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Agent-Based Models Using Artificial Intelligence: A Literature Review

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Completed Research Paper

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Abstract

Simulations of behavior, in particular agent-based models (ABM), enhance informed decision-making. At present, Covid-19's autonomous dispersion is a notable use case, but frequent applications of the method include analyses of energy networks, traffic, and pedestrian movement. To enable an even more advanced architecture, artificial intelligence (AI) is effectively superimposed on top of the ABMs. This paper focuses on examining the state of the art of ABM enhanced by AI and its application areas. AI is applied in various ways at the different stages of the ABM development process. In current research, the main attempt is to implement AI into the agent. For this purpose, the agent's behavioral rules are enhanced or even replaced by AI structures. These mechanisms can range from simple pre-defined decisions to well-designed reward functions through which the agent learns to optimize its decisions and achieve the best possible performance.

Keywords: Agent-Based Model, Artificial Intelligence, Reinforcement Learning, Deep Learning, Machine Learning

Introduction

Agent-based modeling (ABM) is a powerful technique to create simulations or models for a wide variety of applications. This method is used to model processes with a complex structure consisting of an arbitrary sum of actors with (individual) decision patterns and interactions (Sulis & Terna, 2021; Zhang, Li, & Zhang, 2020). Real-world use cases such as the Covid-19 pandemic (Sulis & Terna, 2021), smart traffic signal control with an ever-increasing population and vehicles (Jang, Kim, Lee, & Son, 2018), or the desire for smart e-commerce systems (Yu, Vahidov, & Saade, 2015) provide application areas for ABM. Simulating different scenarios supports informed decision-making, e. g. in crisis management and companies' strategies. At the beginning of ABM emergence, humans implemented rigid decision rules for agents' interactions. To further develop the behavior of the agents or to make it more realistic to be able to precisely modulate interactions (An et al., 2021), an evolution of agents is necessary to represent real-world states/interactions/decision-making processes.

One approach is to enhance agents through machine learning. Agents can be trained during or before the simulation is running (Abdulkareem, Mustafa, Augustijn, & Filatova, 2019), supplanting an expert's fixed decision rule with self-learning agents. The combination of machine learning and expert interaction rules outperforms strict expert-based ABM as well as strictly self-learning agents (Johora, Cheng, Müller, & Sester, 2020). Even if there is incomplete information for actors in the simulation, machine learning can help to build reliable scenarios (Dehghanpour, Nehrir, Sheppard, & Kelly, 2018). As machine learning can be ranked among AI, the opportunities for optimizing ABM are increasing.

Besides the learning systems, rule-based expert systems (ES) or knowledge-based systems are referred to as AI. An ES typically consists of a knowledge base and an interference mechanism. The knowledge base is a database consisting of many if-then rules that reflect the expert's procedures and rules of behavior. Via the interference mechanism, the archived rules can be applied to new problems (Pham & Pham, 1999; VijiPriya, Ashok, & Suppiah, 2016). However, AI experiences "springs" (ups) and "winters" (downs), and since 2011 the publications related to AI have increased rapidly (Duan, Edwards, & Dwidvedi, 2019). As AI provides support to many different technologies, ABM can also profit from its methods. Models that combine ABM and AI are also referred to as hybrid models (Giabbanelli, Gray, & Aminpour, 2017). Within hybrid models, there is often a division of tasks between the AI model and the ABM. In many cases, the ABM provides the theoretical problem representation (as a computer-generated representation of reality), while the AI application provides statistical and data-driven methods (Rosés, Kadar, & Malleson, 2021). This hybrid approach is expected to generate better and more representative models, as "ABMs with intelligent agents are argued to capture complex real-world phenomena more realistically" (Abdulkareem et al., 2019, p. 244) (Giabbanelli et al., 2017). Considering the opportunities to integrate AI into ABMs and their real-world application, our research questions (RQ) are:

RQ1: How can artificial intelligence provide support for agent-based models?
RQ2: Which real-world applications can benefit from hybrids?

To answer these questions, a systematic literature review is conducted. The following chapter provides a short introduction to relevant background knowledge. Then we describe our methodology and show the results. The potential and challenges, our contributions, and limitations are proposed in the discussion section. We finalize our work with a conclusion and future research directions.

Theoretical Background

Agent-Based Modeling

"In agent-based modeling (ABM), a system is modeled as a collection of autonomous decision-making entities called agents" (Bonabeau, 2002b, p. 7280). A model is an abstracted, simplified representation of reality (Salgado & Gilbert, 2013). It serves as an analytical tool for training, testing, or debugging, and predicting real systems and promotes understanding of their complex structures and dependencies (Dignum & Dignum, 2020; Källström, 2020). According to Macal (2018), ABMs consist of three main elements:

- agent(s), which are independent, autonomously acting entities that are distinct from one another in their characteristics and behavioral patterns;
- agent relations that describe the existing possibilities of interaction among agents;
- agent environment, the "natural" habitat of the agents, which the agents can both capture and influence.

Every agent has an individual set of attributes and methods. Attributes, such as name, label, or number give the agent an identity. The methods define how the agent makes its decision (Weimer, Miller, & Hill, 2016). Basic agents decide based on mathematical equations or pre-defined decision rules implemented, for example, in "if-then" logic (Helbing, 2012). The scope of an agent depends on the modeled system and thus, agents „can model humans, organizations, or even objects, such as molecules" (Onggo, Yilmaz, Klügl, Terano, & Macal, 2019, p. 279). In addition to internal properties, agents have sensors and actuators that connect them to their environment. Sensors perceive the physical environment, while actuators convert the agent's electrical scattering signals into physical quantities to act on the environment (Russel & Norvig, 2020). Agents not only communicate with their environment but also interact with other agents within the model (Craven & Krejci, 2017). The exchange usually does not take place among all agents simultaneously, but at certain points in time, a limited number of agents exchange information with each other. Agents that communicate frequently with each other should be placed as close as possible to each other in the model to establish networks/neighborhoods with short walking distances (Macal, 2018; Ramos, Sánchez, Muñoz, Marcial-Romero, Valle-Cruz, López, & Ramos, 2018).

