Dialogues in Health 4 (2024) 100179

Contents lists available at ScienceDirect

Dialogues in Health

journal homepage: www.elsevier.com/locate/dialog

Incorporating endogenous human behavior in models of COVID-19 transmission: A systematic scoping review

Alisa Hamilton [a,b,*], Fardad Haghpanah [a], Alexander Tulchinsky [a], Nodar Kipshidze [a], Suprena Poleon [a], Gary Lin [a,c], Hongru Du [b], Lauren Gardner [b], Eili Klein [a,d,e]

[a] One Health Trust, 5636 Connecticut Avenue NW, PO Box 4235, Washington, DC 20015, USA
[b] Department of Civil & Systems Engineering, Johns Hopkins University, 3400 North Charles St, Baltimore, MD 21218, USA
[c] Johns Hopkins Applied Physics Laboratory, 1110 Johns Hopkins Rd, Laurel, MD 20723, USA
[d] Department of Emergency Medicine, Johns Hopkins School of Medicine, Baltimore, MD 21209, USA
[e] Department of Infectious Diseases, Johns Hopkins School of Medicine, Baltimore, MD 21287, USA

ARTICLE INFO

Keywords:
Human behavior
Infectious disease
Mathematical modeling
COVID-19

ABSTRACT

Background: During the COVID-19 pandemic there was a plethora of dynamical forecasting models created, but their ability to effectively describe future trajectories of disease was mixed. A major challenge in evaluating future case trends was forecasting the behavior of individuals. When behavior was incorporated into models, it was primarily incorporated exogenously (e.g., fitting to cellphone mobility data). Fewer models incorporated behavior endogenously (e.g., dynamically changing a model parameter throughout the simulation).
Methods: This review aimed to qualitatively characterize models that included an adaptive (endogenous) behavioral element in the context of COVID-19 transmission. We categorized studies into three approaches: 1) feedback loops, 2) game theory/utility theory, and 3) information/opinion spread.
Findings: Of the 92 included studies, 72% employed a feedback loop, 27% used game/utility theory, and 9% used a model if information/opinion spread. Among all studies, 89% used a compartmental model alone or in combination with other model types. Similarly, 15% used a network model, 11% used an agent-based model, 7% used a system dynamics model, and 1% used a Markov chain model. Descriptors of behavior change included mask-wearing, social distancing, vaccination, and others. Sixty-eight percent of studies calibrated their model to observed data and 25% compared simulated forecasts to observed data. Forty-one percent of studies compared versions of their model with and without endogenous behavior. Models with endogenous behavior tended to show a smaller and delayed initial peak with subsequent periodic waves.
Interpretation: While many COVID-19 models incorporated behavior exogenously, these approaches may fail to capture future adaptations in human behavior, resulting in under- or overestimates of disease burden. By incorporating behavior endogenously, the next generation of infectious disease models could more effectively predict outcomes so that decision makers can better prepare for and respond to epidemics.
Funding: This study was funded in-part by Centers for Disease Control and Prevention (CDC) *MInD-Healthcare Program* (1U01CK000536), the National Science Foundation (NSF) *Modeling Dynamic Disease-Behavior Feedbacks for Improved Epidemic Prediction and Response* grant (2229996), and the NSF *PIPP Phase I: Evaluating the Effectiveness of Messaging and Modeling during Pandemics* grant (2200256).

1. Introduction

Forecasting infectious disease epidemics, as with other complex systems (e.g., weather), is hampered by pervasive uncertainty. Unlike weather forecasts, however, the trajectory of an epidemic can affect the future dynamics as people respond to risk [1]. A plethora of dynamical forecast models was created during the COVID-19 pandemic, but their ability to effectively describe future trajectories of cases and hospitalizations was mixed, with models producing both under- and overestimates [2]. A major challenge for these models in evaluating future

* Corresponding author at: Center for Systems Science and Engineering, Department of Civil and Systems Engineering, Whiting School of Engineering, Johns Hopkins University., USA.
E-mail address: ahamil33@jh.edu (A. Hamilton).

https://doi.org/10.1016/j.dialog.2024.100179
Received 16 February 2024; Received in revised form 4 May 2024; Accepted 5 May 2024
Available online 7 May 2024

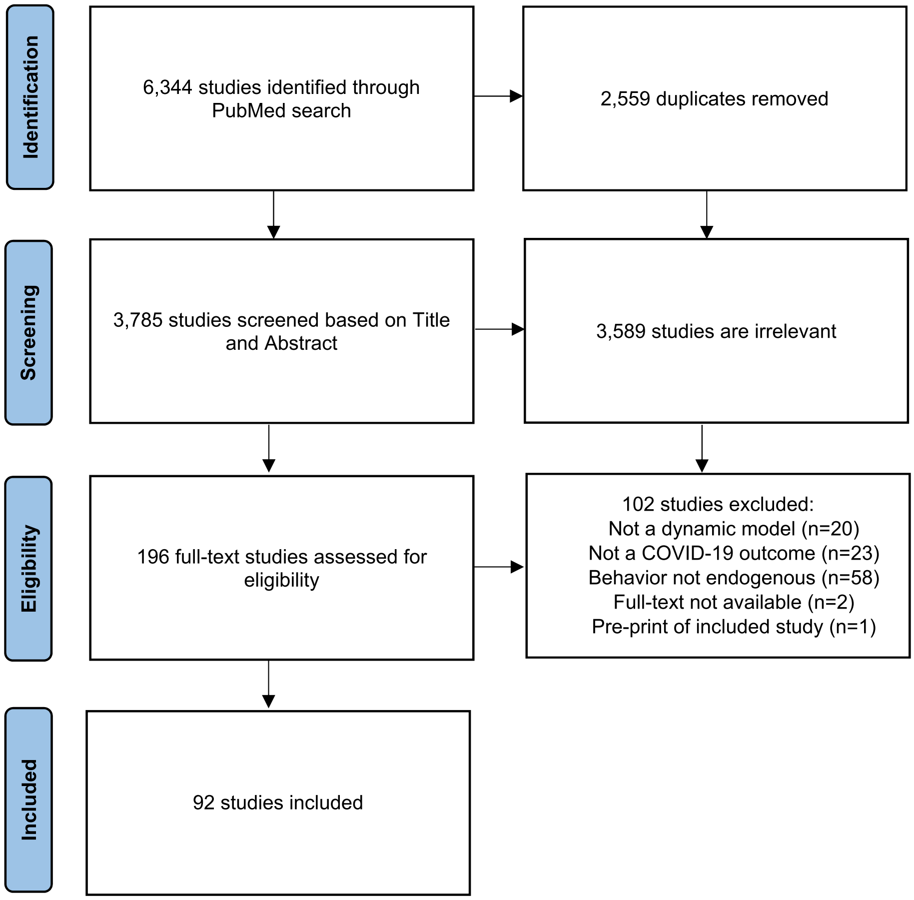

Fig. 1. PRISMA Flow Chart.

trends was forecasting the behavior of individuals, which was largely incorporated exogenously through changes in public health guidance. While public health guidance influenced behavior, several other endogenous factors, including age, gender, socioeconomics, health and wellbeing, and trust influenced risk perception and ultimately the behavior of individuals [3,4] but were largely lacking from models [5].

