A Survey of Multi-Agent Systems in Artificial Intelligence and Software Engineering

Abstract

This survey paper explores the transformative role of multi-agent systems (MAS) in artificial intelligence and software engineering, emphasizing their integration with large language models (LLMs) and natural language processing (NLP) to solve complex problems through distributed computing. MAS facilitate the decomposition of intricate tasks into manageable components, enhancing adaptability across domains such as space exploration, smart grids, and manufacturing. They play a crucial role in optimizing distributed energy resources, reducing emissions, and advancing internal logistics with Autonomous Mobile Robots (AMR). The integration of LLMs within MAS frameworks marks a shift towards collaborative problem-solving, fostering innovation while posing challenges related to technical complexity and implementation costs. The survey identifies key issues in optimizing task allocation, reasoning, and memory management, and highlights the potential of MAS in enhancing decentralized, lifelong-adaptive learning. The paper also discusses the significance of MAS in risk management, privacy protection, and the integration of blockchain technologies. Despite challenges in framework coordination, scalability, and security, MAS continue to drive advancements in AI-driven solutions across various sectors. The survey concludes by advocating for continued research to address these challenges and fully harness the potential of MAS in enhancing complex system interactions and decision-making processes.

1 Introduction

1.1 Significance of Multi-Agent Systems

Multi-agent systems (MAS) are essential in distributed computing and problem-solving, enabling complex task decomposition through coordinated efforts of autonomous agents [1]. This paradigm effectively transforms intricate problems into collaborative endeavors, addressing challenges across diverse domains such as space exploration, smart grids, and machine learning [2, 3].

In manufacturing, MAS play a critical role in managing distributed energy resources, reducing CO2 emissions, and supporting sustainability [4]. Their integration into dynamic environments enhances operational efficiency by adapting to customer demands for diverse, small-batch production [5]. Furthermore, MAS have revolutionized internal logistics via Autonomous Mobile Robots (AMR), surpassing the limitations of traditional Automated Guided Vehicles (AGV) [6].

In exploration tasks, MAS provide innovative solutions under speed and budget constraints, enhancing system performance [2]. Their adaptability in software engineering highlights their importance in solving complex engineering tasks [3]. The integration of Large Language Models (LLMs) within MAS frameworks signifies a shift towards collaborative efforts, fostering innovation despite challenges related to technical complexity and high implementation costs [1, 5].

MAS demonstrate their significance through decentralized, lifelong-adaptive collaborative learning, enhancing cooperation among agents without a central server [7]. However, challenges in optimizing

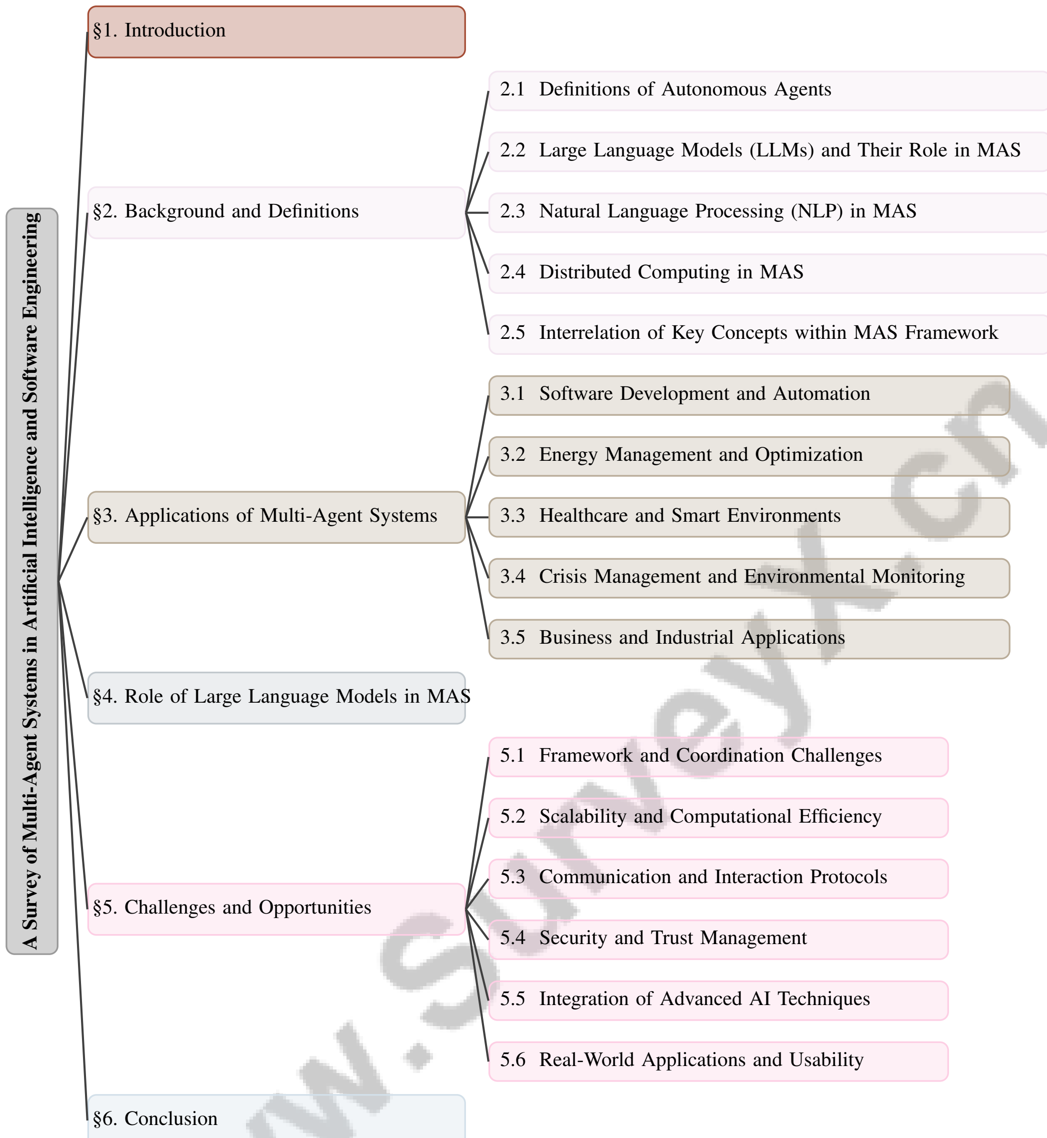

Figure 1: chapter structure

task allocation, reasoning, and memory management persist [6]. Heterogeneous Multi-Robot Systems (HMRS) exemplify MAS's cooperative potential, enabling diverse robots to execute complex missions, albeit often constrained by human-crafted protocols [4].