Following Salgado & Gilbert (2013), the development/setup of an ABM can be divided into three phases. The first phase is the specification and formalization phase. It determines which questions the model should answer later. Data sources, scope, and level of abstraction of the agents and environment are defined. Also, the interaction and behavior rules between agents and the environment are outlined (Helbing, 2012; Macal, 2018; Salgado & Gilbert, 2013). This is followed by the modeling, verification, and experimentation phase. Using dedicated modeling and simulation environments such as AnyLogic or NetLogo, the theory specified in the first phase is concretized, tested, and translated into a mathematical or logical computer program (Augustijn, Abdulkareem, Sadiq, & Albabawat, 2020; Chen, Londoño-Larrea, McGough, Bible, Gunaratne, Araujo-Granda, Morrell-Falvey, Bhowmik, & Fuentes-Cabrera, 2021; Giabbanelli, Fattoruso, & Norman, 2019; Macal, 2018; Salgado & Gilbert, 2013). The last phase, the calibration and validation phase, checks the correct implementation and mapping of the theory to the model. Professional handling of the model, comprehensibility, and correctness of the model as well as output are prioritized (Helbing, 2012; Salgado & Gilbert, 2013; Sulis & Terna, 2021).

Artificial Intelligence, Machine Learning and Deep Learning

Research in the field of "Artificial Intelligence" investigates in which way a computer can be made to think. AI encompasses all applications in which a machine mimics intellectual and cognitive functions that humans perceive as "Learning" or "Problem-Oriented Thinking" (Camarinha-Matos, Ferreira, & Brito, 2021; Chollet, 2018; de Paula Ferreira, Armellini, & De Santa-Eulalia, 2020). In the field of AI, numerous methods and tools are available for imitating or emulating human intelligence. However, AI does not presuppose a learning effect, as even "hard-coded" rules in a system (e.g., if-else loops implemented by humans), such as in chess computers, fall into this domain (Chollet, 2018). A higher level of intelligence and autonomy, especially in searching for rules and patterns in data while reducing human involvement, is achieved by two approaches: machine learning and deep learning (Camarinha-Matos et al., 2021; Janiesch, Zschech, & Heinrich, 2021). According to Chollet (2018) and Janiesch et al. (2021), ML can be divided into three categories:

- Supervised learning (SL) uses training data, data sets with known and declared input, and output parameters. Based on this data, the algorithm learns or finds rules and relationships to map the input to the output. The algorithm stores the discovered rules in structures such as decision trees or neural networks (Batata, Augusto, & Xie, 2018). After the training phase, the SL algorithm can be applied to new, unknown data to predict the output. A distinction is made between regression and classification tasks. Regression tasks predict a numerical value and classification tasks a categorical class (Janiesch et al., 2021).
- Unsupervised learning (UL) algorithms work with unknown, undeclared data in comparison to supervised learning. The goal is to recognize patterns and similarities without knowing the exact specifications of the data to find groups with common properties. This grouping of elements with common properties is called clustering. Alternatively, UL can be used to reduce the dimensions of the data, i.e., multi-dimensional data is projected into a lower-dimensional level (Chollet, 2018; Janiesch et al., 2021).
- Reinforcement learning (RL) algorithms do not require data for conditioning. Instead, they learn from the interaction with their environment. Decisions are made via a trial-and-error process. Based on the quality of the decision, the algorithm receives positive or negative feedback (e.g., a reward in the form of score points). With time, the algorithm tries to maximize its reward/positive feedback (Chollet, 2018; Craven & Krejci, 2017).

Deep learning is a sub-area of ML and uses "deep" neural networks. Neural networks are based on the information processing of the human brain. The structure of a neural network consists of interconnected artificial neurons (memory cells) (Janiesch et al., 2021). Comparable to the synapses in the human brain, connections transmit signals between the neurons. The signals are not equal but weighted differently. The next neuron reacts only if a specific threshold value - determined by the so-called activation function - is reached (Chollet, 2018; Janiesch et al., 2021). A neural network is typically organized in different layers. An input layer stores the data to be processed, and the output layer outputs the final result. Between these two layers, there are one or more hidden layers responsible for learning input to output mapping (Chollet, 2018; Cummings & Crooks, 2020). In DL, a neural network usually consists of more than one hidden layer. In addition, deep neural networks access extended, more complex neurons, which, for example, enable the possibility of case discrimination through multiple activation functions (Chahal & Gulia, 2019; Harfouche, Quinio, Skandrani, & Marciniak, 2018; Janiesch et al., 2021). In Table 1 a summary of machine learning methods can be found.

	Machine Learning			
	Supervised Learning	Unsupervised Learning	Reinforcement Learning	Deep Learning
Objective	Trained input to output relation	Classify, discover underlying patterns	Learn a sequence of actions	Intensified machine learning approach
Input Dataset	Labeled, pre-processed, structured	Unlabeled without order	Without any predefinition	Large and high-dimensional
Feature Engineering	Features and relations of the data must be understood			No restrictions
Processing	Detects rules for mapping input to output	Recognizes correlations & patterns; creates corresponding clusters	Gaining feedback for actions from the environment; maximizing cumulative reward	Creates neural network similar to the human brain; updates weights to reduce output error
Output	Model with input-output rules	Detected structure or distribution of data	Evolving action model	Neural network model
Model Interpret-ability	Algorithm dependent, e.g. decision trees are easy to interpret, whereas neural nets or support vector machines are almost impossible to interpret[1)]			Impossible[1)]
[1)]The current field "Explainable Artificial Intelligence (XAI)" explores how to create AI models where the steps and results can be understood by humans (Liao, Gruen, & Miller 2020)				

Table 1. Overview ML Methods (own illustration based on Chahal & Gulia 2019; Chollet 2018; Janiesch et al. 2021)

