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# BRIEF SURVEY ON COLLABORATIVE AND NON-COLLABORATIVE BEHAVIORS IN MULTI-AGENT SYSTEMS

BY

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**Abstract.** Multi-Agent Systems (MAS) are extensively studied and defined differently in literature. A MAS can be described as an environment with multiple agents that interact with each other or the environment, following predetermined rules to achieve individual or shared goals. This work represents a survey focused on collaborative and non-collaborative behaviors within MAS. The survey presents the key characteristics, benefits and drawbacks of each behavior type and provides a structured review of the literature, emphasizing on the applications of these behaviors in different domains. Understanding these behaviors in MAS can have benefits in both academic research and day-to-day life. This understanding may help researchers and practitioners to design and implement MAS and to provide guidance for different behaviors that may be suitable based on specific scenarios.

**Keywords:** Multi-Agent Systems (MAS), Autonomous agents, Collaboration, Non-collaboration, Coordination.

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## 1. Introduction

The concept of Multi-Agent System (MAS) is widely used, with multiple definitions in the literature. A MAS can be defined as an environment that contains multiple individual agents that interact with each other or with the environment, based on a set of predefined rules, in order to achieve a **common** or an **individual** goal (Ferber, 1999; Dorri *et al.*, 2018; Wooldridge, 2009). Understanding the behaviors of the agents within the environment is crucial for optimizing system performance and decision-making processes. One important aspect in characterizing agent behaviors is the distinction between the two behaviors: collaborative and non-collaborative.

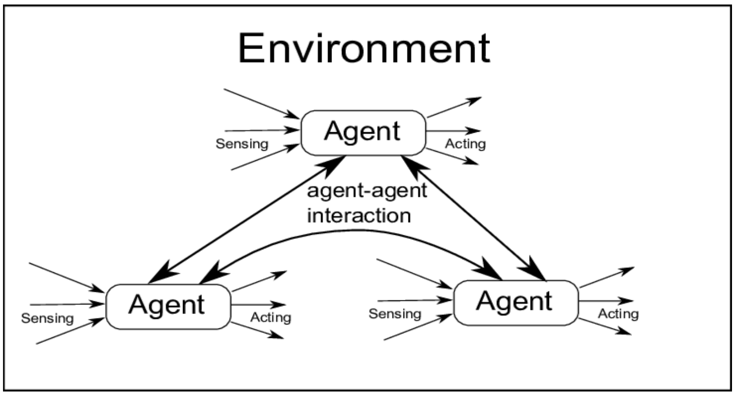


Fig. 1 – "Multiple agents forming a Multi Agent System (MAS)" (Telgen, 2017).

Collaborative behaviors in MAS refer to agents that work together in a cooperative manner, actively exchanging information, coordinating actions, and making collective decisions to achieve a shared goal. Collaboration enables agents to leverage their individual abilities, resources, and knowledge, leading to improved collective outcomes. Studies have investigated the benefits and implications of collaborative behaviors in MAS, highlighting the emergence of unpredictable behaviors and global optimizations where the collective outcome surpasses the sum of individual contributions (Yang Y. *et al*., 2022; Zhang *et al*., 2020; Kankam *et al*., 2023; Yang D. *et al*., 2022; Wang *et al*., 2022; Zhao *et al*., 2022; Vecliuc *et al*., 2022, Syzdykbayev *et al*., 2019; Malik *et al*., 2021).

In contrast, non-collaborative behaviors involve agents that act independently, making decisions guided by their individual objective, with minimal interactions with other agents and with the focus to maximize their gain. These types of behaviors offer advantages such as autonomy, fast decision-making, and diverse problem-solving approaches. They are particularly relevant in scenarios where coordination is unnecessary or challenging, and individual expertise is crucial (Zhao *et al*., 2022; Voulgaris and Elia, 2022).

Understanding the characteristics, benefits, challenges, and applications of these behaviors is crucial for both academic research, industry implementations and daily scenarios. In academic research, a deeper understanding of these behaviors has the ability to help researchers to design more effective algorithms for coordination of the agents. Industry and "daily life" scenarios can greatly benefit from the recommendations on what behavior is the most suitable and what is the expected outcome based on the context (e.g.: improve the collaboration between the robots in a warehouse, understand the collaborative/competitive behavior in scenarios of autonomous vehicles or understand/advise human behaviors in different scenarios such as evacuation in case of emergency, etc.).