Mathematical models of disease have been important drivers of public policy since the eighteenth century; however, the incorporation of endogenous behavior driven by risk perception is a relatively recent phenomenon [1,6–9]. Behavior is endogenous to a model when the parameter(s) associated with behavior is a function of another time-dependent variable within the model. Including behavior endogenously can enhance the utility of a model by providing a mechanism for how behavior varies in response to both control measures as well as the epidemic dynamics. In turn, the behavioral response can alter the epidemiological dynamics within the simulation by changing the disease state of individuals, modifying parameters, or modifying the contact structure of a network [6]. Models incorporating this recursive element can project periodic waves of infection with multiple epidemic peaks, which more closely matches real-world data [10–12].

Incorporation of endogenous behavior in disease models prior to the COVID-19 pandemic has largely been restricted to models of HIV and vaccination choices [6], though there has been some extension of prevalence-dependent behavior to other domains [6–9], such as influenza [13]. Increasingly, there is awareness of the importance of endogenous behavior in models of COVID-19 [14]. To understand the extent to which endogenous behavior was incorporated into COVID-19 models, we conducted a systematic scoping review of the mathematical approaches for including endogenous behavior. Models in which behavior was included as an exogenous input variable or changed at fixed points of policy change were not considered. The goal of this review is to inform researchers and decision-makers on the importance of incorporating endogenous behavior in dynamic models to increase their use in future outbreaks.

2. Methods

We conducted a search of the literature for studies that used models of COVID-19 transmission dynamics that included human behavior as an endogenous variable. We did not place any restrictions on the language or date published. The following sections describe the search strategy, selection criteria, inclusion and exclusion criteria, and data extraction and analysis.

2.1. Search strategy

A PubMed search was conducted in July 2022 using a comprehensive search strategy comprised of three concepts: 1) dynamic modeling, 2) COVID-19, and 3) human behavior. Keywords were searched using the 'Text Word' field, which includes all words in the title, abstract, and MeSH terms. Keywords and subject headings were combined using the OR Boolean operator for each concept, and the concepts were combined using the AND Boolean operator (See Supplementary Table 1 for the complete search strategy). The search was re-run in June 2023 to capture studies published after July 2022.

2.2. Selection criteria

Search results were imported into the Covidence Platform [15], and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for scoping reviews were followed [16]. Six reviewers (AH, AT, FH, NK, SP, and GL) conducted title and abstract

Table 1
Summary of Extracted Data by Approach to Endogenous Behavior

	All studies 92 (100%)*	Feedback Loop 66 (72%)*	Game/Utility Theory 25 (27%)*	Information/ Opinion Spread 8 (9%)*
Model Type				
Compartmental	82 (89%)	57 (86%)	23 (92%)	6 (75%)
ABM	10 (11%)	8 (12%)	3 (12%)	2 (25%)
Network	14 (15%)	9 (14%)	3 (12%)	6 (75%)
System Dynamics	6 (7%)	5 (8%)	0 (0%)	2 (25%)
Markov	1 (1%)	1 (2%)	0 (0%)	0 (0%)
Effect of Behavior Change				
Modifies parameter(s)	56 (61%)	42 (64%)	13 (52%)	5 (63%)
Changes state	27 (29%)	15 (23%)	12 (48%)	2 (25%)
Modifies network structure	14 (15%)	11 (17%)	1 (1%)	1 (13%)
Decision Maker				
Individual	87 (95%)	60 (91%)	25 (100%)	8 (100%)
Central planner	18 (20%)	12 (18%)	5 (20%)	2 (25%)
Population Heterogeneity				
	30 (33%)	24 (36%)	6 (24%)	3 (38%)
Spatial Heterogeneity				
	9 (10%)	8 (12%)	1 (4%)	0 (0%)
Stochasticity				
	37 (40%)	24 (36%)	10 (40%)	8 (100%)
Data fitting for parameterization				
	63 (68%)	49 (74%)	15 (60%)	2 (25%)
Compared forecasts to real-world data				
	23 (25%)	21 (32%)	2 (8%)	0 (0%)
Compared models with and without endogenous behavior				
Sensitivity analysis	34 (37%)	24 (36%)	10 (40%)	3 (38%)
Data fitting	4 (4%)	3 (5%)	1 (4)	0 (0%)

* Percentages are not exclusive and expressed vertically; for example, 88% of studies using a feedback loop approach employed compartmental models.

screening as well as full-text screening using a customized screening tool (Supplementary Table 2). Title and abstract screening was conducted using Covidence, and information gathered during full-text screening was compiled in an Excel spreadsheet. One reviewer was needed to screen each study. If a reviewer was unclear on the eligibility of a study, a second reviewer was consulted.

2.3. Inclusion and exclusion criteria

We included studies that modeled a COVID-19 outcome, such as cases, deaths, hospitalizations, or the basic or effective reproduction number and excluded studies of other infectious diseases. We restricted analysis to studies that used dynamic models (i.e., used systems of equations to capture the epidemiological dynamics of disease). These include compartmental models, agent-based models (ABMs), network models, system dynamics models, and Markov chain models (Supplementary Table 3). We excluded conceptual models without mathematical equations and statistical and machine learning models which only use prior data and exogenous factors to predict future burden. We included studies that incorporated behavior endogenously as a function of another time-dependent variable within the model. Studies that included human behavior simply as an exogenous longitudinal input variable (e.g., cellphone mobility data) were excluded, as were studies that modeled behavioral responses by adjusting parameters exogenously at fixed time points based on policy changes. We only considered original research articles published in academic journals or pre-print platforms, such as *medRxiv*, and we excluded letters, protocols, abstracts, conference proceedings, and reviews.

2.4. Data extraction and analysis

During the full-text screening, seven reviewers (including HD) read each article in-depth and collated extracted data in an Excel spreadsheet later used for counting statistics. We recorded data on model type, approach to endogenous behavior, compartments or states, population scale and mixing, randomness, time-step and simulation length, spatial information, modeled outcomes, parameterization, forecast validation, sensitivity analyses, and health equity considerations. Each article was read by at least one reviewer, and a second reviewer was consulted to resolve uncertainties.

2.5. Role of the funding source

This work was funded by the Centers for Disease Control and Prevention (CDC) MInD-Healthcare Program (grant number 1U01CK000536) and the National Science Foundation (NSF) Modeling Dynamic Disease-Behavior Feedbacks for Improved Epidemic Prediction and Response grant (award number 2229996). The funders had no role in the design, analysis, decision to publish, or preparation of the manuscript.

3. Results

The PubMed search resulted in 6344 articles, among which 2559 duplicates were removed, leaving 3785 for title and abstract screening (Fig. 1). One hundred ninety-six studies were selected for full-text screening, among which 104 studies did not meet inclusion criteria. Twenty were excluded because the model was not dynamic, 23 were excluded because the outcomes modeled did not pertain to COVID-19, and 58 were excluded because the behavior element was not endogenous. Full-text versions were unavailable for two studies, and one paper was a pre-print of an already included study. Ninety-two studies met all inclusion criteria. Full results from data extraction are presented in the supplementary file Included_Studies_Dialogues.xlsx, and a summary is provided in the following sections and in Table 1.