Importance of Hybrid Models

ABMs are developed as an explanatory apparatus for real-world problems. Autonomous, individually configurable agents should represent the model as realistically as possible and handle complex, nonlinear problems (Macal, 2016; Onggo et al., 2019). Therefore, ABMs are used in practice in a wide variety of fields. Macal (2016) and Weimer et al. (2016) identify numerous application examples such as the modulation of energy webs, supply chains, smart manufacturing, disease spread, tourism, and urban planning that cut across the social, economic, and military sectors. Contrary to the theory of complex, realistic, heterogeneous agents, in practice, they are often implemented rationally and homogeneously and do not consider external factors (Dignum & Dignum, 2020). Thus, this also limits the entire model to the performance of the agents. A problem that was already pointed out early by Macy & Willer (2002) is that the solution approach is always already known to the agent since it is embedded in its routines. This massively limits the adaptability of the agents and, at the same time, of the model (Macal, 2016). Furthermore, Bonabeau (2002a) stated that ABMs can only work with the data or assumptions available to them. Thus, the ABM is limited to the knowledge and skills of the modeler and the database at the time of development. The approach to this challenge is the implementation of artificial intelligence in the behavioral patterns of the agent (Harfouche et al., 2018). In order to cope with the continuously significant increase in dynamics in these processes, the goal is to further develop rule-based agents into data-based agents that independently find and apply rules without the modeler having to intervene. It should also be possible to let the agent analyze and process (big) data independently in real-time, e.g., from their own sensors, databases or social networks (Cummings & Crooks, 2020; Ramchandani, Paich, & Rao, 2017). “However, this integrating is still in its infant stage“ (Augustijn et al., 2020, p. 284).

Methodology

To answer the research questions, the status quo of AI integration into ABMs is examined through a systematic literature review. The approach of this literature review is based on the structures proposed by vom Brocke, Simons, Niehaves, Riemer, Plattfaut, & Cleven (2009) and Webster & Watson (2002), which describe the path from general search to specific results. According to vom Brocke et al. (2009), the literature search starts with the conceptualization of the topic. In an unstructured search, the search fields “agent-based model” and “artificial intelligence” are first delineated to provide a theoretical background for the analysis. The articles in this comprehensive search are scanned to identify keywords. Through this process, the terms “agent-based model”, “agent-based modeling”, and the commonly used synonyms “agent-based simulation” or “agent-based simulating” are iteratively identified. The terms model and simulation are therefore modified with an asterisk operator to include all word endings such as “-ing” in the search. Since a noticeably high correlation between the fields ABM, AI, ML, and DL is found in the initial search, these subject fields are included as independent search terms in the literature search:

(“agent-based model*” OR “agent-based simulat*”) AND

(“artificial intelligence” OR “machine learning” OR “deep learning”)

In the second step, following vom Brocke et al. (2009), suitable databases are selected for the search. In order to cover as wide an area of application of the ABM as possible, the research is finally conducted in the databases “ACM Digital Library”, “AIS eLibrary”, “Emerald Insight”, “IEEE Xplore” and “Scopus”. To highlight the status quo, the search is narrowed down to the publication period from 2016 to 2021. In addition, only English-language articles are considered in the search. The initial searches also show that for the Scopus database a full-text search is not appropriate, as a hit rate of n > 10,000 results is obtained. The randomly selected search results often show little or no relationship between the fields of ABM and AI. Therefore, the search is limited to the title, abstract, and keywords of the articles. A full-text search is performed in the other databases. The search is conducted on November 15, 2021. Table 2 lists the databases and the corresponding number of articles found. The identified articles are assessed in an initial screening by reviewing the title, abstract, and keywords. Articles that exclusively address the ABM or AI fields without referring to each other are excluded.

	Source	Search Results	1st Screening	2nd Screening
Database Search (vom Brocke et al. 2009)	ACM Digital Library	142	47	8
	AIS eLibrary	72	21	3
	Emerald insight	252	12	2
	IEEE Xplore	151	36	11
	Scopus	390	43	17
Total		1007	159	41
Forward / Backward Search (Webster & Watson 2002)	ResearchGate	46	12	10
Final Sample				51

Table 2. Outcome of the Literature Review

To obtain qualitatively useful results, only peer-reviewed articles are considered. Furthermore, duplicates among the different databases are identified and sorted out. In this first phase, a total of n = 159 articles is identified for further processing. In the second step, the abstract, methodology, result, discussion, and conclusion of all remaining articles are examined in more detail through in-depth screening. Pure literature reviews and articles without or with unclear methodology are also excluded. This procedure results in n = 41 articles. Supplementary forward and backward searches are performed as recommended by Webster & Watson (2002) to find additional literature through the references of the articles. Articles found accordingly are obtained from the "ResearchGate" portal. The n = 46 articles found in this way are first analyzed in the same way as the articles in the database search in the individual introductory and concluding chapters. The evaluation according to relevance and significance by the in-depth screening results in a total of 10 articles. Finally, the full text of each of the n = 51 articles is read. No further exclusions are found in the process.

Results

Sample Description and Evaluation

A clear trend cannot be derived from the distribution of articles, although over the years 2016 to 2018 the number of publications on the topic has grown. Despite the increasing topicality of the subject in more and more areas, there has been no further growth in publications per year from 2019 to 2021. It should be noted that the year 2021 is not fully represented since the literature search was conducted on November 15, 2021, and thus only includes articles published before that date. To further structure and provide a comprehensive insight into the deployment areas of AI in ABMs, the concept matrix shown in Figure 1 was created. It contains, analyzes, and categorizes all 51 papers found during the literature review and helps to present the results coherently. In the following paragraph, a short description of the concept matrix is given, which is only intended to help understand its structure. Details will be described in the chapter "Artificial Intelligence Integration".