This work is organized as a survey and its goal is to provide an overview of the collaborative and non-collaborative behaviors in MAS, with the focus on the characteristics of these opposite behaviors, on the impact that they can have in certain scenarios and on the benefits and challenges of such behaviors. Please note that these two behaviors are not the only ones that exist. However, they represent the area of interest for this study, thus the survey focuses exclusively on them.

By surveying and analyzing the existing literature, the objective is to consolidate the current knowledge, highlight the key findings and examine the implications of these behaviors in various situations in order to emphasize their practical relevance and potential impact.

The main contributions are the following:

- Survey the literature for relevant works for the topic of interest,
- Consolidate and organize the collected information in a structured and coherent format,
- Summarize and synthesize the key findings and insights from the reviewed literature.

The rest of the paper is organized as follows. Section 2 clarifies the concepts of collaborative and non-collaborative behaviors, explores the benefits and drawbacks associated with each behavior type and provides a comparative analysis, highlighting the similarities and differences between them. Section 3 contains an analysis of the literature with focus on applications and implications of the collaborative and non-collaborative behaviors with the help of multi-agent systems in various domains. Finally, Section 4 concludes the survey and summarizes the key findings, discussing future research directions.

## 2. Comparative Analysis of Collaborative and Non-Collaborative Behaviors: Exploring Benefits, Drawbacks and Characteristics

In order to proceed to the investigation of the applications of collaborative and non-collaborative behaviors in the literature, it is essential to conduct an analysis of both behaviors. The analysis emphasizes on the distinguishing characteristics, as well as the benefits and drawbacks associated with each behavior type.

### 2.1. Collaborative Behaviors

Collaboration or cooperation refers to the ability of the agents to work together, actively exchange information, coordinate actions and make collective decisions in order to achieve a common goal.

Several characteristics found in the literature that may describe a collaborative behavior, include, but are not limited to:

- **Communication**: agents communicate with each other to exchange information and coordinate their actions (Sioutis, 2006; Wen *et al*., 2012; Dorri *et al*., 2018, Belbachir *et al*., 2019),
- **Division of labor**: agents specialize in different tasks, and work together to achieve a common goal, (King and Peterson, 2019; Raveendran *et al*., 2021),
- **Coordination**: agents coordinate their actions to avoid conflicts and ensure that their actions are complementary (Ossowski, 2008; Wang *et al*., 2017; Skobelev, 2015; Kleiman-Weiner *et al*., 2016),
- **Cooperation**: agents cooperate by sharing resources, supporting each other, and adapting to changes in the environment (Sioutis and Tweedale, 2006; Zheng *et al*., 2020; Le Gléau *et al*., 2020; Skobelev, 2015; La *et al*., 2014),
- **Trust**: agents trust each other to carry out their assigned tasks and to work towards the common goal (Sioutis and Tweedale, 2006; Ramchurn *et al*., 2004),
- **Negotiation**: agents negotiate with each other to resolve conflicts and reach agreements (Sioutis and Tweedale, 2006; Wen *et al*., 2012; Luo *et al*., 2018; Skobelev, 2015),
- **Adaptability**: agents are adaptable to changing situations and can modify their behaviors to better achieve the common goal (De La Iglesia *et al*., 2014; Skobelev, 2015),
- **Social norms**: agents follow social norms and conventions to regulate their behaviors and interactions with other agents (Santos *et al*., 2018; Yu *et al*., 2013).

Some of the benefits of the collaborative behaviors include, but are not limited to:

- **Increased efficiency**: collaboration can help agents achieve their goals more efficiently by pooling resources, sharing information, and dividing labor (Zheng *et al*., 2020; Le Gléau *et al*., 2020, Malik *et al*., 2021; Vecliuc *et al*., 2022; Belbachir *et al*., 2019),

- **Improved decision-making**: collaborative agents can make better decisions by pooling their knowledge, skills, and perspectives (Malik *et al*., 2021; Belbachir *et al*., 2019),
- **Greater adaptability**: cooperative behaviors can help agents adapt to changing circumstances more quickly and effectively (De La Iglesia *et al*., 2014),
- **Enhanced resilience**: collaborative agents can better withstand disruptions, failures, and attacks by pooling their resources and sharing risk (Chiou and Lee, 2016; Phan *et al*., 2020).

