

TITLE

Centering human cognition in epidemiological models

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Viral infectious disease poses a threat to the health of individuals and the functioning of society. Projecting infection dynamics and assessing the efficacy of potential interventions is key to controlling the spread of disease and minimizing its impacts. Mathematical models of infectious disease, known as epidemiological models (EMs), are an important tool for projecting the spread of infectious disease and for examining the efficacy of proposed interventions. EMs have

traditionally assumed that individuals occupy a small set of states with respect to disease, e.g. susceptible to disease (S), infectious (I), or recovered (R), with transitions between states governed by treating individuals as gas-like particles colliding with each other—this forms the foundation of the classic SIR model. Variations on the SIR model have introduced additional states to account for specific disease stages or interventions, for example, asymptomatic stages, quarantines, or more detailed descriptions of how people interact with each other [1–4].

The COVID-19 pandemic illustrated the inability of many EMs to capture the disease case trajectories observed in populations [5,6]. This failure stems, in part, from the limited treatment of human behavior in EMs: when behavior is included, it is typically represented as a fixed or instantaneous function of disease state rather than as the outcome of cognitive processes that unfold on their own timescales. Behavior strongly mediates the spread of infectious disease and can introduce non-linear effects, context dependence, delays, etc. When individuals decide to adopt protective behaviors such as isolation, social distancing, hand washing, or use of masks, they reduce the transmission of virus. Decisions to be vaccinated or to use antiviral drugs can reduce both viral transmission and health impacts in infected individuals. Behavioral decisions are related to perceptions of risk from both the disease and the protective behaviors themselves, and are also influenced by socio-cultural context and governmental policy. For example, perceived social norms (How are people around me behaving?) signal how people should behave while policy can facilitate what behaviors people can engage in (e.g., Are vaccines available? Are they subsidized?). Behavioral adoption influences the spread of the behavior itself in addition to mediating the spread and severity of disease, modifying risk perceptions, and the socio-behavioral context. In this context, infectious disease is not primarily a biophysical phenomenon but rather a dynamic, coupled human-pathogen system dominated by socio-behavioral processes. Skillful projections and understanding of disease dynamics depend on the accurate representation of both system components—the human socio-behavioral system and the biophysical system [7–9].

Many EMs do incorporate some representation of human behavior [10–17], and the question is therefore not whether to include behavior but how. Some models use behavioral proxies to reduce contact rates in response to increasing disease prevalence, encoding the implicit assumption that people adopt protective behaviors with increasing disease prevalence [18,19]. In other models, cognitive states are represented as discrete switches (e.g., aware/unaware) that diffuse through populations to determine behavior [20]. Behavior has also been represented as a continuous trait that is mediated by individual beliefs and social structure [21]. Others have used game-theoretic approaches for economic optima [10–17] or evolutionary game theory to model social learning with imitation dynamics [16,22,23]. Algorithmic rules are used to map disease state to contact rates and disease transmission in agent-based models that can incorporate structured networks of interactions between individuals [24–26]. While this variety of approaches all incorporate some representation of behavioral response, they do not treat cognition and behavior as separate processes with distinct temporal dynamics. In addition, these modeling approaches often utilize frameworks that conflict with the structure of traditional EMs based on compartmental models and this can limit their utilization.

The structure of models reflects the biases and expertise of those that develop them. EMs, largely developed by mathematicians and biologists, have focused on the mathematical representation of

underlying biological processes of disease spread, leaving the human behavioral component of the human-pathogen system underdeveloped. EMs would benefit from increased focus on the socio-behavioral processes, the explicit incorporation of social and psychological theory into the representation of human behavior, and from direct collaborations with social and behavioral scientists throughout the process of model development and analysis [27]. We also believe that this can be done within the compartmental structure of traditional EMs.

Behavioral scientists have developed a large set of theories to describe human cognitive and behavioral processes [28–33]. Cognition describes how humans process and interpret information to form behavioral intentions. Cognitive states are unobservable, nonlinear, interact with the environment, and are dependent on past states. Cognition and behavior operate on different timescales: Cognitive states evolve continuously in response to information about disease prevalence and virulence as well as the social and cultural context, and these states in turn mediate the discrete behavioral choices that drive disease transmission. We refer to EMs that represent cognitive states as continuously evolving state variables, alongside traditional disease compartments, as cognitive epidemiological models (CEMs). By separating cognition from behavior, CEMs enable modeling of interventions at different time scales: information-based interventions (e.g., public health messaging) that shape cognitive states and resource-based interventions (e.g., vaccine availability) that directly constrain or enable behavioral options.