The reliability of information sharing among MAS is critical, as classical methods often inadequately address measurement uncertainty [5]. Specialization within MAS is vital for efficiency and optimization across fields such as ecology and economics [1]. Moreover, the integration of MAS with blockchain technologies highlights their potential in addressing scientific and technological challenges [3]. MAS also facilitate collaboration in Human-Robot Interaction (HRI), tackling complex challenges [7].

The demand for explainable AI systems underscores the importance of MAS in complex problem-solving scenarios [6]. Pre-configuration of MAS for specific tasks remains challenging, necessitating new approaches to enhance performance predictability and security [1]. The multi-objective nature of real-world problems emphasizes the need for MAS to optimize agents' policies beyond single objectives [2]. MAS also address complex data integration challenges posed by diverse data types on the Internet [5].

MAS are indispensable in distributed computing, offering scalable, efficient, and secure solutions across multiple domains. Their integration with LLMs and other advanced AI techniques continues to drive innovation and address the evolving complexities of modern technological landscapes [4]. The development of partially controlled multi-agent systems (PCMAS) aims to influence uncontrollable agents' behavior through controllable designs, enhancing MAS robustness [3]. The AutoFlow framework exemplifies the automation of workflow generation for LLM-based AI agents, emphasizing MAS's significance in efficiently solving complex tasks [2]. The believable simulation of multi-user behavior is crucial for understanding complex social systems, underscoring MAS's role in societal contexts [6]. The evolution of programming abstractions from procedures to agents highlights MAS's historical significance in software development [1]. As autonomous software entities, MAS manage connected devices within smart cities, enhancing urban living through personalized services [7]. The integration of devices into the Web facilitates a worldwide ecosystem of heterogeneous, loosely coupled entities, easing the creation of hybrid Web of Things (WoT) applications [3]. MAS are pivotal in surgical risk management, addressing complex interactions and scenarios [5]. Finally, the growing privacy protection challenges in MAS applications, particularly in sensitive areas like power systems and intelligent transportation, underscore the need for robust privacy solutions [1]. Ensuring reliable coordination among MAS is crucial, as agent failures can adversely affect overall system performance, necessitating robust coordination mechanisms [4].

1.2 Structure of the Survey

The survey is organized into six comprehensive sections, each addressing critical aspects of multi-agent systems (MAS) in artificial intelligence and software engineering. The initial section introduces the topic, emphasizing the significance of MAS in distributed computing and problem-solving, and highlighting the role of large language models (LLMs) and natural language processing (NLP) in enhancing MAS capabilities [1].

The second section provides essential background and definitions, offering a detailed overview of key concepts such as autonomous agents, LLMs, NLP, and distributed computing, and explaining their interrelations within the MAS framework [3].

The third section explores various applications of MAS across different domains, including software development, energy management, healthcare, crisis management, and business applications, illustrating how MAS leverage LLMs and NLP to tackle complex challenges [2].

The fourth section delves into the role of LLMs within MAS, focusing on their integration for decision-making, communication enhancement, and scalability improvements [5].

Challenges and opportunities in MAS implementation are discussed in the fifth section, identifying issues related to framework coordination, scalability, communication protocols, security, and the integration of advanced AI techniques. This section also explores the usability of MAS in real-world applications [6].

Finally, the conclusion summarizes the key points discussed, reflects on the current state and future prospects of MAS, and underscores the importance of continued research and innovation in this rapidly evolving field [4].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Definitions of Autonomous Agents

Autonomous agents are integral to multi-agent systems (MAS), designed to operate independently while making decisions and executing tasks without human intervention [6]. These agents are equipped with capabilities for planning, reasoning, and learning, enabling them to adapt to dynamic environments and pursue complex objectives [4]. This autonomy is crucial for real-time decision-making, particularly in applications like smart cities, where agents manage interactions among numerous connected devices.

In MAS, autonomous agents not only function independently but also collaborate with other agents to achieve shared goals. This is especially important in domains like supply chain management, where agent collaboration optimizes system performance [8]. Complex interactions are evident in multi-agent human-robot interaction (HRI) systems, where sophisticated exchanges between humans and robots occur.

Systems like HYPERAGENT demonstrate the role of autonomous agents in managing the software engineering lifecycle through specialized roles such as Planner, Navigator, Code Editor, and Executor [8]. This highlights the scalability and versatility of autonomous agents in handling intricate tasks. Achieving explainability in autonomous agents, particularly regarding decision-making processes, underscores the importance of transparency and user trust in MAS [6].

The development of autonomous agents often employs formal methods and languages that enhance understanding and facilitate rigorous analysis, ensuring that transformations and implementations in MAS are property-preserving and error-free. This methodological rigor is essential for ensuring goal reachability in environments where agents and coordinating base stations may encounter failures [4]. Consequently, autonomous agents are foundational to the effectiveness and innovation of MAS, driving advancements across various fields.

2.2 Large Language Models (LLMs) and Their Role in MAS

Large Language Models (LLMs) have become transformative in multi-agent systems (MAS), significantly enhancing capabilities in natural language processing and understanding. By integrating LLMs, MAS can process complex language inputs, facilitating sophisticated communication and decision-making among agents [9]. This integration is crucial in task-oriented communication scenarios, where LLMs enhance agents' abilities to comprehend and respond to nuanced language cues, thereby improving overall system performance [2].

Role-playing frameworks, incorporating inception prompting, exemplify how LLMs can be integrated into MAS to enhance agent interactions and collaborations [9]. Systems like BudgetMLAgent illustrate the practical application of LLMs in automating machine learning tasks within MAS, optimizing operational costs while maintaining efficiency through a combination of no-cost and low-cost LLMs [2].

In software engineering, the HYPERAGENT system demonstrates LLM integration in managing software development tasks. By mimicking human developer workflows, HYPERAGENT utilizes LLMs to enhance planning, navigation, code editing, and execution processes, showcasing the versatility of LLMs in addressing complex software engineering challenges [8]. This underscores the adaptability of LLMs across diverse applications and their potential to improve the efficiency of MAS in dynamic environments.

The ongoing advancement of LLMs is poised to significantly enhance MAS functionality, fostering collaborative frameworks where diverse intelligent agents work together to tackle complex tasks. This evolution promotes innovation by integrating multimodal capabilities and external tools, driving the development of more efficient AI-driven solutions across sectors, including artificial general intelligence and enterprise applications. Addressing challenges such as system scalability, security, and ethical considerations facilitates the democratization of AI technologies, making them more accessible and practical for a wider range of users and industries [10, 11, 12].

