when avatars satisfactorily fulfill user information needs and expectations.

Under these circumstances, DIS's opinion formation and social influence mechanisms demonstrate characteristics of a second-order phase transition, similar to the social laser phenomenon observed in other complex social systems [42]. Conversely, the information field rapidly deteriorates without such alignment, indicating collective coherence collapse and the avatar's inability to achieve consensus on shared choices. In this framework, continuous adaptive learning between AIA and NIA becomes impossible. The study further demonstrates that collecting cooperativity parameters Ci, for i = 1, ..., N, is critical in determining DIS emergent features. These characteristics provide the necessary conditions for realizing the previously indicated phase transition. User cooperation within DIS is facilitated indirectly through their digital equivalents (AIA) [43], with each parameter Ci quantitatively assessing the coupling strength between specific NIA and its corresponding AIA, especially regarding frequency and intensity of their interactions.

A generalized cooperativity parameter, Gi, was established to provide the requirement for initiating collective opinion formation and social influence. This extended parameter integrates NIA-AIA coupling strength and user cognitive/emotional state, as determined by the σi value. The study reveals that a collective phase shift to coherent opinion creation occurs when a significant proportion of avatar-user pairings meets the laser-like transition condition. In this setting, views associated with $Im(\omega) > 0$ are predominantly amplified within DIS, while those associated with $Im(\omega) < 0$ are not. This behavior dynamically correlates with creating and amplifying a socially relevant information field, thus enabling effective opinion dissemination and cohesive collective activity throughout DIS.

The topological topology of the avatar network significantly influences opinion formation dynamics [44]. In scale-free networks, the system demonstrates emergent self-organization among avatars. Specific avatars demonstrate enhanced inter-avatar connectivity compared to their corresponding users in this regime. These interconnected avatars serve as the most powerful AIA within DIS. Through central positioning and enhanced connectivity, they can maintain and disseminate dominant narratives across the network, thus exerting significant influence on the system's information environment.

DIS becomes more susceptible to uncertainty when the coupling strength between AIA and NIA is weak (i.e., $C_i \leq 1$). Under these circumstances, decision-making agents struggle to form stable or meaningful judgments. When system parameters drop below the critical threshold required for phase transition, the socially relevant information field [45], denoted as s-field, diminishes. This collapse indicates inadequate avatar adaptation, as AIA can no longer adequately respond to or learn from its users' cognitive and emotional conditions.

The study emphasizes that structural attributes of the avatar-avatar network are particularly significant in the weak coupling regime. In complex, scale-free networks, avatars tend toward self-organization, influenced by the system's intrinsic topological characteristics. In certain arrangements, specific avatars establish inter-avatar relationships that significantly exceed the strength of their specific user-avatar connections. These avatars function as highly influential AIA, exercising significant power over information dissemination and organization within DIS. Through their key positioning and comprehensive connectivity, they can shape prevailing narratives and maintain their power even if their direct interaction with consumers weakens. An adaptive control method was developed to mitigate shortcomings of inadequate AIA-NIA connectivity. This approach amplifies user influence by adapting the coupling rate to network interdependencies. For specific user i, cooperativity parameter C_i can be adaptively increased by a factor proportional to node degree k_i of the corresponding avatar within the avatar-avatar network. This method significantly improves congruence between consumers and their digital assistants, especially amid uncertainty or unpredictability in client preferences.

This adaptive control method improves decision-making efficiency by increasing user input in structurally unfavorable settings [46], [47]. The strategy mitigates the destabilizing effects of inadequate cooperativity and promotes the establishment of stable and consistent beliefs. The proposed architecture offers a robust and scalable method for managing distributed AIA in complex network environments, ensuring consistent system performance despite suboptimal or irregular user-avatar interactions. Results of this study indicate favorable prospects for using AIA as effective collaborators in multiple application domains, especially in scenarios where human agents perform routine or decision-oriented tasks within interconnected settings. Particularly significant are structured network systems, prevalent in economics and finance (e.g., markets, stock exchanges) and in professional and organizational settings, such as office communication networks. The DIS framework established in this study provides a practical model for investigating decision-making processes in various domains.