In contrast to the enumerated benefits, there exists a list of potential drawbacks:

- **Coordination overhead**: collaborative behaviors can require additional communication and coordination between agents, which can increase overhead and slow down decision-making (Voulgaris and Elia, 2017; Ding *et al*., 2020),
- **Resource allocation challenges**: cooperative agents may need to allocate resources fairly and effectively, which can be challenging in some cases (Anders *et al*., 2015; Kaur and Kumar, 2020),
- **Conflict and competition**: collaboration may break down when agents have conflicting interests or when competition arises (Roketskiy, 2018; Wang *et al*., 2022).

### 2.2. Non-Collaborative Behaviors

Non-Collaborative/Non-Cooperative behaviors refer to the actions of agents in a MAS that prioritize their own interests over the interests of other agents or the system as a whole. This behavior typically involves agents acting independently even in opposition to one another (competitive), rather than working together.

Various attributes of non-collaborative behaviors have been identified in the literature, not limited to:

- **Selfishness**: the agent acts solely in its own self-interest and does not take into account the goals or desires of other agents (Zhao *et al*., 2022; Voulgaris and Elia, 2022),
- **Lack of Communication**: the agent does not communicate or share information with other agents, which can lead to suboptimal outcomes for the group as a whole (Vecliuc *et al*., 2022),
- **Aggressiveness**: the agent may use aggressive or competitive tactics to achieve its goals, which can harm or interfere with other agents (Wray *et al*., 2018, Wang *et al*., 2022),

- **Unpredictability**: the agent's actions are difficult to predict and may be inconsistent or irrational, making it difficult for other agents to interact with or cooperate with the agent (Dannenhauer *et al*., 2018),
- **Non-compliance**: the agent does not follow agreed-upon rules or norms, which can lead to conflicts with other agents and suboptimal outcomes for the group as a whole (Dannenhauer *et al*., 2018),
- **Goal Misalignment**: the agent's goals are not aligned with the group's goals, which can lead to conflict and suboptimal outcomes for the group as a whole (Dannenhauer *et al*., 2018).

Some of the benefits of the non-collaborative behaviors include, but are not limited to:

- **Efficiency**: individualist agents can act quickly and decisively without needing to consult with or coordinate with other agents, potentially leading to faster decision-making and action (Zhao *et al*., 2022; Voulgaris and Elia, 2022; Voulgaris and Elia, 2017),
- **Resource Utilization**: individualist agents may be more effective in utilizing resources for their own purposes, without having to allocate resources to support other agents (Voulgaris and Elia, 2017),
- **Adaptability**: individualist agents may be more adaptable to changing circumstances or unexpected events, as they can quickly adjust their actions and strategies without needing to coordinate with other agents,
- **Innovation**: individualist agents may be more innovative and creative in their approaches to problem-solving, as they are not limited by the perspectives and constraints of other agents (Goncalo and Staw, 2006).

The identified list of potential drawbacks is:

- **Suboptimal Outcomes**: individualist agents may pursue their own goals at the expense of the group, leading to suboptimal outcomes for the system as a whole (Vecliuc *et al*., 2022; Zheng *et al*., 2020),
- **Conflict**: non-cooperative agents may create conflict and competition with other agents, leading to suboptimal outcomes and potentially damaging the system (Roketskiy, 2018; Wang *et al*., 2022),
- **Lack of Coordination**: non-collaborative agents may not coordinate their actions effectively with other agents, leading to inefficiencies and suboptimal outcomes,
- **Unpredictability**: non-cooperative agents may be unpredictable and difficult to interact with, leading to uncertainty and instability in the system,

For a better overview of the benefits and drawbacks of the two behaviors, they are listed in Table1 and Table 2.

**Table 1**
*Benefits of the two types of behaviors*

| Benefits | |
|---|---|
| **Collaborative** | **Non-collaborative** |
| *Increased efficiency* | *Efficiency* |
| *Improved decision-making* | *Resource Utilization* |
| *Greater adaptability* | *Adaptability* |
| *Better problem-solving* | *Innovation* |
| *Enhanced resilience* | - |

**Table 2**
*Drawbacks of the two types of behaviors*

| Drawbacks | |
|---|---|
| **Collaborative** | **Non-collaborative** |
| *Coordination overhead* | *Suboptimal Outcomes* |
| *Resource allocation challenges* | *Conflict* |
| *Conflict and competition* | *Lack of Coordination* |
| - | *Unpredictability* |

This section analyzed the collaborative and non-collaborative behaviors, highlighting their main characteristics, and a set of advantages and drawbacks. This analysis helped to get a better understanding of both behaviors along with their implications. We explored the potential benefits and limitations of collaboration and non-collaboration in different contexts. Next section will build on this foundation by exploring practical applications and real-world case studies that illustrate these behaviors.