2.3 Natural Language Processing (NLP) in MAS

Natural Language Processing (NLP) plays a crucial role in enhancing multi-agent systems (MAS) by enabling sophisticated language understanding and communication among agents. Systems like AIMADDS utilize NLP techniques to analyze conversation context and generate empathetic responses, improving interaction quality and effectiveness [13]. This ability to process and respond to natural language inputs is essential for seamless human-agent and agent-agent interactions within MAS frameworks.

The complexity of intent detection in MAS is highlighted in scenarios where user utterances may invoke multiple agents, necessitating advanced NLP capabilities to accurately parse user intents. The TESS Multi-Intent Parser addresses challenges in multi-agent conversational systems by enhancing intent detection [14]. Accurate interpretation of user intentions enhances the responsiveness and adaptability of MAS, allowing for more precise and contextually relevant interactions.

NLP is also instrumental in organizing and evaluating ideas generated during creative processes within MAS. For instance, using natural language to document ideas in creativity workshops illustrates how NLP facilitates the organization and assessment of creative outputs, augmenting decision-making and problem-solving capabilities [15]. This highlights the importance of NLP in managing and processing large volumes of unstructured language data within MAS.

The inherent ambiguity of natural language poses challenges for MAS, complicating the development of formal theories in linguistics, philosophy, cognitive psychology, and artificial intelligence [16]. Addressing these ambiguities requires advanced NLP models capable of disambiguating and interpreting complex language constructs, thereby improving the robustness and reliability of MAS.

NLP significantly enhances the evolution of MAS by equipping agents with advanced linguistic capabilities that facilitate seamless communication, interaction, and collaboration. This integration allows for the development of sophisticated applications, such as multimodal systems that simplify AI adoption through no-code platforms, enhancing the efficiency of complex tasks across various domains, including healthcare and organizational decision-making. By enabling intelligent agents to engage in collaborative problem-solving and knowledge exchange, NLP improves the operational effectiveness and adaptability of MAS across diverse industries [10, 11, 17, 18]. Its integration into MAS frameworks not only enhances the system's ability to process and understand human language but also drives innovation in creating more intelligent and responsive multi-agent environments.

2.4 Distributed Computing in MAS

Distributed computing is fundamental to the architecture of multi-agent systems (MAS), enabling the decomposition and execution of complex tasks across a network of interconnected agents. This paradigm is vital for achieving scalability, efficiency, and resilience in environments where centralized control is impractical [19]. The integration of distributed computing into MAS allows autonomous agents to coordinate effectively, optimizing resource allocation and task scheduling in massively distributed settings [20].

A key challenge in distributed computing within MAS is ensuring efficient communication and coordination among agents, particularly when communication resources are limited. Advanced frameworks like the Distributed Set Membership Filtering (DSMF) enable agents to estimate their states using both absolute and relative measurements from neighboring agents, enhancing the overall system's robustness and accuracy [21]. The CATLNet framework further emphasizes the need for effective communication protocols to ensure that agents meet complex specifications, underscoring the critical role of distributed computing in facilitating coordination [22].

Decentralized evolutionary algorithms exemplify the relevance of distributed computing in MAS, allowing fully autonomous and asynchronous agents to evolve independently, thus enhancing system adaptability and scalability [23]. Frameworks designed for intelligent multi-agent systems, particularly those addressing large-scale machine learning applications, further illustrate the importance of distributed computing in optimizing data processing and analysis.

In real-time applications, distributed computing mitigates the limitations of traditional centralized methods, which often struggle with scalability and speed [24]. By distributing workloads across multiple agents, MAS achieves higher processing speeds and greater scalability, crucial for applications requiring rapid data processing and decision-making.

Distributed computing is essential for ensuring that local and global specifications are satisfied simultaneously. For instance, designing controllers that enforce local Linear Temporal Logic (LTL) specifications while meeting global safety requirements for the entire system benefits from the distributed nature of MAS [25].

2.5 Interrelation of Key Concepts within MAS Framework

The intricate interrelation of key concepts—agents, roles, actions, and norms—within the multi-agent systems (MAS) framework is vital for enhancing system capabilities and adaptability across diverse application domains, including healthcare, robotics, and smart cities. This interconnectedness fosters the development of intelligent distributed systems that can effectively manage complex tasks and promote collaboration while addressing accountability and trust through emerging technologies like blockchain [26, 27, 28]. Autonomous agents, distributed computing, Large Language Models

(LLMs), and Natural Language Processing (NLP) collectively contribute to the overall functionality and efficiency of MAS, facilitating complex problem-solving and decision-making processes.

Autonomous agents form the foundation of MAS, operating independently while collaborating to achieve shared objectives. Their ability to adapt to dynamic environments enhances overall system performance at each time-step [3]. Collaboration is exemplified in systems that enhance tool planning capabilities through specialized agents, improving LLM performance and adaptability [29]. The synergy among agents is further enhanced by role-playing frameworks that promote effective interactions and collaborations, emphasizing the importance of autonomous cooperation in MAS [9].

Distributed computing is integral to MAS, providing the infrastructure for decentralized control and efficient resource allocation. Proposed approaches synthesize distributed symbolic controllers utilizing control barrier functions (CBFs) to ensure that both local and global specifications are met without excessive computational overhead [25]. This decentralized approach is crucial for managing the complexities of interconnected agents and ensuring robust system operation across diverse environments. Key innovations include modeling the coupled behavior of agents and objects as a finite transition system, enabling the design of high-level plans that satisfy Linear Temporal Logic (LTL) specifications [4].

LLMs enhance the communication and decision-making capabilities of MAS, allowing dynamic adaptation to changing environments and user needs. Their integration fosters sophisticated task-oriented communication, improving the system's ability to process and respond to nuanced language cues [9]. Multi-agent frameworks incorporating various LLMs enhance performance through collaborative task-solving, leveraging the strengths of different models [2]. This capability is essential for extending MAS applications into domains requiring advanced language understanding and interaction.

NLP further augments MAS by equipping agents with tools for processing and understanding natural language inputs. This capability enhances seamless communication among agents and between agents and humans, improving interaction quality and effectiveness [5]. The integration of NLP into MAS frameworks supports the development of intelligent systems capable of engaging in real-time adaptive interactions, enhancing decision-making and problem-solving processes. The survey categorizes existing research into phases of explanation generation, communication, and reception, highlighting the interrelation of these phases within the explainability framework [6].

The integration of these key concepts also addresses challenges related to system reliability and fault tolerance. Effective communication is crucial for maintaining a shared mental model and achieving optimal performance in dynamic environments [30]. The necessity for a new approach that accommodates the simultaneous promotion and alignment of multiple values, particularly in heterogeneous agent environments, illustrates the importance of balancing individual autonomy with collective rationality [31].

