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A REVIEW OF AGENT-BASED MODELING APPLICATIONS IN SUBSTANCE ABUSE POLICY RESEARCH

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ABSTRACT

This study provides a systematic review of existing studies that used agent-based modeling (ABM) to inform substance abuse policies and identifies future research directions. The detailed review included 20 articles, among which, tobacco, alcohol, cannabis, opioids, and heroin substance abuse were studied. These studies examined substance abuse interventions and the associations between substance use and social behavior, such as peer interaction and selection. Effective interventions included retailer density reduction policies, restriction of trading hours of licensed venues, ecstasy pill-testing and passive-alert detection dogs by police at public venues, and a mass-media drug prevention education policy. ABM can capture the dynamic interactions among and between agents and environments, making it appropriate to model complex substance abuse behaviors. Limitations in current studies include a lack of ABM validation efforts and generalizable data. Future studies should use generalizable and abundant information to inform their ABM, as well as have an explicit validation method.

1 INTRODUCTION

Substance abuse refers to the use of a psychoactive substance, including opioids, methamphetamine, cannabis, alcohol, or tobacco, that causes a hazardous psychological or physiological reaction (Robins and Rutter 1990). Substance abuse may result in cycles of dependence and severe physical and mental health consequences, making it a crucial cause of death internationally and the leading cause of preventable death in the United States (US) (NIDA 2023a). Drug-related substance abuse prompts more than 109,000 premature deaths per year globally, and alcohol-impaired driving causes almost 10,000 deaths annually in the US (UNODC 2021). Substance abuse also incurs an economic burden on society. The abuse of legal and illegal substances may lead to substance use disorders that cost the US $740 billion annually due to substance abuse-related homelessness, crime, unemployment, and welfare dependence (Daley 2013; NIDA

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2023b). As the burden of substance abuse grows, effective prevention and treatment policies are needed to improve public health and reduce costs (Butwicka et al. 2017).

Systems science has been used increasingly in public health to inform the design and evaluation of interventions and policies (Li et al. 2016). Among the available systems science approaches, agent-based modeling (ABM) is a type of dynamic modeling that uses computer simulation to examine how elements of a system behave as a function of their interactions with each other and their environment (Luke et al. 2017). Compared to statistical models, ABM can capture population heterogeneity, feedback loops, and dynamic changes of different risk factors, which makes it well-suited for examining real-world complexities (Rahmandad and Sterman 2008). In an ABM, agents can be individuals, homes, or any other real-world entity with characteristics and the ability to interact with other agents (Bonabeau 2002). The model developers determine agent characteristics and the conditions under which agents interact with empirical data or reasonable assumptions.

ABM has many potential applications across different fields, from the modeling of business plans to predicting the spread of diseases and nationwide energy consumption patterns (Rai and Henry 2016; Nianogo and Arah 2015). For instance, prior to and during the COVID-19 pandemic, ABM has been vastly used to develop and evaluate infectious disease control policies (Aleman et al. 2011; Tracy et al. 2018; Lorig et al. 2021; Ibrahim 2023). ABM has also been applied to HIV and AIDS epidemic modeling to study the transmission dynamics and the effect of pre-exposure prophylaxis (Tirado-Ramos and Kelley 2013; Rubio et al. 2023). The research was also conducted on the application of ABMs to form strategies that would decrease obesity rates in the US and inform bio-war management strategies, which further demonstrates the versatility and effectiveness of ABM (Kasman et al. 2019; Morshed et al. 2019; Zhang et al. 2015).

Recently, public health researchers and policymakers started using ABM to investigate substance abuse-related policies. The US Food and Drug Administration (FDA) has used ABM to assess whether the regulations will affect population-level rates of tobacco use, initiation, cessation, and relapse, and their ABM considered overall health risks to both tobacco users and nonusers (Rigotti and Wallace 2015). In 2015, the Institute of Medicine (IOM) recommended ABM as a useful tool to study tobacco control policies (Wallace et al. 2015). ABM was also used to study drinking behaviors and promote moderation of alcohol consumption (Garrison and Babcock 2009; Gorman et al. 2006).

Despite the promise that ABM shows in the study of substance abuse policy, current literature lacks a systematic understanding of the applicability of ABM to understand substance abuse and generate policy insights. To fill this gap, this study provides a systematic review of articles studying ABM for substance abuse policy research, identifies research gaps, and informs researchers about future research directions.

