Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

AN ITERATIVE ANALYSIS METHOD USING CAUSAL DISCOVERY ALGORITHMS TO ENHANCE ABM AS A POLICY TOOL

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ABSTRACT

Agent-based modeling (ABM) is becoming a popular policy tool by modeling the reasoning processes and interactive behaviors of individuals against external environments. However, the presence of heterogeneous agents, non-linear interactions and complex emergent patterns raised by even simple behavior rules pose challenges in the model explanation process. In this work, we propose a novel iterative analysis method that leverages causal discovery algorithms to facilitate policy formulation and evaluation based on a causal understanding of the model. It strengthens the explanation power of ABM by elucidating causal relations among modeled components. We applied the method to an agent-based simulator that models passengers' routing behaviors in a virtual airport terminal. By discovering the causal relations among passengers' goals, actions, and an airport terminal environment under different COVID-19 regulations, we showed that the method can inform more effective indirect-control policies leading to positive passenger experiences, compared with a conventional ABM analysis method.

1 INTRODUCTION

Agent-based modeling (ABM) is becoming a popular policy tool. It is a powerful means to understand complex social systems by modeling the reasoning processes and interactive behaviors of heterogeneous agents against different situations (Gilbert 2008), and therefore has been deployed to inform and evaluate policy alternatives (Lempert 2002). Understanding the model behavior under different policy interventions has been a research focus for ABM modelers and practitioners. However, the presence of heterogeneous actors, non-linear interactions between agents and environments, and complex emergent patterns caused by even relatively simple behavioral rules pose challenges to the model explanation process for policy-making.

Both quantitative and qualitative analysis methods have been proposed to understand ABM model behaviors. Statistic methods and machine learning methods have been proposed to evaluate the impact of input parameters on the model output (Lee et al. 2015). Qualitative methods have been applied to explain the model behavior from the perspective of agents' behaviors by using pattern mining and clustering methods (Yamane et al. 2018; Yamada et al. 2020). Although these methods are important and useful in explaining the relation between input parameters and simulation outcomes, they may not be as effective as causal explanations to understand model behavior (Miller 2019). Therefore, there has been a trend of applying causal discovery methods to find causal relations between model parameters and the simulated phenomenon.

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Furthermore, a series of analysis methods have been developed to evaluate different policies by examining model behaviors across different scenarios (Goto and Takahashi 2011), yet the causal mechanisms that can explain why certain policies are effective remains unclear. To support policy-making by using ABM, insights gained from the relations between model inputs and outcomes under different policy interventions may not be sufficient. Instead, understanding the causal mechanisms between agents' goals, their interactive actions against the environment and policy interventions, especially when the agents are modeled to perceive the environment to update their goals and adjust actions, are critical yet challenging for policy-making.

To this end, to better support policy formulation and evaluation using ABM as a policy tool, a systematic analysis method for ABM that can discover the causal relations between different model components and explain the causal impact of policies is vital yet still lacking, which forms the motivation of this work.

1.1 Related Works

Many efforts have been devoted to understanding the relation between input and output variables of agent-based models. Conventionally, a large number of simulation runs are conducted to generate sufficient parameter space for model evaluation, and a sensitivity analysis is performed to provide a relatively complete description of the relations between input and output variables (Angione et al. 2022). Machine learning methods, such as random forest regression and neural networks, have been applied to build simplified meta-models or surrogate models for capturing the correlation between input parameters and the output and determining the most influential parameters (Edali and Yücel 2019; Chen et al. 2021). However, although these types of analyses are useful to determine the correlations, the causal relationships that are important to understand and explain agents' behaviors and the emergent macro-level phenomenon are still lacking.

In contrast to the correlation analysis, a causal inference task is focused on estimating the causal effects of a treatment based on the actual outcome and counter-factual outcomes by conducting randomized experiments (Rubin 1974), whilst a causal discovery task is focused on discovering the causal structure among variables from observational data (Spirtes et al. 2000). Similar to randomized experiments but without ethical constraints, ABM can overcome the *fundamental problem of causal inference* (Holland 1986) by simulating counter-factual outcomes and investigating the causal effect of policy interventions. Casini and Manzo (2016) argued that agent-based modeling itself can serve as a tool to derive causal conclusions if the model is well designed by theories, as well as being calibrated and validated against real data. We focus more on the causal discovery rather than causal inference in this work.

