Optimal Agent Framework: A Novel, Cost-Effective Model Articulation to Fill the Integration Gap between Agent-Based Modeling and Decision-Making

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Research Article

Optimal Agent Framework: A Novel, Cost-Effective Model Articulation to Fill the Integration Gap between Agent-Based Modeling and Decision-Making

Abolfazl Taghavi, Sharif Khaleghparast, and Kourosh Eshghi
Sharif University of Technology, Tehran, Iran

Correspondence should be addressed to Sharif Khaleghparast; sharif.khaleghparast@ie.sharif.edu

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Making proper decisions in today’s complex world is a challenging task for decision makers. A promising approach that can support decision makers to have a better understanding of complex systems is agent-based modeling (ABM). ABM has been developing during the last few decades as a methodology with many different applications and has enabled a better description of the dynamics of complex systems. However, the prescriptive facet of these applications is rarely portrayed. Adding a prescriptive decision-making (DM) aspect to ABM can support the decision makers in making better or, in some cases, optimized decisions for the complex problems as well as explaining the investigated phenomena. In this paper, first, the literature of DM with ABM is inquired and classified based on the methods of integration. Performing a scientometric analysis on the relevant literature lets us conclude that the number of publications attempting to integrate DM and ABM has not grown during the last two decades, while analysis of the current methodologies for integrating DM and ABM indicates that they have serious drawbacks. In this regard, a novel nature-inspired model articulation called optimal agent framework (OAF) has been proposed to ameliorate the disadvantages and enhance the realization of proper decisions in ABM at a relatively low computational cost. The framework is examined with the Bass diffusion model. The results of the simulation for the customized model developed by OAF have verified the feasibility of the framework. Moreover, sensitivity analyses on different agent populations, network structures, and marketing strategies have depicted the great potential of OAF to find the optimal strategies in various stochastic and unconventional conditions which have not been addressed prior to the implementation of the framework.

1. Introduction

In today’s complex world, decision making (DM) is a crucial task. Human beings can make wrong decisions because of mental limitations. In many situations, our minds cannot consider all the details and interactions among components in a complex system. As a result, we cannot predict the consequences of our decisions on different parts of complex systems precisely [1]. In order to overcome this disability, operations research (OR) models can help us in a DM process. There are different OR models for different purposes.

In some cases, analysts need to know the best possible decision considering the existing constraints and the objectives simultaneously. For this purpose, usually, optimization models will be employed. These kinds of OR models, which suggest the decision maker a closed-form optimal solution for the problem, are called prescriptive models.

Although prescriptive OR models are helpful in many real-world applications, sometimes analysts may not achieve their goal utilizing prescriptive models. There are some cases in which we want to have a better understanding of the system’s behavior under certain conditions and observe the dynamic mechanism of the system rather than just finding an optimal solution. In this case, a closed-form solution prepared by an optimization model may not be solely helpful. However, having a model which describes the
behavior of system dynamically may bring more advantages. Such models are known as descriptive models among the OR community. A simulation is a powerful tool for building descriptive models. With the help of simulation models, we can create a virtual version of the real-world problem and examine our ideas in this virtual world rather than the real world to observe the consequences of our decisions before applying them. Even though the descriptive models help the decision maker to have a better intuition of the problem, they cannot suggest a proper decision that aids the decision maker to make even a near-optimal decision. Optimization models may help to cover the lack of prescription aspects in simulation models. As a result, integrating optimization with simulation models may lead to achieving a more robust model that prescribes a proper decision for a problem as well as describing it [2]. In this paper, by proper decisions, we mean decisions causing improvement in the overall behavior of the system in the long term.

There are various methods for building simulation models of complex systems. Agent-based modeling (ABM) is one of the popular approaches in the literature. ABM allows us to model heterogeneous agents, complex agent-agent and agent-environment interactions, agents’ learning and adaption, and the emergent behavior generated by the local interaction between agents. Since heterogeneity, complex agents’ interactions, adaption, and emergence can be observed in many complex systems, ABM methodology enables us to create proper simulation models of complex systems. As a result, ABM has been getting more attention for complex system simulation during the last decades. ABM has been employed for modeling and simulating complex systems in a variety of fields (e.g., land use, geography [3], social science [4], medicine [5], economics [6], and supply chain management [7]). In some of the fields mentioned above, agent-based (AB) models had a revolutionary influence on the field and changed some fundamental thoughts. For example, in economics, AB models have shown that many economic agents decide in a deductive manner and not rationally or inductively [6].

One of the applications of ABM is developing policies in which agents’ decisions would result in a desirable emergent pattern for the system. To find an effective policy, the AB model should be evaluated under different scenarios and circumstances. Each scenario is a distinct combination of the model’s parameters and the agent’s decision rules. Since in AB models usually there are a lot of agents and each agent has some attributes, the number of the scenarios which should be investigated may be too much. Consequently, checking all possible alternatives is glacial. In addition to the difficulty of trying a lot of possible alternatives, the stochastic aspect of AB models and the complexity of interactions between agents can make it more difficult to find an appropriate policy. On account of the limitations mentioned above, if the modeler tries to optimize a policy by examining a limited number of scenarios, finding the best possible policy is not guaranteed. Integrating optimization with ABM may help modelers deal with some of the mentioned limitations in designing a good policy.

There are various ways for integrating ABM and optimization or DM, which is discussed in Section 2.2. However, in all of the mentioned methods, a suitable mathematical model of the real-world should be defined. In order to find the optimal solution for the problem, the optimization model should be solved using an appropriate method. There are lots of optimization methods for different kinds of optimization models in the literature. From a general point of view, we can consider two categories for optimization methods. The first one is analytical optimization methods like “Simplex” or “Branch and Bound” (B&B). These algorithms return mathematically optimal output, and usually, they are easily implementable. However, finding a mathematically optimal solution requires some simplification assumptions.

Consequently, solving an optimization problem with an analytical method needs a simplified model. In complex systems with complicated and nonlinear interactions between agents, these simplified models may not suggest the actual optimum solution for the problem. Besides, some analytical models lose their efficiency when the optimization model becomes more extensive, and the number of decision variables increases rapidly. In ABM, usually, there are lots of agents, and each agent has some decisions to make, so designing an optimization model for an AB model needs many decision variables. Based on the mentioned limitations of analytical methods in complex systems, analytical optimization methods may not be appropriate for optimization in ABM.

The other category of optimization methods is heuristic methods. In contrast to the analytical methods, these methods will not generally produce mathematically optimum points. Heuristic algorithms are based on searching in solution space efficiently to find a good guess of optimal point [7, 8]. There are lots of different heuristic algorithms. Most of them are inspired by nature and natural phenomenon (e.g., Genetic Algorithm (GA), which is originated from evolution [9]). Among these algorithms, some of them are population-based algorithms (e.g., Ant Colony Optimization (ACO) [10], Particle Swarm Optimization (PSO) [11], and Artificial Bee Colony (ABC) [12]). These algorithms are also called swarm-based heuristic algorithms, and the basic idea of these algorithms is the swarm intelligence or collective wisdom. Population-based heuristic algorithms represent each solution as an agent of a population that can interact with each other. The interaction between the agents can either be direct, like the agents’ interaction in PSO, or indirect, like the kind of interaction we have in ACO. Defining a population of agents and considering the interactions among them in optimization procedure creates a huge potential base for population-based heuristic algorithms to be integrated with ABM.

According to the pieces of evidence provided in Section 2.3, optimization and DM are the missing parts in ABM and vice versa. Integrating ABM with optimization models can enrich both fields. Since in ABM, most of the researchers devote their time and effort to build a model representing the observed behavior of the real world, researchers cannot focus on involving optimization to this type of complex
In complex system modeling, there is a trade-off between how much modelers want to simplify their model and how much they want to hold the model close to the real world. On the one hand, if they simplify the model very much, the phenomenon which is being modeled may be misunderstood. In some cases, too much simplification for building the model will change the system’s behavior [13]. On the other hand, constructing a complicated model, even if the model is validated, makes it difficult to analyze the model and design effective system policies. Recognizing the structure producing the outputs of the model is difficult when the constructed model is too complicated. In order to solve this problem, we propose employing optimization in ABM. If we integrate optimization and ABM, there is no need to be worried about the difficulty of understanding the structure of the system, and the optimization will help the modeler to make a better decision even in a complicated AB model. As a result, integrating optimization with ABM may help us trade off better between the complexity of the model and the model’s validation. Our primary goal in this paper is to facilitate the procedure of integrating optimization and ABM by doing comprehensive research about the concept of optimization in ABM and presenting a framework for efficiently integrating ABM and DM. In contrast to the existing integration methods, the novel proposed framework does not integrate two different models (DM and AB) in one model because integrating two complex models in one model may be inefficient or even infeasible in complex cases. Instead, the DM is added to the AB model by defining an indication process during the modeling part. Thus, the framework does not require defining a separate DM model anymore, and there is one simulation model that DM is structurally embedded in it.

The rest of this paper is organized as follows. Section 2 includes the required theoretical background, literature review, and a scientometric analysis. As the theoretical background, ABM and DM tools are discussed in this section. In the literature review, the previous publications which integrated DM and ABM are reviewed. As the last part of Section 2, a scientometric analysis has been conducted to have a better understanding of the research gap. In Section 3, a novel framework for efficiently integrating DM and ABM has been proposed and explained by an example based on the Bass model of diffusion of innovation. Section 4 presents the results of the simulation for the model developed by OAF and discusses the research achievements. As the last part of our research, we provided the conclusion and future works.