The integration of autonomous agents, distributed computing, LLMs, and NLP within the MAS framework significantly enhances adaptability, scalability, and efficiency by enabling collaborative task handling, dynamic specialization, and seamless interaction with external tools. This advancement propels the capabilities of artificial intelligence in complex, real-world applications [10, 32, 11, 12]. This integration equips MAS to tackle complex challenges across various domains, driving advancements in AI-driven solutions and fostering innovation in multi-agent technologies.

3 Applications of Multi-Agent Systems

The transformative potential of multi-agent systems (MAS) spans numerous sectors, significantly impacting software development, automation, energy management, healthcare, crisis management, and industrial applications. As organizations face complex computational challenges, MAS offer innovative solutions that enhance efficiency, adaptability, and collaboration. Figure 2 illustrates the diverse applications of MAS across these domains, highlighting key areas such as Software Development and Automation, Energy Management, Healthcare, Crisis Management, and Business Applications. This figure showcases the transformative potential of MAS in enhancing efficiency, adaptability, and innovation. This section explores MAS applications across these domains, emphasizing their role in task management, resource optimization, and advancing practices.

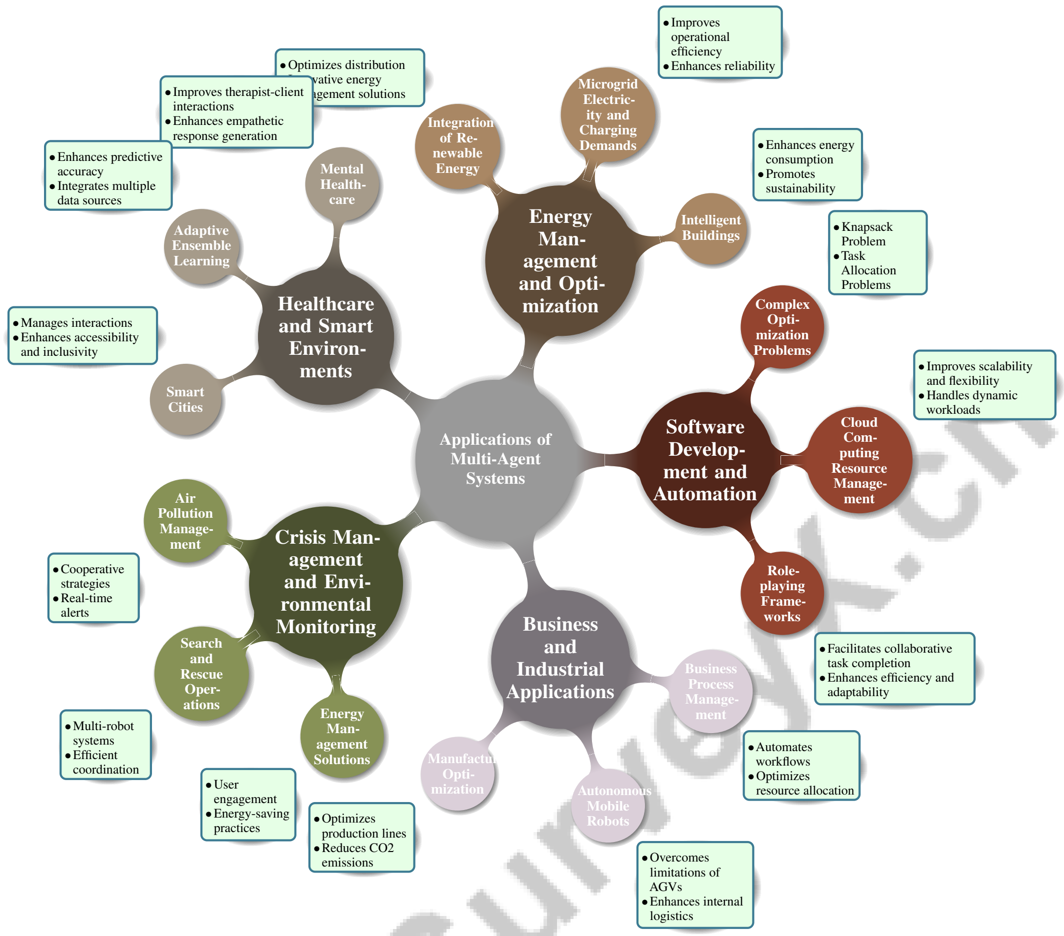

Figure 2: This figure illustrates the diverse applications of Multi-Agent Systems (MAS) across various domains. It highlights key areas such as Software Development and Automation, Energy Management, Healthcare, Crisis Management, and Business Applications, showcasing the transformative potential of MAS in enhancing efficiency, adaptability, and innovation.

3.1 Software Development and Automation

In software development and automation, MAS revolutionize complex task management, boosting efficiency and adaptability. As illustrated in Figure 3, which depicts the hierarchical classification of key concepts in this domain, the focus on MAS's role in task management, tools and frameworks, and advanced applications highlights their significance in streamlining development processes. Role-playing frameworks facilitate collaborative task completion via multi-turn agent conversations, streamlining development processes [9]. MAS improve cloud computing resource management by enhancing scalability and flexibility, essential for handling dynamic workloads [33]. They address complex optimization problems, such as the Knapsack and Task Allocation Problems, demonstrating efficacy in structured interactions and decision-making [34]. Employing multiple LLM agents with distinct roles further showcases MAS versatility in machine learning tasks [2].

Tools like the Goal Net Designer simplify the creation of complex agent behaviors [35], while HYPERAGENT enhances efficiency across programming languages [8]. EthicalEvalMAS monitors dialogue agents' behavior in customer service, maintaining ethical standards [5]. Continuous control integration with high-level task specifications enables realistic multi-agent interactions, crucial for applications like motion planning [4]. Recent advancements include a multimodal MAS powered by LLMs within a No-Code platform, lowering AI adoption barriers and enhancing productivity [10, 36], affirming MAS's indispensable role in streamlining critical software development tasks.

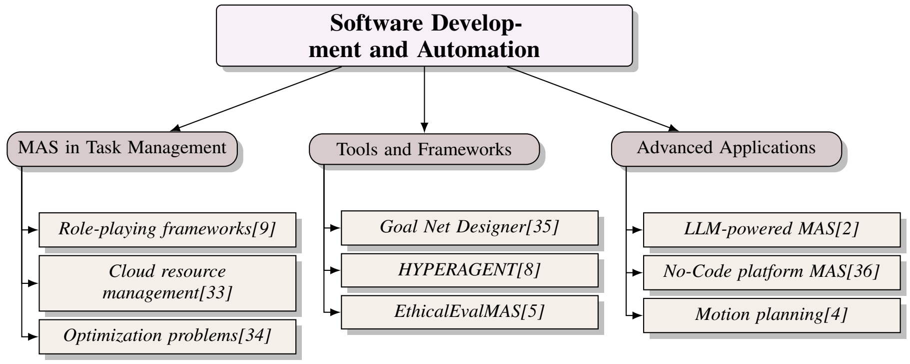

Figure 3: This figure illustrates the hierarchical classification of key concepts in software development and automation, focusing on MAS's role in task management, tools and frameworks, and advanced applications.