A key uncertainty is identifying which cognitive processes from the broad set of theory should be included in CEMs and how to represent them in models. There is a rich body of theory on cognition, but no single dominant framework for representing it in models. Rather than advocating for any particular theory, we distill from this literature a set of cognitive processes that mediate behavioral responses to disease. We frame human cognition fundamentally as a mechanism for receiving and processing information that determines the perception of risk and the formation of a behavioral intention; this intention is mapped against the set of possible behaviors, leading to the adoption of a behavior. We briefly describe the processes we believe are important to represent in CEMs.

Perceived risk is the individual's continuously evolving internal representation of the threat posed by a disease or a protective behavior and is formed by processing available information with existing beliefs. Information provides cues on risks and how to behave from multiple sources, including direct experience (e.g., perceived prevalence and/or virulence of a disease), observations of how others behave (e.g., social influence), and guidance from authorities (e.g., government policy). Information processing mechanisms include biased assimilation, which reflects how individuals give greater weight to information that aligns with their prior beliefs or trusted sources, and habituation, in which the weighting of information decays over time as individuals become desensitized or adjust their expectations in light of recent experience. Perceived risk is shaped by social influence and culture (e.g., which information sources are trusted), and in turn shapes behavioral intention.

Social influence describes how the behaviors of others affect an individual's behavior and includes perceived social norms and social learning. Perceived social norms constrain behavior to be similar to others' behaviors, while social learning expands the set of accepted behaviors as individuals observe and adopt others' efficacious behaviors. Perceived risk together with social

126 influence drive behavioral intention, which is the mental commitment to act in a particular way.
127 Social influence both mediates perceived risk and provides an independent driver of behavioral
128 intention, and is mediated by culture.

129 **Culture** is a population-level trait that mediates the processing of information as well as the
130 mapping of behavioral intention to behavior. Material culture, for example, constrains or
131 facilitates behavioral choices through resource availability (e.g., are vaccines or masks
132 available?) while non-material culture (e.g., social norms, values, and policies) mediates
133 information flow and processing and constrains the range of acceptable behaviors (e.g.,
134 vaccination, mask wearing). Culture mediates information processing (which sources are trusted,
135 how information is weighted) and constrains the mapping from intention to behavior, while itself
136 slowly evolving as aggregated individual behaviors change population-level norms.

137 **Learning** describes how individuals adjust their cognitive states and behavior in light of
138 continuously evolving information on disease prevalence and intervention outcomes. Learning
139 updates perceived risk, social influence, and the formation of behavioral intentions, closing the
140 feedback loop between disease and cognition.

141 These processes are dynamic and linked through feedback loops: Socio-behavioral processes
142 drive disease spread, and prevalence of disease drives the socio-behavioral processes. Individual
143 cognitive processes aggregate to population-level patterns, changing culture. These processes
144 thus operate across social scales from individuals to populations and on distinct timescales:
145 perceived risk shifts in days, behavioral intention in days to weeks, and cultural norms in months
146 to years, producing the delayed and heterogeneous responses that distinguish CEMs from
147 instantaneous-response models.

148 Cognitive processes can be modeled at the individual level or as the aggregate behavior of
149 individuals. Agent-based models explicitly represent individual heterogeneity in cognitive states,
150 allowing emergent population-level dynamics to arise from individuals. Alternatively,
151 compartmental models treat populations as homogeneous in combined cognitive-epidemiological
152 states (e.g., susceptible individuals with high vs. low perceived risk). Compartmental models
153 can also represent distributions of cognitive states using mean-field approximations where
154 population-level averages are represented by state variables (e.g., a population-level perceived
155 risk) that evolve alongside traditional disease compartments.

