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# A Conceptual Framework for Digital Twins of Multi-Agent Systems

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**Abstract**

Multi-agent Systems (MASs) are complex systems made up of agents that can be any entities with the ability to interact autonomously and make decentralized decision-making to solve complex problems. Data-driven Agent-based Modeling and Simulation (DDABMS) equips MASs with access to decisions based on near-real-time data, allowing for more informed decisions for systems' enhancements. Digital Twins (DTs) can further enhance MASs by serving as virtual replicas that enable what-if scenarios exploration and allow continuous validation and refinement of the underlying models with real-time data from MASs. However, we discovered a gap in systematically integrating DTs with DDABMS, as existing efforts focus on specific problems and domains rather than providing a generalized framework to develop DTs with DDABMS. This paper addresses this gap by proposing a generalized framework to develop DTs for MASs with DDABMS. To demonstrate the practicability of our proposed framework for modeling and simulation of complex systems, we present an illustrative case study based on an epidemiological Susceptible-Infected-Recovered model.

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*Keywords:* digital twins; multi-agent systems; data-driven agent-based modeling; agent-based modeling and simulation; decision making

## 1. Introduction

The increasing complexity of real-world data and systems necessitates the development of more precise and efficient methods for data-driven modeling and simulation. Multi-agent Systems (MASs), that emerged in the 1980s from the domain of Distributed Artificial Intelligence (DAI), are an innovative technology for distributed problem-solving [1]. We define MASs as complex systems that consist of multiple "agents" which could be any entities, such

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as robots, humans, human teams, etc., that can physically or computationally exist and influence real-world outcomes through autonomous decision-making. The capabilities of agents, to act autonomously, exhibit dynamic behaviors, and interact within a system, can outperform traditional modeling and simulation methods by enabling more accurate representations of complex systems.

One approach to building simulation models of MASs is through Data-driven Agent-based Modeling and Simulation (DDABMS), which equips MASs with access to decisions based on real-world data, benefitting from more informed decisions. Although DDABMS has been employed to model agents' interactions and behaviors in specific applications, systematic methodologies remain underdeveloped. Existing efforts are largely problem-specific, focusing on particular challenges rather than presenting a generalized framework [2–5]. This highlights a critical gap and an opportunity to develop structured and comprehensive approaches. Addressing this gap would enable development of Digital Twins (DTs) for MASs. DTs are virtual replicas of physical systems that enable real-time monitoring, simulation, and optimization [6]. DTs have been widely used across various domains, especially in manufacturing [6–11], and can serve as essential tools for representing the physical assets of supply chain systems with maximum fidelity [7].

In this paper, we propose a structured conceptual framework for developing DTs of MASs that utilizes data-driven agent-based models as the core. By developing DTs for MASs, systems can utilize a virtual environment for simulations based on near-real-time data. When near-real-time data is incorporated, DTs can continuously update and adapt, to reflect dynamic changes in the actual systems [6,7]. This promising synergy of DTs and MASs [9] optimizes the analysis and predictive insights of complex systems, enhances decision-making processes.

Our paper is structured as follows. We provide background of MASs, DDABMS, and DTs in Section 2. In Section 3, we describe our proposed framework, followed by a case study illustration in Section 4 to demonstrate its practicability. Finally, we conclude with insights and future directions in Section 5.

## 2. Background

### *2.1 Multi-agent Systems (MASs)*

MASs are composed of two or more agents, which can be either basic agents or intelligent agents [12]. MASs are also referred to as a special type of complex systems, defined as systems with multiple components that interact with one another [13,14].

What exactly is an agent? Definitions vary across the literature and domain of applications. Wooldridge defines an agent as a software or hardware entity situated in either a physical or digital environment, autonomously reacting to changes in that environment, with autonomy being its most important characteristic [12,15]. Franklin and Graesser [16], on the other hand, consider an agent as an analytical construct for examining systems rather than as a strict classification between agents and non-agents [17]. Unlike purely mathematical constructs, agents operate in real-world contexts where boundaries and definitions are often imprecise [16].