For the purposes of this study, “model type” refers to the type of model, for example, compartmental, ABM, or Network (See Supplementary Table 3 for a general overview of model types). Eighty-nine percent of studies ($N = 82$) used a compartmental model, 11% ($N = 10$) used an ABM, 15% ($N = 14$) used a network model, 7% ($N = 6$) used a system dynamics model, and 1% (N = 1) used a Markov chain model (Fig. 2). Nineteen percent of studies ($N = 18$) used hybrid models of two

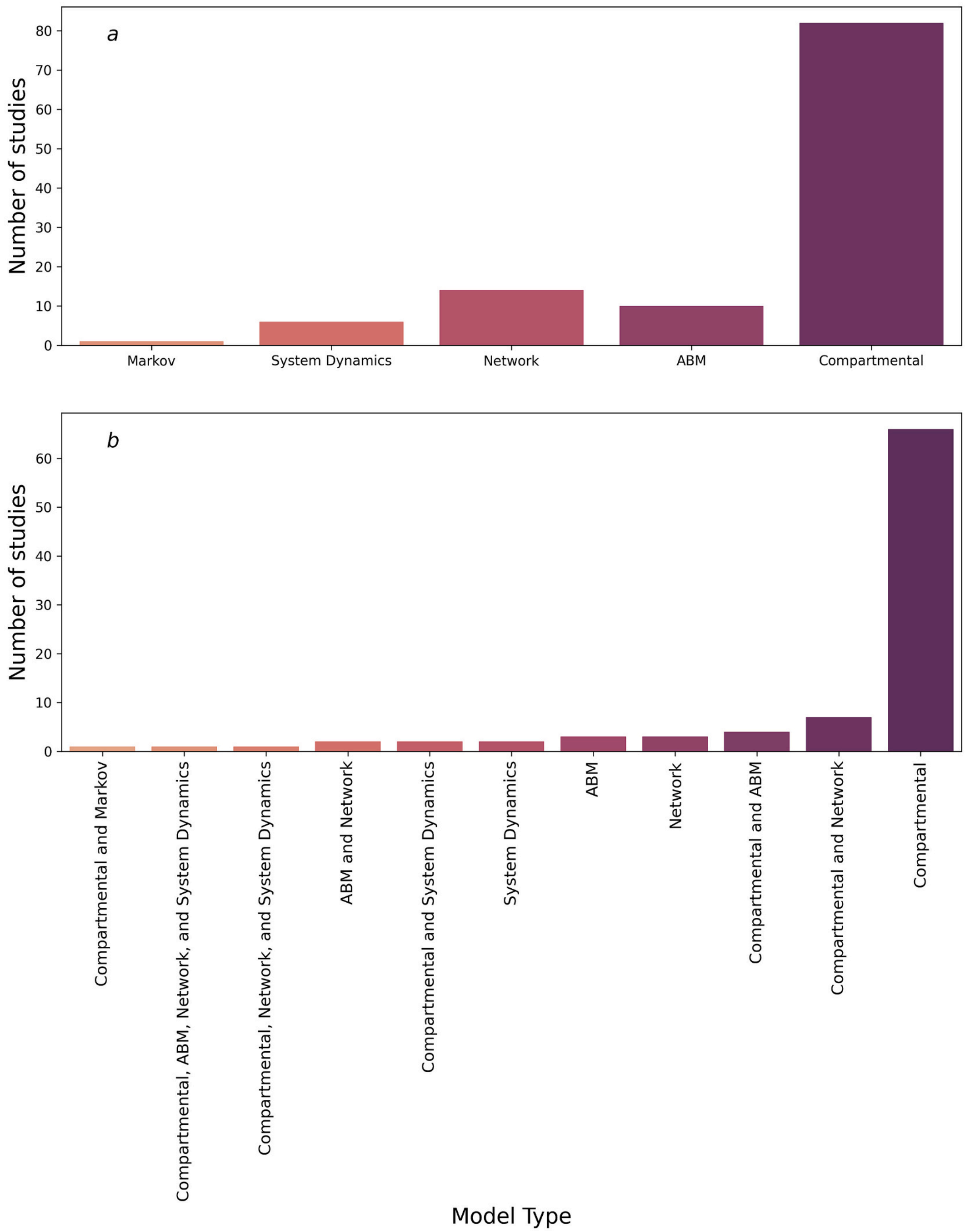

Fig. 2. Number of Studies by Model Type. a) Number of studies by model type including overlap from hybrid models (values will sum to over the total number of studies). b) Number of studies by model type without overlap (categories are mutually exclusive).

or more types, hence percentages sum to over 100, while the rest used a single model type.

Behavior change resulted in three mathematical effects as described by Funk et al. 2010 [6] (Fig. 3). These included: i) modifying a model parameter (61%, $N = 56$, e.g., decreasing the transmission rate in response to increasing prevalence to simulate protective behaviors [17]), ii) changing the disease state of individuals (29%, $N = 27$, e.g., moving to a vaccinated state [18]), and iii) modifying the contact structure of the network (15%, $N = 14$, e.g., decreasing contacts to simulate social distancing [19]). Other descriptors of behavior included limiting mobility, mask wearing, adhering to restrictions, and unspecified protective behaviors. Regardless of the terms used to describe behavior, we found behavior changes always resulted in one or more of the three mathematical effects.

Behavior change was instigated by individuals in 95% ($N = 87$) of studies (e.g., wearing masks, social distancing, etc.) and by a central planner in 20% ($N = 18$, e.g., forced quarantine, closing schools, etc.). Thirty-three percent ($N = 30$) of studies introduced population heterogeneity, usually via age-stratification, and 10% ($N = 9$) introduced spatial heterogeneity (e.g., stratifying by US census block group). Sixty-eight percent ($N = 63$) of studies used data fitting for parameterization, and 25% ($N = 23$) compared forecasted data to real-world data either qualitatively (i.e., visual comparison) or with a quantitative metric (e.g., Root Mean Square Error). Studies that compared forecasts to real-world data after the calibration period matched observed data well regardless of the stage of the pandemic.