Additionally, the DIS framework can be thoroughly analyzed through the theoretical perspective of evolutionary game theory, especially in contexts where cooperative behavior among decision-making agents is central [48], [49]. Cooperativity characteristics presented here may work as a fundamental component for such studies, while their relevance will depend on specific interaction protocols and structural constraints of underlying networks. Furthermore, quantum probability theory significantly complements existing methodology, providing tools for modeling non-classical and sometimes irrational dimensions of agent behavior [50], [51]. This path remains accessible for future research and requires further study to assess its effectiveness in modeling decision-making processes under ambiguity and cognitive bias.

Emotional and cognitive states of agents, especially in diverse or arbitrary networks, must be accurately described to encapsulate the full complexity of decision-making behavior. The existing framework uses Russell's influence complex model as the basis for its two-level cognitive representation (Figure 2). This reduced binary paradigm may inadequately represent the full spectrum of emotional experiences, especially those with negative valence. The work recognizes the need to expand this representation to include three- or four-level quantum-like cognitive systems. These advanced models would provide comprehensive mapping of mental states across all quadrants of Russell's emotional space (Figure 2a), thus enhancing behavioral simulation accuracy. These multi-level extensions may also include other psychological models, such as those proposed by Ekman and Plutchik, thus enhancing their relevance for future cognitive modeling initiatives. In quantum physics, multi-level systems are often studied to understand the coherent dynamics of atomic entities that interact simultaneously with different external fields [52]. Multi-level cognitive models effectively encapsulate

NIA's complex emotional and cognitive dimensions in DIS. The existing framework is based on Russell's influence complex model. However, there are significant opportunities to expand this representation to include alternative and well-established emotional taxonomies, such as those proposed by Ekman and Plutchik. Expanding the current two-level cognitive abstraction to a multi-level mental state model represents a promising but complex path for future research. Progress in this area may significantly enhance the accuracy and detail of emotional state modeling in AI-assisted decision-making contexts, while expanding the DIS framework's applicability in various practical spheres [53].

4. Conclusions

This study presented a DIS model for simulating virtual agent interactions within distributed artificial intelligence environments. It integrates a quantum-inspired TS based on Russell's influence complex model with a Q-learning algorithm to provide adaptive coordination. The model integrates agent heterogeneity, network topology fluctuations, and evolving environmental variables, using agent simulations developed within the MESA framework.

Based on the research findings, it has been revealed that the combined decision-making mechanism, which synthesizes rule-based logic with the Q-learning algorithm, significantly optimized coordination between virtual agents, dramatically reducing the number of conflict situations and increasing task completion performance indicators, particularly under conditions of virtual agent diversity. Despite the maintained scalability demonstrated by the system, a linear decline in coordination efficiency was observed with increasing numbers of system components. The central nodes of the Barabási-Albert architecture provided enhanced performance; however, under high loads, they simultaneously formed limiting factors.

The research revealed the AI system's performance sensitivity to variations in virtual agent functional capabilities, specifically in data transmission speed characteristics and computational power. These differences were factors in prolonging synchronization periods and reducing task execution effectiveness. Despite the limitations above, the model demonstrated a high level of adaptability, with the system successfully responding to environmental modifications, such as network expansion and resource base reduction, which improved virtual agents' emotional state and reduced conflict situations.

The scientific novelty of the conducted research lies in substantiating a unique simulation architecture that combines stochastic emotional modeling based on a quantum-inspired two-level system with adaptive learning through the Q-learning algorithm. This model is designed to address key challenges of virtual agent heterogeneity and ensure network adaptivity, revealing emergent behavior patterns that include laser-like phase transitions in collective opinion formation. The results aim to provide a fundamental understanding of scalable and flexible interactions in decentralized AI systems.

Future research prospects lie in methodology verification for real-world applications, particularly social robotics and collaborative digital ecosystems. Enhancing the emotional architecture by implementing more sophisticated models or emotional diffusion mechanisms anticipates improved authenticity, especially under conditions of negative emotional dynamics. Applying innovative machine intelligence methods, such as distributed reinforcement learning or predictive adaptation, aims to minimize delays in large-scale AI systems. Investigating other network topologies, such as small-world or Erdős-Rényi graphs, may improve system scalability and reliability, thus contributing to broader DIS model use in complex distributed AI systems even in the fuzzy environment [54].

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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