2 METHODS

This literature review mainly aims to answer the question: "how can researchers use ABM to study public policies that improve public health and welfare through their effects on substance abuse outcomes?" The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol helped capture several articles (Liberati et al. 2009). These articles were analyzed and their limitations and future research directions were reported.

2.1 Search Method

First, a Google Scholar search of "a literature review of agent-based simulation modeling for substance abuse" revealed relevant articles. Keywords extracted from the articles' titles, abstracts, and/or methods gave rise to three categories of keywords: 1) Substance Type, including "Heroin", "Marijuana", "Alcohol", "Cocaine", "Opioid", "Smoking", and "Tobacco"; 2) Approach, including "agent-based modeling", "agent-based simulation", "individual-based modeling", and other variations of these terms; and 3) Domain (e.g., "public health", "public policy", "epidemiology", "economic", etc.).

Second, small strings with at least one keyword from all three categories informed searches in Google Scholar, Web of Science, and Science Direct. The relevance of the results generated by the academic databases provided feedback to modify the small strings and led to the development of one or more large strings. Searches in each database with large strings revealed the most relevant articles.

2.2 Selection Criteria

Articles for the literature review were selected from the large string search results based on the relevance of the keywords in their titles and further eliminated from a ranking of the relevance of their abstract, methodology, and keywords, see the section "Risk of Bias (Quality) Assessment for Article Selection". The literature review only included peer-reviewed articles published in English after 2008 that conducted an experiment of ABM and substance abuse.

2.3 Risk of Bias (Quality) Assessment for Article Selection

To reduce bias during final article ranking and selection, two researchers ranked all the articles selected from the large string results with the same scoring method. Each researcher ranked half of the articles from the large string results based on the relevancy of their abstract, methodology, and keywords. The abstract was given a value of 4/10, the methodology was 4/10, and the keywords were 2/10. All articles with a ranking of 7 or above from either researcher were reviewed by both researchers for new rankings. Bias was reduced by having both researchers review each article with a ranking of 7 or above. Discrepancies were discussed between both researchers, and articles with a final ranking of 7 or above from both researchers were included in the literature review.

2.4 Article Analysis

The last step was summarizing information about study characteristics, model design, platform, model calibration and validation, interventions, key parameters, and outcomes from the selected studies. The limitations and future potentials are then identified.

3 RESULTS

3.1 Number of Articles Selected

As shown in Figure 1, a preliminary search with large strings identified 2,088 articles, of which 82 had titles that did not contain keywords related to ABM or substance abuse or were duplicates from a previous search. An additional 1951 articles were excluded because they did not meet the literature review criteria or had a final ranking below 7. More studies that were not peer-reviewed, literature reviews, and articles without relevant analysis were also excluded, leaving 20 studies for the literature review. Information in all 20 articles, including their study characteristics, platform, model calibration and validation, interventions, key parameters, limitations, future direction, and outcomes were extracted.

3.2 Model Characteristics and Major Findings

In these studies, the agents include adolescent students, college students, adults, and/or individuals of an unspecified age group or multiple age groups. Seven studies investigated adolescent students, two studied college students, one studied adults, and ten studied individuals of unspecified ages or multiple age groups.

All ABMs in these studies were developed with real data. Ten of the studies collected data with a research team or individual institutions, while the rest relied on previously obtained data from organizations like the National Longitudinal Study of Adolescent to Adult Health (Add Health) and National Survey on Drug Use and Health (NSDUH). Data from surveys was used to assign agent characteristics. For example, each agent in an ABM could be assigned a drinking rate from a lognormal distribution based on survey