2. Theoretical Background and Literature Review

In this section, at first, an overview of the required theoretical background is provided. Since, in this paper, we want to address how to use ABM for making proper decisions in complex systems, an overview of ABM and DM is also reported for better understanding. The first part of the theoretical background is devoted to reviewing the methodology and recent notable applications of ABM. In the second part, the DM tools used for integrating DM and ABM in the literature are reviewed. Then, the literature of DM in conjunction with ABM is reviewed. Generally, the AB-DM literature can be categorized into two parts, which are policymaking and intelligent modeling. In each part of the mentioned categories, the literature is divided into subcategories according to the methodology used for integrating ABM and DM. As the last part of this section, an analysis of relevant publications in the literature is performed to help us have a more clarified understanding of the research gaps. Figure 1 shows a road map of this section.

2.1. Theoretical Background

2.1.1. Agent-Based Modeling. ABM is a computational modeling methodology for simulating individuals’ behavior. In this methodology, the behavior of each agent in the system will be modeled by defining some decision rules. The agents will take action and interact with each other based on the determined rules. Consequently, the overall behavior of the system will be the result of interactions among the agents. ABM can help us describe a wide range of phenomena and situations; however, because of the high computational cost of AB models, it is better to use ABM when it is indispensable [14].
(1) Methodology. Researchers have used different methodologies for building AB models. In [15], the authors presented the first standard protocol for describing and simulating AB as the individual-based model. A guideline for rigorous development of AB models appeared in [16]. We review the procedure step by step based on the aforementioned protocol and the guideline, adding relevant, valuable practices from other studies to enrich the content.

Step 1. Is ABM suitable for the problem?
ABM can be used for modeling almost any natural phenomenon. However, there are some cases in which the computational cost of using ABM exceeds its benefits, and using other methodologies may be more cost-effective. For example, a ball falling off a specified height can be modeled by the ABM approach; however, there are analytical formulas for this purpose that describe the mentioned phenomena correctly and very close to the real-world observation [14]. As a result, before starting to build the model, we need to ensure that ABM is appropriate for the problem. Some indicators are recommended in the literature, which may help us to decide whether using ABM is suitable for the problem or not.

Medium Number of Agents. When the number of agents is small, other approaches like game theory may be easier and more helpful to be used [16]. On the other hand, for the problems in which there are tens of thousands or even million agents, other methodologies (e.g., system dynamics (SD) or statistical regression) may perform better than ABM. ABM is most appropriate for systems composed of a medium number of agents [17].

Local Interactions Based on Local Information. When there is no central governance in the model and agents make their decision based on their information from their neighborhood and the local information, using ABM may be more beneficial than the other methods [18].

Heterogenous Agents. In ABM, every single part of a system can be modeled as an agent. As a result, when there are different components in the system which act distinctly, using ABM may help us have a more accurate model of the system in comparison to some other approaches like SD, which assumes the homogeneity and perfect mixing of the agents.

Agents Are Interacting in a Network Structure. ABM enables us to construct models with a specified network structure. When the structure of the network plays an essential role in the agents’ interactions, it is better to use ABM rather than the other methods like SD [13].

Randomness. If a problem involves randomness and the interactions between the agents are stochastic, ABM is a more powerful tool for modeling the phenomena than the other methods to capture the problem’s dynamics.

These are not strict rules for determining the suitability of the ABM approach for a problem. The modeler should consider the aforementioned factors and decide whether using ABM is necessary for the problem or not.

Step 2. Building a conceptual model.
In this step, each part of the AB model should be determined. Considering the following items in the conceptual model may help us have a proper conceptual model of the phenomena.

Model Scope. The model boundary should be specified so that the modeler may know where to focus.

Agent Types. Different kinds of agents should be defined.

Properties of Agents. Every agent has some properties or attributes that should be described in the conceptual model.

Behaviors of Agents. Each agent should be able to do its related tasks. This ability will be provided for the agents by defining some behaviors or functions for each one of them. In order to have a better understanding of how to define the agents’ behavioral rules, see [19], which provides a literature review on different ways of defining the agents’ behavioral rules in ecological AB models.
Environment. The environment where the agents interact with each other must be determined. This environment can be a geographic information system (GIS) [20], a network [21], or a conceptual space.

Input and Output. It should be determined which parameters and data are required as the model’s input and what results are desired.

For building this conceptual model, graphical modeling languages like Unified Modeling Language (UML) may help us have a structured design. There are different diagrams in UML that can be used to describe a conceptual model in ABM. One of these diagrams is the class diagram. A class diagram is a type of static structure diagram in the UML that demonstrates the structure of a system by showing the system’s classes, their attribute, operations, and the relationship between classes [22]. For example, reference [23] uses a class diagram to have a general view of different agent types in a supply chain.

Step 3. Model development.
In this part, the model should be implemented using simulation software or a programming language. Some toolkits are specialized for building AB models. For more information about ABM toolkits, see [24]. Some of these toolkits are based on basic programming languages (e.g., Repast [25]), which is based on Java programming language, and some of them have their own programming language (e.g., NetLogo [26]).

Step 4. Verification.
Every model needs to be verified. For verification, it is necessary to answer the question “is this the model I wanted?” In other words, we should assess whether the existing model matches the conceptual model or not. In the verification process, the model should be debugged, and the coding errors should be resolved [27]. Sufficient documentation for conceptual and implemented models and adequate commenting within the code may help us verify the model [28]. To have structured documentation in ABM, the proposed guidelines in [29] may be helpful. Test cases are also convenient in the verification phase. Test cases are artificially generated data for examining if the results of the constructed model are as expected.

Step 5. Validation.
For validation, it is necessary to answer the question “does this model represent the real world?” It should be analyzed if the outputs of the simulation match the data collected from the real world. By this definition, it is almost impossible to validate a model thoroughly [30]. However, there are some guidelines that may help us be more confident in the validity of a model. One of the valuable methods for validation is comparing the outputs of the simulation to real-world time-series data in order to see if they have the same behavior [31].

Verification and validation (V&V) are the most critical parts of the ABM methodology. It has been said that before V&V, the model is just a toy, and after that, the model becomes a tool for DM [31]. As a result, careful implementation of V&V is necessary to ensure the quality of the model for a variety of stakeholders and help the decision makers make a proper decision using the AB model.

Step 6. Simulation and results.
After V&V, the AB model should be simulated to see the results. In some cases, the result of the AB model is the simulation itself. In other words, in some AB models, our goal is to observe the behavior of the agents during the simulation course and see how the local interaction between agents leads to an emergent pattern [32]. However, there are some cases in which calculating some statistics which give the user a summary of what is happening in the model may be helpful to have a better vision of the outputs of the AB model [33].

One crucial point about AB models is that almost all of them are stochastic. The stochastic nature of the AB models results in different outputs for every simulation run. As a result, a single run of the model may not accurately estimate the outputs. It is better to run the AB models for several independent replications and use the results for calculating the statistics to describe the outputs of the simulation. In this way, the estimation error will be lower than getting results from a single run.

Step 7. Using the model.
AB models have the great potential to support DM, and there are different ways to use AB models as DM tools. Policymaking, conducting what-if experiments, parameter variation, and optimization are some of the proposed methods in the literature, enabling us to make better decisions with the help of AB models.

(2) Applications.

Healthcare. ABM has been used in different parts of healthcare systems. ABM can be used in operational levels (e.g., scheduling for different parts of the hospital). The authors in [34] developed an AB model for mitigating the overcrowding problems in emergency departments in hospitals. ABM has the potential to be also used for making strategic decisions in healthcare. Currie et al. [35] listed strategic decisions affecting the disease transmission in the case of the COIVD-19 pandemic and then discussed which one of the ABM, SD, and discrete-event methodologies could be appropriate for helping decision makers in each situation. Another application of ABM is the immune system and disease simulating. In [5], the AB models in the field of the immune system and disease simulators and their platforms have been reviewed.

Social Science. Since ABM allows us to capture the individual behavior, make interactive heterogeneous agents, and model complex nonlinear interactions between the agents, it has a great potential to be used for analyzing human behavior in complex social phenomena. One of the first AB models was presented in [32] to model a social phenomenon. This model shows how the local interaction of agents for choosing
their neighborhood leads to an emergent segregation pattern. The interesting point about this model is that it was simulated manually and without using a computer back then. After that, ABM has been used for modeling a variety of social phenomena. For example, an AB model was presented for civil violence [36]. In recent years, ABM has been the center of attention for modeling the behavior of people in social networks. One of the essential subjects about social networks is the diffusion of information through the network. The literature of the ABM and diffusion in social networks and a new AB model that analyzes the viral video diffusion in social networks were presented in [37]. Another subject that has been studied in AB models of social networks is analyzing how the structure of a network changes over time [38].

Supply Chain Management. Supply chain management includes many strategic, tactical, and operational decisions in different parts of the supply chain, from product development and manufacturing to transportation. ABM can aid decision makers and managers in making better decisions in each part. An AB model to evaluate processes in a manufacturing system is presented in [39]. Optimizing the supply network has always been a problem for manufacturers. ABM has been used for optimizing network configuration in the supply chain [39, 40]. Supplier evaluation and selection problems are among the most critical logistics decisions in supply chain management. A hybrid AB and optimization approach for solving this problem could be found in [41]. ABM has also been used for modeling and controlling the bullwhip effect in the supply chain [42]. Furthermore, ABM can be used for solving different optimization problems in supply chain management (e.g., scheduling, logistics, and transportation). A literature review about the publications which employed an AB approach for solving the mentioned optimization problems instead of classical optimization techniques was reported in [43].