In MASs, basic agents are entities that follow predefined rules and respond to environmental changes with limited flexibility. In contrast, intelligent agents have greater autonomy and flexibility. Intelligent agents are reactive, proactive, and socially capable—they can communicate with other agents and adapt their behaviors dynamically to achieve their individual or system goals [1,12,14,15,18,19].

Complex systems are part of our daily lives [20], extending beyond technological fields to encompass a wide range of real-world phenomena, such as bird flocks, global climate systems, traffic networks, and economic markets. Agent-based Modeling and Simulation (ABMS) offers a structured way to represent these complex systems as computational model by modeling each element of the problem as an individual "agent". In our research, we consider agents as entities that can exist either physically, computationally, or any entities that represent components of a complex system and contribute to understanding its system dynamics. For example, in a manufacturing system, basic agents might represent simple machines, while intelligent agents could represent workers or more advanced machines that monitor production, manage inventory, and communicate with one another. The environment, including the production line and inventory systems, provides the setting for interactions among agents (both basic and intelligent) to achieve their own specific goals.

In the following, we provide an overview of DDABMS as an advanced ABMS approach that utilizes real-world data to further enhance agent-based modeling accuracy.

*2.2 Data-driven Agent-based Modeling and Simulation (DDABMS)*

Data-driven approaches utilize data to inform decision-making, strategies, and processes across various disciplines, including business [21–23], life science [24], and technology [25]. These approaches began to gain popularity in the early 2000s, driven by the advent of big data technologies, increased data availability, and advancements in the technologies to collect, store, and analyze large data sets. Consequently, this evolution enhanced simulation methodologies, enabling more accurate modeling and simulation [26].

How can we integrate data-driven approaches into ABMS? According to Jamali and Lazarova-Molnar [17], developing an Agent-based Model (ABM) involves three main processes: model design (extraction), calibration, and validation. Incorporating streaming real-world data into each of these processes can reduce biases in the model design phase [5] and ultimately lead to more accurate and reliable ABMs, as the data-driven approach employs real-time data and data streams to continually inform and update the model. Additionally, Jamali and Lazarova-Molnar [17] proposed a fourth key component for DDABMS: the data pipeline, focusing on collecting, processing, and preparing data before using it for the other three processes. Their framework emphasizes extracting models directly from data to enhance accuracy of ABMs, which we use it to build part of our MASDT framework.

Despite advancements in data-driven approaches, significant challenges remain. Key challenges in data-driven modeling, as identified by [5,26] , include data selection and scope, timing and flexibility in data decisions, dynamic data relevance, quality standards of data, data validation, the risk of oversimplification due to limited datasets, labor-intensive data preparation and cleaning, the need for standardized data formats, data quality, interoperability and consistency across datasets, and enabling efficient comparison of results. These challenges should be carefully considered when applying data-driven methods in ABMS for modeling complex systems.

DDABMS have been applied to specific problems in the domains of land use simulation [28], urban planning [5], infectious disease outbreak modeling [4,29], economy modeling [30], and many more. These applications show the potential and versatility of DDABMS across various fields.

*2.3 Digital Twins*

Digital Twins (DTs) are virtual replicas of physical systems that enable real-time monitoring, simulation, and optimization [6]. Michael Grieves first introduced the concept of DTs for production engineering in the early 2000s but has only gained more attention recently because digital technology is becoming more common in our lives [31]. DTs have been widely studied across various domains, particularly in manufacturing [6–11], and essential for representing the physical components of supply chain systems with maximum fidelity [7]. One of DTs' key strengths is their ability to simulate system changes without altering the original physical system, allowing the exploration of various 'what-if' scenarios and the prediction of outcomes through digital simulations. This capability is achieved through information fusion, where DTs integrate data from multiple sources to create a comprehensive, continuously updated view of a system's past, present, and potential future states [32]. In general, DTs provide valuable insights into systems' behaviors and predictability, enabling informed and data-driven decisions that optimize efficiency, productivity, and other performance metrics in complex systems [32].