3.2 Energy Management and Optimization

MAS applications in energy management optimize modern power system complexities. They enhance energy consumption in intelligent buildings, crucial for sustainability in urban settings [37]. MAS optimize microgrid electricity and charging demands, particularly for PHEVs, improving operational efficiency and reliability through decentralized decision-making [38, 39]. The JAM framework exemplifies MAS versatility in integrating renewable energy sources and optimizing distribution [40], while in Bangladesh, MAS technology offers innovative solutions to energy management challenges [41]. Multi-agent learning frameworks enhance resilience against traditional ICS security measures, dynamically adapting to energy demands and supply conditions [42]. MAS integration in energy management represents a transformative leap toward sustainable systems, aligning with modern power system needs, particularly in decentralized contexts [37, 41].

3.3 Healthcare and Smart Environments

MAS integration in healthcare and smart environments enhances service delivery and operational efficiency. The AIMADDS system exemplifies MAS application in mental healthcare, improving therapist-client interactions through context analysis and empathetic response generation [13]. Adaptive Ensemble Learning (AEL) in healthcare settings demonstrates MAS's ability to enhance predictive accuracy by integrating multiple data sources [43]. MAS streamline the Prior Authorization process, enhancing trust and transparency in healthcare operations [17]. In smart environments, MAS manage interactions within smart cities, assisting individuals with reduced mobility, thereby enhancing accessibility and inclusivity [44]. Future research should explore MAS applications in various domains to harness their potential in improving service delivery and operational efficiency [11]. MAS's continuous evolution promises innovation in intelligent systems addressing complex challenges across critical sectors.

3.4 Crisis Management and Environmental Monitoring

MAS play a pivotal role in crisis management and environmental monitoring, enabling coordinated responses to complex challenges. Their application in managing air pollution crises employs cooperative strategies to manage emission sources and enhance air quality [45]. The O3RTAA system automates air quality monitoring, providing real-time alerts that improve response strategies. In crisis management, MAS enhance search and rescue operations through multi-robot systems, enabling efficient coordination and resource allocation [46]. The collaborative decision-making approach emphasizes stakeholder coordination, crucial for effectively addressing crises [47].

MAS-based solutions extend to energy management, surpassing traditional methods in user engagement and energy-saving practices [37]. Future research should focus on developing languages like ANA-ML for disaster management, showcasing MAS capabilities [27]. Experiments in simulated environments highlight MAS's potential in integrating real-world data for enhanced decision-making [48]. Governance of adaptive normative MAS, as evaluated in intelligent intersections in Brazil, underscores the importance of regulating normative behaviors for effective traffic management during crises [49]. Modifying communication protocols, like the Contract Net Protocol (CNP), enhances MAS performance in dynamic environments [50].

MAS provide a comprehensive framework for tackling complex challenges in crisis management and environmental monitoring by facilitating enhanced coordination, adaptability, and innovative solutions tailored to diverse operational contexts. This collaborative decision-making approach, particularly in unpredictable environments, leverages advanced technologies like blockchain to ensure accountability and trust in data management, ultimately improving outcomes across multiple sectors [27, 41, 47, 28, 51].

3.5 Business and Industrial Applications

In business and industrial contexts, MAS enhance operational efficiency and decision-making. In manufacturing, MAS optimize production lines and manage distributed energy resources, reducing CO_2 emissions and promoting sustainability [4]. They enable real-time adaptation to fluctuating customer demands, facilitating diverse production while improving efficiency [5]. MAS revolutionize internal logistics through Autonomous Mobile Robots (AMR), overcoming limitations of traditional Automated Guided Vehicles (AGV) [6]. In business process management, MAS automate workflows and optimize resource allocation, exemplified by the AutoFlow framework, which automates workflow generation for LLM-based AI agents [2]. This capability is particularly beneficial in rapidly changing business environments.

Integrating MAS with blockchain technologies addresses scientific and technological challenges, providing secure data exchange and enhancing stakeholder trust [3]. MAS play a crucial role in risk management within industrial operations, particularly in power systems and intelligent transportation, emphasizing the need for robust privacy solutions to safeguard sensitive information [1]. Reliable MAS coordination is essential, as agent failures can negatively impact overall performance, necessitating robust coordination mechanisms [4].

MAS applications in business and industrial contexts continue to drive advancements in operational efficiency, resource management, and innovation. Their adaptability and seamless integration with emerging technologies, such as blockchain and large language models, establish MAS as foundational elements in transforming modern practices, enabling intelligent data management, enhanced accountability, and improved accessibility to AI-driven solutions across various sectors [10, 52, 28, 51].

4 Role of Large Language Models in MAS

4.1 LLMs in Decision-Making Processes

Large Language Models (LLMs) significantly enhance decision-making in multi-agent systems (MAS) by improving language comprehension and processing. These models enable agents to analyze complex data, interpret nuanced contexts, and respond autonomously, thereby refining decision-making workflows. For instance, the Planning Agent decomposes intricate requests into sub-tasks while the Answer Agent synthesizes cohesive responses, streamlining processes [29]. Within role-playing frameworks, LLMs facilitate autonomous agent cooperation, reducing human intervention and enabling real-time collaboration in dynamic environments [9].

As illustrated in Figure 4, the role of LLMs in enhancing decision-making processes within MAS is multifaceted, highlighting key agent roles, optimization frameworks, and real-time decision-making strategies. LLMs elucidate optimization trade-offs, as seen in the CMAOE framework, empowering agents with a nuanced understanding of decisions [34]. Multi-objective evolutionary algorithms further align agent actions with diverse objectives, enhancing decision-making efficacy [31]. The HYPERAGENT system exemplifies LLMs' ability to replicate human-like workflows, optimizing software engineering tasks [8]. Moreover, frameworks optimizing communication based on the Age of Information (AoI) metric demonstrate LLMs' role in ensuring real-time decision-making [53].

The EMAI approach highlights the importance of evaluating individual agent contributions to optimize interactions and system rewards [3]. LLM integration in MAS fosters sophisticated, adaptable decision-making frameworks where agents collaborate on complex tasks, enhancing task decomposition and specialization. This integration addresses scalability, security, and ethical challenges, driving innovation in fields like healthcare automation and model training [12, 10, 11, 54, 17]. LLMs enhance communication, coordination, and decision-making, advancing AI-driven solutions across various domains.