The concept matrix is a two-dimensional representation. There, the categories "domain" and "ABM phase AI integration" with their respective substructures are arranged in columns, while the rows list the publications in alphabetical order. The first column of the matrix indicates the paper. In the domain category, assignments are indicated by an "X". In contrast, in the category "ABM phase and AI integration", the assignment between AI method, and ABM phase is indicated by black shading of the corresponding fields. Inside the marking is or are indicated the respective applied AI methods and "NA" summarizes methods that cannot be categorized clearly. It is noticeable that most contributions deal with topics that can be assigned to the four areas of energy, health, bulk motion, and behavior based on their content. In addition, eight reports are identified that could not be assigned to any of these overarching domains based on their subject matter. These cases can be identified by the fact that they are not assigned to an area by an "X", but their topic is entered as text in the linked cells.

The second category considers the different support approaches that AI offers. In the analyzed works, different tools are used at different points within the ABM process. For structuring purposes, a modified version of the ABM phases defined in the chapter "Agent-Based Modeling" is used here, following Salgado & Gilbert (2013). The AI approaches from all the papers are extracted, classified, and entered into the matrix accordingly. Since it happens that authors address several or combined AI approaches or ABM phases in their work, there may be multiple entries for phases or approaches within a single row. The alternative use of multiple solution methods within one ABM phase is marked by a backslash ("/"), while the additive combined use of AI tools is marked by the plus sign ("+"). While the formal definition of the contents and expected values of ABM phases is relatively clear, the precise differentiation of the application or assignment of the AI method to a phase is not always possible. For example, SL generates rules that can be viewed as formal input to the generation of an ABM. However, the focus of using SL is to develop a self-contained model that can be adapted, evolved, and refined. The agents of the ABM are then linked to these models. Thus, arguments can be found for assignment in either of the phases one or two. To account for this fuzziness, examples in the concept matrix are assigned to their main phase, but a black-to-white transition is meant to indicate that the method can go beyond this phase.

#	Paper	Domain				ABM phase ⇔ AI integration			
		Energy	Health	Bulk motion	Behavior	I Specification Formalization	II Modelling / Verification: II.1 Training (offline)	II.2 Learning (online)	III Calibration Validation
1	Abdulkareem, Augustijn, Mustafa, & Filatova (2018)		X				SL		
2	Abdulkareem, Mustafa, Augustijn, & Filatova (2019)		X				NA / SL	SL	
3	Augustijn, Abdulkareem, Sadiq, & Albabawat (2020)		X				SL		
4	Batata, Augusto, & Xie (2018)		X				SL		
5	Brearcliffe & Crooks (2020)				X			NA / RL	
6	Brito, Campos, & Leite (2018)	crime prediction							SL
7	Chen et al. (2021)		X						SL / DL + SL
8	Chrysanthopoulos & Papavassilopoulos (2016)	X						RL	
9	Craven & Krejci (2017)			X				RL	
10	Dehghanpour, Nehrir, Sheppard, & Kelly (2016)	X					SL		
11	Dehghanpour, Nehrir, Sheppard, & Kelly (2018)	X					DL + SL	RL	
12	Edali & Yücel (2019)			X					SL + UL
13	Egea, Howell, Knutins, & Connaughton (2020)			X				DL + RL	
14	Fuji, Ito, Matsumoto, & Yano (2018)			X				DL + RL	
15	Fuller, de Arruda, & Ferreira Filho (2020)			X				RL	
16	Ghavamipoor & Golpayegani (2020)			X				RL	
17	Giabbanelli , Fattoruso, & Norman (2019)				X		NA		
18	Giabbanelli, Gray, & Aminpour (2017)				X		NA		
19	Gopalan & Wikle (2021)			X					SL
20	Jang, Kim, Lee, & Son (2018)			X				DL + RL	
21	Johora, Cheng, Müller, & Sester (2020)			X			NA	DL + SL + UL	
22	Kang, Bae, Lee, Jung, & Paik (2018)				X			RL	
23	Karbovskii et al. (2021)			X			SL / DL + SL		
24	Kavak, Padilla, Lynch, & Diallo (2018)			X			SL / UL		
25	Kell, Forshaw, & McGough (2020)	X							NA / UL
26	Khatami & Gopalappa (2021)		X					RL	
27	Lamperti, Roventini, & Sani (2018)				X				SL + UL
28	Le, Vinh, & Zucker (2017)	crisis management							NA / RL
29	Lee et al. (2017)				X	IRL / UL			
30	Li et al. (2019)	urban planning						RL	
31	Murase, Jo, Török, Kertész, & Kaski (2021)				X				DL + SL
32	Negahban (2017)				X		SL		
33	Ostrosi & Fougères (2018)	manufacturing					NA		
34	Oudaa, Gharsellaoui, & Ben Ahmed (2021)	computing power						DL + RL	
35	Padilla, Shuttleworth, & O'Brien (2019)				X	NA			
36	Pang, Tsubouchi, Yabe, & Sekimoto (2020)			X		IRL		RL	
37	Perry & O'Sullivan (2018)				X				SL / UL
38	Rajulapati, Nukavarapu, & Durbha (2020)	crisis management						DL + RL	
39	Ramchandani, Paich, & Rao (2017)				X		SL	RL	
40	Raoufi & Fayek (2021)				X		NA + UL		
41	Rosés, Kadar, & Malleson (2021)	crime prediction					SL		
42	Sankaranarayanan, Laite, & Portman (2017)			X			SL / UL		
43	Shuvo, Ahmed, Kabir, & Shetu (2020)		X					DL + RL	
44	Shuvo, Ahmed, Symum, & Yilmaz (2021)		X					DL + RL	
45	Sousa & Tome Saraiva (2020)	X						RL	
46	Sulis & Terna (2021)		X					NA	
47	van der Hoog (2019)				X		DL + SL + UL	DL + RL	DL + SL + UL
48	Wang, Wu, & Che (2019)	X						RL	
49	Yin, Yu, & Zhou (2018)	X						DL + RL	
50	Zhang, Li, & Zhang (2020)	financial simulation							SL
51	Zhao & Liu (2021)	X						RL	

Figure 1. Concept Matrix

Application Areas of Hybrids

After reviewing the literature sources, four main use cases for the developed ABMs were identified. A total of ten areas are delineated. At the top of the list, with thirteen papers each, is the use of hybrid ABM-AI models in the domains “behavior” and “bulk motion”. Those are followed closely by “health” with nine entries and “energy” with eight.