To build the underlying models of DTs, Agent-based Simulation (ABS) is more suitable compared to traditional Discrete Event Simulation (DES). ABS allows various levels of abstraction and can connect digital systems (as agents) to create higher-level digital representations [33]. Beyond selecting suitable modeling methods, maximizing the potential of DTs requires addressing several key properties. Lazarova-Molnar [27] emphasizes the importance of data-driven simulation, highlighting that DTs should be goal-oriented and focus on specific objectives to solve defined problems [26]. Furthermore, DTs require a feedback loop to facilitate bidirectional communication [35,39]. Another key consideration is that DTs enable the automatic extraction of simulation models from continuous data collection, including all existing and potentially known knowledge [27].

In the next section, we introduce our framework for developing DTs for MASs, utilizing DDABMs as underlying models. Our proposed framework aims to establish a structured approach for developing DTs for MASs.

## 3. Proposing a Framework for Digital Twins of Multi-Agent Systems

Based on our earlier work on data-driven simulation modeling, we propose a framework for developing DTs for MASs, which we refer to as MASDT in the following. The MASDT framework combines elements from our data-driven DTs' framework, initially developed by Friederich et al. [8] which later extended by Lazarova-Molnar [27], and our DDABM framework, proposed by Jamali and Lazarova-Molnar [17]. The setup for MASDT framework consists of a real-world MAS and MAS's data-driven DT. A real-world MAS can be any complex system that exists in our daily lives and possesses properties such as interconnectivity between components (agents), emergent behavior, and adaptability to changes. For instance, MASs can include supply chains, urban traffic systems, natural systems like bird flocks, epidemic spread models, and others.

Fig. 1 visualizes the MASDT framework, in which the left component represents a real-world multi-agent system and the right component is the Data-Driven Digital Twin (to which we refer to as DT in the following). The DT consists of three sub-components which are Data Pipeline, Model Development, and Analysis.

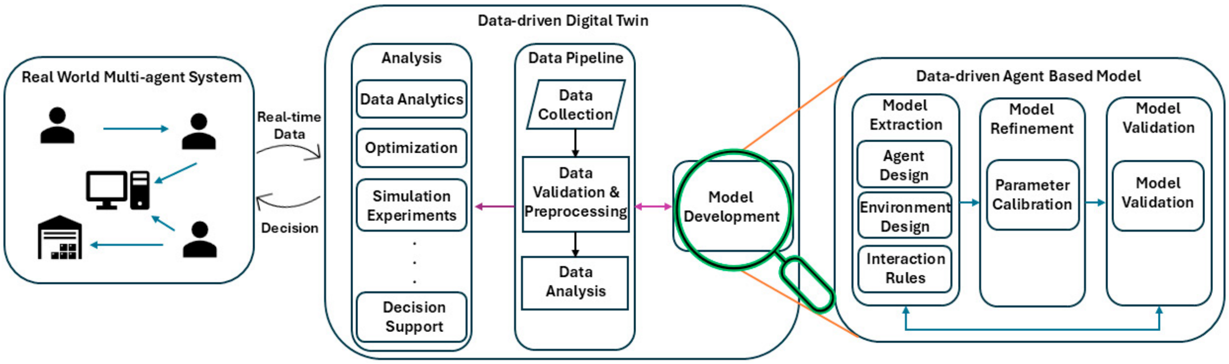


Fig. 1. An overview of MASDT framework.

To enhance the data-driven ABM development as an underlying model of the DT, additional and expanded components, including the Data Pipeline and DDABM (as Model Development element) are introduced and integrated in MASDT. We explain these components in the following.

The DDABM, illustrated by the zoomed-in part of the Model Development process within DT, illustrates the application of a data-driven approach for extracting the underlying DT model. This approach enhances the potential for more accurate representation of real-world complex systems and improves the fidelity of the DT models compared to traditional approaches, provided that the DDABM is well-calibrated and validated against real data.