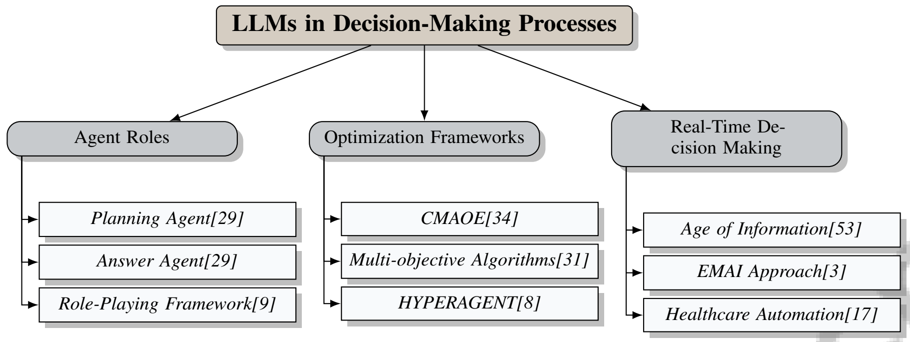

Figure 4: This figure illustrates the role of Large Language Models (LLMs) in enhancing decision-making processes within multi-agent systems, highlighting key agent roles, optimization frameworks, and real-time decision-making strategies.

4.2 Enhancing Communication and Coordination

LLMs are crucial in enhancing communication and coordination in MAS. Their language comprehension capabilities enable sophisticated, context-aware interactions, improving system coherence. LLMs facilitate novel communication protocols, allowing selective communication based on beliefs and team needs, as seen in epistemic planning [30]. In multi-agent reinforcement learning (MARL), LLMs enhance communication, promoting effective collaboration in dynamic environments [55]. The small-world model optimizes information exchange pathways, reducing overhead and enhancing responsiveness [56].

The Decentralized Dominant Value Voting method leverages social structures within agent groups for coherent knowledge integration and decision-making [48]. This approach emphasizes collective behavior and self-organization, showcasing LLMs' potential to enhance consensus formation [57]. Interaction protocols in MAS support flexible business process integration, enabling agents to adapt to changing conditions [58]. LLM integration represents a significant advancement in communication and coordination, driving system performance improvements and fostering innovation.

4.3 Scalability and Efficiency Improvements

Integrating LLMs into MAS enhances scalability and efficiency by optimizing communication, coordination, and task execution. Self-adaptive MAS monitor and analyze system states for proactive resource management, aligning with Quality of Service (QoS) expectations [33]. LLMs handle complex specifications in a decentralized manner, enhancing efficiency and scalability. Cooperative planning frameworks automate controller synthesis, reducing centralization and enabling efficient operations [59]. Optimizing synthesis by addressing local specifications before safety constraints reduces conservatism and enhances scalability [25].

The EMAI framework captures dependencies between agents and across time, optimizing task and resource allocation [3]. This understanding is vital for effective decision-making and system scalability. LLM integration into MAS frameworks enhances scalability and efficiency by optimizing communication, coordination, and resource allocation. Intelligent agents independently perceive, control, and interact with their environment, enabling dynamic task decomposition and specialization. This integration addresses scalability, security, and ethical challenges, fostering applications across domains like 6G communications and enterprise AI adoption [32, 12, 10, 60, 11]. These advancements empower MAS to address complex challenges across diverse fields.

AI-generated, for reference only.

Category	Feature	Method
Framework and Coordination Challenges	Autonomy and Norms	EEMAS[5], HCF[4]
Scalability and Computational Efficiency	Agent-Based Scalability	ACS-MAS[59]
Communication and Interaction Protocols	Adaptive Strategies	AAEAI[58]
Security and Trust Management	Trust Management	AIMADDS[13], PSO-Trust[61], MACF[11], FGMT[62], MAS-APS[63], MAS-SCM[64]
Integration of Advanced AI Techniques	Collaborative Systems	NOVA[31], HA[8], BMA[2], CBF-DSC[25]
Real-World Applications and Usability	Dynamic System Adaptation	ARA[65]
	Collaborative Interaction	CCIDEAS[15], MAS-DP[66], CDMA[47], SCM[30]
	Immediate Data Tracking	DADA[67], O3RTAA[45]

Table 1: This table presents a comprehensive summary of various methods addressing key challenges in multi-agent systems (MAS), categorized into six domains: framework and coordination, scalability and computational efficiency, communication and interaction protocols, security and trust management, integration of advanced AI techniques, and real-world applications and usability. Each category includes specific features and the corresponding methods employed to tackle these challenges, as referenced in the literature. The table serves as an overview of the current state-of-the-art solutions and their applicability in enhancing MAS performance across diverse scenarios.

5 Challenges and Opportunities

The exploration of challenges and opportunities in multi-agent systems (MAS) reveals a complex interplay of theoretical and practical considerations essential for enhancing system performance and applicability. Table 1 provides a detailed overview of the methods employed to address the multifaceted challenges in multi-agent systems, highlighting the diverse approaches across various categories such as framework coordination, scalability, and security. Additionally, Table 4 offers a comprehensive comparison of methods addressing critical challenges in multi-agent systems, illustrating their application across framework coordination, scalability, and communication protocols. Addressing these challenges, particularly those related to framework and coordination, is crucial for the successful deployment of MAS across various domains.

5.1 Framework and Coordination Challenges

MAS development and coordination face significant challenges that impede integration and functionality. A primary concern is representing norms that regulate agent behavior while preserving autonomy, crucial for ensuring agents operate within defined parameters without compromising independent decision-making [7]. This issue is pronounced in ethical decision-making contexts, such as chatbots, where existing methods often fail to provide context-sensitive evaluations, highlighting the need for robust frameworks [5].

Coordinating agent movements and object transportation under continuous dynamics and collision avoidance constraints presents another challenge, necessitating sophisticated planning strategies [4]. Additionally, the lack of frameworks for explaining agent behaviors in complex scenarios underscores the need for tailored explanations to foster transparency and trust in MAS [6].

The heterogeneity of agents and incompatibility of values when aligning with norms pose critical challenges. Existing methods often inadequately accommodate diverse agent types and value systems, leading to conflicts and inefficiencies [31]. In software engineering, task-specific agent design limits real-world applicability, indicating a need for more versatile frameworks [8].

In crisis management, the absence of a structured process that adapts to evolving crises and facilitates stakeholder communication is a significant barrier, emphasizing the need for MAS frameworks that dynamically adjust and support effective engagement [47]. Furthermore, treating communication as separate from planning often leads to inefficiencies, underscoring the importance of integrating communication within the planning framework [30].