Apart from using ABM itself as a policy-making tool for delivering causal insights, causal inference and causal discovery methods have been applied in understanding agent-based models as well. To analyze the emergent phenomenon in agent-based modeling, Janssen et al. (2019) proposed a methodological framework incorporating causal discovery methods to generate causal relations between model input and output variables, and demonstrated its applicability with two case studies. Kvassay et al. (2017) developed a method on the basis of non-linear structural causality to determine the contributing factors of model behaviors at an early stage of analysis. Chang et al. (2023) leveraged a pattern mining algorithm and causal discovery methods to strengthen the explanation power of ABM and to support group-specific policy-making, yet the causal relations among model components are still unclear .

Furthermore, a number of analysis methods have been developed particularly to facilitate policy-making on the basis of qualitative explanations of model behaviors. Without considering multiple scenarios, Ohori and Takahashi (2012) proposed a micro-dynamics analysis method that explains social phenomena from the perspective of agents' behaviors. Yamane et al. (2018) later proposed a systematic micro-dynamics analysis method that automatically identifies the most important causes of a target phenomenon and thus relies less on modelers' skills and domain knowledge in the analysis process, in light of which policies can be offered to improve the phenomenon. To evaluate and compare multiple scenarios, a landscape analysis method was proposed to understand the model behavior when a set of policy alternatives were implemented (Goto and Takahashi 2011), yet it still depends on modelers' skill and domain knowledge to design various scenarios.

Limitations. While the aforementioned analysis methods have proven effective and efficient in policy-making, there are still a few problems to be addressed. First, to support systematic policy formulation, there is a lack of methods that enable explicit elucidation of model behaviors in terms of causal paths between model components. This is particularly important for formulating realistic indirect-control policies, where interventions implemented in the environment may influence the target phenomenon indirectly. Second, to evaluate policy alternatives for facilitating communications, only demonstrating the changes in model outcomes across scenarios is insufficient. Extra efforts are necessary to explain the causal relation between proposed policies and the model behavior.

Contribution. On the basis of the aforementioned discussion, we propose a novel iterative analysis method to strengthen the explanation power of ABM as a policy-making tool. By leveraging multiple causal discovery algorithms, our method can identify the causal paths between model components leading to a target phenomenon in order to formulate indirect-control policies and explain how the proposed policies affect model components to improve system outcomes.

We introduce our proposed method in Section 2. In Section 3, we apply our method to the simulation outcomes of an agent-based simulator that simulates passengers' routing behaviors at an airport terminal, and demonstrate how it can inform practical indirect-control policies toward promoting positive passenger experiences of non-aeronautical activities. We then evaluate the method by comparing it with a conventional micro-dynamic analysis method and show its advantages in formulating effective policies that can resolve a trade-off between different positive experience indicators. We conclude with a brief summary and mention of future work in the last section.

2 PROPOSED METHOD

We propose an iterative analysis process composed of **problem identification**, **policy formulation** and **policy evaluation**, as illustrated in Figure 1, to facilitate the policy-making process on the basis of a causal understanding of ABM. This method will systematically discover the causal paths between model components, specifically between agents' goal, actions, environmental factors and analysis target for guiding policy formulation. The proposed policy alternatives will then be evaluated by both the changes of macro-level phenomenon and micro-level causal links considering the effect of implemented policies. The procedures are explained in detail in the following subsections.

2.1 Problem Identification

ABM has been widely applied to understand complex social phenomena by modeling the decision-making process of heterogeneous agents, ranging from relatively simple rules to highly complex interactions. In general, agents with certain goals can observe the environment and make decisions on the basis of these perceptions and their internal states. Policy alternatives and environmental factors will have an impact on agents' behaviors directly or indirectly through their reasoning processes.

2.1.1 Model Target Phenomenon (S1.1)

We assume well-designed and validated ABMs exist that model particular social phenomena. An operational definition of a target phenomenon observed from the simulation output is provided as the analysis target. We aim to discover the causal relations between model components including agents' goals, actions, environmental factors, scenario settings and target phenomenon for examining how they affect the target phenomenon.