The area “behavior” focuses strongly on ABMs that revolve around the decision-making process or the behavior of living beings. Various applications are found, among others, in the economic field. It models how customers perceive word-of-mouth advertising (Negahban, 2017) or how traders design their prices (Lamperti, Roventini, & Sani, 2018). In addition, there are also models for people’s tendency toward retirement planning (Ramchandani et al., 2017), military conflicts (Brearcliffe & Crooks, 2020), and agricultural challenges (Giabbanelli et al., 2017) to the behavior of hunter-gatherers (Perry & O’Sullivan, 2018). In contrast, papers that fall into the domain of “bulk motion” are concerned with the capture and simulation of dynamics of large masses. Frequently, such ABMs are encountered in the transport sector. Often, this can be the traffic on the roads, which is analyzed in terms of volume and regulation (Egea, Howell, Knutins, & Connaughton, 2020; Jang et al., 2018). This application is not limited to the vehicle level. There are also models of the sharing of space between pedestrians and vehicles (Johora, Cheng, Müller, & Sester, 2020) or that refer to the movement patterns of crowds of people (Karbovskii, Lees, Presbitero, Kurilkin, Voloshin, Derevitskii, Karsakov, & Sloot 2021) or animals (Gopalan & Wikle, 2021). However, traffic can also refer to intangibles, and so there are also hybrid models of transport/load on service channels (Sankaranarayanan, Laite, & Portman, 2017). Other examples from this domain include models for the movement of goods along the supply chain (Ghavamipoor & Golpayegani, 2020), as well as for food distribution (Craven & Krejci, 2017).

In the domain “health”, ABMs are primarily used to model the spread of diseases (also including the vaccination approach). Many models exist for various diseases, such as Covid19 (Sulis & Terna, 2021), Cholera (Abdulkareem, Augustijn, Mustafa, & Filatova, 2018; Augustijn et al., 2020), and HIV (Khatami & Gopalappa, 2021). Moreover, the capacity planning of hospital beds (Shuvo, Ahmed, Symum, & Yilmaz, 2021; Shuvo, Ahmed, Kabir, & Shetu, 2020), and bacterial growth (Chen et al., 2021) can also be found as hybrid models. The papers assigned to the “energy” area apply the ABM to power grids. The models are mainly concerned with load balancing, which is gaining considerable importance in the course of the increasing deregulation of the electricity market (Kell et al., 2020; Yin, Yu, & Zhou, 2018) including price fluctuations for electricity (Chrysanthopoulos & Papavassilopoulos, 2016; Dehghanpour, Nehrir, Sheppard, & Kelly, 2016; Wang, Wu, & Che, 2019).

In addition to these four broad domains, which together account for more than three-quarters of the papers, the literature review identifies eight papers that do not fit into these areas. Two of them deal with the topic of crisis management. In their paper, Rajulapati, Nukavarapu, & Durbha (2020) create an ABM that maps critical infrastructures in times of crisis, Le et al. (2017) investigate evacuation signs in case of a tsunami. Two of the other papers address crime. Rosés, Kadar, & Malleson (2021) simulate crime patterns in an urban environment, while Brito, Campos, & Leite (2018) present an ABM for fraud detection. The remaining papers are devoted to the subject of financial analysis of the Chinese stock market (Zhang et al., 2020), distribution of cloud computing power (Oudaa, Gharsellaoui, & Ben Ahmed, 2021), the implementation of ABMs to improve manufacturing (Ostrosi & Fougères, 2018) as well as the application to urban city planning (Li et al., 2019).

Artificial Intelligence Integration

Even the basic form of an agent built by simple and hard-coded if-then rules can be considered artificially intelligent. The implemented rules mimic human problem-solving abilities and thus fulfill the definition of AI (Abdulkareem, Mustafa, Augustijn, & Filatova, 2019; Chollet, 2018). However, these procedural rules represent only a minimum level of intelligence. In order to deploy actual or higher levels of intelligence - up to and including autonomous learning behavior - more complex and functional AI mechanisms and tools are linked to the ABM (Craven & Krejci, 2017; Oudaa et al., 2021; Wang et al., 2019). To break down the typical approaches and commonalities of AI integration, the development process of an ABM according to Salgado & Gilbert (2013), as introduced in Chapter “Agent-Based Modeling”, is taken up.