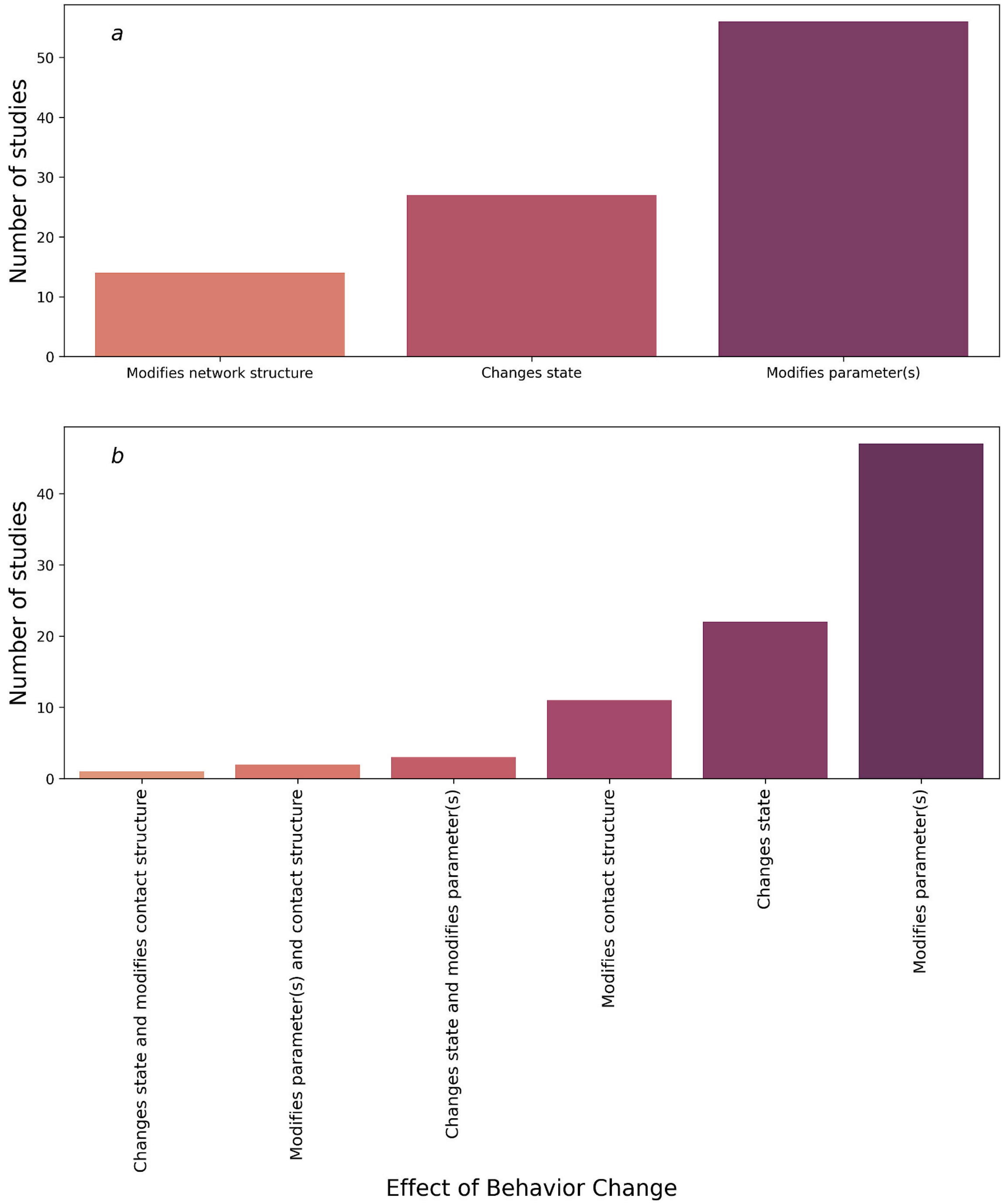

Fig. 3. Number of Studies by Effect of Behavior Change. a) Number of studies by effect of behavior change including overlap from hybrid models (values will sum to over the total number of studies). b) Number of studies by effect of behavior change without overlap (categories are mutually exclusive).

Forty-one percent ($N = 38$) of studies compared the model with endogenous behavior to a version of the same model without endogenous behavior. Thirty-four of these studies used sensitivity analyses in which parameters associated with dynamic behavior were adjusted, and four studies fitted both versions of the model (with and without endogenous behavior) to observed data. Introducing endogenous behavior often led to a smaller and delayed initial epidemic peak, could simulate multiple waves, and matched observed data well upon visual comparison regardless of the stage of the pandemic.

We categorized the method of incorporating behavior into three "approaches": i) feedback loop (72%, $N = 66$), ii) game theory/utility theory (27%, $N = 25$), and iii) information/opinion spread (9%, $N = 8$) (Figs. 4 and 5). Six percent (N = 6) of studies used more than one approach while the rest used a single approach (Fig. 5). Approaches by model type and effect of behavior are presented in Figs. 6 and 7, respectively. The following sections describe each approach for including endogenous behavior in models of COVID-19 transmission with examples from studies that compared simulations to real-world data.

3.1. Feedback loop

A feedback loop, or feedback control system, uses the prevalence of a disease outcome to stimulate a change in behavior within the model

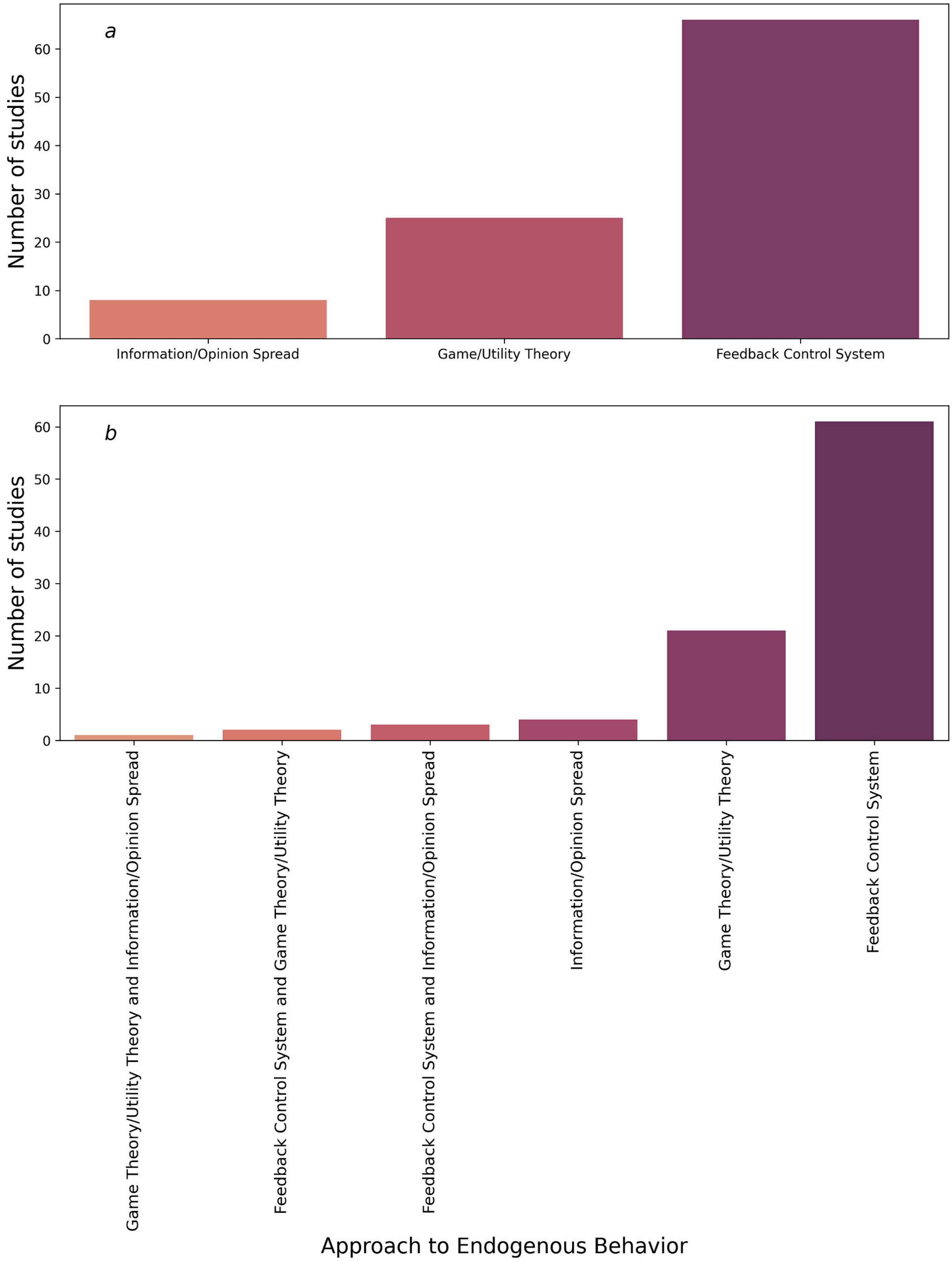

Fig. 4. Number of Studies by Approach to Endogenous Behavior a) Number of studies by approach to endogenous behavior including overlap from hybrid models (values will sum to over the total number of studies). b) Number of studies by approach to endogenous behavior without overlap (categories are mutually exclusive).