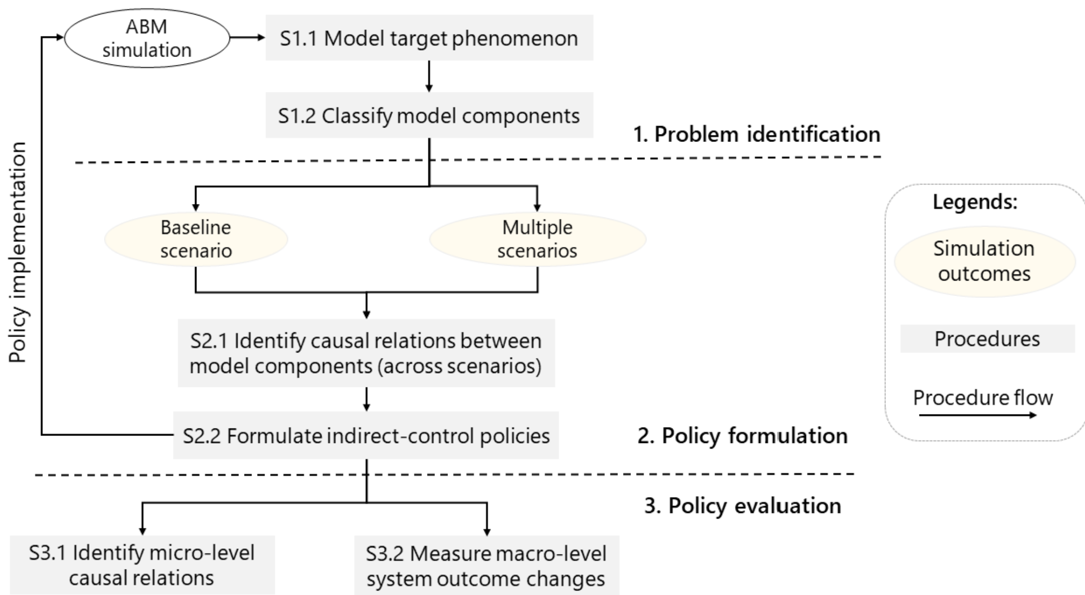

Figure 1: An iterative ABM analysis method leveraging causal discovery methods for policy-making.

2.1.2 Classify Model Components (S1.2)

We simulate the ABM model under different scenarios and record the logs including agents' characteristics, behaviors through the simulation and simulation settings. We categorize the simulation logs into agents' goals and actions, environmental factors and scenario settings as model components.

- Goal: agents' planned tasks.
- Action: agents' behaviors as realizing their goals.
- Environmental factor: what agents can perceive to update their goals and actions.
- Scenario: policies or regulations that may change the environmental factors and indirectly affect agents' actions.

2.2 Policy Formulation

To formulate policies for improving the target phenomenon, we provide qualitative explanations of agents' behaviors by discovering causal relations between agents' goals, actions and environmental factors under different scenarios. Since our analysis purpose is to discover the causal structure among model components, rather than estimating the causal effect, we apply multiple causal discovery methods to derive causal relations by analyzing simulation logs and represent the relations using causal graphs.

2.2.1 Identify Causal Relations between Model Components (S2.1)

Causal discovery methods have been proven useful in discovering causal relations between variables, represented as causal graphs, that approximate well-established and known evidence (Shen et al. 2020). The methods can be roughly categorized as constraint-based methods, score-based methods, and methods based on functional causal models (Glymour et al. 2019). Constraint-based methods statistically estimate the conditional independence among variables to describe the causal structure, while score-based methods select the causal structure among a number of generated ones on the basis of a score associated with each of them. Functional causal models impose additional assumptions on the data distribution and represent each variable as a deterministic function of its causes and unmeasurable noises (Shen et al. 2020).

Since these methods pose different assumptions on the input datasets, handle confounders differently, and are hard to verify, it is challenging to use them in practical applications. Therefore, we apply multiple causal discovery methods to provide more informative results (Kotoku et al. 2020; Janssen et al. 2019; Chang et al. 2023). We choose the most classic or well-performed method from each type separately, namely, the constraint-based method Fast Causal Inference (FCI) (Spirtes et al. 2000), the score-based method Fast Greedy Equivalences Search (FGES) (Ramsey et al. 2017), and Greedy Fast Causal Inference (GFCI) (Ogarrio et al. 2016) that combines the two aforementioned methods.

Table 1: A comparison of causal discovery methods.

Method	Type	Input data	Confounder
FGES (Ramsey et al. 2017)	Score-based method	Continuous and Discrete	No
FCI (Spirtes et al. 2000)	Constraint-based method	Continuous and Discrete	Yes
GFCI (Ogarrio et al. 2016)	Combined	Continuous and Discrete	Yes

Table 1 shows a comparison of the algorithms in terms of the types of variables they can handle, whether the presence of latent confounders is assumed and whether they can output exact causal structures. We apply the causal discovery methods on the classified simulation records generated in the previous step. To perform the causal search with graphical representations of causal relations, we use TETRAD, a software package that implements a set of causal discovery tools (http://www.ccd.pitt.edu), for implementing FCI, GFCI, and FGES. Python is used to analyze and plot the results.