### 2.3. Exploring Applications and Implications of Collaborative and Non-collaborative behaviors in MAS Across Different Domains: A Literature Analysis

This section contains a collection of research papers to explore the applications and implications of collaborative and non-collaborative behaviors across different domains. By summarizing the insights and findings from these studies, the aim is to gain an understanding of the role played by social interactions within MAS and discover valuable insights that can shape future research and applications in this field.

The authors of the paper (Belbachir *et al*., 2019) proposed a self-adaptive mechanism for traffic regulation that utilizes cooperative agents. The primary focus is to optimize intersection behavior by employing intelligent agents to represent infrastructure elements. Through local-level interactions, the cooperative behavior emerges dynamically, allowing the agents to minimize traffic congestion. The authors experimented with both collaborative and non-collaborative behaviors and the experimental results showed that the traffic congestion is mitigated more efficiently when the intersection agents collaborate.

The study emphasizes the importance of collaborative behavior among intersection agents in achieving more efficient congestion mitigation.

The study presented (Adu-Kankam *et al*., 2023) proposes a solution to optimize the efficient organization and management of households (in the context of smart cities) with the help of MAS. The work aims to illustrate collaborative behaviors within a Collaborative Virtual Power Plant Ecosystem (CVPP-E). The collaborative roles played by the CVPP manager and Collaborative Home Decision Technologies (CHDTs) are examined, including opportunity-seeking, goal formulation, coalition formation, acceptance or decline of invitations, and sharing of common resources. A prototype model is developed using a multi-method simulation technique, which explores various collaborative scenarios and behaviors. The study demonstrates the potential benefits of collaborations in a Renewable Energy Community (REC) ecosystem and establishes the feasibility of autonomously forming coalitions or virtual organizations to address specific problems or goals.

This paper (Siedler, 2022) focuses on autonomous drone-based reforestation using collaborative multi-agent reinforcement learning (MARL). The proposed communication protocol is a Graph Neural Network (GNN), allowing agents to share location information and coordinate reforestation efforts. The results demonstrate that “communication enables collaboration”, leading to increased “collective performance, planting precision and risk-taking propensity of individual agents”. The work quantifies rewards in terms of: tree drop count, distance reward and cumulative reward, taking into account autonomous navigation of the drone to the “spawning and servicing point”. The work analyzes the results in scenarios when agents are able to communicate and in (a) scenario(s) where agents do not possess the ability to communicate. The experiments showed that the agent's communication solution outperforms the non-communication solution.

In this study (Yang *et al*., 2022), the authors investigate the link between multi-agent collaboration and the logistics park project performance, based on survey data from Yunnan Province in China. The experimental results indicate that if the agents/parties involved (government, development enterprises and settled enterprises) in the logistical park can form a collaborative mechanism to achieve management and information collaboration, then they can avoid a series of problems caused by: inconsistent interest demands, improper department connection, poor information communication among multiple subjects.

The work done in (Wang *et al*., 2022) represents an extensive survey that explores the concepts of cooperation and competition in multi-agent systems, with the focus on optimization and decision making. The study then expands into cooperative and non-cooperative games, addressing both global and individual cost minimization. The survey does not focus on comparing the two types of behaviors, but rather on different optimization methods applicable for both behaviors. The analysis provides insights into the progress made in multi-agent systems and highlights areas for further research and development.

This research (Zhao *et al.*, 2022) examines the role of sociality regimes (selfish, egalitarian or altruistic) in homogeneous and heterogeneous teams in the context of multi-agent reinforcement learning (MARL) algorithms. The experiments are conducted in a Predator-Prey environment. The findings reveal that the selfish regime is advantageous for both prey and predator teams in all situations. Egalitarian rewards do not align well with the policy learning algorithms, while altruistic rewards produced the lowest performance. The study also compares different MARL algorithms and highlights that they perform similarly in heterogeneous teams. The study concludes that the importance of the sociality regime has the potential to influence MARL algorithms.