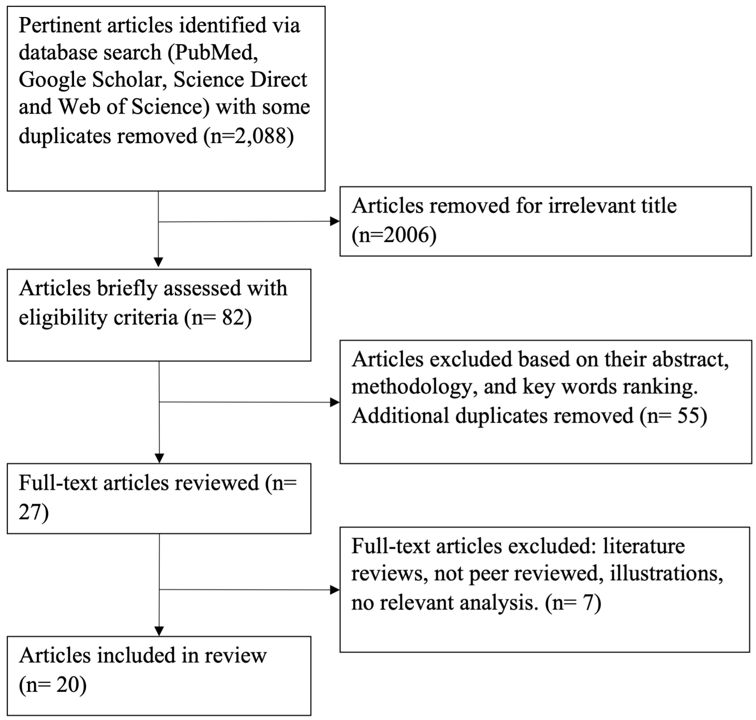

Figure 1: Flow diagram showing search procedure.

data and his/her identity type (Scott et al. 2016). Attributes or parameters that could not be described from existing data, such as initial friendship networks, could be constructed with random data in the ABM (Scott et al. 2016).

Of the 20 articles, half studied the abuse of drugs like cannabis and opioids, while others studied the abuse of tobacco and alcohol (Table 1). Nine studies examined the effect of control policies such as retailer reduction policies on substance use, while eleven studies explored the associations between substance use and social behavior such as peer selection and influence, along with appropriate intervention strategies (Atkinson et al. 2018; Di Clemente and Pietronero 2012; Dray et al. 2008; Hallgren et al. 2017; Levy et al. 2010; Luke et al. 2017; Schaefer et al. 2013; Sun and Mendez 2017; Wang et al. 2017; Wang et al. 2018; Dray et al. 2012; Fitzpatrick et al. 2016; Keane et al. 2018; Scott et al. 2016). In most studies, intervention methods were designed to mitigate risk factors, which were paramount to reducing further substance use (Atkinson et al. 2018; Di Clemente and Pietronero 2012; Dray et al. 2008; Fitzpatrick et al. 2015; Hallgren et al. 2017; Levy et al. 2010; Luke et al. 2017; Schaefer et al. 2013; Sun and Mendez 2017; Wang et al. 2017). In studies that explored the influences of social networks, covariates, such as parental monitoring, were also considered to investigate the impacts in different scenarios (Schaefer et al. 2013; Sun and Mendez 2017; Wang et al. 2018).

Seven studies modeled more than one type of agent, including drug users, drug dealers, police officers, and outreach (treatment) workers (Dray et al. 2008). The state of agents in three articles varied according to parameters like agent drinking rate (Luke et al. 2017). The dynamic interactions among agents, or between agents and environments were considered in approximately one-third of reviewed articles. Among these 20 articles, eight did not consider the physical environment in their models. In articles that did consider the physical environment, the agents in the simulation represented certain groups of a known location. For most studies relevant to spatial locations, the environment was active under inherent rules. Moreover, in addition to describing the conceptual model by text, eight studies used equations (Di Clemente and Pietronero 2012; Fitzpatrick et al. 2015; Hallgren et al. 2017; Levy et al. 2010; Sun and Mendez 2017;

Table 1: Study overviews.

Study, Year	Abused substance				Objective		Research Object (Agent in the Model)			
	Heroin	**Tobacco**	**Alcohol**	**Other Drugs** (Opioids, Cannabis, etc.)	**Control policies**	**Social influences**	**Adolescent students**	**College Students**	**Adults**	**Individuals** (not specified, or varying)
Dray et al. 2008	√				√					√
Levy et al. 2010		√			√					√
Schaefer et al. 2013		√				√	√			
Sun et al. 2017		√				√				√
Luke et al. 2017		√			√				√	
Wang et al. 2018		√	√	√		√	√			
Mundt et al. 2012			√			√	√			
Osgood et al. 2013			√			√	√			
Wang et al. 2015			√			√	√			
Fitzpatrick et al. 2015			√			√		√		
Fitzpatrick et al. 2016			√			√		√		
Scott et al. 2016			√		√					√
Wang et al. 2017			√			√	√			
Hallgren et al. 2017			√			√	√			
Atkinson et al. 2018			√		√					√
Moore et al. 2009				√	√					√
Dray et al. 2012				√	√					√
Di Clemente et al. 2012				√	√					√
Perez et al. 2012				√		√				√
Keane et al. 2018				√	√					√
Total	**1**	**5**	**10**	**6**	**9**	**11**	**7**	**2**	**1**	**10**

Wang et al. 2018; Mundt et al. 2012; Perez et al. 2012) and two studies used a diagram (Fitzpatrick et al. 2015; Perez et al. 2012) (Table 2).