Generate causal graphs. For each causal discovery method, we bootstrap the samples for 200 times. We use the “preserved” setting in TETRAD for bootstrapping, which will return the densest set of edges, as the causal graph, as well as the probability of occurrences for each returned edge. Generating a very dense final graph may include incorrect causal relations between variables, whilst generating a very sparse one may miss certain causal relations (Janssen et al. 2019). To yield a more robust final causal graph, we merge the causal graphs which are generated by the different causal discovery methods on the basis of a confidence score of each edge as follows.

1. Each causal discovery method m, where $m \in \{FCI, FGES, GFCI\}$, will return a causal graph G_m.
2. We denote the probability of occurrence by $P_{ij}(m)$ for each edge $e_{ij} \in G_m$ between variables i and j. This value is 0 when there is no connection.
3. We determine the maximum value of $P_{ij}(m)$ across m and denote it by $maxP_{ij}(m)$.
4. We plot this edge e_{ij} in the final causal graph if $maxP_{ij}(m) > t$, where t is a pre-defined threshold.

FCI and GFCI will output causal relations represented by Partial Ancestral Graphs (PAG), which contains directed, bi-directed, partially directed and non-directed edges. Partially directed and non-directed edges indicate the possibility of having a latent confounder influencing both variables. FGES will produce causal graphs with only directed and bi-directed edges. For the merged final graph, we treat partially directed edges as directed edges and non-directed edges as bi-directed edges without considering the influence of confounders. The effect of confounders can be investigated by examining the original causal graphs produced by FCI and GFCI, depending on the needs.

2.2.2 Formulate Indirect-Control Policies (S2.2)

The aforementioned causal analyses provide us insights on the causal relations among model variables. On the basis of these causal understandings, indirect-control policies can be proposed that do not intervene with the analysis target directly, but indirectly intervene with the agent actions that lead to the analysis target through environmental factors.

The process is iterative in the sense that variables can be added or removed iteratively for the causal analysis on the basis of domain knowledge or insights yielded from each analysis cycle.

2.3 Policy Evaluation

We re-simulate the model with the proposed policies implemented as different scenarios and evaluate them from both the macro- and micro- level.

For **S3.1 micro-level evaluation**, in the same way to the analyses at the policy formulation stage (S2.1), we examine the causal relations across scenarios to provide a causal explanation on how the proposed policy affects the model components and the target of analysis. For **S3.2 macro-level evaluation**, similar to the other scenario analysis methods, we evaluate the changes of target system outcomes using pre-defined macro-level metrics.

This causal-based evaluation assesses the effect of policies from a causal perspective by clarifying the causal paths between policies and model components. It would benefit the communication among policy makers, modelers and other stakeholders who may have different domain backgrounds, when using ABM as the policy tool.

3 APPLICATION

We apply the method to analyze an agent-based model (Ohori et al. 2016), which is developed to facilitate the airport design and management by simulating passengers' walking behaviors and their interactions with the signs and facilities in a virtual airport terminal. The case description and agents' characteristics and behaviors are briefly reviewed first, followed by the policy-making process by the proposed method. For large-scale models with more variables, the proposed method can be applied iteratively starting from a smaller set of selected variables and expanding the analysis as desired.

We argue that the proposed analysis method can be applied to general models that simulate the routing behaviors of individuals as walking through facilities or spots against environmental factors, such as signs providing the congestion information and route plans, in order to complete a list of pre-defined goals within a limited time. The potential applications may include amusement parks and large-scale exhibitions, not limited to the following airport terminal model.

3.1 Agent-based Model

This agent-based model abstracts the airport terminal as a cellular space including a variety of facilities and signs. As illustrated in Figure 2, three signs are allocated in places proven to be the most effective for providing information of facilities and areas (Ohori et al. 2016). Facilities are represented by blue dots. Passengers with pre-defined goals will enter the terminal, plan their route, walk and select facilities to take up services on the basis of their goals and perception of the external environment before leaving for departure.

Characteristics of agents and environment. We define Passenger as agents, and Facility and Sign as external environments.

Facility is defined by $\{fpos, type, cap, queue, area\}$, where *fpos* represents its position in terms of coordinates in a cellular space, *type* represents its type in an airport, such as restaurants, ATMs, currency exchange, souvenir shops, and so on, *cap* represents the capacity, *queue* represents the number of queuing agents and *area* represents the area of this facility.