Land Use. One of the popular ABM applications in land use is geographic information system- (GIS-) based models. Integration of ABM and GIS enables a decision maker to track the dynamics of space changes [20]. An integrated AB and GIS model was developed for urban growth prediction in India [44]. Also, they integrated ABM with a neural network for better prediction. Another application of ABM in land use is evaluating the impact of land-use policies on different system parts. The effectiveness of the greenbelt for reducing the destructive effect of residential development on the environment has been studied in [45].

Pedestrian Dynamics. Since ABM can help us model the individual behavior of agents in a population, it has been used for tracking the behavior of pedestrians in different situations. One of the applications of ABM in this field is designing evacuation plans in the case of an emergency. With the help of ABM, the real-world situation can be recreated on the computer, and different kinds of evacuation plans can be tested. An ABM approach to model agents’ behavior considering factors such as speed, age, and obstacles was discussed in [46]. An AB model was developed for designing a better evacuation plan in [47]. They constructed a 3D model of the building and analyzed the evacuation pattern under two different evacuation plans to decide which one is better. Another recent application of ABM in pedestrian dynamics is evaluating the interaction between pedestrians and automated vehicles (AVs) [48]. The authors examined the effect of pedestrians’ characteristics in crossing the road in front of AVs under different circumstances.

Business Administration. ABM has been used in different business administration fields, from organizational science [49] to marketing [50]. ABM has been applied very much for modeling marketing phenomena. Most of the applications of ABM in marketing is related to the diffusion of information. Many researchers have integrated ABM and network theory for modeling the diffusion of information [12, 48, 49]. A comprehensive literature review about the applications of ABM in marketing was provided in [16].

2.1.2. Decision Making with AB Approach. AB models can be helpful in understanding complex systems; however, using an AB model for making decision needs using some external DM methods. Among the existing methods, Artificial Intelligence (AI) algorithms have an outstanding contribution in DM by AB models. In this section, we will briefly review some of the AI algorithms that seem to be useful for DM in AB models.

There are several algorithms for different purposes in AI. Two types of AI algorithms seem to be helpful for DM in AB models. Heuristic optimization algorithms and Reinforcement Learning (RL) algorithms are two types that have been applied successfully on AB models. Different algorithms have been developed in each of the aforementioned types of AI algorithms.

(1) Heuristic Optimization Algorithms. Heuristic optimization algorithms can be categorized based on different aspects. One of the aspects is the number of solutions that are produced or population size in each iteration. There are two categories of heuristic algorithms from the population aspect. A heuristic algorithm can be either a single-agent population (e.g., Simulated Annealing (SA) and Tabu Search (TS)) or a multi-agent population (e.g., ACO and PSO) [51]. Since almost all AB models are composed of a population of agents, this classification leads us to concentrate on population-based heuristic algorithms that seem to be more compatible with ABM, like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO).

(2) Reinforcement Learning (RL) Algorithms. During the last decade, using AI algorithms in ABM has been growing. Among the different AI algorithms, Reinforcement Learning
(RL) has the most contribution to this field. Most of the time, authors use RL in ABM to perform optimization tasks or making adaptive agents [52]. In RL, the agents take action and get a numerical reward instead, and they are trying to maximize their reward [53]. This reward function is in the form of maximization and will be found by the ad hoc method. The learner agent must discover the most beneficial action according to the reward function by examining different actions and interacting with the environment [54]. There is a set of states, a set of available actions, and a reward function which maps each combination of state and action to a numerical reward. RL enables us to create adaptive agents in our ABM models, and Q-learning is the most common type of RL for this purpose [52]. In this algorithm, there is a Q matrix that keeps the value of each state-action combination. In each iteration of the algorithm, the agent chooses an action based on the current Q-values in the Q matrix and gets a reward instead. At the end of the iteration, the matrix will be updated through the reward which the agent got. Since RL enables the modelers to build adaptive pedestrian agents that can respond to the situation and agent got. Since RL enables the modelers to build adaptive pedestrian agents that can respond to the situation and environment, it has been applied for modeling pedestrian systems [55]. Several works used RL in motion-graphs-based animations [56, 57] or for creating basic agent behavior [58]. RL has also been used in building models for path planning [59].

2.2. AB-DM Literature Review. In this part, we will review some of the previous research in the literature which integrated DM and ABM. Different methods have been proposed for this purpose. Policymaking and intelligent modeling are among the most applied methods in the literature. In the following paragraphs, an overview of these methods and their application is provided.

2.2.1. Policymaking

(1) Scenario Planning. Scenario planning is one of the most useful methods, which is more efficient than the other methods for using DM by ABM in terms of computational costs. In this method, the validated model will be simulated under different scenarios in order to observe the consequences of each scenario so that the decision maker would be able to design policies that have more benefits and fewer consequences. Scenario planning for DM by ABM has been applied in studying the dynamic behavior of pedestrians recently. This method can be performed in different ways. In some cases, scenario planning is the base of the modeling, and ABM is a tool for simulating the scenarios. In this approach, a number of different scenarios will be designed, and for each scenario, a separate AB model will be built. The described method has been discussed in [55] for simulating the behavior of pedestrians in different situations. Five scenarios have been designed, and for each scenario, an AB model has been developed. Another approach to use scenario planning for DM by ABM is designing different scenarios on AB models. In this way, the AB model will be built at first, and the model will be examined under the scenarios that the decision maker wants to test. An AB model for simulating the road crossing behavior of pedestrians has been developed in [48]. After model development, the AB model has been used for examining the behavior of a pedestrian in crossing a road in different conditions. In this case, scenario planning helped the decision maker to make policies that guarantee the safety of the pedestrians. Another example of the second approach to perform scenario planning in ABM was presented in [47], where a 3D AB model for the pedestrians who are walking in a building was developed. The AB model was developed for capturing the evacuation behavior of pedestrians in an emergency. After model development, the model was examined by two different evacuation plans. In this case, scenario planning helped the decision maker to design a safe evacuation plan for the building.

(2) Calibration. Calibration can be used for different purposes in ABM. Calibration can help the modelers in the validation, where our goal is to make the output of the AB model closer to the real-world data in order to make a valid model. It is hard to estimate all the parameters of an AB model accurately. As a result, using calibration for adjusting the unknown parameters will help the model builders to validate their models [60]. In addition to validation, calibration can help to obtain optimal policies for the system. In this case, the desired outcome and also the parameters should be determined for the model. Choosing suitable policies can adjust the model’s parameters. Afterward, the previously mentioned parameters should be calibrated so that the model outcome would be desirable for the decision maker. These calibrated parameters are the optimal policies for the system, and the decision maker should adopt policies that change the parameters from the current values to the calibrated values. Using calibration for achieving the optimal policy has been presented in [61, 62].

(3) Sensitivity Analysis. Sensitivity analysis may help us to understand the impact of the model inputs on the outcomes of the model. The main target of the sensitivity analysis is to determine the most significant parameters in the model and to quantify how the parameter’s uncertainty influences the outcomes [63]. The understanding of the relationship between inputs and outputs, which is provided by sensitivity analysis, helps decision makers design policies that change parameters in a way that model outcomes would be desirable. There are different approaches to perform sensitivity analysis. This method has been used in environmental and ecological applications of ABM lately by presenting two approaches for applying sensitivity analysis in ABM for scenario analysis [64]. The first approach is a one-at-a-time approach, where each parameter will be varied one after the other, while the rest of the parameters are fixed so that the sensitivity of the model to a particular parameter will be determined. The second approach is the Monte Carlo random sampling approach where random sets of parameter values are related to outputs of the simulation. The presented methods have been applied for scenario analysis in an AB model to show the interaction between farmers,
environment, and government in a rural area [65]. This study assists us in understanding how the government's policies affect the resilience of the system. An AB model integrated with a novel sensitivity analysis method for DM has been published in [66] to model the response of a bird population to the changes in their living environment. A Bayesian sensitivity analysis approach has also been presented for identifying the input parameters that have more effect on the outcome of the model.

2.2.2. Intelligent Modeling. Another approach for integrating DM with ABM is using AI algorithms to make intelligent AB models in which the best policy or decision can be learned during the simulation time. Intelligence in ABM can be applied at the system level or agent level.

(1) Intelligent Systems. In this approach, AI algorithms will be used in order to find a policy that optimizes the system’s behavior. In this method, an AI algorithm will be integrated with the AB model. Figure 2 shows how the AI algorithm and AB model are related to each other [67]. The AI algorithm gets the current state of the system and, based on this information, finds the best policy for the system. The AB model will receive the policy and change the state of the model by applying the policy. This cycle will go on until the AB model reaches the optimal policy.