Table 2: ABM Characteristics.

Study, Year	Data source		Agents		Environment		Dynamic interactions	
	Real data	**Population health survey**	**More than 1 type**	**Varied states**	**Spatial location**	**Active**	**Among agents**	**Between agents and environments**
Dray et al. 2008	√		√		√	√	√	√
Levy et al. 2010	√	√	√					
Schaefer et al. 2013	√	√						
Sun et al. 2017	√	√						
Luke et al. 2017	√				√			√
Wang et al. 2018	√	√			√	√		
Mundt et al. 2012	√	√					√	
Osgood et al. 2013	√				√		√	
Wang et al. 2015	√	√		√			√	√
Fitzpatrick et al. 2015	√			√			√	√
Fitzpatrick et al. 2016	√	√		√			√	√
Scott et al. 2016	√		√		√			
Wang et al. 2017	√	√	√		√	√		
Hallgren et al. 2017	√	√		√	√		√	√
Atkinson et al. 2018	√		√	√	√			
Moore et al. 2009	√			√				
Dray et al. 2012	√		√					√
Di Clemente et al. 2012	√		√	√			√	
Perez et al. 2012	√	√		√			√	
Keane et al. 2018	√		√					
Total	**20**	**10**	**8**	**8**	**8**	**3**	**9**	**7**

In the reviewed literature, ABMs suggested that peer influence and selection play a significant role in smoking and drinking behavior, and public policy and intervention strategies have the potential to decrease substance abuse. Effective strategies for reducing substance abuse included comprehensive retailer density reduction policies, restriction of trading hours of licensed venues, promotion of ecstasy pill-testing or passive-alert detection (PAD) dogs by police at public venues, and a mass-media drug prevention education policy. These observations provided rich information and evidence to support public health decision making.

3.3 Model Platform, Calibration, and Validation

Among the 20 studies, one used Java (an open-source object-oriented programming language) with Oracle JDK (Oracle Corporation, Redwood City, CA) within Repast (Argonne National Laboratory), six used Rsiena (a package of the statistical system R, which is an open-source programming language for statistical computing and graphics), one used AnyLogic (The AnyLogic Company), two used MATLAB (The Matrix Laboratory), one used NetLogo (The Center for Connected Learning and Computer-Based Modeling, Northwestern University), one used CORMAS (Common-Pool Resources and Multi-Agent Systems, written in Smalltalk (Bousquet et al. 1998)) and the other eight articles did not provide information about their platform. Six studies used a predictive validation by comparing some parameters in the simulation to those in the real-world, and four studies used sensitivity analysis validation with statistical tests, such as the goodness-of-fit test (Table 3).

Table 3: Platform, Calibration, and Validation Statistics

Study, Year	**Platform**								**Validation**		
	Repast	**Rsiena**	**Any-Logic**	**MATLAB**	**NetLogo**	**Java**	**Cormas**	**Not specified**	**Parameter Compared**	**Statistical Tests**	**Not specified**
Dray et al. 2008								√			√
Levy et al. 2010								√	√		
Schaefer et al. 2013		√									√
Sun et al. 2017								√		√	
Luke et al. 2017	√					√					√
Wang et al. 2018		√									√
Mundt et al. 2012								√			√
Osgood et al. 2013		√							√		
Wang et al. 2015		√								√	
Fitzpatrick et al. 2015				√					√		
Fitzpatrick et al. 2016				√						√	
Scott et al. 2016								√			√
Wang et al. 2017		√								√	
Hallgren et al. 2017		√							√		
Atkinson et al. 2018			√								√
Moore et al. 2009								√	√		
Dray et al. 2012								√			√
Di Clemente et al. 2012								√			√
Perez et al. 2012							√		√		
Keane et al. 2018					√						√
Total	**1**	**6**	**1**	**2**	**1**	**1**	**1**	**8**	**6**	**4**	**10**

4 DISCUSSION

The characteristics of the ABMs in all 20 articles, the strengths and limitations of ABM, and the future research directions are discussed below.