Sign is defined by $\{spos, areaInfo_g, facilityInfo_f, range\}$, where *spos* represents the position, $areaInfo_g$ represents the route information to area g and the information on facilities existing in this area, $facilityInfo_f$ represents the route information to facility f and *range* determines the positions in the cellular space within which agents can recognize the sign.

Passenger is defined by $\{EvokedSet, areaInfoSet, facilityInfoSet, choiceSet, Destination, agentType\}$, where *EvokedSet* represents a set of facility types that agents want to visit, *areaInfoSet* and *facilityInfoSet* represent the set of route information they have to certain areas and facilities, respectively, *choiceSet* represents the set of facilities that are recognized as destination candidates and *Destination* represents the position in terms of coordinates where agents choose to go next. Each type of facility in *EvokedSet* is associated with a probability of being chosen; one type will be chosen as the *agentType* of passengers and assigned with the highest probability, whilst others share the same probability.

Routing behaviors. Passengers will enter and leave the virtual terminal depending on their schedule. After entering the virtual terminal, a passenger will first choose a facility type from *EvokedSet*. They will then walk randomly until entering the range of a sign. *areaInfoSet* and *facilityInfoSet* are updated in accordance with the information gained from the sign w.r.t. $areaInfo_g$ and $facilityInfo_f$, respectively. A passenger may get lost in the airport, regarded as forgetting the information by removing the value from the two variables, after a certain time period. If the information they gained contains the route to facilities of the type they want to visit, they will set the area as the destination and add the facilities to *choiceSet*. Furthermore, by evaluating the utility of each facility i in this set as $Util(i) = \alpha_i + \beta time_i$, where α_i is the attractive rate and $time_i$ is the estimated walking time to it multiplied by a weight β, agents will visit the facility with the highest probability calculated as $exp(Util(i))/\Sigma_{n \in choiceSet} exp(Util(n))$.

Upon arrival at the facility, if it is congested, i.e., there is a waiting queue, agents will decide whether to wait and for how long depending on the simulation setting. The threshold of leaving the queue follows a normal distribution w.r.t. their type. Agents will stay at the facility as completing the planned task and repeat the process by choosing the next task.

Scenarios. We define scenarios as COVID-19 regulations, namely social distancing and capacity restriction. Social distancing (Regulation 1) indicates that the length of the queue will be doubled compared with the normal situation, whilst capacity restriction (Regulation 2) indicates that the capacity of certain facilities, such as restaurants and souvenir shops, will be reduced to half of the original. These regulations are not restricted to the COVID-19 situation and can be generalized in other contexts.

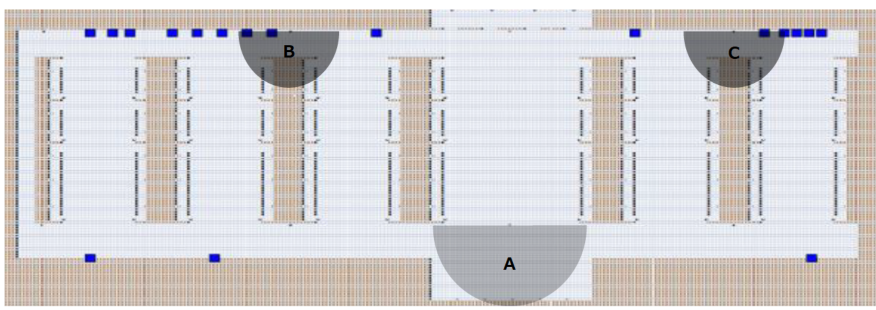

Figure 2: Floor map of the terminal before departure — Semicircles represent signs and blue dots represent facilities (Ohori et al. 2016).

3.2 Model Analysis

We run the simulation for 10 times with different random seeds and extract the records of agents who are at the terminal during time units 2000 and 3000. Variables recorded during the simulation for the following analysis are explained in Table 2. We first analyze the results of the baseline situation without any COVID-19 regulations, and then analyze the results under different COVID-19 regulations as scenarios. Each scenario may contain the record of around 5900 to 6700 agents. S^4 Simulation System, a modeling environment (http://msi.co.jp/s4/products/index.html), is used for the simulation.

3.2.1 Problem Identification

By applying the proposed analysis method, we aim to offer indirect-control policies to promote positive passenger experiences by enabling a causal explanation on how passengers' goals, actions as a result of perceiving the signs and environmental factors affect the experience.

Table 2: Variables explanation.