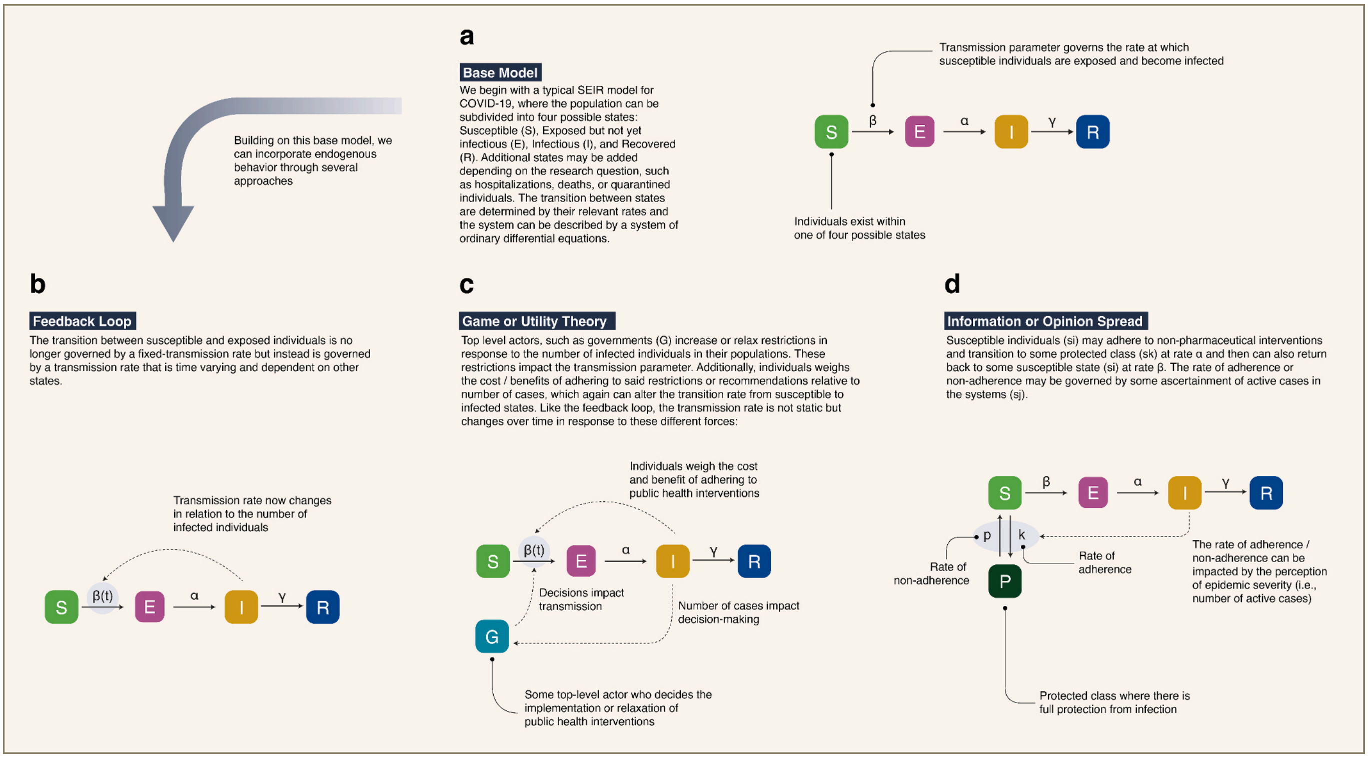

Fig. 5. Three Approaches of Incorporating Endogenous Behavior in COVID-19 Transmission Models. Each box illustrates a simplified expression and can be employed in the states of compartmental, network, or agent-based models.

(Fig. 5b). For example, people increase protective behaviors, such as vaccination, in response to rising case counts and reduce protective behaviors in response to dropping case counts. This approach is often referred to as "prevalence-dependent behavior" [20] or "risk-driven response" [12]. Feedback loops are relatively straightforward to implement and easy to understand. The data needed for this approach is usually available in the form of cases, hospitalizations, or deaths. Feedback loops allow for high-level analyses without individual-level data. In an analysis by Rahmandad et al. 2022, a relatively simple compartmental model with a feedback loop performed just as well an ensemble of CDC models in forecasting COVID-19 deaths [14]. Feedback loops do ignore some important human decision processes, however. Behavior is assumed to be protective, and heterogeneity in behavioral responses due to demographic factors is often ignored by assuming homogenous populations.

In an example of a feedback loop captured by this review, Menda et al. 2021 employ a "reactive-SEIRD" model in which the infection rate is a function of disease prevalence over time [17]. After calibrating the model, they ran simulations from March to September 2020, which reproduced multiple epidemic peaks as observed in real-world data from the United States. Using Root Mean Square Error (RMSE) and a Tukey Mean Difference Plot, they showed that the reactive behavior model had less error when compared to a standard SEIRD model without a behavior feedback loop.

3.2. Game theory/utility theory

Game theory is a technique to model how people make decisions in response to each other or some external initiative [21]. Game theoretic frameworks are commonly implemented in computational models using utility functions, which incorporate costs and benefits of different outcomes to determine the preferences of the players (i.e., individuals or a central authority). In the context of epidemic modeling, this is incorporated by having individuals or population groups maximizing their utility of engaging voluntarily or complying with mandated restrictions given the state of the outbreak (e.g., current case growth or mortality rate). Huang and Zue 2022 [22] provide a comprehensive review of game-theoretic methods in models of other infectious diseases.

Game theoretic methods incorporate individual-level decision processes that can vary based on population demographics. This approach is useful when thinking about tradeoffs; for example, a government weighing the health and economic costs and benefits of certain policies. Game theory assumes rational decision makers that make optimal decisions, and fine grain data on forces driving decisions are often unavailable. For example, applications of a cost utility approach in modeling people's decision to stay home from work when sick may be limited without survey data on worker preferences, which will vary depending on demographic factors. Without this information, the utility function may not accurately capture the nuances of real-world choices, leading to less accurate predictions. These preferences may change over time as well, so continual surveys may be needed.

In the context of COVID-19, Jovanović et al. 2021 use a hybrid model in which individuals weigh the costs and benefits of getting vaccinated based on local information (infected and immune nearest neighbors) and global information (total infections within the simulation) [18]. Vaccination payoff and anti-vaccination payoff are modeled as functions of these information sources in the vaccination game, resulting in individuals changing their vaccination state.

3.3. Information/opinion spread

In models of information or opinion spread, an individual's behavioral susceptibility to infection is affected by opinions or attitudes acquired from others in the population. Factors affecting behavior may include anti-vaccine views, compliance with government policies, emotional state, and risk awareness. Epstein et al. 2008 [23] refer to this approach as "coupled contagion" in a model in which fear, as well as a disease, spreads throughout a population [23]. In these models, individual behavior is influenced by a mixture of information reflecting the actual state of the epidemic (e.g., case counts) and information that may