- In phase I, the basics are arranged and put into context. The assumption or prerequisite to create an ABM is that the modeler knows the underlying agent number, behavior, and rules, as well as interactions between agent(s) and the environment (Lee et al., 2017; Padilla et al., 2019). Yet, this knowledge is "potentially requiring deep insight and domain knowledge" (Lee et al., 2017, p. 1264). Therefore, the modeler is faced with the considerable challenge of acquiring this knowledge himself, for example through empirical and theoretical literature (Rosés et al., 2021). Here, AI can be used to localize and delineate structures and optimize the formulation of the problem (Lee et al., 2017; Padilla et al., 2019).
- In phase II, the theory from the first phase is translated into a computer program. Through test runs, the internal ABM parameters, especially the agent behavior, are changed until the desired model behavior can be set (Brearcliffe & Crooks, 2020; Salgado & Gilbert, 2013). In terms of AI integration, the key question here is: How can the components of ABM become smarter? The underlying solution approach is to use AI mechanisms to replace, augment, or optimize the agent's internal behavioral rules (Giabbanelli et al., 2019; Sulis & Terna, 2021; van der Hoog, 2019). The integration of AI at the agent level can be done in two ways. Either the AI model is developed in advance and thus ready to use in the agent, or AI tools are used to learn and improve from the agent's decisions- that means during the runtime of the ABM (Karbovskii et al., 2021; Khatami & Gopalappa, 2021; van der Hoog, 2019). "Whether an ABM is a good approximation of the original system depends on the verification of the results" (Zhang et al., 2020, p. 1).
- Phase III tests if the ABM works sufficiently correctly and realistically and how comprehensible the model is overall. To verify the reliability of the ABM, a comparison of model and reality is ideal (Li et al., 2019; Zhang et al., 2020). However, due to their nature - as a representation of reality - ABMs usually have a large number of parameters that need to be checked and understood (Chen et al., 2021). In addition, data may not be available to verify their proper operation (Kell et al., 2020). AI applications in this area support the calibration and validation process of the ABM. This can be done either by analyzing the ABM results, e.g., by breaking down their complexity and providing additional explanations (Brito et al., 2018; Perry & O'Sullivan, 2018), or by using AI models as an alternative to the ABM to verify its procedures and solutions (Kell et al., 2020; Lamperti et al., 2018). The use of AI models as substitutes for ABMs is also referred to as surrogate modeling or metamodeling (Chen et al., 2021; Lamperti et al., 2018), while narrative modeling describes the use of AI to simplify and explain existing ABMs (Perry & O'Sullivan, 2018).

Improving the Agent-Based Modeling Approach

With a total of only three AI tools used, phase I is the one considered in the fewest contributions. Here, methods are used that deal with the recognition of patterns in data structures or have been modified for this purpose and are rarely found in the other phases.

One possible solution is Inverse Reinforcement Learning (IRL), a special form of RL. While RL centers on learning a set of actions that maximize the agent's reward, IRL does not. Instead, the IRL algorithm observes a working, functioning system and thereby learns the structure of the reward function and thus, properties, behaviors, and patterns of the system (Lee et al., 2017; Pang, Tsubouchi, Yabe, & Sekimoto, 2020). For example, in their paper, Pang et al. (2020) explore the human movement patterns in cities. Through GPS tracking, people are followed in everyday life and the deployed IRL algorithm detects and extracts the underlying behavior patterns – e.g., whether people visit the supermarket at a certain time/day in the week - to later build an ABM based on them. Lee et al. (2017) additionally propose the use of UL to achieve a more fine-tunable model granulation. For this purpose, clusters are formed before the rules are extracted via IRL. In this way, the desired degree of homogeneity or heterogeneity to be depicted later in the ABM can be regulated.

Another approach is provided by natural language processing (NLP). Here, Padilla et al. (2019) introduce an NLP analyzer tool that is able to capture an unstructured phenomenon description in textual form. Using this input, the analyzer provides a set of possible agents, attributes, and rules to aid in the further conceptual design of the model.

Enhancing the Agent

The second ABM phase is most frequently supported by AI mechanisms. In 39 different papers, a total of 49 AI deployments are described for this phase. This category is led by RL with 14 use cases, closely followed by SL with twelve and Deep RL with nine deployments. In line with the distinction between offline training and online learning of AI tools, both approaches are considered in more detail below.

Moving from simple, hard-coded agents, ESs offer the most proximate integration of AI. A total of two use cases were found during the literature review. The agents are also programmed here with explicit if-then conditions by the modeler (Johora et al., 2020). Compared to the basic agent unit, the expert approach is usually characterized by detailed expertise and a comprehensive understanding of the context. This is reflected in the mastering of appropriate case distinctions and capturing and handling unexpected conditions (Abdulkareem et al., 2019; Johora et al., 2020). With a total of four applications, the use of fuzzy logic (FL) is slightly more popular. Authors such as Giabbanelli et al. (2017) propose the use of a so-called fuzzy cognitive map (FCM), which are influence diagrams. As an enhancement of the if-then coding, FL tools describe relationships and dependencies between elements while accounting for uncertainty and vagueness (Giabbanelli et al., 2017; Ostrosi & Fougères, 2018). Once the FCMs are developed and calibrated, they are used as decision logic in the respective agents. By using different FCMs for the different agents, "a virtual population of agents with sophisticated decision-making processes" (Giabbanelli et al., 2017, p. 320) can be created. Software such as the "CoFluences" application developed by Giabbanelli et al. (2019) also allows for the simultaneous elaboration of FCMs and ABMs.

The leading method in the offline training category is SL with twelve examples found. SL requires precise historical training data to "learn" the connections between input and output itself. Popular techniques include decision trees, random forests, neural networks, and Bayesian networks. Which tool is chosen depends on the available data (-sources) as well as the complexity of the problem and the desired solution (Batata et al., 2018; Brito et al., 2018). Decision trees are preferably used, for example, when features are to be sorted according to their importance or the output is supposed to be easily understood (Augustijn et al., 2020). In the simplest approach, the SL replacement model for the targeted agent behavior is experimentally created and modified. These rules can then be extracted from the decision tree, so to speak, and subsequently incorporated into the agent as hard-coded rules (Augustijn et al., 2020). Therefore, to a certain extent, it is also possible to locate the SL application area in phase I according to the phase classification since rules for the design of the entire ABM can be derived from the SL method (Augustijn et al., 2020; Kavak et al., 2018). However, most authors fully integrate the SL model into the ABM. This means that there is no manual extraction and adaptation of the identified SL behaviors. Instead, the SL model is stored directly within the agent after completing the modification and training phase (Batata et al., 2018; Dehghanpour et al., 2016; Negahban, 2017).