The described method has been used in [68] to find the optimal radiotherapy plan for destroying cancer cells without hurting the healthy ones. An AB model has been developed for simulating tumor growth. In specific time steps, radiotherapy will be used, and according to the radiation dose, the state of the AB model of the tumor will be changed. Calculating radiation dose is a tricky and challenging task that needs to be optimized. On the one hand, a little radiation dose may not destroy the cancer cells. On the other hand, so much radiation dose may destroy healthy cells. So, an optimal radiation dose should be used in each radiotherapy session. In order to optimize dose calculation, a Q-learning algorithm has been applied for making decisions on the amount of dose radiation in each radiotherapy session. Another example of this method has been given in [69], where an integrated AB model with GA is presented for optimizing the passenger flow guidance information to find the best policy for monitoring passengers who start from different points and have the same destination. The optimal policy has been defined as a plan that determines when, where, and what type of information should be given to the passengers to have the least congestion in the paths. Then, an AB model has been developed for capturing the passenger choice behavior considering the congestion and guidance information. For finding the optimal guidance policy, a GA has been used as a part of the DM approach. The same method for making an intelligent traffic system has been employed in [70] to minimize the congestion in the traffic system. They used ACO as the AI algorithm for optimization. The intelligent system approach may be helpful for the decision makers to find the optimal response to a disruption. A dynamic decision support model has been proposed in [71] by applying the intelligent system approach to find the best optimal protection policy in real time when the urban water distribution system faces dangerous contamination for public health. It is an indisputable fact that integrating ABM and an AI algorithm will increase the computational costs of the model. However, some researchers have attempted to reduce the excessive computational cost caused by ABM and AI integration through some innovative methods. In [72], an illustrative example of such methods has been shown to find the optimal set of features for a specified mobile phone to maximize product sales in a market. In order to do this, a simulation-based optimization based on an agent-based model of Bass diffusion of innovation has been built to find the optimal solution. In this model, two simulation models have been presented, which are identical in all aspects except the number of agents. The simpler simulation model has been employed in the optimization algorithm so that the solution provided by the optimization algorithm could be executed rapidly on this model before being examined on the original model. As a result, the solutions that did not perform well in the simpler model would not be examined on the original model as an innovative way to reduce the computational cost.

(2) Intelligent Agents. The purpose of intelligent agents is to find the optimal decisions for each agent in the model. In this approach, an AI algorithm will be embedded into the agent so that the agents can learn the optimal decision by interacting with each other and the environment during the simulation. In other words, in this method, the DM rule of the agents will be designed on the basis of an AI algorithm that enables the agents to make optimal decisions. A framework for integrating RL and ABM multi-stakeholder forest management has been presented in [73]. A forest company, the government agency, and conservationists are the main agent types in the model, and each of them has different objectives. Each of the agent types has a cognitive map based on which the agents of that agent type will make their decision. These cognitive maps will be updated using an RL algorithm to let the agents make optimal decisions. Another example of using intelligent agents to obtain optimal decisions has been proposed in [74], where the goal is to find end users’ optimal consumption patterns in US electricity markets. A combination of different but related theoretical concepts, including social network, social science, complexity theory, diffusion theory, and decision theory, has been used for making a comprehensive AB model of US electricity markets. Each end user in this AB model is trying to maximize its reward function. In each iteration of the model, the agents have to decide whether to keep their current consumption behavior or change it. Since embedding an AI algorithm into each agent increases the computational costs, this method cannot be applied in an AB model with many agents. For resolving the computational cost of this method, researchers have proposed different methods. The intelligent agent method for building a new version of the Schelling segregation model [32] has been used in [75]. They combined RL and ABM to build a model.
in which agents make decisions using an RL algorithm called Deep-Q network. However, they modified the original segregation model to decrease the computational cost of the integration. In the original model, agents could move any place they wanted; however, in the RL and ABM integrated model, the agents have just five options in each iteration: to stay still or to move left, right, up, or down. Another difference is the number of agents. In the RL and ABM integrated model, there are fewer agents than the original model.

2.3. Overview of AB-DM Integration

2.3.1. AB-DM in a Nutshell. In this section, the major publications in using ABM with DM tools are reported in Table 1. Moreover, the methods of integrating ABM with DM based on policymaking or intelligent modeling are also shown. For each paper, some details like its ABM implementation tool, DM strategy, and application are also reported.

From Table 1, it can be seen that integrating DM and ABM has been used in a wide range of applications, from robotic to land use. This shows an excellent potential for using an integrated DM and ABM model for supporting the DM process in a variety of applications. However, to our knowledge, there is no review paper in this field. In this paper, we have reviewed the most relevant publications that integrated ABM and DM in different ways and categorized the literature so that researchers from different fields of study can use it.

In Table 2, the percentage of the publications in each part of policymaking or intelligent modeling is shown. The most popular method for integrating DM and ABM is policymaking by comparing different possible scenarios. Note that these results have been obtained from the papers which had DM or optimization as their keywords; however, as far as we are concerned, in all the ABM publications, this number will be more significant. Policymaking has two advantages that made it so popular among researchers: easy implementation and low computational cost. However, this method may lose its power when the alternative scenarios and the combination of the adjustable parameters increase.

The intelligent system is the second popular approach for integrating DM and ABM. An interesting point about this methodology is that 50% of publications that used this methodology chose GA for their DM tool in the integrated model. This fact implies that GA can be a successful DM tool when intelligent system methodology is going to be used. Another conclusion is that there are other metaheuristic algorithms that have not been tested yet for integrating DM and ABM by intelligent system methodology. Future researchers can examine the algorithms which have not been used yet to evaluate their efficiency for integrating ABM and DM by intelligent system methodology.

Policymaking with calibration is the least popular. There is only one paper that used this method, and it was published recently in 2020. This implies that this method is a novel
method that has not been used in any other application, and future researchers can use this method for policymaking in applications in which this method has not been used yet.

2.3.2. Scientometric Analysis. To understand the state of DM and optimization in ABM publications, we performed a scientometric analysis using ScientoPy. ScientoPy is an open-source scientometric analysis tool that is based on Python open-source programming language [88]. To do this analysis, we collected the required data from the Scopus database. We collected information of the publications with agent-based modeling in their abstract, title, or keywords which were published between 1991 and 2020. The original number of papers extracted from the Scopus database was 15269. By default, ScientoPy filters publications classified in one or more of the following document types: conference papers, journal articles, review, proceedings papers, and articles in the press. Since these documents are more useful for researchers due to higher SJR (SCImago Journal Rank) and JCR (Journal Citation Reports) indicators, other documents, such as book chapters, short surveys, letters to editors, and software and hardware reviews, are excluded. Therefore, 1545 publications were omitted, and 13724 papers remained. Also, 159 duplicated papers have been removed, and finally, 13565 papers were left for consideration

### Table 1: AB-DM literature in a nutshell.

| Reference                        | ABM and DM integration method                      | ABM implementation tool | DM methodology                   | Application          |
|---------------------------------|---------------------------------------------------|-------------------------|-----------------------------------|----------------------|
| Guzy et al. [76]                | Policymaking-scenario planning                     | NetLogo                 | Scenario simulation               | Ecology              |
| Anderson and Dragičević [77]   | Policymaking-scenario planning                     | Repast                  | Scenario simulation               | Ecology              |
| Nguyen-Trong et al. [78]        | Policymaking-scenario planning                     | GAMA                    | Scenario simulation               | Waste management     |
| Delcea et al. [79]              | Policymaking-scenario planning                     | NetLogo                 | Scenario simulation               | Healthcare           |
| Cabrera et al. [80]             | Policymaking-scenario planning                     | NetLogo                 | Scenario simulation               | Pedestrian dynamics  |
| Martinez-Gil et al. [55]        | Policymaking-scenario planning and intelligent modeling-intelligent agent | Open dynamics engine    | Scenario simulation and RL         | Robotics             |
| Zia et al. [81]                 | Policymaking-scenario planning                     | NetLogo                 | Scenario simulation               | Pedestrian dynamics  |
| Razmi Rad et al. [48]           | Policymaking-scenario planning                     | AnyLogic                | Scenario simulation               | Pedestrian dynamics  |
| Rendón Rozo et al. [47]         | Policymaking-scenario planning                     | NetLogo                 | Scenario simulation               | Pedestrian dynamics  |
| Chennoufi and Bendella [82]     | Policymaking-scenario planning                     | NetLogo                 | Scenario simulation               | Ecology              |
| Raimbault et al. [61]           | Policymaking-calibration                           | NetLogo                 | GA                                | Ecology              |
| Schouten et al. [64]            | Policymaking-sensitivity analysis                  | Unspecified             | Sensitivity analysis              | Ecology              |
| Parry et al. [66]               | Policymaking-sensitivity analysis                  | C++                     | Author-defined                    | Land use             |
| Jalalimanesh et al. [68]        | Intelligent modeling-intelligent system           | NetLogo                 | RL                                | Healthcare           |
| Yin et al. [69]                 | Intelligent modeling-intelligent system           | C#                      | GA                                | Traffic management   |
| Humann and Madni [83]           | Intelligent modeling-intelligent system           | NetLogo                 | GA                                | Military             |
| Mei et al. [67]                 | Intelligent modeling-intelligent system           | MATLAB                  | GA                                | Urban planning       |
| Alves et al. [84]               | Intelligent modeling-intelligent system           | NetLogo                 | GA                                | Scheduling           |
| Rashek and Brumbelow [71]       | Intelligent modeling-intelligent system           | EPANET                  | Multi-objective evolutionary algorithms | Urban planning     |
| Yu et al. [85]                  | Intelligent modeling-intelligent system           | NetLogo                 | Local branching algorithm         | Maintenance          |
| Ye et al. [86]                  | Intelligent modeling-intelligent system           | NetLogo                 | PSO                               | Ocean management     |
| Bone and Dragičević [73]        | Intelligent modeling-intelligent agent            | Unspecified             | RL                                | Land use             |
| Haghnevis et al. [74]           | Intelligent modeling-intelligent agent            | Unspecified             | Author-defined                    | Energy               |
| Sert et al. [75]                | Intelligent modeling-intelligent agent            | Python                  | RL                                | Social science       |
| QuanLi et al. [87]              | Intelligent modeling-intelligent agent            | Repast                  | ACO                               | Land use             |

Table 2: Percentage of publications in each part of the literature.

| ABM and DM integration method | Percentage of publications |
|-------------------------------|---------------------------|
| Policymaking-scenario planning | 40                        |
| Intelligent modeling-intelligent system | 32                     |
| Intelligent modeling-intelligent agent | 16                       |
| Policymaking-sensitivity analysis | 8                       |
| Policymaking-calibration      | 4                         |

method that has not been used in any other application, and future researchers can use this method for policymaking in applications in which this method has not been used yet.
Complexity

after these preprocessing steps. The preprocessing results are shown in Figure 3.