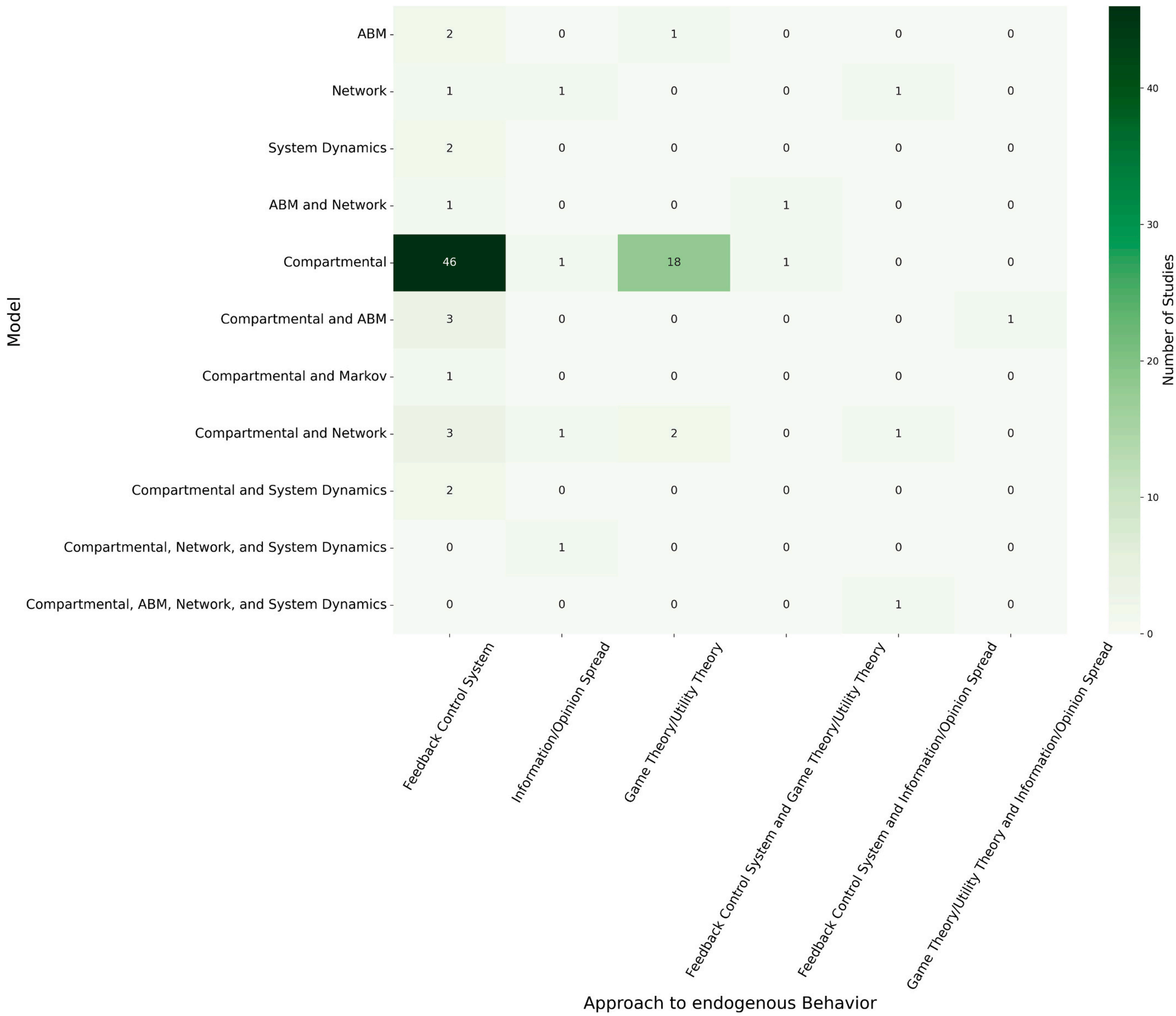

Fig. 6. Approach to Endogenous Behavior by Model Type.

not be reflective of the epidemic at all (e.g., opinions of neighbors). Unlike in feedback loops and game theoretic approaches, information/opinion spread models can include irrational behavior. For example, choosing not to get vaccinated due to anti-vaccine views among neighbors may increase health burden both locally and globally. Information/opinion spread models may be useful in modeling misinformation and superspreading events.

In the hybrid model by Guo et al. 2021, adoption of NPIs is determined by individuals' emotional state (indifferent, worried, afraid, and numb) [24]. The rate at which individuals transfer between emotional states depends on the "concern" variable which is dynamically influenced by local and global information about the epidemic. They calibrated their model using infection counts from six cities over the first 40 days of the pandemic, demonstrating a good fit between their model and the data.

4. Discussion

During the COVID-19 pandemic, public health policy makers and officials relied heavily on mathematical models of disease transmission that predicted epidemic spread to inform decision-making. While many models incorporated human behavior exogenously, either by using longitudinal input data (e.g., cellphone mobility data) or by changing parameters at fixed time points of policy change, these approaches were often suboptimal in capturing the dynamics of disease [14], especially after the first epidemic peak. For example, correlations between COVID-19 case counts and mobility data proved to be weak after the first wave of the pandemic [25]. Similarly, trying to predict the extent and timing of future public health restrictions is difficult and this cannot capture future adaptations in human behavior to disease spread. In contrast, modeling behavior endogenously using dynamic parameters attempts to capture the fluctuating nature of human behavior in response to a continuously changing epidemic [11] and has the potential to simulate more accurate depictions of disease burden. This review aimed to capture models that included an adaptive behavior element in the context of COVID-19 transmission. We categorized studies into three main approaches, including feedback loops, game theory/utility theory, and information/opinion spread.

Most studies in this review employed a feedback loop with a compartmental model in which the behavior change modified a model