4.1 Model Characteristics

Of the 20 articles that were studied, the most popular way to explore intervention and policing strategies and risk factors for substance abuse is modeling more than one agent type in a specific spatial location with interactions among agents and their environments. In the ABMs, the agents were given the key characteristics that allowed them to exhibit real-world behaviors. Under these characteristics and articulated transition rules, the agents interacted with each other and their environment. When the ABM had more than one type of agents, the dynamic system consisted of interacting individuals with differing attributes. In the literature reviewed, some interacting agents included drug users, drug dealers, police officers, and outreach (treatment) workers. The ABMs in the literature were able to capture the agent's behavioral patterns, sometimes with varying states. One specific instance of varying states was changing alcohol consumption rates based on the agent's observations of their peers (Fitzpatrick et al. 2016). In some literature, the environment was not described in the model. This was a reasonable assumption when the environment was not predicted to impact the behavior of the agents (Schaefer et al. 2013; Sun and Mendez 2017). With evolving drug markets, drug legalization and accessibility, and social media influence, it is important to fully delineate the environment to gain the understanding of a bigger picture of substance abuse for population health and health economics (Bobashev et al. 2020). Meanwhile, complex models integrating multi-faceted elements can be difficult to calibrate and manage, thus demanding extensive efforts and computational resources. Appropriate assumptions and choices of agents are key to obtain meaningful simulation results while reducing the computational burden.

4.2 Platforms

The platform choice depended on the scale of the model, the cost of platform usage, and the researcher's preferences, such as coding language. Over the past decades, the ABM community has developed several modeling toolkits with a variety of characteristics, such as AnyLogic, NetLogo, and Repast. These platforms were used in at least one of the articles reviewed. Other popular ABM platforms include Altreva Adaptive Modeler, Cougaar, and MASON. The majority of them were developed using JAVA programming language. Of all the reviewed literature, Rsiena was the most popular ABM platform (Table 3). Rsiena is a package of the statistical system R in which the SIENA (Simulation Investigation for Empirical Network Analysis) methods are available (Siena 2023b). The purpose of Rsiena is to perform simulation-based estimation of stochastic actor-oriented models for longitudinal network data collected as panel data (Siena 2023a). Rsiena is an open-source platform and relatively easy to learn, and this observation suggests that, among the various features of ABM platforms, the cost of platform usage (license) and the programming skill requirement are primarily concerned.

4.3 ABM Validation and Calibration

More than half of the reviewed articles did not explicitly state their ABM validation method, which, however, is necessary to ensure a realistic model. Validation is important because it provides critical information to assess the amount of variance between the simulation model and the real-world system that the model imitates. Validation methods mentioned in the literature included empirical validation, statistical validation, conceptual validation, internal validation, operational validation, external validation, structural validation, and process validation (d'Aquino et al. 2001; Klügl 2008; Windrum et al. 2007; Ngo and See 2011). For instance, the model can be tested for internal validity over multiple replications to understand the internal, stochastic variability within the model, and tested for parameter variability to understand how input parameters affect the output performance measures. It should be noted that verification is typically performed before validation to ensure a simulation model is correctly implemented and free of programming errors. Because the verification process is quite standardized, i.e., debugging software, looking for incorrect implementation of conceptual models, and verifying the calculations, they were not explicitly discussed in the articles we reviewed.

Given the absence of a real system (e.g., when exploring the impact of a policy intervention), validation of the ABM for substance abuse behaviors is a challenging undertaking. Instead of comparing the model output to real data, which can be infeasible, many studies focused on ensuring the model parameters are the best representation of the observed data. An ABM should be calibrated to determine how to input real-world data into the model. Calibration also involves running the model with different parameters and testing using a degenerate test or extreme condition test to determine if the output is sensible under appropriate and extreme values of the input parameters. The calibration process is iterative and expert knowledge plays an important role in this process. In particular, individuals who are knowledgeable about the system can attest to the reasonable behavior. The optimal method to validate and calibrate depends on the nature of the ABM and the parameters used. Calibration and validation will remain a key challenge until more guidance is provided in the literature.