Variable	Meaning	Value
agentType	Main purpose	1: ATM; 2: Exchange; 3:Restaurant; 4: Duty free; 5: Souvenir
sign	Which sign visited most	1: Sign A; 2: Sign B; 3 Sign C; 4: Others
areaRoute	Route after entering the terminal	0: Go straight; 1: Otherwise
routeWalkTime	Total walking time towards dest.	Normalized in [0, 1]
activeTime	Total active time at the terminal	Normalized in [0, 1]
infoSearchTime	Total info. searching time	Normalized in [0, 1]
pwaitTime	Total waiting time at the terminal	Normalized in [0, 1]
cwaitTime	Total waiting time at facilities	Normalized in [0, 1]
covidNo	COVID-19 regulations	0: No regulation 1: Social distancing 2: Capacity restriction
Objective	To what extent planned tasks are completed	1: $>=50\%$: 0: Otherwise

S1.1 Model target phenomenon. Passenger experiences of non-aeronautical activities have become an important concern when designing and managing airports. For this application, we define the analysis target as whether passengers can complete over 50% of their planned tasks in $EvokedSet$.

S1.2 Classify model components. We categorize the variables in Table 2 into the passenger's goal, actions, environmental factors, scenarios and the analysis target as follows. Variables sign, infoSearchTime and cwaitTime are categorized as environmental factors since they are resulted by passengers' interactions against the environment.

- Goal: agentType
- Action: areaRoute, routeWalkTime, activeTime, and pwaitTime
- Environmental factor: sign, infoSearchTime and cwaitTime
- Scenario: covidNo
- Analysis target: Objective

3.2.2 Policy Formulation

We apply the causal discovery methods on the above variables. We provide prior knowledge to those methods, which may help confirm the orientation of causal relations between two variables, and thus improve the accuracy of results (Shen et al. 2020). The prior knowledge pose restrictions in the way that the target of analysis could not be the cause of any other variables since it is not encoded in any behavioral rules. Also, the agent type is not affected by any other variables.

S2.1 Identify causal relations between model components. For the analysis of the baseline scenario without any regulation implemented, we plot the merged final graph in Figure 3 (Left). The analysis results show that the preferred goal of passengers and the time spent searching information from signs are major causes of whether passengers can complete over half of their goals. The time spent waiting at facilities is not frequently identified as a cause ($maxP(m) = 0.69$), but has the highest causal effect on the analysis target. The primary goal of passengers is the root cause of subsequent actions, the signage system design has a non-trivial causal impact on the analysis target by influencing the information searching time, and a congested situation may prolong the waiting time leading to the situation that passengers need to have sufficient time for completing more planned tasks.

We further analyze the simulation outputs from multiple scenarios, in which the COVID-19 regulations are implemented. COVID-19 regulations worsen the congestion situation of facilities, especially restaurants. This phenomenon can be explained or triangulated by the causal relation between different regulations

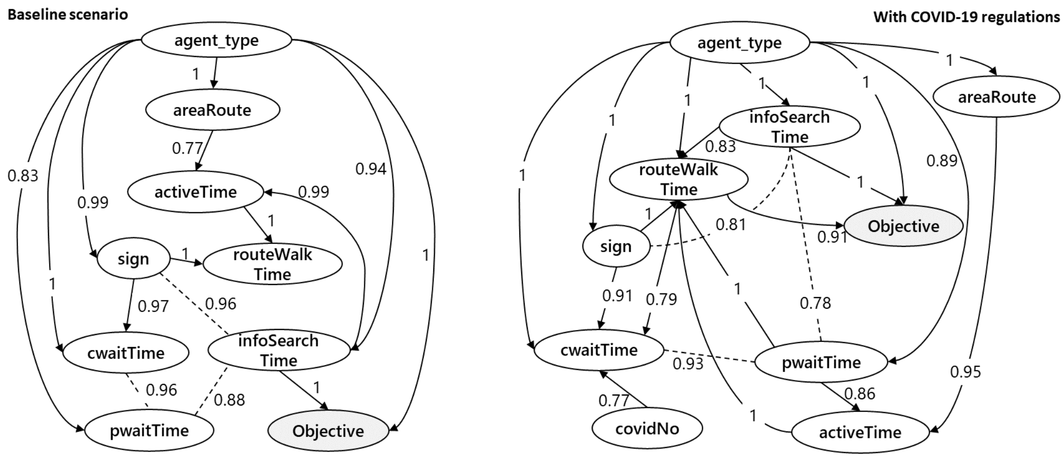

Figure 3: Causal relations with $maxP_{ij}(m)$ displayed on each edge for baseline scenario without (Left) and with (Right) regulations when $maxP_{ij}(m) > 0.75$; $X \rightarrow Y$ indicates that X might be a cause of Y, and dotted line between X and Y represents a bi-direction edge and indicates either X is a cause of Y or vice versa.

and the waiting time at facilities as illustrated in Figure 3 (Right). Since these two regulations mainly pose restrictions on the waiting length and capacity of facilities, passengers may have a higher probability of waiting at facilities especially under Regulation 2. On the other side, there is a trade-off between the waiting time and completion rate of tasks for prompting a positive experience. Choosing to wait at facilities may increase the probability of entering the facility and completing more tasks, yet a longer waiting time is normally treated as a negative experience.