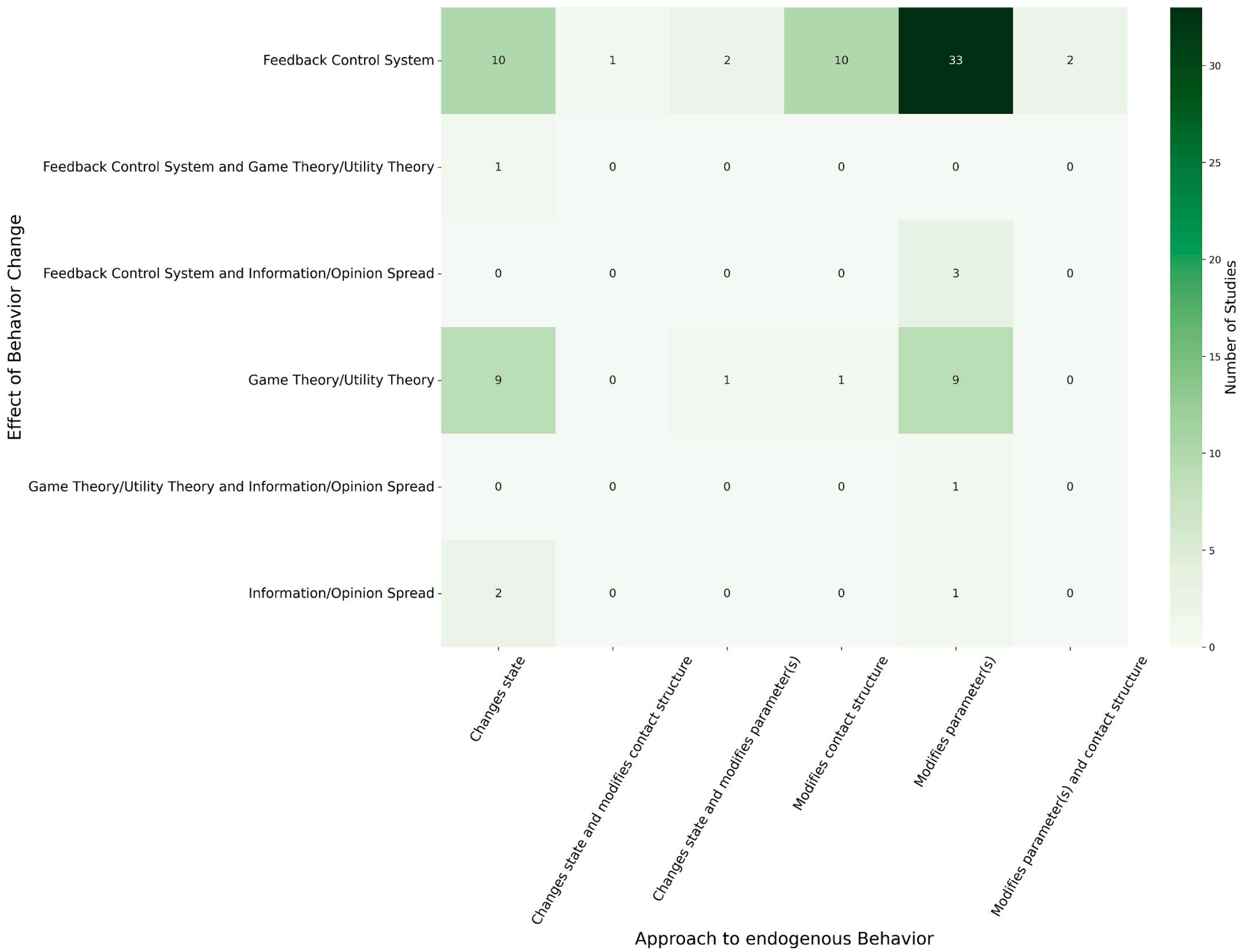

Fig. 7. Approach to Endogenous Behavior by Effect of Behavior Change.

parameter. Compartmental models have a long history in infectious disease modeling and making the transmission parameter a function of a disease outcome (cases, deaths, etc.) is relatively straightforward and does not require additional data on behavior or preferences. Researchers have been proposing this method for years in response to past epidemics [6–9], such as the H1N1 influenza epidemic [13], in which reactive human behavior was an important driver of disease spread. However, relatively few models in the CDC influenza forecasting hub [26] or the COVID-19 hubs [27,28] use this approach.

Other approaches to endogenous behavior and model types can be more complicated and need finer grain data, which may explain why they were not represented as much in our review. Game/utility theory approaches benefit from survey data on player preferences, but such data may be difficult to collect from a representative sample. Network models may be particularly suited to the information/opinion spread approach where a social network is required within which to transmit information. However, generating a realistic contact network, especially one that is geographically realistic, can be very involved. ABMs can capture demographic and geographic heterogeneity better than compartmental models given their ability to assign attributes to individual agents, but this can be computationally expensive. System dynamics models are often very complex with many assumptions that are difficult to validate. Similarly, adding complexity with a Markov chain model may not be necessary when a compartmental model performs just as well.

Variability in model design, target population, and reporting made comparing the performance of models in this review difficult. Thus, we were unable to prescribe the most effective method or most relevant behavior to embed. Several studies compared versions of their model with and without endogenous behavior, usually via sensitivity analyses in which behavior parameters were adjusted or "turned off". Almost all models that conducted parametric analysis in this way found that simulations with endogenous behavior more closely matched real-world data. The incorporation of endogenous behavior often led to a reduced and delayed initial peak followed by periodic waves of disease burden. For example, in Rypdal et al. 2020, changing parameters associated with intervention fatigue impacted the magnitude and frequency of multiples peaks [29]. Sensitivity analyses are useful to describe how endogenous behavior impacts simulated results, but they are not sufficient to quantify model performance against real-world outcomes. In order to claim that the inclusion of endogenous behavior brings added value, both models (with and without endogenous behavior) must separately be calibrated to the same dataset to demonstrate that the model with endogenous behavior fits the data better. Only four studies in this review calibrated both versions of their model to the same dataset. Thus, we cannot conclude that models with endogenous behavior outperform models without endogenous behavior (e.g., models with exogenous behavior) from studies in this review.

While to some extent the choice of method is dependent on data availability, resources and time constraints of the modeling team, the model type, and the behavior modeled, a process to validate different mechanisms of embedding endogenous behavior is urgently needed to prepare for the next pandemic. A standardized reporting protocol, such as the EPIFORGE checklist [30], will help when comparing models to better understand the different facets of behavior and how they impact disease dynamics. Furthermore, while some data that could potentially drive behavior change may be readily available, such as local case/hospitalization counts, investments are needed to develop new data streams that can aid model development and provide context during a crisis.

Understanding how heterogeneity in human behavior during infectious disease outbreaks is another crucial area that many of the models examined did not account for. Only 33 % of studies in our analysis included population heterogeneity by stratifying populations based on demographic factors. Heterogeneity in response to disease outbreaks can be highly dependent on social stratifiers, such as age, race, ethnicity, class, education level, geographic location, ability, and sexual orientation [31]. Incorporating these factors in models more accurately represents real-world disease dynamics with regards to behavior and differential health outcomes. This is particularly important for lower socioeconomic populations (e.g., individuals without savings or lacking telework options) that often must make important tradeoffs between health and financial security. Not including how populations may differ in their perception and response to an epidemic undermines our ability to evaluate policies that take various dimensions of well-being into account. Furthermore, the lack of demographic, and particularly socioeconomic differences, limits the ability to assess equitability of policy options, including distributional consequences across socioeconomic groups. Including social heterogeneity in models can help identify complex interactions among subgroups and can provide insight into the impact that varying groups have on the spread of diseases and adoption of health-related behaviors.

Our inclusion criteria captured a substantial number of COVID-19 models; however, this review is not exhaustive and has some limitations. First, we excluded models of other infectious diseases for which human behavior is an important component impacting transmission. Second, our last search was run in June 2023, and our review does not include studies published after this date. Third, we only searched one database and only required one reviewer to screen each study. Fourth, we excluded unpublished models; many COVID-19 modeling efforts were not published but played an important role in public health decision making during the pandemic. To address this limitation, we reviewed models in the USA CDC Forecasting and Scenario Hubs ($N = 21$) and the European Forecasting Hub ($N = 61$). We found five models in the USA CDC efforts that included endogenous behavior in model design. Finally, we did not exclude studies if they employed a model from another included study; therefore, some studies may use modified versions of the same model. Despite these limitations, we believe this review represents COVID-19 modeling efforts adequately enough to summarize different approaches for incorporating endogenous behavior in COVID-19 models.

5. Conclusion

We have more to learn about what exactly drives human behavior in infectious disease outbreaks (e.g., fear, altruism, or obedience). Multidisciplinary collaboration between epidemiologists, economists, mathematicians, psychologists, and social scientists is needed to build the next generation of models that more accurately represent real-world dynamics. We must think creatively about the kinds of data needed to capture human behavior in order to build robust models with justifiable assumptions. Now is the time to invest in building capacity for these models to prepare for and better respond to the next pandemic.

Contributors

AH, FH, AT, NK, SP, and GL conducted title/abstract screening and full-text screening. AH, FH, AT, NK, SP, GL, and HD conducted data extraction. AH, FH, AT, NK, SP, and HD drafted sections of the manuscript. NK, HD, and SP generated figs. AH managed the review process, created tables, and compiled the manuscript. LG provided subject matter expertise and revised the manuscript. EK conceived of the study, supervised the review process, and revised the manuscript. All authors reviewed the manuscript before submission.