Addressing framework integration and coordination challenges is crucial for enhancing MAS capabilities and enabling efficient operation in dynamic environments. Leveraging advanced technologies, such as No-Code platforms and intelligent LLMs, can facilitate user-friendly development and management of AI systems, lowering adoption barriers. Implementing MAS can streamline complex data integration processes and adapt to evolving demands in sectors like power and energy, particularly in rapidly changing regions. Overcoming these challenges can harness MAS's full potential, leading to improved productivity and responsiveness across diverse applications [10, 11, 41, 51].

5.2 Scalability and Computational Efficiency

Scalability and computational efficiency are critical challenges in deploying MAS across diverse domains. As MAS are applied to complex environments, computational demands escalate, often resulting in performance bottlenecks [59]. The coupling between agents complicates the satisfaction of individual high-level tasks under timed constraints, presenting a significant scalability challenge [59].

Existing controller synthesis methods struggle with the computational complexity and scalability required for large-scale MAS, often facing difficulties in processing vast datasets essential for real-time validation and alarm triggering [25]. These inefficiencies limit scalability and computational efficiency in various scenarios.

Simulating larger societies or intricate interactions often exceeds current frameworks' capabilities, exacerbating computational bottlenecks. Addressing these challenges is crucial for advancing MAS capabilities in dynamic environments. Future research should prioritize scalable frameworks that adapt to the dynamic requirements of various industries, leveraging No-Code platforms to lower barriers to AI adoption. Recent studies highlight MAS applications in complex data integration, requirements engineering, and multimodal AI implementations, emphasizing the need for frameworks that evolve alongside technological advancements [68, 10, 36, 11, 51].

5.3 Communication and Interaction Protocols

Effective communication and interaction protocols within MAS are essential for seamless information exchange among agents. Establishing robust protocols that accommodate the dynamic and heterogeneous nature of MAS environments is a fundamental challenge [30]. The complexity of interactions, particularly with multiple agents possessing diverse capabilities and objectives, necessitates advanced communication frameworks that adapt to varying conditions.

Integrating communication as a natural action within the planning framework, rather than as a separate process, is crucial for enhancing coordination and decision-making capabilities [30]. Additionally, developing interaction protocols that support flexible and autonomous business process integration is vital for enabling agents to adapt to changing requirements [58].

The heterogeneity of agents and their diverse communication needs complicate the design of interaction protocols. Existing methods often struggle to accommodate varied communication requirements, leading to inefficiencies and breakdowns in operations. The absence of standardized protocols to address these communication needs poses a significant obstacle to operational efficiency in MAS, as recent research advocates for synthesizing interaction protocols and agent-based architectures to enhance integration and complex data management [10, 58, 51].

Scalability of communication protocols is critical, especially in large-scale MAS applications. The demand to process extensive information and synchronize multiple agents imposes substantial requirements on communication infrastructure, leading to potential bottlenecks. This challenge is particularly evident in complex environments such as 6G communications and distributed computing systems, where integrating advanced technologies like LLMs with MAS is crucial for enhancing efficiency. Multi-agent systems can optimize resource allocation and load balancing, while LLMs facilitate natural language processing tasks, improving communication among agents. However, overcoming data privacy concerns and logical reasoning limitations is essential to fully realize their potential [60, 19, 68, 36]. Developing efficient communication protocols that handle high data volumes and support real-time interactions is necessary to address these scalability challenges.

5.4 Security and Trust Management

Security and trust management are critical in deploying MAS, especially as these systems integrate into sensitive environments. Maintaining user trust and confidentiality is paramount, particularly in applications like AI-assisted therapy, where personal data security is crucial [13]. The complexity of managing interactions among numerous agents introduces potential security risks, necessitating robust evaluation mechanisms to ensure system integrity and trustworthiness [11].

Method Name	Security Challenges	Trust Management	Technological Integration
AIMADDS[13]	Privacy Concerns	User Trust	Multiple AI Agents
MACF[11]	Security Risks	Reliable Interactions	Blockchain Incorporation
PSO-Trust[61]	Security Risks	Trust Evaluations	Particle Swarm Optimization
FGMT[62]	Proximity Safety	Decentralized Evaluation	Blockchain
MAS-APS[63]	-	-	-
MAS-SCM[64]	Trust Challenges	Reliable Information Sharing	-

Table 2: Comparative analysis of various Multi-Agent Systems (MAS) methods highlighting their security challenges, trust management strategies, and technological integration features. The table provides insights into how different approaches address privacy concerns, security risks, and the incorporation of advanced technologies like blockchain and AI agents.

The PSO-Trust model illustrates an advanced approach to trust management in MAS, leveraging co-operative knowledge sharing to enhance trust evaluations beyond traditional methods [61]. Similarly, the factor graph model provides a unified framework for modeling interdependent behaviors and trust, leading to more reliable decision-making in collaborative environments [62].

Despite advancements, achieving consensus in decentralized networks remains a challenge, particularly when integrating blockchain technology (BCT) into MAS. While BCT offers potential solutions for enhancing security and trust, it introduces new issues requiring effective management [28]. The ideal communication between agents, often assumed in MAS, may not reflect real-world interaction complexities, highlighting the need for more realistic trust models [63].

In supply chains, ensuring trust and reliable information sharing among autonomous entities is particularly challenging due to the complexity of managing multiple negotiation processes [64]. These challenges underscore the importance of developing sophisticated trust management frameworks that adapt to the dynamic nature of MAS environments. Table 2 presents a comprehensive comparison of several methods used in Multi-Agent Systems (MAS) to address security and trust management issues, illustrating the diverse strategies and technological integrations employed across different approaches.

Addressing security and trust management issues is vital for the successful deployment of MAS across various domains. Enhancing trust evaluation methods through subjective logic mechanisms and integrating robust security measures, such as misbehavior detection and isolation of faulty agents, can significantly improve shared information reliability. This fosters greater user confidence and facilitates MAS adoption in critical applications like Intelligent Transportation Systems and healthcare automation. Incorporating blockchain technologies can ensure data management accountability, promoting innovation and wider MAS acceptance across industries [17, 10, 28, 69].

5.5 Integration of Advanced AI Techniques

Integrating advanced AI techniques into MAS presents significant opportunities for enhancing capabilities across various domains. Future research should focus on balancing conservatism and flexibility in controller design, optimizing larger systems, and enhancing MAS adaptability in dynamic environments [25]. Developing multi-modal communication strategies is crucial for improving explainability and addressing user-specific explanation needs, fostering transparency and trust in MAS operations [6].