The Data Pipeline (adapted from [16]) is a critical addition to the DTs Setup, enabling the collection, validation, preprocessing, and analysis of data from real-world MAS, before it can be used for any other processes in Model Development. As illustrated in Fig. 1, the Data Pipeline consists of three key processes: Data Collection, Data Validation, and Preprocessing, as well as Data Analysis. This automated Data Pipeline facilitates the creation of ABMs from ongoing data collection, resulting in more accurate and dynamic underlying models of DTs. By enabling the automatic derivation of simulation models from real-time data, this addition addresses a key consideration for DTs [27] and represents a significant improvement over existing DT frameworks. More importantly, clean and validated data is vital for ensuring the accuracy and reliability of the extracted models [17].

Data collection is a critical step in data-driven DTs, as it precedes all other tasks in DTs' workflows [8]. In the MASDT framework, Data Collection gathers real-time data from sources such as databases or raw data files (e.g., Excel). The collected data is then validated, preprocessed, and analyzed to ensure it meets quality and accuracy requirements for Model Development. By ensuring data validity and reliability, the Data Pipeline improves the fidelity of the derived simulation models [17].

The Model Development component encapsulates three core processes in DDABM: Model Extraction, Model Refinement, and Model Validation. The first process, model extraction, utilizes the processed data from the Data Pipeline to identify agents, the environment, and interaction rules. The second process, model refinement, involves tuning of model's parameters to reflect the real-world MAS precisely. Lastly, model validation verifies that the extracted model aligns with the behavior of the real-world MAS, considering predefined simulation objectives. The process results with a data-driven ABM as an underlying core model of the corresponding DT. This addresses the needs for a generalized framework to develop a data-driven ABMs, in contrast to the domain or problem specific models found in existing literature [2-5]. Moreover, it represents an advancement over existing DT frameworks by introducing a structured approach to develop the underlying DT models.

The Analysis sub-component in the DT extracts insights from real-time data and simulation outputs. It incorporates functionalities such as Data Analytics, Simulation Experiments, Decisions Support and more. This sub-component runs simulation experiments using the underlying data-driven ABM, and the results of these simulations are then processed to derive insights and recommendation to support decisions. These simulation-informed insights and recommendations are fed back to the real-world MAS, creating a feedback loop. This loop facilitates bidirectional data flow, essential for ensuring that DTs can reflect real-world changes in near real-time. As a result, our MASDT framework fulfils the criteria for a DT, as emphasized by [8,27].

In summary, our MASDT framework provides a conceptual foundation for a generalized, data-driven approach for developing DTs for MASs. By integrating components like Data Pipeline, Model Development, and Analysis, we aim to initiate a process of addressing gaps in existing literature by offering a conceptual and flexible framework for creating DTs that feature ABMs as underlying models that are not domain-specific. The incorporation of real-time data through the Data Pipeline and DDABM enhances model fidelity and supports more-informed decision-making. Overall, the MASDT framework aims to enable more accurate and near-real-time reflection of complex systems.

## 4. Illustrative Case Study

To demonstrate the practicability of our proposed framework, we use an illustrative case study based on the classic epidemiological Susceptible-Infected-Recovered (SIR) model of the spread of infectious diseases [36,37]. This case study aims to show how the MASDT framework can be utilized to convert a real-world MAS into an ABM through a data-driven approach and enable a DT for epidemiological modeling.

In our case study, the real system/phenomenon is the spread of an infectious disease in a population, whereas the simulation model is an ABM, with parameters derived directly from the system. The extracted DT model is used to run what-if scenarios as simulation experiments and outcomes are fed back to the real system as recommendations. We assume a population of 10,000 individuals in a town, categorized in three groups, based on their disease status: **Susceptible (S):** Individuals who are not infected but are at risk of becoming infected; **Infected (I):** Individuals who have the disease and can transmit it to others; and **Recovered (R):** Individuals who have recovered from the disease and are assumed immune to reinfection.