S2.2 Formulate indirect-control policies. As informed by the aforementioned causal analysis, the proposed policy should take signage system design into account and be able to resolve the trade-off between waiting time and completion rate to promote positive passenger experiences. We propose two different ways to provide the congestion information, i.e., the length of waiting queues at facilities, as the indirect-control policies and evaluate them as scenarios by re-simulation. The first policy (s1) provides congestion information at Sign A, which is allocated at the entrance of the terminal, whilst the second policy (s2) provides congestion information at Signs B and C, which are allocated at each side of the terminal and nearer to facilities. When passengers check the sign, they will get congested information of facilities in addition to route information, and decide on the basis of this whether to choose the facility as the destination.

3.2.3 Policy Evaluation

We implement these two policies under different COVID-19 regulations respectively, and evaluate them from both the macro- and micro- level.

S3.1 Micro-level analysis. We plot the causal relations in Figure 4. Different information distribution policies are represented by signNo. Under COVID-19 Regulation 2, distributing the congested information at Sign A, or at Signs B and C, may not have a frequent causal impact on the facility waiting time. In contrast, different ways of distributing the congestion information may influence the total waiting time at facilities and information searching time under Regulation 1, which has a causal impact on the target of analysis. We could further analyze the changes of causal effects across scenarios to have a deeper understanding of the causal relations, but due to the page limit, results are not plotted here.

S3.2 Macro-level analysis. We plot the log distribution of waiting time at facilities across all scenarios in Figure 5 (b) and Figure 5 (c). It indicates that COVID-19 regulations will increase the waiting time at facilities. The provision of congested information at Signs B and C can help reduce the average waiting time more significantly. Furthermore, the improvement of waiting time does not affect the degree of completing

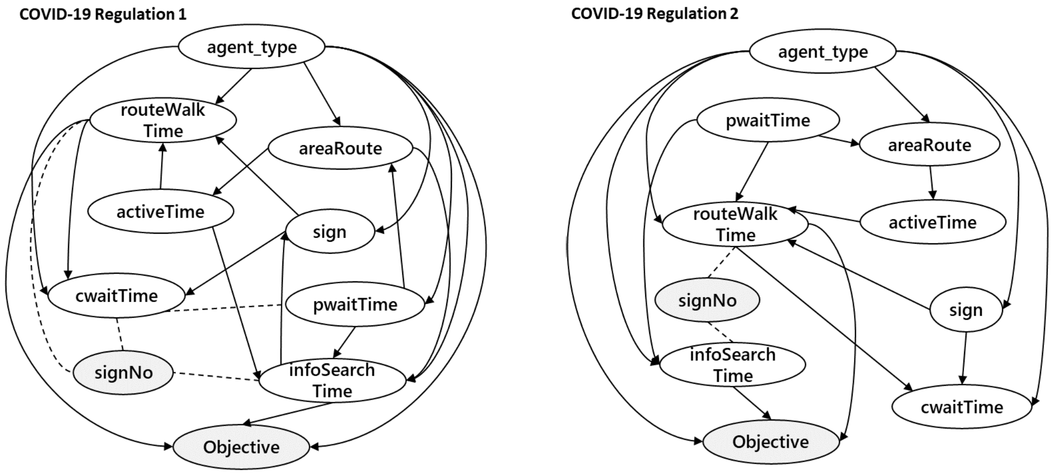

Figure 4: Causal relations with policies (denoted by signNo) considered when $maxP_{ij}(m) > 0.75$. Left: Under Regulation 1; Right: Under Regulation 2. Value of $maxP_{ij}(m)$ for each edge is not displayed.

the planned activities, as illustrated in Figure 5 (a). This demonstrates that providing congestion information near the facilities can direct passengers to less congested ones, and the passengers can finish the planned tasks with a shortened waiting time.

3.3 Comparison with Micro-Dynamic Analysis

We compare our method with the conventional micro-dynamic analysis (MDA) method (Yamane et al. 2018). This method applies clustering methods to identify the combinations of clusters that are closest to the target agents by evaluating the F1 score and removing identified agents to improve the system outcome.