Exploring agent collaboration and task-specific performance enhancements is vital for integrating advanced AI techniques in MAS, enabling systems to adapt more effectively to complex challenges [2]. Additionally, integrating an automatic reasoner for solution recommendations and developing online mechanisms for multi-value alignment can significantly enhance decision-making processes within MAS [31].

Enhancing the integration of systems like HYPERAGENT with development environments, refining knowledge bases, and applying them in specialized domains such as security-focused code reviews are promising research areas [8]. The proposed collaborative decision-making approach utilizing ontologies and MAS can significantly improve real-time decision-making in crisis situations, emphasizing the importance of integrating advanced AI techniques to enhance responsiveness and coordination [47].

AI-generated, for reference only.

Furthermore, leveraging frameworks like EMAI for developing more effective attack and patch methods and interpreting policies in complex multi-agent scenarios is essential for advancing MAS robustness and reliability [3]. The integration of advanced AI techniques into MAS promises to drive innovation and improvement, enabling these systems to tackle complex problems across various domains and adapt to evolving challenges.

5.6 Real-World Applications and Usability

Method Name	Adaptability	Collaborative Capabilities	Diverse Applications
ARA[65]	Adaptive Feedback Loop	Iterative Interactions	Clinical Environments
CCIDEAS[15]	Adaptive Features	Enhanced Collaboration	Creativity Workshops
O3RTAA[45]	Data-driven Decision	Intelligent Agents Collaboration	Environmental Monitoring Systems
MAS-DP[66]	Refine The Process	Collaboratively Tackle Challenges	Data Mining Process
DADA[67]	Dynamic Learning Capability	-	Various Domains
CDMA[47]	Dynamic Situations	Real-time Collaboration	Crisis Management
SCM[30]	Dynamic Environments	Enhanced Collaboration	Simulated Tasks

Table 3: This table presents a comparative analysis of various Multi-Agent Systems (MAS) based on their adaptability, collaborative capabilities, and diverse applications. The methods listed, including ARA, CCIDEAS, O3RTAA, MAS-DP, DADA, CDMA, and SCM, highlight the versatility and practical benefits of MAS across different domains such as clinical environments, creativity workshops, and environmental monitoring systems. Each method demonstrates unique strengths in adapting to dynamic situations and enhancing collaborative efforts, underscoring the significance of MAS in optimizing complex processes.

Table 3 provides a detailed overview of different Multi-Agent System (MAS) methods, emphasizing their adaptability, collaborative capabilities, and applications across various real-world domains. The real-world applications and usability of MAS are increasingly evident across diverse domains, where their adaptability and collaborative capabilities drive significant advancements. In clinical decision-making, LLMs integrated within MAS frameworks demonstrate the potential to adaptively learn and improve over time, enhancing the accuracy and reliability of medical diagnoses and treatment recommendations [65]. This adaptability is crucial in dynamic healthcare environments, where timely and precise decision-making is paramount.

MAS play a pivotal role in managing creative processes, particularly in environments requiring idea organization and evaluation, such as creativity workshops. Integrating ontology within MAS facilitates enhanced collaboration and idea management, positively impacting overall creative output [15]. This application underscores the importance of MAS in fostering innovation and improving collaborative efforts in creative industries.

In environmental monitoring, the O3RTAA system exemplifies MAS application in real-time air quality assessment, providing valuable insights for environmental management [45]. Future research aims to expand this system's architecture to encompass a broader network of meteorological stations, enhancing usability and impact in real-world scenarios.

The adaptability of MAS is further demonstrated in data mining processes, where hybrid systems effectively address challenges such as missing data during preprocessing stages, significantly improving data accuracy and overall quality [66]. Such advancements highlight the critical role of MAS in optimizing data-driven applications and ensuring robust data management.

Moreover, the DADA framework showcases MAS adaptability to data changes, improving anomaly detection accuracy and suitability for real-time applications [67]. This adaptability is essential for applications requiring rapid responses to evolving data patterns, such as financial market analysis and network security.

Future research should focus on enhancing algorithm robustness and exploring applicability in more complex digital ecosystems [70]. Additionally, integrating more stakeholders into MAS frameworks, particularly in crisis management, can improve adaptability and broaden application scopes [47]. Evaluating MAS models against additional benchmarks and exploring the impact of different mental model components on team performance are promising areas for further investigation [30].

The real-world applications and usability of MAS are rapidly expanding, driven by their inherent capabilities to adapt, collaborate, and optimize complex processes across diverse fields such as software development and artificial general intelligence. Recent studies demonstrate the effectiveness of employing MAS in automating requirements elicitation and analysis, where intelligent agents utilize advanced LLMs to generate, assess, and prioritize user stories from initial requirements. Innovative frameworks that integrate multiple intelligent agents have shown promise in enhancing task efficiency and addressing challenges like security risks and scalability, showcasing the versatility and practical benefits of MAS across various domains [11, 36]. These systems hold the potential to revolutionize industries by enhancing decision-making, improving data management, and fostering innovation.

Feature	Framework and Coordination Challenges	Scalability and Computational Efficiency	Communication and Interaction Protocols
Challenge Addressed	Agent Autonomy	Performance Bottlenecks	Information Exchange
Key Feature	Norm Representation	Scalable Frameworks	Robust Protocols
Applications	Crisis Management	Data Integration	Distributed Systems

Table 4: This table provides a comparative analysis of various methods used to address key challenges in multi-agent systems (MAS), focusing on framework coordination, scalability, and communication protocols. It highlights the specific challenges addressed, key features, and applications of each method, offering insights into their practical implications and effectiveness in diverse domains.

6 Conclusion

The survey elucidates the transformative impact of multi-agent systems (MAS) across various sectors, emphasizing their evolving capabilities and future potential. The integration of Large Language Models (LLMs) within MAS has notably enhanced their planning and reasoning functions, as demonstrated by frameworks like Smurfs, which proficiently handle intricate tasks. The Goal Net Designer exemplifies advancements in agent development, improving accessibility and bridging the gap between design and implementation, suggesting its potential for widespread application.

In real-time monitoring and control contexts, the proposed co-design framework significantly boosts performance, achieving improvements of 18-82

Despite these advancements, challenges remain, particularly in inter-agent explainability and the need for context-aware communication. The BudgetMLAgent experiments showcase notable improvements in machine learning task success rates and cost efficiency compared to single-agent systems. Additionally, the EMAI framework offers deeper insights into agent importance, enhancing our comprehension of individual contributions within MAS.

The survey advocates for ongoing research to address existing challenges and fully exploit MAS's potential in enhancing complex system interactions and decision-making. The diverse applications and continuous evolution of MAS frameworks highlight the necessity for innovation and expansion in MAS research and development.

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