One common limitation among the reviewed literature was the lack of generalizability of the data used to develop the model parameters and agent behavior. Gathering all data required to populate a simulation model entails collecting data from various disciplines and domains. These data sets might be owned by various entities (e.g., government surveys, hospital administrative data, individual medical records), and are not commonly shared or publicly accessible. Studies might need to rely on limited data points for model development. For instance, one study on adolescent students and substance abuse utilized data from two schools to develop parameters for their ABM. Thus, the findings may not be generalizable since the roles of popularity and influence may diverge in different schools and different locations (Schaefer et al. 2013; Wang et al. 2017). Sparse data could also lead to inaccurate assumptions, such as assuming that the environment does not play a role in agent behavior when it plays a pivotal role in the real-world (Levy et al. 2010). The use of outdated data may also lead researchers to develop inaccurate parameters and unreasonable agent behavior (Wang et al. 2018; Wang et al. 2015). This lack of appropriate data makes it even more difficult to validate the model developed. There is a call for nationwide data collection, management, and FAIR (Findable, Accessible, Interoperable, Reusable) sharing to achieve public health intelligence.

4.4 Advantages of ABM for Informing Substance Abuse Policy Decisions

Agents in the ABMs in these studies were endowed with properties similar to real-world individuals or places, such as gender, age, smoking rate, mode of transport, wage, home and work location, and alcohol consumption rate. These properties allow the ABMs to perform with a higher fidelity compared to analytical models (e.g., Markov models). Additionally, the ability to model complex properties with ABM was shown in the articles, such as adaptive behaviors (e.g., the agents can change their drinking behavior according to system state (Fitzpatrick et al. 2015)), feedback loops (the behavior of an individual would move toward the average behavior of one's friends and the effect of peer influence can be reinforced over time (Mundt et al. 2012)) and contextual effects (the retailer properties are affected by the economic factors and varied in suburban rich towns and urban poor areas (Luke et al. 2017)).

Approximately half of the articles explored the relationship between substance abuse and policing strategies, and the rest investigated the effects of social influence and social selection on substance abuse. Some studies that investigated policing strategies varied interventions to determine the most effective policy (Di Clemente and Pietronero 2012; Levy et al. 2010; Keane et al. 2018), while some studies that investigated social influences on substance abuse indicated what interventions may be more efficacious within different social contexts (Fitzpatrick et al. 2015; Hallgren et al. 2017). Most of the reviewed studies had observational (Atkinson et al. 2018; Di Clemente and Pietronero 2012; Dray et al. 2008; Fitzpatrick et al. 2015; Hallgren et al. 2017; Schaefer et al. 2013; Dray et al. 2012; Perez et al. 2012; Osgood et al. 2013), interventional (Levy et al. 2010; Luke et al. 2017; Schaefer et al. 2013; Sun and Mendez 2017; Wang et al. 2017; Keane et al. 2018; Scott et al. 2016; Wang et al. 2015), or mixed designs (Wang et al. 2018; Fitzpatrick et al. 2016; Mundt et al. 2012; Moore et al. 2009). In the observational studies, the simulation model aimed to examine some emerging phenomena (e.g., the peer influence on smoking outcomes (Schaefer et al. 2013)) or investigate some causal effects (e.g., behavioral mechanisms and effects of tobacco control policies (Luke et al. 2017)). In contrast, the interventional studies were designed to focus on knowing what would happen if a given intervention or exposure had been implemented or not implemented. For example, in one piece of literature, the researcher explored how three street-level policing interventions—random patrols, hot-spot policing, and problem-orientated strategies—influenced drug market dynamics (Dray et al. 2008). These interventional policies are usually hard to test in the real-world due to high costs, extensive research time, and moral limitations. With ABM, researchers could predict outcomes of any intervention they are interested in on the same population and in a similar environment. ABMs enable us to build a policy sandbox: the simulation results enable researchers to explore the relationship between risk factors and substance abuse and, consequently, compare the effectiveness of varied interventions.

4.5 Future Directions

The systematic search for literature on the use of ABM to study substance abuse policy effectiveness revealed that there is currently only a sparse number of studies. Of the 20 articles included in the literature review, about half directly assessed the impact of policies on substance abuse, while the rest focused on social influences. In the future, more ABMs could be developed to study a broader set of policy decisions, e.g., including health behavior interventions, for curbing substance abuse.