CRediT authorship contribution statement

Alisa Hamilton: Writing – review & editing, Writing – original draft, Project administration, Formal analysis, Data curation. **Fardad Haghpanah:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Alexander Tulchinsky:** Writing – review & editing, Writing – original draft, Formal analysis. **Nodar Kipshidze:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Suprena Poleon:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis. **Gary Lin:** Writing – review & editing, Formal analysis. **Hongru Du:** Writing – review & editing, Visualization, Formal analysis. **Lauren Gardner:** Writing – review & editing, Supervision, Funding acquisition. **Eili Klein:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Eili Klein reports financial support was provided by Centers for Disease Control and Prevention. Eili Klein reports financial support was provided by National Science Foundation. Lauren Gardner reports financial support was provided by National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data extraction for all included studies is presented in the supplementary file Included_Studies_Dialogues.xlsx.

Acknowledgements

This study was funded in-part by Centers for Disease Control and Prevention (CDC) *MInD-Healthcare Program* (1U01CK000536), the National Science Foundation (NSF) *Modeling Dynamic Disease-Behavior Feedbacks for Improved Epidemic Prediction and Response* grant (2229996), and the NSF *PIPP Phase I: Evaluating the Effectiveness of Messaging and Modeling during Pandemics* grant (2200256). The funders had no role in the design, analysis, decision to publish, or preparation of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.dialog.2024.100179.

References

[1] Klein EY, Laxminarayan R, Smith DL, Gilligan C, a.. Economic incentives and mathematical models of disease. Environ Dev Econ 2007 Oct;12(05):707–32.

[2] Colonna K, Nane G, Choma E, Cooke R, Evans J. A retrospective assessment of COVID-19 model performance in the USA. R Soc Open Sci 2022 Oct 19;9.

[3] Hanna K, Clarke P, Woolfall K, Hassan S, Abba K, Hajj TE, et al. The perception of risk in contracting and spreading COVID-19 amongst individuals, households and vulnerable groups in England: a longitudinal qualitative study. BMC Public Health 2023 Apr 5;23(1):653.

[4] Cipolletta S, Andreghetti GR, Mioni G. Risk perception towards COVID-19: A systematic review and qualitative synthesis. Int J Environ Res Public Health 2022; 19(8).

[5] Nixon K, Jindal S, Parker F, Reich NG, Ghobadi K, Lee EC, et al. An evaluation of prospective COVID-19 modelling studies in the USA: from data to science translation. Lancet Digital Health 2022 Oct 1;4(10):e738–47.

[6] Funk S, Salathé M, Jansen V, a a.. Modelling the influence of human behaviour on the spread of infectious diseases: a review. J Roy Soc Interface Roy Soc 2010 Sep;7 (50):1247–56.

[7] Funk S, Bansal S, Bauch CT, Eames KTD, Edmunds WJ, Galvani AP, et al. Nine challenges in incorporating the dynamics of behaviour in infectious diseases models. Epidemics 2015 Mar 1;(10):21–5.

[8] Perra N, Balcan D, Gonçalves B, Vespignani A. Towards a characterization of behavior-disease models. PLoS One 2011 Aug 3;6(8):e23084.

[9] Weston D, Hauck K, Amlôt R. Infection prevention behaviour and infectious disease modelling: a review of the literature and recommendations for the future. BMC Public Health 2018 Mar 9;18(1):336.

[10] Berestycki H, Desjardins B, Weitz JS, Oury JM. Epidemic modeling with heterogeneity and social diffusion. J Math Biol 2023 Mar 25;86(4):60.

[11] Arthur RF, Jones JH, Bonds MH, Ram Y, Feldman MW. Adaptive social contact rates induce complex dynamics during epidemics. PLoS Comput Biol 2021 Feb 10; 17(2):e1008639.

[12] Rahmandad Hazhir, Ran Xu, Ghaffarzadegan Navid. A missing behavioural feedback in COVID-19 models is the key to several puzzles. BMJ Glob Health 2022 Oct 1;7(10):e010463.

[13] Poletti P, Ajelli M, Merler S. The effect of risk perception on the 2009 H1N1 pandemic influenza dynamics. PLoS One 2011 Feb 7;6(2):e16460.

[14] Rahmandad H, Xu R, Ghaffarzadegan N. Enhancing long-term forecasting: learning from COVID-19 models. PLoS Comput Biol 2022 May 19;18(5):e1010100.

[15] Covidence systematic review software [Internet]. Melbourne, Australia: Veritas Health Innovation [cited 2022 Nov 30]. Available from: https://www.covidence.org/.

[16] Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med 2018 Oct 2;169(7):467–73.

[17] Menda K, Laird L, Kochenderfer MJ, Caceres RS. Explaining COVID-19 outbreaks with reactive SEIRD models. Sci Rep 2021 Sep 9;11(1):17905.

[18] Jovanović R, Davidović M, Lazović I, Jovanović M, Jovašević-Stojanović M. Modelling voluntary general population vaccination strategies during COVID-19 outbreak: influence of disease prevalence. Int J Environ Res Public Health 2021;18 (12).

[19] Corcoran C, Clark JM. Adaptive network modeling of social distancing interventions. J Theor Biol 2022 Aug 7;(546):111151.

[20] Kassa SM, Ouhinou A. Epidemiological models with prevalence dependent endogenous self-protection measure. Math Biosci 2011 Jan 1;229(1):41–9.

[21] Von Neumann J, Morgenstern O. Theory of games and economic behavior. Princeton NJ: Princeton University Press; 1944.

[22] Huang Y, Zhu Q. Game-theoretic frameworks for epidemic spreading and human decision-making: a review. Dynam Games Appl 2022 Mar 1;12(1):7–48.

[23] Epstein JM, Parker J, Cummings D, Hammond R, a.. Coupled contagion dynamics of fear and disease: mathematical and computational explorations. PLoS One 2008 Jan;3(12):e3955.

[24] Guo X, Tong J, Chen P, Fan W. The suppression effect of emotional contagion in the COVID-19 pandemic: A multi-layer hybrid modelling and simulation approach. PLoS One 2021 Jul 28;16(7):e0253579.

[25] Gatalo O, Tseng K, Hamilton A, Lin G, Klein E. Associations between phone mobility data and COVID-19 cases. The Lancet Infectious Diseases [Internet] [cited 2021 Feb 23. 2021. https://doi.org/10.1016/S1473-3099(20)30725-8.

[26] Centers for Disease Control and Prevention. FLUSIGHT: Forecasting for Influenza Prevention and Control [Internet]. Centers for Disease Control and Prevention; 2024. Apr [cited 2024 Apr 28]. Available from: https://www.cdc.gov/flu/weekly/flusight/flu-forecasts.htm.

[27] Centers for Disease Control. COVID-19 Forecast Hub [Internet]. Centers for Disease Control and Prevention [cited 2024 Apr 28]. Available from: https://covid19forecasthub.org/.

[28] Centers for Disease Control. COVID-19 Scenario Modeling Hub [Internet]. Centers for Disease Control and Prevention [cited 2024 Apr 28]. Available from: https://covid19scenariomodelinghub.org/.

[29] Rypdal K, Bianchi FM, Rypdal M. Intervention fatigue is the primary cause of strong secondary waves in the COVID-19 pandemic. Int J Environ Res Public Health 2020;17(24).

[30] Pollett S, Johansson MA, Reich NG, Brett-Major D, Del Valle SY, Venkatramanan S, et al. Recommended reporting items for epidemic forecasting and prediction research: the EPIFORGE 2020 guidelines. PLoS Med 2021 Oct 19;18(10): e1003793.

[31] Buckee C, Noor A, Sattenspiel L. Thinking clearly about social aspects of infectious disease transmission. Nature 2021 Jul 1;595(7866):205–13.