In their research (Vecliuc *et al.*, 2022), the authors focus on studying evacuation scenarios using an MAS and explore the impact of collaborative and non-collaborative behaviors on the overall evacuation process. The experiment involves variations in parameters such as the number of agents, exits, agents' knowledge about the exits, layout and behavior. The findings indicate that a mixed population of agents with different collaborative behaviors can significantly improve the evacuation process compared to scenarios with a non-cooperative population, resulting in a time decrease of 20%–30%. The speed of information spreading is influenced by the presence of collaborative agents, particularly when a significant percentage of agents possess omniscient knowledge. Additionally, even a small percentage of collaborative agents can have a positive impact on evacuation time, with results 10% to 20% better than those with a non-collaborative population. However, in complex evacuation layouts, the positions of collaborative agents play a crucial role in their effectiveness, as agents positioned in zones from where they cannot help other agents may lower their impact on the evacuation process. The analysis also reveals that the average evacuation time per agent increases significantly when the number of collaborative agents decreases and the non-collaborative population grows. A balanced distribution of 50% collaborative and 50% non-collaborative agents minimizes the loss between the two populations. The research includes both static and dynamic environments, and future work aims to explore more complex scenarios and investigate the potential application of the evacuation problem to the prisoner's dilemma.

**Table 3**
*Applications of Collaborative and Non-Collaborative Behaviors in Multi-Agent Systems: Examples from the Literature*

| **Scientific work** | **Behavior type** | **Application type** |
|---|---|---|
| Belbachir *et al.*, 2019 | Collaborative | Traffic regulation |
| Adu-Kankam *et al.*, 2023 | Collaborative | Smart city energy management |

| | | |
|---|---|---|
| Siedler, 2022 | Collaborative | Autonomous drone reforestation |
| Yang D. *et al*., 2022 | Collaborative | Logistics park management |
| Wang *et al*., 2022 | Collaborative & Non-collaborative | Optimization and decision-making in MAS |
| Zhao *et al*., 2022 | Non-collaborative | Sociality regimes in MARL |
| Vecliuc *et al*., 2022 | Collaborative & Non-collaborative | Emergency evacuation |

## 3. Conclusions and Future Work

This analysis highlights the importance of considering both collaborative and non-collaborative behaviors in multi-agent systems (MAS) and emphasizes that there is no generally optimal behavior to choose. The pros and cons associated with each behavior highlight the need for a context-dependent approach when determining the most suitable behavior. The choice of behavior should be determined by analyzing factors such as the specific domain, environmental conditions and the objectives of the agents or individuals involved.

To extend our understanding, future work should encompass a wider variety of studies across different domains, enabling us to capture a more comprehensive perspective on the applications and implications of collaborative and non-collaborative behaviors in MAS. With the emerging of the Generative AI agents, there is a whole new area to explore. Expanding the research scope reveals additional insights and promotes the development of more context-aware and adaptable MAS strategies.

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## RECENZIE SUCCINTĂ PRIVIND COMPORTAMENTUL COLABORATIV ȘI NECOLABORATIV ÎN SISTEMELE MULTI-AGENT

(Rezumat)

Sistemele multi-agent (SMA) sunt studiate extensiv și definite diferit în literatură. Un SMA poate fi descris ca un mediu cu mai mulți agenți care interacționează între ei sau cu mediul, urmând reguli prestabilite pentru a atinge obiective individuale sau comune. Sondajul se concentrează pe comportamentul colaborativ și necolaborativ în cadrul SMA. Pentru a introduce cititorii în tematică, o descriere a termenilor este prezentată, urmată de o analiză a comportamentelor colaborative și necolaborative, cu atenția îndreptată asupra caracteristicilor, beneficiilor și dezavantajelor fiecărui comportament. În continuare este prezentată o recenzie a literaturii existente, analizând aplicațiile comportamentelor menționate, în diferite domenii. Ambele comportamente prezintă avantaje și dezavantaje, ce sunt explorate în lucrarea curentă. Înțelegerea acestor comportamente în cadrul sistemelor multi-agent poate aduce beneficii atât în cercetarea academică, dar și în scenarii din viața de zi cu zi. Această înțelegere îi poate ajuta pe cercetători să proiecteze și să implementeze sisteme multi-agent și să ofere recomandări către diferite comportamente care ar putea fi benefice în anumite contexte.