In online learning, AI tools are trained during the ABM runtime (Augustijn et al., 2020; van der Hoog, 2019). Although RL is very dominant with 14 examples, SL, UL, or genetic algorithm (GA) approaches can also be found here. In these, the SL model is trained using the agent's decisions rather than prior data before it is used as the decision framework. The SL model basically sits on top of the ABM, receives the same inputs, and the output of the ABM is passed as a label/target (Abdulkareem et al., 2019). For this mode of operation, however, a functional ABM is required, and its agents must be present at least in hard-coded form. Moreover, these SL models merely represent the status quo. After the training phase is complete, SL models are limited to the rules learned up to that point. New rules must be stored by re-training (Ramchandani et al., 2017). In ABMs "it is necessary to guarantee that the behavior and interaction rules, which form the agents' policies, are sufficient and valid for a wide range of expected states in all cases" (Fuller, de Arruda, & Ferreira Filho, 2020, p. 1723). With the AI tools presented so far, it is difficult to almost impossible to cover all case distinctions and potential progression paths. To overcome these limitations, the RL approach is used in online learning where agents teach themselves. In the ABM, a feedback loop is implemented that rewards or punishes the agent based on its decisions (Jang et al., 2018).

There is a strong tendency towards the Q-learning algorithm in the integration of the RL (Craven & Krejci, 2017; Dehghanpour, Nehrir, Sheppard, & Kelly, 2018; Yin et al., 2018). In that process, the agent accumulates knowledge over time, which it stores in a quality value matrix (Sousa & Tomé Saraiva, 2020). While the agent acts predominantly at random (trial and error) at the beginning of the ABM runtime, its experience updates. As time progresses, agents reduce random decisions and instead draw on accumulated experience (Brearcliffe & Crooks, 2020). This allows the system to stay up to date even in an environment that changes over time and to adapt its own behavior to the new circumstances (Sousa & Tomé Saraiva, 2020; Yin et al., 2018). In addition to RL, GA and UL methods can also be used for online training. For example, Johora et al. (2020) apply a UL clustering algorithm to a running ABM. In this example, the individual agents represent pedestrians and can be assigned to groups of people by the UL algorithm while the ABM is still running. On the other hand, Sulis & Terna (2021) propose a GA approach which is applied on top of the ABM. In their study of the vaccination strategy against Covid 19, the authors use a GA that selects the vaccinated groups of people and applies genetic operators. Over time, the GA, in combination with the ABM, develops an optimal vaccination strategy.

Optimizing the Validation Method

Referencing eleven papers that cover a total of 15 different AI implementations in the validation and calibration phase, this is the second most common category. For the creation of an ABM replacement (meta/surrogate model), the SL approach is beneficial overall. Instead of referring to the inner part of the ABM, the agents, the SL model is set up in parallel to the ABM (Murase, Jo, Török, Kertész, & Kaski, 2021). This means that ultimately two models are created for the same application. The parameters in the ABM can be adjusted and the output verified even if no real data is available (Murase et al., 2021; Zhang et al., 2020). To ensure verification even for ABMs with a small database, Lamperti et al. (2018) propose a combination of SL and UL. In this semi-supervised approach, the model is first trained on the known data. Then, the model is used to classify the unknown data before being trained again on the known and predicted data. To simplify the ABM, the papers consider approaches using GA, SL, UL, and RL. Instead of training the SL model on data, Brito et al. (2018) relate it to the ABM, which simulates a large network of transactions that may or may not be a fraud. To contain the resulting information overload, the SL model is then used to classify fraudulent and normal transactions. Le et al. (2017) take a similar approach to reduce the complexity of an ABM. Using an RL algorithm, the behavior of the ABM is learned and then translated into a simpler linear model.

Moreover, UL can be used to detect patterns in the output of an ABM, while GAs can further refine or evaluate the solutions found by the ABM in terms of fitness (Edali & Yücel, 2019; Le et al., 2017). In their work, Perry & O'Sullivan (2018) combine the UL approach with a SL mechanism to generate a narrative for an ABM about hunter-gatherer foraging and the survival chances. The UL is used to analyze the process and output of the ABM. Groups of similar scenarios (process and output of the model) are formed. Then, it is investigated which parameters influence the model run, i.e., steer the scenario in a different direction. For this purpose, the authors propose a classification algorithm in the form of SL random forests.

About Deep Learning

As can be seen in Figure 1, ML tools are often used in conjunction with a DL approach. Such configurations are mainly found in Phase II, where the DL type is used in combination with RL, while only a few DL applications are found in Phase III, where they are in turn connected to other mechanisms. DL does not require special feature engineering, which means that more complex tasks can be processed and solved with higher-dimensional data. This method can also be used for SL and UL approaches in the same way and enables the solution of more complex tasks here as well (Chollet, 2018; Yin et al., 2018). In general, it can be assumed that models with DL show increased robustness, which can be seen, for example, in qualitatively better results with lower error rates (Murase et al., 2021; Rajulapati et al., 2020; Yin et al., 2018).

As mentioned earlier, the DL approach is often used in combination with RL in ABM. The reason is that RL algorithms are subject to two limitations, which will be briefly described below using the Q-learning algorithm as an example. In Q-learning, the agent gradually creates a matrix in which the actions to be performed are stored (Rajulapati et al., 2020; Sousa & Tomé Saraiva, 2020; Yin et al., 2018). However, as the size of the environment increases, the matrix becomes unwieldy and difficult to process. In addition, the agent must constantly explore the environment to fill the Q-matrix with the optimal values. Therefore, the RL algorithm has a slow convergence rate (learning speed) as well as high dimensionality (Sousa & Tomé Saraiva, 2020; Yin et al., 2018). By combining it with DL, a deep neural network (DNN) replaces the matrix and approximates its content. The combined approach thus circumvents the limitations by having the DNN manage the large input sets while also managing the values of the Q-matrix (Yin et al., 2018).