We set a negative passenger experience as completing less than 50% of the tasks as the analysis target for MDA. The analysis shows that the cluster with the shortest waiting time at facilities is that with the highest F1 score and therefore chosen as the most important cause leading to the analysis target. We follow the method to propose a policy as removing the agents in this cluster, and compare it with ours in terms of waiting time and completion rate by re-simulation, as shown in Figure 5.

Comparatively, our method identified the causal impact of the signage system design explicitly and provided a causal explanation of the effectiveness of the policy by showing the causal paths between passengers' goals, actions affected by the external environment and the proposed policy. In addition, the policy proposed by MDA sacrifices the waiting time to improve the completion rate, whilst our proposed indirect-control policies resolve the trade-off between waiting time and completion rate. In other words, the policies improve passengers' experiences by reducing the waiting time whilst avoiding influencing the completion rate, even though the completion rate is not improved significantly.

4 CONCLUSION AND FUTURE WORKS

Promoting ABM as a policy-making tool is an important yet challenging task when offering and evaluating practical policies to facilitate the communication between modelers and policy makers. In this work, we innovatively leveraged causal discovery methods to strengthen the explanation power of ABM in policy formulation and evaluation. The proposed analysis method enables a causal explanation of model behaviors, especially that of the causal relations among model components and causal changes across scenarios to enhance policy-making. We applied our method to a case that aims at promoting positive passenger experiences of non-aeronautical activities in a virtual airport terminal. Our findings show that it can guide the formulation of effective indirect-control policies for handling a trade-off to promote positive experiences, compared with the conventional micro-dynamic analysis method. The policy evaluation with

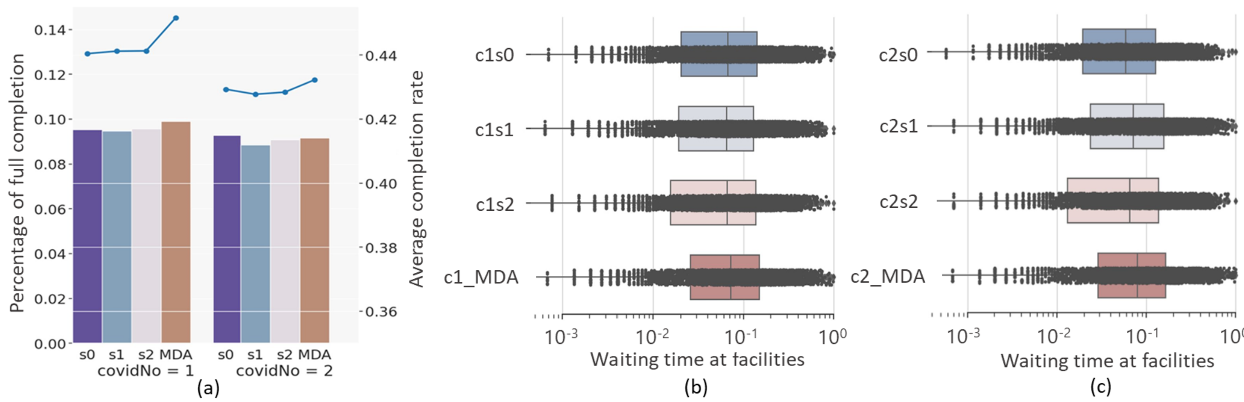

Figure 5: Comparison with MDA. (a) Left y-axis (bars): Percentage of agents who complete all planned tasks; Right y-axis (lines): Average completion rate of all agents. (b) Waiting time at facilities under Regulation 1. (c) Waiting time at facilities under Regulation 2. *cxsy* represents COVID-19 regulation x and proposed policy y. Pair-wise comparison between the MDA scenario and our scenarios on the waiting time shows that they are significantly different by both t-test and KS test with p-value < 0.001.

a causal explanation can further facilitate the communication among stakeholders when using ABM as a policy-making tool.

We expect our proposed method to be performed at the start of the analysis to inspire discussions, rather than to close discussions for conclusions. There are several future directions to strengthen its applicability. First, this method should be more rigorously evaluated when applied in real applications. Second, with an increased number of variables, the global structure of the causal relations may become complicated and harder to verify. Domain knowledge or advanced causal discovery methods are necessary to provide reliable explanations. Finally, this method aims to formulate and evaluate practical indirect-control methods on the basis of a causal explanation of model components, rather than to provide optimized solutions. Optimization methods may be integrated in the analysis process to fulfill this purpose.

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