We also assume that the disease spreads through direct contact between individuals with the rate of transmission influenced by multiple factors, including mobility patterns and intervention measures implemented by local authorities. These intervention measures may include social distancing, mask-wearing, and vaccination.

The case study is organized as follows: Section 4.1 covers data collection from the real system, Section 4.2 describes the conversion to an ABM, and Section 4.3 details the DT development using the MASDT framework.

### *4.1 Data Collection from the Real System (Data Pipeline)*

We assume the following collection of near real-time data from the system:

- *Population Data:* Population size (N), categorized by individual's disease state (Susceptible, Infected, Recovered); Demographics (age, gender, occupation); Mobility patterns (e.g., location data, and context, e.g., work, school, or home) influence disease transmission; *Data sources*: Local government census datasets (for population and demographics) and GPS data (e.g., GPS data for mobility patterns).
- *Infection Data:* Initial number of infected individuals; Transmission rate ($\beta$) and Recovery rate ($\gamma$) that define the dynamic of disease spread. *Data sources*: Public health reports.
- *Environmental Data:* Intervention measures (e.g., social distancing, mask-wearing, vaccination rates); Quantitative data on social behaviors (e.g., probability of adherence to public health guidelines). *Data Sources*: Health department guidelines and surveys.

This data collection serves as a foundation for extracting an underlying ABM of the DT, aimed to accurately reflect the real-world situation. The data-driven approach enables the DT to simulate and evaluate the impact of various intervention measures based on near-real-time data before implementation. Prior to the development of the underlying DT's model, the collected data undergoes validation and preprocessing to address issues such as inconsistencies, incorrect formatting, and missing values. E.g., missing values, such as unreported case counts, can be imputed using multiple imputation technique [38]. Incorrect or implausible values can also be handled using data imputation methods.

### *4.2 Developing an Agent-Based Model (Model Development)*

Using the MASDT framework, the collected real-world data supports the ABM extraction process by informing agent design, environment design, and interaction rules [17] , as shown in Table 1:

Table 1: Components for Agent-Based Model Development in MASDT

| Component | Key Elements | Description/ Data |
|---|---|---|
| ***Agent Design*** | State, Attributes | Each agent is characterized by state Susceptible (S), Infected (I), Recovered (R) and attributes such as age, gender, and occupation, based on infection data and demographic data. |
| ***Environment Design*** | Locations, Mobility Patterns, Interventions | Includes locations (e.g., work, school, home), mobility patterns (transportation data influencing disease spread), and interventions and social behaviors (e.g., social distancing, vaccination, from environmental data). |
| ***Interaction Rules*** | Contact Patterns, Dynamic Rules | Defines agents' state transitions ($S \rightarrow I \rightarrow R$): $S \rightarrow I$ upon contact with infected agents (contact patterns, influenced by transmission rate and environmental factors), and $I \rightarrow R$ when agents recover. R, determined by recovery rate ($\gamma$), influenced by interventions and behaviors. |

Following the ABM extraction, refinement and validation are performed. During refinement, the model parameters, such as transmission rate ($\beta$) and recovery rate ($\gamma$), are adjusted based on available real-world data. E.g., transmission rate may be fine-tuned to match the observed infection condition. In the validation process, the accuracy of model is evaluated by comparing the output, such as historical real-world data and infection trends. Importantly, the pre-processed data from Data Pipeline are used in these two processes, ensuring model's reliability.

### *4.3 Demonstrating our Digital Twin Framework on the Case Study*

The ABM, extracted from data, would serve as an underlying model of the SIR system's DT. The model is then utilizing analysis functions such as data analytics, optimization, simulation experiments, and decision support. These functions employ the preprocessed real-time data from the Data Pipeline (described in Section 4.1) to run simulations and provide more accurate decisions based on the current disease spread.

The DT is continuously updated with real-time data streams from the MAS, such as changes in agents' states, the latest transmission rate and recovery rate. As new interventions are implemented or lifted (e.g., vaccination campaigns or social distancing), the system adjusts accordingly, feeding simulation results back into real-world decision-making. This bidirectional feedback loop ensures that the DT is refined in real-time, while simulation outcomes inform decisions about public health measures.