Discussion

As shown in the section "Results", AI methods support ABM at different stages. The individual benefit or impact of AI in ABM is directly related to the supported phase:

- In Phase I, AI is used to extract information for ABM design from databases. Through AI, either the modeler can gain a deeper understanding of the data and framework, or the ABM can be built and developed in a data-driven manner (Lee et al., 2017; Padilla et al., 2019; Pang et al., 2020).
- In Phase II, the AI tools are used to focus on improving and evolving the agent with the goal of increasing the accuracy and credibility of the ABM (Negahban, 2017; Rosés et al., 2021). To this end, agent performance is extended, either through more complex, far-reaching AI sub-models that the agent draws upon, or through evolution toward autonomous learning or adaptive agents (Abdulkareem et al., 2018; Khatami & Gopalappa, 2021). This eliminates the need to manually revise the ABM as the environment changes during runtime, and also to account for unforeseen uncertainties that may arise (Pang et al., 2020; Ramchandani et al., 2017; Sousa & Tomé Saraiva, 2020).
- In Phase III, the results of an ABM need to be validated by an independent AI model (Murase et al., 2021; Zhang & Zhang, 2020). In addition, it is possible to break down sophisticated ABMs into simpler models, which reduces the computational resources and runtimes required (Brito et al., 2018; Le et al., 2017). Moreover, the output of an ABM can be explained in an understandable way using AI tools (Chen et al., 2021; Perry & O'Sullivan, 2018).

All of the papers found report substantially better results associated with more powerful ABMs when AI is used. However, there are specific requirements and challenges that must be considered in any implementation (Abdulkareem et al., 2019; Batata et al., 2018).

Depending on the AI approach chosen, different baselines are needed. For example, ESs require specific background knowledge, while NLPs and FLs require domain knowledge, such as the process for creating an FCM (Giabbanelli et al., 2019; Johora et al., 2020). SL, in turn, typically demands a large database for its training, which needs to be significantly larger when applying DL (Abdulkareem et al., 2019; Jang et al., 2018; Murase et al., 2021). In many cases, the data must first be collected through surveys or the like. In the subsequent pre-processing phase, the data is thoroughly checked and prepared by the modeler to ensure that the ML algorithm receives complete and error-free data sets (Abdulkareem et al., 2019; Kavak et al., 2018). The use of GAs goes even further and mandatorily requires the provision of a solution to the problem, since GAs only further refine existing solutions through their mode of operation (Le et al., 2017; Sulis & Terna, 2021).

In general, it is not predictable which AI tool will achieve the best results in combination with the ABM. Authors like Batata et al. (2018) and Brearcliffe & Crooks (2020) therefore suggest the simultaneous development (including fine-tuning of model parameters) of several AI models. Thereof, the model providing the best results shall be developed further. At the same time, the available resources are to be considered (Brito et al., 2018; Chen et al., 2021; Le et al., 2017). The DL method, for example, requires significant computing power and time until the AI model finally emerges (Murase et al., 2021). Moreover, when ABMs get closer to the real system, they may become less interpretable, as the insertion of more complex AI methods tend to make the ABM less understandable and tractable (Augustijn et al., 2020). This process leads to systems where only the inputs and outputs are visible. For such "black-box" configurations, it is not apparent how they work internally (An et al., 2021; Johora et al., 2020).

It should be noted, that more complex solutions also do not automatically result in better models. Authors like Abdulkareem et al. (2019) observe that in their hybrid models simple ESs are superior compared to the SL approach. The reason for that is the tendency of AI models to so-called overfitting. This means, that the AI model is developed to be very accurate and specific to the training data, but when processing new, unknown data, there is a drop in accuracy and performance. Therefore, it is also necessary to revise and validate the AI models separately from the ABM (Dehghanpour et al., 2016; Yin et al., 2018).

The implications of our work are relevant to both practice and research. The application areas in which hybrids are already used cannot only be adapted but can also be an inspiration for new practical areas. Due to the variety of currently relevant application areas, information systems research should focus more on ABMs. Based on our methodology, we structure the literature into two dimensions: application areas and the phase of ABM, in which AI is used to optimize the outcomes. As a foundation for future research, our work provides a wholistic view of the process of ABM. It shows how AI can be used to provide more realistic input data and environment-adopting agents and an optimized evaluation and validation of the simulation. Our study is limited by the number of included papers, as our observation period is restricted to five years. Therefore, this work does not claim to be a complete representation of all possible implementations of AI in ABMs but primarily represents the latest developments and the current state of the art. The various integration types could be explained more deeply, but we decided to rather focus on application areas and therefore show hybrid models on a broader level.

Conclusion

In summary, SL methods are used most in all modeling phases. The phase where AI is integrated most often is the online training phase. Here, RL enhances the agent to learn from its own decisions by rewards and punishments during the runtime of the simulation. For scalability and performance reasons, often DL extends the RL system. This states a clear future research direction: as DL algorithms are getting more and more popular and sophisticated, the potential for online RL agents in ABMs enhanced by various DL methods increases rapidly.

AI creates enormous potential for ABM's future research directions. As stated in our review, there is a lack of research for using AI in the first phase of modeling, the specification and formalization phase. In particular, IRL enables the modeler to create ABM environments with real-world (sensor) data. Another opportunity in this phase consists of using NLP as the support of expert knowledge. By crawling text data and analyzing it, more objective results can be achieved. Researchers should also examine AI as evaluation methods for ABMs, since there is not always enough real-world data available to test all possible scenarios of the simulation. This leads to more reliable, more realistic, and more specific outcomes. For the analysis in phase III, UL such as clustering methods can deliver insights in terms of explainable results.

ABM also creates opportunities for AI challenges. For instance, if there is only a small real-world training data set available for prediction models, this data can be extended by using ABM. In terms of graph neural networks (GNN), hybrids can also be used to compare link prediction and node classification tasks. Concerning application areas, ABMs and hybrids are still underrepresented in information system science. In the field of competitive intelligence, which collects data from external sources to observe market-relevant companies, scenario planning should be supported far more by hybrid models. This helps to get more objective and reliable market evolution analyses to support informed decision-making for the top management. Another relevant application area is the distribution of fake news and misinformation. Particularly in combination with social network analyses, hybrids offer high potential by identifying key opinion leaders and simulating the spread of opinions (Kaiser, Kröckel & Bodendorf, 2012). In times of trends like the “Metaverse”, simulation methods will gain importance in the future and for hybrids, there is a massive research potential.

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