Much of the literature also lacked explicit validation methods for their ABM, which is necessary to ensure a realistic model. While inputs and outputs are present in these studies, the influence of the processes within the models is tangled and nonlinear. As a consequence, validating the model behavior is difficult. Future studies should include a clear validation method and could explore the optimal validation method based on the goal of the ABM, the model parameters, and the desired agent behavior. This is an area where advancements in statistical and machine learning methods can work in concert with simulation modeling to generate new insights. The growth of the field of uncertainty quantification and the ability of machine learning-based surrogate models opens up new possibilities for making ABMs more transparent (Silverman et al. 2021). For instance, a framework for the calibration of ABMs using history matching and approximate Bayesian computation drawing from uncertainty quantification theory has been proposed in (McCulloch et al. 2022), where history matching is used to rule out implausible models and reduce the size of the parameter space that needs to be searched prior to calibration, and approximate Bayesian computation is used to provide credible intervals over which the given parameters could have created the observed data. Another work has attempted to tackle parameter space exploration and calibration of ABMs combining supervised machine learning and intelligent sampling to build a surrogate meta-model, and the surrogate is then employed for detailed exploration of the possibly wild parameter space to reduce the computational burden (Lamperti et al. 2018). In addition, reinforcement learning has been used to simulate the behavior of the agent to calibrate the state transfer probability (Song et al. 2021). Integrating machine learning and ABM has been seen in various complex biomedical systems modeling (Sivakumar et al. 2022) and we envision a variety of synergistic ABM and machine learning integration for substance abuse policy research.

The data quantity and quality were common limitations in the literature. The findings produced by these 20 articles may require replication with new sets of generalizable data since many of them utilized small sets of specific data to inform their model parameters. Therefore, one future direction for most studies is to determine whether the findings apply to more populous settings (Atkinson et al. 2018; Wang et al. 2018; Fitzpatrick et al. 2016; Osgood et al. 2013; Wang et al. 2015). Researchers are also encouraged to develop novel data integration and management systems that make data appropriately accessible by all relevant stakeholders to address the issue of lacking data generalizability.

The literature has also made it clear that substance abuse is sequential, leading to the abuse of additional substances (NIDA 2023a). Adolescent substance abuse could lead to concurrent substance abuse that lasts into adulthood. Future work should investigate policies to mitigate substance abuse from an early age, as this could prevent cycles of dependence that follow individuals late into their adulthood. Of the 20 articles studied, only seven of them investigated relationships between adolescents and substance abuse, leaving a gap in the literature. Thus, future studies are expected to examine how intervention policies or social networks affect adolescent substance abuse. Many of the studies listed were also conducted on the relationship between substance abuse and social networks rather than substance abuse and policy development. In the future, more ABMs should explore how realistic policies, such as easy access to rehabilitation, could affect the substance abuse rate.

Moreover, the relationship between the environment and the agents is not sufficiently accounted for. Future ABMs could investigate the role of the environment in substance abuse, which could lead to the effective development of policies targeting the environment, such as optimal locations of rehabilitation centers.

4.6 Strengths and Limitations

This study presented a systematic review of utilizing ABM to study policy development for substance abuse, including a detailed summary of key information from included studies, common findings, future directions, and limitations. A systematic search was conducted from three databases with broad search strings to maximize the likelihood that all relevant papers would be included in this literature review. Two researchers also reviewed the articles for relevance, decreasing bias in article selection.

Although this literature review had strengths, it also had limitations. Only literature written in English was included in the review, which may cause this literature review to exclude valuable studies in other languages and decrease the generalizability of the findings. Second, the review is limited to the abuse of heroin, tobacco, alcohol, cannabis, and opioids, and does not include studies that do not specify the type of substance or general illicit drug use behavior. In the future, an expanded review could include medication used to treat attention deficit hyperactivity disorder, insomnia, and anxiety, which are relevant public health concerns.

5 CONCLUSIONS

Substance abuse is an important issue in public health. ABM is an effective way to investigate the relationship between individuals, their environment, public policy, and intervention outcomes. However, there is currently not much literature exploring the effectiveness of ABM in informing substance abuse policy decisions. This literature review examined substance abuse ABM platforms, agent types, model parameters, data used to inform model parameters, and general limitations of existing research, along with future directions. It is concluded that the dynamic nature and interaction among agents in ABM show promise for exploring the effectiveness of public policy on substance abuse. Future studies should use generalizable and abundant information to inform their ABM, as well as have an explicit validation method.

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