We have filtered the publications which have DM or optimization in their keywords. Figure 4 shows the number of publications each year, from 1991 to 2019, which has optimization or optimisation in their keywords separately, and Figure 5 shows the integrated graph.

Figure 6 presents the same graph for publications that have decision-making or decision making in their keyword separately, and Figure 7 shows it when two graphs are integrated.

It seems that the number of publications that are related to DM and optimization is increasing. However, this may be related to the rapid growth of ABM during the last two decades. Figure 8 shows the number of publications, which have ABM in their abstract, title, or keywords. As shown in Figure 8, the number of publications in ABM has been growing during the last two decades.

In order to find out whether the growth of using optimization and DM in ABM publications is correlated to the growth in ABM publications, we tested whether the Pearson correlation coefficient between them is zero or not.

The conclusion about the correlation between the growth of optimization publications in ABM and the increase in correlation coefficient between them is zero or not. In this case, the statistic for the formal hypothesis testing is defined by the following equation:

\[ H_0: \rho = 0, \]
\[ H_1: \rho \neq 0. \]  \hspace{1cm} (1)

The statistic for the formal hypothesis testing is defined by the following equation:

\[ t^* = \frac{r \sqrt{n - 2}}{\sqrt{1 - r^2}} \]  \hspace{1cm} (2)

where \( n \) is the number of the data and \( r \) is an estimate of the Pearson coefficient, which can be calculated by the following equation:

\[ r = \frac{\sum_{i=1991}^{2019} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1991}^{2019} (X_i - \bar{X})^2 \sum_{i=1991}^{2019} (Y_i - \bar{Y})^2}} \]  \hspace{1cm} (3)

where \( X_i \) is the number of the publications which have optimization or optimisation as their keywords in the year \( i \). Level of significance \( \alpha \) or the probability of Type 1 error (rejecting \( H_0 \) when it is true) is considered to be 0.05 in this research. The critical value of the formal hypothesis test is 2.052, and the calculated value for the statistic is 10.258. Since the statistic value is more significant than the critical value, the conclusion of the formal hypothesis testing is to reject the null hypothesis and that there is adequate evidence that the increase in DM publications in ABM is correlated to the growth of the ABM publications.

According to the aforementioned hypothesis tests, we cannot conclude from Figures 5 and 7 that using optimization and DM in ABM publications has been growing.

To recognize the top research fields inside a research area, ScientoPy lets us extract them based on the top authors' keyword topics. For having a better understanding of the optimization and DM growth in ABM, we used a bar chart in ScientoPy to see more frequent keywords in ABM publications in three different time periods. The first period is from 1991 to 2010, where the timeline graphs show an increase in the number of publications of DM and optimization in ABM. The second period is from 2011 to 2015, and the last one is from 2016 to 2019. This classification helps us to know the state of the optimization before its sudden growth around 2010 and observe how the number of related publications has changed during the last decade. Figure 9 shows the bar chart for the top 30 frequent author keywords in the first period. Figures 10 and 11 show the same chart for the second and third periods.

To find out how DM and optimization publications have changed in the three periods mentioned above, we have tracked the rank of optimization and DM as the two most relevant keywords in the previous bar charts. Table 3 shows the rank of these two keywords in the three mentioned periods.

From Table 3, we understand that in the first period, DM in ABM has not been studied very much. However, in the last two periods, which represent the last decade, optimization got among the top 30, and this shows that optimization and DM in ABM publications had an ascending trend, which is previously shown by the timeline graphs. Although it seems that the number of optimization and DM publications in ABM has generally been growing, it seems that this growth has been stopped during the last decade. Since the optimization rank has not changed significantly in the last two periods, we can claim that the number of publications in this field has no ascending trend during the last decade.

In order to test this claim, a regression analysis has been done. For this regression analysis, the year of publications is considered the independent variable \((y)\), and the number of publications with the keyword of optimization is considered the dependent variable \((x)\). We performed the regression analysis to see whether the slope of the regression line is zero or not. For fitting the regression line, Python open-source programming language has been used. Based on the mentioned data, the regression equation is shown in the following equation:

\[ y = -871.65455 + 0.43636 * x. \]  \hspace{1cm} (4)

Figure 12 shows the regression line and the data in a plot. The conclusion about the slope of the regression line is made by a formal two-tail hypothesis test. The hypothesized
Figure 3: Preprocessing result from ScientoPy.

Figure 4: Timeline graph for publications with optimisation or optimization as keywords during the period 1991–2020.

Figure 6: Timeline graph for publications with decision-making or decision making as keywords during the period 1991–2020.

Figure 5: Integrated timeline graph for publications with optimization or optimisation as keywords during the period 1991–2020.

Figure 7: Integrated timeline graph for publications with decision-making or decision making as keywords during the period 1991–2020.
slope is denoted as $\beta_1$. The null and research hypotheses are defined as follows:

$$H_0: \beta_1 = 0,$$
$$H_1: \beta_1 \neq 0.$$  \hspace{1cm} (5)

The statistic for the formal hypothesis testing is defined by the following equations:

$$t^* = \frac{b_1 - \beta_1}{s_{b_1}}.$$  \hspace{1cm} (6)
where $b_1$ is the coefficient of the independent variable representing the slope of the sample regression line and $S_{b_1}$ is the standard deviation of the slope of the regression line.

The critical value of the formal hypothesis test is 18.307, and the calculated value for the statistic is 2.170. Since the statistic value is lower than the critical value, the conclusion of the formal hypothesis testing failed to reject the null hypothesis, and there is no sufficient evidence that the number of optimization publications in ABM has been growing during the last decade.

3. **Optimal Agent Framework Establishment**

There are different approaches to DM by ABM in a complex system. In some cases, researchers try to build an AB model as complex as the real-world system to have a realistic model that mimics the real-world results at a desirable accuracy [89]. However, understanding and controlling the structures which are generating the outputs of the AB model in this approach is complicated, and DM will be hard to be performed in this approach. Since the structures producing the results may be unknown to the modeler, we call this kind of AB models Black-Box AB (BBAB) models. Some researchers have used a simplification approach to build AB models that can be analyzed more comfortably than BBAB models. We call this kind of AB model the White-Box AB model (WBAB). Model simplicity causes decision making in WBAB models to be easier than BBAB models. Although the WBAB models can be understood and analyzed easier than BBAB models, they may lead to results that are far from the real-world behavior of the system. Optimization is another approach for making proper decisions in a complex system. In contrast to the last two approaches, which are descriptive, an optimization is a prescriptive approach that suggests the optimal decision to the decision makers. However, in complex systems, defining an optimization model that includes all the complexities in the system and could be solved in a polynomial time is not an easy task. In some cases, researchers use a combination of optimization and ABM, which has been discussed thoroughly in the literature review. Using this method enables us to have a descriptive model that has a prescriptive aspect too. However, this method increases the computational cost of the model. Table 4 compares the previously mentioned approaches from three discussed aspects. The disadvantages are indicated in bold, the advantages are indicated in italics, and the underlined value indicates that it depends on the model conditions.
All of the four approaches, which are shown in Table 4, have at least one disadvantage that makes them inefficient when the system complexity increases, and it may be one of the reasons that DM by ABM publications have not been growing very fast in the last decade. In this paper, we will present a novel framework that may facilitate DM by ABM in complex systems and does not have any of the mentioned disadvantages. Our proposed framework has a higher power of capturing complexity, lower computational cost, and higher power of controlling the model. (The Bass model of the diffusion of innovations has been used as a sample case to explain the framework.

Our framework, which is called OAF, is inspired by the acid-base indication process in chemistry. In chemistry, for determining whether an unknown liquid is an acid or base, chemists use an acid-base indicator (e.g., phenolphthalein). Acid-base indicators, which are also known as pH indicators, are substances that turn into a particular color when they are dissolved in an acid or base. Phenolphthalein is one of the well-known acid-base indicators that is colorless in an acidic environment and turns pink when it dissolves in a base.

**Table 3: Rank of optimization and DM keywords in the top 30 keywords in 3 periods.**

| Period     | Keyword          | Rank          |
|------------|------------------|---------------|
| 1991–2010  | Optimization     | Not in the top 30 |
|            | DM               | Not in the top 30 |
| 2011–2015  | Optimization     | 23            |
|            | DM               | 26            |
| 2016–2019  | Optimization     | 24            |
|            | DM               | Not in the top 30 |

Figure 11: Bar chart of the top 30 authors’ keywords during 2016–2019.
As discussed, through the indication process, we can diagnose the identity of the unknown liquid. We used this notion to build a framework that enables us to make decisions in complex systems with a low computational cost. In OAF, an indication process will be defined to depict the proper decision in a system that we cannot analyze easily and is unknown to us. In the following parts, OAF is described, and then an example of OAF implementation is provided.