156 We illustrate how cognitive processes can be incorporated within a compartmental framework,
157 considering a minimal CEM built on an SIR model. We add a single state variable, population-
158 level perceived risk P , that increases with disease prevalence I (or, alternatively, with the rate of
159 new cases) and decays through habituation: $dP/dt = \alpha I - \delta P$, where α weights incoming
160 information and δ is the rate of habituation. Perceived risk drives the fraction of the population
161 adopting a protective behavior, $b(P)$, represented by a saturating (e.g., sigmoidal) function to
162 capture both a threshold for action and a ceiling on adoption. Adoption reduces the effective
163 transmission rate to $\beta(1 - \epsilon b)$, where ϵ is the efficacy of the behavior and β is the baseline
164 transmission rate. In this minimal model, perceived risk has its own dynamics and can produce
165 behavior that lags prevalence, overshoots it, and continues to relax after prevalence has declined,
166 in contrast to models in which contact rates respond instantaneously to prevalence [18,19]. Other

cognitive and socio-behavioral processes enter as modifications of this core model: biased assimilation and trust make α depend on the information source; social influence adds a term in which adoption depends on the current fraction of adopters (a perceived norm) as well as on P ; culture sets population-specific parameter values (which sources are trusted, which behaviors are available and acceptable); and learning updates α , δ , and the intention-to-behavior mapping as outcomes accumulate. Each addition is an ordinary differential equation or a parameter dependency, and so remains compatible with the compartmental models, numerical solvers, and inference tools already in use. The resulting model can be thought of as two coupled layers: a biophysical layer of disease compartments and a cognitive layer of continuously evolving state variables, linked by two feedbacks. Disease prevalence and intervention outcomes enter the cognitive layer as information, and behavior enters the biophysical layer through its effect on the transmission rate or, in the case of vaccination, on the flow from S to R . Information-based interventions act on the first link; resource-based interventions act on the second.

While cognitive states cannot be directly observed, this does not preclude their inclusion in models. Epidemiologists routinely estimate unobserved quantities (e.g., the number of asymptomatic infections, the time-varying reproduction number, the rate at which immunity wanes) by treating them as latent states and constraining them with the data that are available. Cognitive states can be treated in the same way. Perceived risk and behavioral intention can be constrained by repeated population surveys, which were fielded at high frequency and large scale during the COVID-19 pandemic [34], and by behavioral experiments. Behavior can be constrained by mobility data, observed mask use, and vaccination uptake. The parameters linking cognition, behavior, and transmission can be estimated jointly with epidemiological parameters using the same state-space and Bayesian methods used to fit latent disease compartments [6]. Behavioral data remain limited and often do not capture demographic and cultural heterogeneity, but this is a reason to collect behavioral data alongside epidemiological surveillance rather than to omit behavior from models. Even where data are sparse, CEMs are useful for exploring the range of behavioral dynamics consistent with what is known and for generating testable hypotheses about the interactions between disease and human behavior.

The representation of cognitive processes in epidemiological models will allow for more realistic behavioral dynamics, improve predictive skill, enhance policy relevance, and ultimately provide deeper insights into how behavior and disease interact and co-evolve over time. A traditional EM might project high uptake of vaccines as an instantaneous response to increasing disease prevalence, while a CEM would capture how cognitive states evolve over time to produce delayed, heterogeneous behavioral responses to government policy, trust in authorities and other socio-behavioral factors. This separation of cognition from behavior allows CEMs to distinguish between information-based interventions that shift cognitive states and resource-based interventions that facilitate behaviors, and provide insight into why different intervention strategies succeed or fail and how interventions might be optimally timed and targeted.

Although our focus here is infectious disease, the framework we propose is broadly applicable to coupled human-natural systems. A recent system dynamics implementation of this framework in the climate domain treats perceived risk, social influence, and culture as interacting state variables that mediate opinion change [35], demonstrating that cognitive processes can be

209 operationalized within a compartmental modeling framework and applied across a range of
210 contested-behavior settings.

211 The representation of cognitive processes that underlie behaviors will initially add model
212 complexity and uncertainty, but will ultimately improve our understanding and forecasts of
213 disease dynamics. CEMs will also improve our understanding of human behavior, which is
214 increasingly important in a world where our most pressing challenges from climate change to
215 biodiversity loss to pandemics fundamentally depend on effectively representing human
216 behavior.

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