Fig. 2 illustrates the operational flow of the MASDT framework in the context of the SIR model. This figure shows the interactions between the real-world complex system and its DT, as well as the data flow and the feedback loop. Real-time data from the SIR system, such as changes in agent states, environmental factors, intervention measures, and behavioral patterns, are sent to the DT. These data are used to continuously update the DTs underlying model, and run simulations/analysis to inform decisions. Based on simulation results, decisions such as implementing new public health measures or relaxing restrictions are fed back into the real-world system, completing the feedback loop.

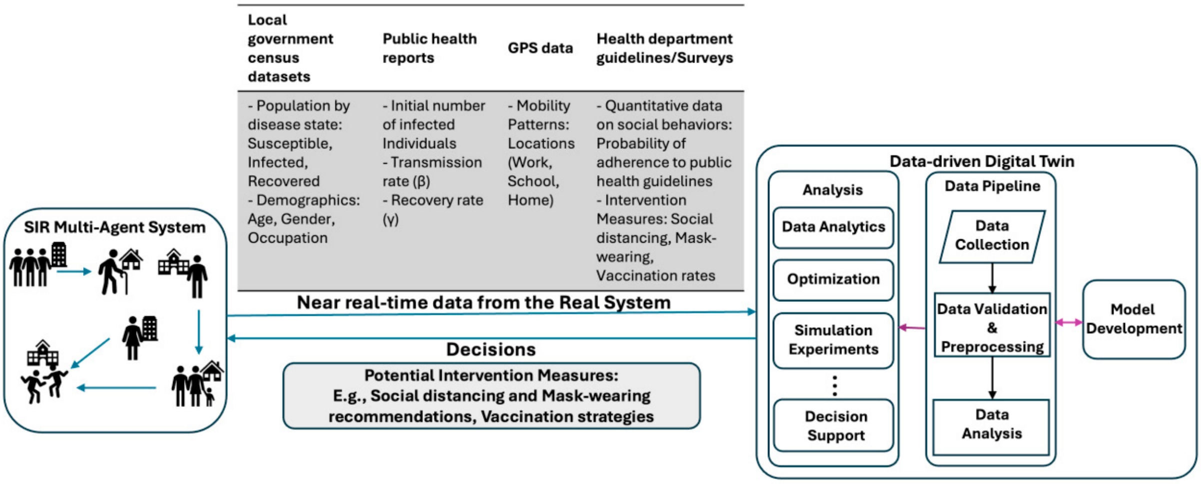


Fig. 2. Visualization of the utilization of our proposed MASDT framework for the described SIR System.

## 5. Summary and Outlook

In this study, we introduce our MASDT framework as a generalized conceptual framework that enables Digital Twins (DTs) of Multi-agent Systems (MASs) by integrating our earlier frameworks for Data-driven Agent-based Modeling and Simulation (DDABMS) and data-driven DTs. Data-driven methods enable DT models to be extracted from real-time data for better-informed decision-making. Real-time data streams from MASs are used to continuously refine and validate DT models. We demonstrated the applicability of the MASDT framework through a conceptual case study using the Susceptible-Infected-Recovered model. This case study illustrated how the MASDT framework can be used to build a DT with an underlying Agent-based Model (ABM) of the spread of infectious disease. The resulting DT would equip authorities with timely data-driven models to explore what-if scenarios through simulations of various intervention measures, enabling the evaluation of potential policies' impact on disease transmission in near real-time. Finally, with the MASDT framework, we aim to provide a generalized approach for DTs of MASs that is applicable across various domains. One limitation of this study is that the MASDT framework remains conceptual at this stage, and its empirical validation has yet to be conducted. Future work will focus on implementing the framework in practical case studies across different domains to evaluate its performance. We also plan to further develop and refine the framework to enhance its ability to build accurate, data-driven ABMs, addressing scalability and adaptability for complex systems.

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