3.1. ODD Description of OAF. In the following paragraphs, OAF is described using the ODD protocol. The ODD protocol is a de facto standard to describe AB models. This description is based on the explanations provided in [15, 90, 91], considering all the updates in the last version, which was released in 2020.

### 3.1.1. Overview

1. **Purpose.** The purpose of OAF is to find a decision-making agent (DMA) that can make more proper decisions in comparison to the other possible DMAs. As it is described before, by proper decisions, we mean decisions that lead to improving the overall behavior of the system in the long term. In other words, the purpose of OAF is not to find an optimal solution but to find an agent that can perform this task and make decisions that the other possible DMAs cannot make.

2. **State Variables and Scales.** In OAF, there are three kinds of agent types.

   a. **DMA.** In every AB model, there are some decisions that should be made. In some cases, there are agents in the AB model that are responsible for DM. In this case, the DMA agent type is previously defined in the AB model, and there is no need to be defined in OAF. This kind of DMA is called predefined.

      There are some cases in which the DMA is not explicitly defined; however, there are some decisions to be made and the modelers themselves decide about them. For example, when the modeler decides about the value of some parameters or defines some mechanism in the model, there is not an agent to make the decision. In this case, we have latent DMA that should be created in the model for implementing OAF. If the DMA is latent, an agent type should be defined to be responsible for making decisions that were previously made by the modeler.

      After determining the DMA, a number of agents should be instantiated from the DMA agent type. These agents make decisions about the same issue; however, each of them uses a different strategy for DM or has different characteristics. In other words, they are different agents trying to make a decision about the same subject.

   b. **Neutral Agent.** Each DMA tries to build its community of neutral agents and grow it. Neutral agents are affected by the DMAs’ decisions, and in each time step of the simulation, they try to join one of the existing DMAs in the model. Some of them choose their desired DMA, and some of them may wait to choose their desired DMA in the next time steps.

      Depending on the behavior of neutral agents, there are two versions of OAF. If the neutral agents are allowed to change their community and join another DMA, we have the dominating version. Since in this version, only one DMA will attract all the neutral agents ultimately, it is called dominating. The other version is called nondominating, in which neutral agents are not allowed to change their DMAs.

   c. **Other.** Each agent type that is not either a DMA or neutral agent will be categorized as “other.” These are the agents that are not involved in OAF directly; however, they are required to build the base model in OAF.

3. **Process Overview and Scheduling.** In addition to the processes existing in the base AB model, OAF has a unique process called indication. This is the process that leads to the recognition of the optimal agent. As previously described, adding an indicator substance (e.g., phenolphthalein) to the unknown liquid is the second phase of the acid-base indication process. The indication process of OAF is similar to this phase. In the indication process of OAF, some indicator agents, which are DMAs and neutral agents, should be added to the model. In this process, a number of DMAs with different characteristics and DM strategies will be added to the model and try to attract neutral agents. In the end, the DMA with the most neutral agent (nondominating OAF) or all the neutral agents (dominating OAF) will be chosen as the optimal DMA among the existing DMAs. Figure 13 shows a graphical view of the indication process.

In OAF, DMAs are like the gladiators in ancient Rome. In ancient Rome, there were contests in which a number of fighters called gladiators would fight until one of them
defeat the other ones and be known as the winner. There were different kinds of contests and gladiators; however, there was one similar concept among all of them that the winner is the one that does not lose to the other ones. The indication process of OAF is inspired by this notion. A number of DMAs that are possible candidates to be the decision maker in the system will be added to the model simultaneously. These DMAs are fighting against each other to obtain the same resource, that is, the neutral agents. The winner is the DMA that attracts the most neutral agent (in dominating OAF) or all the neutral agents (in nondominating OAF).

In OAF, the objective is not finding an optimal decision; however, it is desired to find the DMA that can make optimal decisions in the model. When we hold a contest among the potential DMAs, the agent that defeats the other one has made better decisions, and this resulted in victory. As a result, OAF presents the best possible DMA among the existing DMAs.

3.1.2. Design Concepts

(1) Emergence. The optimal agent that can defeat the other possible DMAs emerge from the behavior of the neutral agent in choosing a DMA to join its community. The neutral agents may choose a DMA to join its community based on the state of the AB model and the DMAs' community.

(2) Adaptation. In the nondominating OAF, adaptation is not involved; however, the dominating version contains adaptation. In the nondominating version, the neutral agents cannot change their DMA, and when they join a community, they will be a member of that community until the end of the simulation, so they do not adapt their decisions. In contrast, in the dominating version, neutral agents can change their community after joining a DMA, and they change their community based on the other neutral agents' decisions. If the community of their current DMA is not growing, they will leave their community and choose a new DMA based on the current state of the AB model and the other DMAs' community sizes.

(3) Sensing. The neutral agents know about the DM strategies and characteristics of DMAs and also know about the number of the neutral agents that joined each DMA.

(4) Interaction. The most important interaction is the interaction between DMAs and neutral agents. As previously described, the neutral agents want to find a DMA and join its community, and the DMAs also want to attract neutral agents and expand their community.

(5) Stochasticity. In OAF, the interaction between neutral agents and DMA may be stochastic. In each time step of the simulation, a number of neutral agents may join the DMAs, and the rest may not take any action, and this process will be stochastic. Since all the neutral agents are the same prior to joining the DMAs, choosing the neutral agents that join the DMAs may be stochastic.

(6) Collectives. In the indication process of OAF, the neutral agents choose a DMA and join its community. The neutral agents will be collected in different communities of the DMAs.

(7) Observation. Since most of the AB models are stochastic, the results should be obtained from running different replications of the model. The winner DMA in each replication may be different, and each of the DMAs may be the winner in a number of replications. As a result, the output of the OAF is the victory percentage for each DMA, and the DMA with the highest victory percentage is the optimal agent.

3.1.3. Details. (1) Initialization. In the initialization of the simulation model in OAF, different instances of DMAs should be created and added to the model. These instances should be defined in a way that could cover all the possible DM strategies. As a result, the winner DMA will be the optimal agent.

3.2. An Example of OAF Implementation. In the following sections, the Bass model of diffusion of innovation is used to provide an example of OAF application. At first, a brief explanation of the Bass diffusion model is provided, and then the Bass diffusion model developed by OAF is described using the ODD protocol.

3.2.1. Bass Diffusion Model. The Bass model of diffusion of innovation is a model in marketing that shows the dynamic of buying a new product that is released in the market. This model was presented for the first time by Bass [92]. In this model, there is a population of consumers who are the potential users of the product. At each time step, some of the potential users will buy the product and become a user. The number of new buyers in each time step depends on two factors, which are advertising and Word of Mouth (WOM). At each step of the model, a constant percentage of the potential users will buy the product through the advertisement.

Moreover, some of the users will contact the potential users to convince them to buy the product with a certain probability. The persons who buy the product on the basis of WOM are called imitators, and the persons who buy the product independently are called innovators. So, the percentage of persons who become users through WOM is called imitation rate, which is denoted by \( q \), and the ones who become users through the advertisement is called innovation rate, which is denoted by \( p \). The original version of the model was an aggregate model based on an SD methodology. To build more realistic models of the diffusion of innovation, some researchers have tried to model the diffusion process with ABM [16, 93]. In [94], a suitable literature review of AB models was provided for innovation diffusion. More explanations on the SD and AB models of Bass diffusion are provided in the Appendix.
3.2.2. ODD Description of Bass Diffusion Model
Developed by OAF

(1) Overview.

Purpose.

As previously mentioned in the OAF description, the purpose is to find a DMA that can make proper decisions, and proper decisions are the ones that improve the overall behavior of the system. In the Bass model, improving the overall behavior of the system means a faster diffusion. As a result, it is desired to find a marketer from the existing marketer population that can accelerate the diffusion process.

State Variables and Scales.

There are two primary agent types in the model: marketer and customer. The relation between these two agent types and their attributes and methods are provided in a class diagram of the model in Figure 14. In this model, customers are the neutral agents, and marketers are the DMAs.

Customer Attributes.

- contactRate: this is a parameter for each customer that determines the number of daily contacts of the customer with the other customers.
- marketerID: this attribute indicates the marketer that the customer picked as its DMA and joined its community. If the customer has not chosen any marketer, the value of marketerID will be 0; otherwise, it would be a number between 1 and \( n \) (the number of marketers).

Marketer Attributes.

- ID: this is an integer number in the range of \([1, n]\).
- p: advertisement parameter for the marketer
- q: WOM parameter for the customer
- attractedCustomers: this attribute is an integer number that shows the number of customers that the marketer attracted. In other words, it indicates the size of the marketer’s community of neutral agents, which are the customers.

Process Overview and Scheduling.

Figure 15 shows the customer’s state chart of the bass diffusion model developed by OAF. Both diagrams have two similar transitions. The first transition, which is denoted as Ad in Figure 15, is advertisement transition. This transition represents the innovation rate in the Bass diffusion model, and it means that in each time step of the simulation, there is a probability that the customer changes its state to a user. In the original model, there is not any marketer, and this probability will be defined by the modeler. However, in the Bass diffusion developed by OAF, there are a number of marketers that each of them has different \( p \) parameters determining the probability of customer attraction via the advertisement for that customer. In this model, in each time step, a number of customers change their state to the user, and after changing their state, each of them will be assigned to a marketer according to marketers’ \( p \) parameters.
parameters. The *roulette wheel* approach has been used to assign each customer a marketer based on the marketers’ focus on advertisement.

The second similar transition is WOM. This transition will be triggered if a customer in the potential user state receives a message to buy the product from one of the other customers who are using the product. The message from the user is a string with the text of “buy from marketer $i$.” When a potential user customer receives this message, the transition is triggered, which may make the customer agent change its state and buy the product. The probability that a customer buys a product after receiving a message is equal to the $q$ parameter of the $i$th marketer.

Each of the marketers has a different combination of $p$ and $q$, and each combination of $p$ and $q$ represents a marketing strategy indicating the importance of advertisement and WOM in that strategy. Considering marketers with various combinations of $p$ and $q$, we can have different marketers with different marketing strategies. Each of these marketers tries to sell the product and build its community of customers. In other words, these marketers are competing together to determine which one can attract more customers. The marketer who attracts the most customers (nondominating OAF) or all the customers (dominating OAF) will be chosen as the optimal agent among the existing marketers.

There is also an internal transition in the state of the user in the state chart. The purpose for defining such a transition is modeling the communication between the users and potential users. This transition makes the user agents randomly choose another agent in the population and send a message to that agent telling them to buy the product from its marketer.

As it is shown in the state charts in Figure 15, there is one difference between dominating and nondominating state charts, which is *losingUsers* transition. This transition allows the customers to change their DMAs, which are the marketers.

Figure 16 shows the indication process in the dominating and nondominating OAF. In addition, it shows the link between acid-base indication and the indication process in OAF.

(2) Design Concepts.

**Emergence.** The optimal DMA, which is one of the marketers, emerges from the behavior of neutral agents, which are customers, in choosing a marketer to join its community.

**Adaptation.** In the nondominating version of the model, the customers that chose one of the marketers may turn back to a *potentialUser* through the *losingUsers* transition. When a customer goes back to the *potentialUser* state, it should repeat the process of choosing a marketer based on the current state of the AB model and the marketer. This repetitive process makes the model adaptive.

**Sensing.** The customers know $p$ and $q$ parameters of all the marketers and also their community size (the number of customers that a marketer attracted).

**Interaction.** There are two kinds of interaction in the model: customer-customer and marketer-customer.

Customer-customer: The customers, who are in the user state, send messages to the other customers and tell them to buy the product from their marketers.

Marketer-customer: The marketers try to attract customers through advertisement and expand their community sizes.

**Stochasticity.** Both of the WOM and Ad transitions are stochastic. The user customers randomly choose an agent to send the message of “buy from marketer $i$” to it, so the internal transition which is used for sending message is also stochastic.

**Collectives.** Each marketer is trying to build its community of customers. As a result, the customers will be aggregated in different communities leading by the marketers.
Observation. Since the model is stochastic, the simulation model should be run in a number of replications, and the winner marketer in the replication will be different. As a result, the marketer who is the winner of the most replications will be selected as the best marketer among the existing DMAs. In other words, the marketer with the highest victory percentage is the optimal agent.

(3) Details.

Initialization. In the initialization, \( p \) and \( q \) parameters of the marketers should be initialized. The initialization should be in a way that each combination of \( p \) and \( q \) represents a different marketing strategy so that we can have a population of marketers with diverse marketing strategy. For example, if one marketer is more focused on the advertisement, there should be another marketer who is more focused on WOM so that we can evaluate which is better. The marketerID parameter for all the customers must be initialized as 0, and the marketers’ ID must be initialized as 1 to \( n \).

4. Results and Discussion

4.1. Simulation Results. We have simulated the Bass diffusion model, which is developed by OAF. In the simple version, which is used for explaining OAF, there are 1000 potential users as neutral agents in a fully connected network. The contact rate of each neutral agent with the other agents is considered a random variant from a uniform distribution between 1 and 3. There are two marketers who represent the gladiators. Each of the two marketers who are used in this simulation experiment has a different marketing strategy. One of them puts most of the effort into advertising, and the other one concentrates on attracting customers through WOM. These two marketers will compete in the model which is developed by OAF to find a better marketing strategy.
strategy. Figure 17 shows the result of the average performance of the simulation model with its standard deviation over 30 independent replications for dominating and nondominating OAF for the Bass diffusion model.

In both graphs, the blue marketer who has focused on WOM defeated the red one who has concentrated on the advertising and attracted more neutral agents. This means that the blue marketer made better decisions than the red one, and under the current circumstances, the blue marketer’s strategy is more successful compared to the red one.

In the nondominating version, the blue marketer has always been the winner of the competition and attracted more consumers totally. Nevertheless, the results of the competition of the dominating version are not always the same. In the dominating version, each replication may have different winners. In this case, in 23 replications out of 30 replications, the blue marketer has won the competition and absorbed all the neutral agents. Since in the seven replications, the blue marketer could not attract any of the neutral agents at the end, the simulation outputs for the dominating version have a much higher standard deviation than the nondominating version in which the blue marketer in all the replications had attracted most of the neutral agents.

The winner marketer in both nondominating and dominating versions can be reported by a Bernoulli distribution. In each replication, the blue marketer wins with the probability of $a$, and the red one wins with the probability of $1 - a$. In other words, the probability of winning for the blue marketer follows a Bernoulli distribution with the parameter of $a$. The parameter of this probability distribution can be estimated by dividing the number of replications that the blue marketer won by the total number of replications. The Bernoulli distribution parameter for the dominating version is estimated at 0.7667 and that for the nondominating version is 1.

### 4.2. Sensitivity Analysis

Sensitivity analysis has been performed by considering three aspects. First, the model is simulated with a different number of neutral agents to assess sensitivity to the number of neutral agents. Secondly, the model is tested in the presence of more than two marketers to check the effect of more marketing strategies on results. Finally, the model is examined with different network structures for the connection between neutral agents. The last analysis helped us investigate the effect of network structure on the model output.

#### 4.2.1. Sensitivity to the Neutral Agents

In order to observe the impact of the different numbers of neutral agents on the simulation outputs, the model has been tested with three different numbers of neutral agents. One hundred neutral agents have been used to represent markets with a low population of potential users, 5000 neutral agents for a market with a lot of potential users, and 1000 neutral agents for simulating a market with a medium number of potential users. Figure 18 demonstrates the simulation results for these three levels of the population for dominating and nondominating versions of the model.

The interesting point about the simulation results is that the result of the low population model is different from the results of the medium and high population models. One hundred neutral agents have been used to represent markets with a low population of potential users, 5000 neutral agents for a market with a lot of potential users, and 1000 neutral agents for simulating a market with a medium number of potential users. The results of the simulations for these three levels of the population for dominating and nondominating versions of the model are shown in Figure 18.

It can be observed from Figure 18 that there is a negative correlation between the number of neutral agents and the number of replications in which the marketer with a focus on advertisement wins. In other words, by increasing the number of potential customers, the chance of winning increases for the marketers concentrating on WOM. This leads us to conclude that in large-scale markets, it is better to focus on WOM rather than the advertisement, and focusing on advertisement is more useful in the small markets.

Another important conclusion from the graphs in Figure 18 is that increasing the number of neutral agents leads to less standard deviation and increases the relative confidence of the model outputs. When there are a few neutral
agents, the standard deviation of the simulation outputs is high, resulting in much uncertainty about the winning strategy. As a result, OAF should be used with a high number of neutral agents, and this is precisely what we wanted. When the number of neutral agents is small, integrating optimization and ABM with the mentioned approaches in the literature review is a better method. However, when there are many neutral agents in the system, OAF can be more effective from computational aspects.

4.2.2. Sensitivity to Marketing Strategy. Adding more gladiators in the second phase of the OAF enables us to assess a broader range of strategies to make better decisions. To do this, 11 marketers with 11 different marketing strategies are added in the second phase. Each of these marketers dedicates a percentage of their efforts to attract neutral agents through advertising, and the rest of their effort will be devoted to attracting consumers from WOM. In other words, it is assumed that marketers have just these two options, i.e., WOM and advertisements, for spending their budget and time on, and also, they will utilize all their

| Population level | Dominating | Nondominating |
|------------------|------------|---------------|
| Low              | 0.3667     | 0.4           |
| Medium           | 0.7667     | 1             |
| High             | 0.9333     | 1             |

Figure 18: Simulation results for different numbers of neutral agents.

Table 5: Bernoulli distribution parameter for different number of neutral agents.
budgets and efforts. As a result, it will be reasonable to assume that the sum of the efforts devoted to WOM and the efforts devoted to advertisements will always be equal to 100%. Figure 19 demonstrates the proportion of the replication in which each of the marketers has won the competition in dominating and the nondominating version where the horizontal axis shows the efforts dedicated to WOM.

In both dominating and nondominating versions, the marketer who puts 30% effort into advertising and devotes 70% to WOM wins more competitions than the other ones. An interesting point about the results demonstrated in Figure 19 is that the marketers who decided to devote all of their efforts to one of the options, either WOM or advertisement, have lost all the competition. These results lead us to conclude that focusing on one of the possible strategies (either WOM or advertisement) is not the optimal solution, and the optimal solution is considering both WOM and advertisements with more concentration on the WOM.

One interesting point of OAF is that OAF has the potential to rank gladiators by the optimality of their strategies and present the optimization gap. For example, we can sort these 11 marketers by their winning percentage and present the first $n$ (a desirable number) gladiators as the best decision makers.

4.2.3. Sensitivity to the Network Structure. For evaluating the model’s sensitivity to the neutral agents’ network structure, we have simulated our original model, which is explained in the methodology section considering five standard network structures, i.e., fully connected, random, ring lattice, scale-free, and small world. Figure 20 presents the results of the simulation for these network structures. The results for the fully connected network are the same as in Figure 17.

Generally, all the results are approximately the same except the results of the ring lattice network, which is different from the results of the fully connected network and the other three networks. In order to compare the results of the random, ring lattice, scale-free, and small-world network to the fully connected network, we calculated Root Mean Squared Error (RMSE) for each of the four mentioned networks, and Table 6 shows the results.

As the graphs and RMSE measure show, the most deviation from the fully connected network is in the ring lattice network. Compared to RMSE measures of random, scale-free, and small world, the RMSE measure of the ring lattice is much higher. There are two noticeable differences in the results. In contrast to the other four networks, the winning strategy in the ring lattice network is putting more effort into getting neutral agents through advertisement. Furthermore, the convergence in the ring lattice network happens much slower than the other ones. As shown in Figure 20, in all the networks, the results converge before the 30th time step; however, in the ring lattice network, the convergence will not happen even in the 100 time steps of the simulation.

Generally, we conclude that the network structure can affect the results, and each network structure may have a different winning strategy.

It should be mentioned that we made these conclusions just based on the results from our model. This framework should be tested on lots of other applications and problems so that we can be more definite about the performance of the framework.

4.3. Discussion. OAF has some benefits that may cover some disadvantages, which have been mentioned for other methods of DM in complex models. In the following paragraphs, we will compare OAF with each of the four methods which have been explained before.

OAF vs. BBAB Modeling. The BABB modeling method is a powerful way to mimic real-world behavior; however, DM and model analysis may be challenging to perform in this method. While keeping the advantage of mimicking real-world behavior, OAF enables us to obtain proper decisions for the system.

OAF vs. WBAB Modeling. WBAB modeling facilitates the DM process through simplification. Nonetheless, this method may cause significant deviations in results from the real-world observations. OAF has been designed in a way that there is no need for simplification in any of the three phases and still facilitates the DM process by adding indicator agents to the model.

OAF vs. Optimization. One of the disadvantages of optimization as a DM tool in complex systems is that it is so difficult to define an optimization model that can consider all the complexities of the system, and also it can be solved through existing methods in a polynomial time. OAF presents a novel point of view to optimization, which does not need to define an optimization model such as described in the literature of optimization. In each optimization model, three essential parts should be defined, i.e., the objective function(s), decision variables, and constraints. Defining these three parts in a complex system in a way that the model can be solved is not an easy task and, in some cases, may not be possible. However, in OAF, optimization can be performed without defining any of those three parts. In OAF, we hold a competition between gladiators with
Dominating Non-dominating
Small world Scale free Ring lattice Random
0 2 04 06 08 0
time step
100 02 0 4 0 6 0 8 0
time step
100

Table 6: RMSE demonstrating the difference between fully connected network and other network structures.

| Network structure | Dominating | Non-dominating |
|-------------------|------------|----------------|
|                   | Blue marketer | Red marketer | Blue marketer | Red marketer |
| Random            | 156.26      | 142.88        | 21.81         | 7.25         |
| Ring lattice      | 625.97      | 301.48        | 633.16        | 387.30       |
| Scale-free        | 34.38       | 40.45         | 13.27         | 2.68         |
| Small world       | 41.24       | 41.24         | 194.03        | 74.97        |

Figure 20: Simulation results for different network structures.
different DM strategies, and the winner gladiator will be selected as the optimal agent, which can make optimal decisions in the system. In other words, in OAF, we are not looking for decision variables that optimize a predefined objective function and also satisfy the model constraints, but we are looking for a decision maker that can improve system behavior in our complex system. Therefore, in OAF, there is no need to define a classic optimization model, which is not easy in complex systems.

**OAF vs. Traditional Simulation and Optimization Integration.** As it is mentioned in the literature review (see Section 2.2.2), currently, there are two approaches for integrating DM and ABM. In both of the approaches, there are a simulation model and an optimization model in which the objective as a whole is to integrate these two models to build a model including both of them. Although this integration method adds a prescriptive aspect to the simulation and also a descriptive aspect to DM, it may impose a high computational cost on the final integrated model. In contrast to the current integration methods, OAF does not require building a DM model and integrating it with the simulation model. OAF adds the prescriptive aspect to ABM by adding an indication process to the simulation. In other words, the current methods in the literature attempt to connect simulation and DM models for the integration; however, OAF tries to revise the simulation in a way that the model performs DM and simulation simultaneously in an ABDM model. Since OAF does not require defining a DM model, it is clear that its computational cost will be much lower than the current methods. Figure 21
Comparative analysis generally compares the traditional integration vs. OAF integration. As Figure 21 shows, the traditional integration of ABM and DM results in a final integrated model composed of both AB and DM models. However, OAF helps the modeler to build an ABDM model capable of performing DM and ABM together.

5. Conclusion

In this paper, at first, we have presented a literature review on DM with ABM, which, as far as the authors are concerned, has not been proposed in the literature previously. By considering the relevant publications and performing a scientometric analysis, it is depicted that the number of publications integrating ABM and DM has not been increasing during the last decade. We investigate the reason and possible disadvantages of the current methods integrating DM and ABM. Then, a novel framework has been presented, which reduces some disadvantages of the current methods. The proposed framework does not require building a DM model to be connected with ABM; however, it adds a DM facet to the simulation by defining an indication process that is inspired by the acid-base indication process and the gladiators’ contests in ancient Rome. To illustrate the novelty of our framework (the outlook is available here), we took the Bass model of the diffusion of innovation as an example and developed a model of Bass diffusion through the OAF. The results demonstrate that our framework can compete with the existing methods for integrating ABM and DM both conceptually and computationally. However, the authors emphasize that more testing and implementations are required to have a firm conclusion about the performance of the framework.

A vision for future work is to apply this framework toward different real-world applications and assess the feasibility of OAF in real-world applications. A further critical element of future work is the development of specialized formal statistical tests for the OAF comparing the significance of the differing DMA performance.

Further computational experiments where the OAF is applied in different contexts could enhance the validity outlined here. For this purpose, some problems should be solved by each of the current methodologies and also OAF to observe and compare the performance of the current methods and OAF in terms of computational cost and quality of the solution. In addition, the complexity at the agent and population level in OAF should be evaluated and compared with the complexity of current simulation-optimization methods to demonstrate the advantage of OAF against current methods.

Developing this novel viewpoint of integrating ABM and DM may result in greater efficiency in decision support systems expediting the correct decision for a high-stakes scenario presented within complex live systems. As a result, developing, improving, and diversifying the applications of the OAF offers significant potential and a valuable contribution to the literature.

Appendix

A. Bass Diffusion Models

A.1. SD model. Figure 22 demonstrates the stock-flow diagram and the simulation output of the Bass diffusion SD model. There is a stock variable called Potential Users, indicating the number of customers that have not purchased the product yet. There is a rate variable called Change to User, which shows the number of potential users turning to a user at each time step of the simulation. Finally, a stock variable called Users is considered for aggregating the number of customers that purchased the product.

Equation (7) is the central equation in the model that should be solved.

\[
\frac{d}{dt} \text{(Users)} = (p + q \times \text{Users}) \times (\text{Total Population} - \text{Users}).
\]

(7)

If we solve differential equation (7), we will have equation (8) for users over time.

\[
\text{Users}(t) = \frac{\left(1 - e^{-\left(p+q\right)t}\right)}{\left(1 + pe^{-\left(p+q\right)t}/q\right)}.
\]

(8)

Since there are just two different states, the sum of potential users and users will always be equal to the total population. As a result, if we calculate one of them, we can easily have the other one.

A.2. AB model. To create an AB Bass diffusion model, we need one agent type called customer, which represents each customer in the model. Figure 23 shows the state chart for the customer agent type.

As shown in Figure 23, there are two ways that individuals change their state. The first way is the advertisement transition and is denoted as Ad in Figure 23. This transition represents the innovation rate in the original Bass diffusion model, and it means that in each time step of the simulation, there is a probability that the customer changes its state to a user, and this probability is equal to the p parameter of the original model.

Another transition that is defined for the customer agent type is WOM. This transition will be triggered if a customer in the potential user state receives a message to buy the product from one of the other customers who are using the product. Once the transition is triggered, it may make the customer agent change its state and buy the product. The probability that a customer buys a product after receiving a message is equal to the q parameter in the original Bass diffusion model.

There is also a third transition in the state chart shown in Figure 23, which is an internal transition. The purpose for defining such a transition is modeling the communication between the users and potential users. This transition makes the user agents randomly choose another agent and send a message to that agent and tell the other customer to buy the product.
Data Availability

The authors have tried to make the paper as self-contained as possible. However, all further data, models, codes, and analyses are available from the corresponding author upon request.

Additional Points

Highlights. (i) A scientometric gap analysis is conducted on decision-making approaches in ABM leading to the creation of OAF. (ii) OAF contributes an embedded prescriptive aspect to ABM by introducing the indication process. (iii) OAF boosts the realization of improved long-term decisions in ABM at a low computational cost. (iv) The applicability of OAF on the Bass diffusion marketing model is represented.

Conflicts of Interest

The authors declare that there are no potential conflicts of interest.

Authors’ Contributions

Abolfazl Taghavi has been responsible for investigation, conceptualization, methodology, validation, visualization, software, original draft preparation, and review and editing. Sharif Khaleghparast has been responsible for conceptualization, methodology, validation, visualization, software, review and extensive editing, supervision, and project administration. Kourosh Esghighi has been responsible for supervision, final review, and editing.

Supplementary Materials

Optimal Agent Framework outlook. (Supplementary Materials)

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