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Psychological Factors in Agent-Based Epidemic Models: how Behavior Shapes Disease Outcomes

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Abstract

In addition to the use of real-world behavioral data, pandemic research profits from behavioral modeling in simulations. In this research, an agent-based model (ABM) was applied to examine the spread of infections under two behavioral assumptions. The modeling approach was implemented using the German Epidemic Modeling System (GEMS) in Julia. The model "Modeling predictors of intervention compliance in epidemics" (MPICE), which accounts for individual perceptions and social influences on adherence to self-isolation measures, was applied to a 120-day simulation, in which we examined the spread of a communicable infectious disease within a population ($N = 10{,}000$). A Two-Sample t-test revealed a significantly higher disease spread for modeled behavior than for random behavior. This showed that unlike the random behavior model, where preventive actions are implemented probabilistically and uniformly, the psychological model likely introduced delays and inconsistencies in adherence due to variability in individual perceptions and social influences. Sensitivity analysis further showed the relevance of the model‘s components.

I. Introduction

Pandemics and the associated circumstances such as hygiene measures and quarantine regulations sometimes have serious psychological effects such as fear or threat [1]. These psychological effects are not only important from an individual health perspective, but can also influence the dynamics of a pandemic through the resulting behavior of individual agents. It is therefore of great relevance to understand this interaction in more detail and thus be able to make better predictions about pandemic dynamics. There are several epidemiological models aiming to offer an approach to analyze pandemic dynamics. Jager (2017) [2] criticizes that traditional models such as the compartmental Susceptible-Exposed-Infectious-Recovered-Model (SEIR) often simplify complex social interactions and emergent phenomena. Therefore Agent Based Modeling (ABM) as an alternative approach is suggested [2],[3],[4].

Agent Based Modeling (ABM) is a simulation method used to model complex systems through the interaction of individual entities, so-called agents. The foundation of ABM lies in its ability to simulate individual agents whose actions reflect various psychological and social influences [2]. ABMs are able to capture the complex dynamics of pandemics by simulating the behavior of individual agents and observing how their interactions lead to macro-level health outcomes [3]. They are well suited to analyze the interplay of psychological factors and pandemic dynamics while considering governmental decisions [3]. Jager (2017) [2] emphasizes ABM as a way to develop robust models that accurately reflect human behavior. This integration not only enhances simulation realism but also contributes to advancing psychological theory by fostering dynamic approaches to understanding human interactions. ABMs allow the simulation of collective behaviors that are shaped by factors like fear, risk perception, and social influence, all of which are vital for understanding pandemic dynamics [3]. Jager (2017) [2] highlights the relevance of social simulation in psychology as a robust tool for modeling individual agents and their interactions within shared environments. Key aspects include that ABM allows researchers to explore complex social dynamics that are challenging to isolate in real-world scenarios and that psychological theories elucidate how individuals learn from others‘ experiences and opinions, impacting both individual and societal behavior. Also, the heterogeneity in populations is a factor that should not be neglected to model behavior diffusion, as different agents (innovators, opinion leaders, followers) exhibit distinct responses to social influences [2].

Kurchyna et al. (2022) [4] stress the importance of habitual behaviors and routines in ABMs, particularly in public health. Their research highlights how adherence-based behavior - such as self-isolation - impact the spread of infections and how these behaviors evolve in response to changing health threats and public policies. Modeling these adaptive behaviors is key to capturing how protective habits form and dissolve during a pandemic. Key insights of agent-based models (ABM) in the context of simulating pandemics include that ABMs allow for the modeling of individual agents and their interactions in a social environment, which is crucial for understanding the spread of infectious diseases [4].

By incorporating psychological frameworks, such as the Health Action Process Approach and Social Cognitive Learning Theory, ABMs can provide insights into how individual behaviors and social influences affect the spread of disease and the adoption of preventive measures. Kurchyna et al. (2022) [4] emphasize the importance of validating ABMs against empirical data from real-world pandemics to ensure their accuracy and reliability. Taghikhah et al. (2021) [5] compare theory-driven and empirical ABMs, emphasizing the importance of a hybrid approach that unites theoretical foundations with real-world data to guide policy decisions effectively. They also argue that aligning theory with empirical data leads to more robust and policy-relevant ABMs. This study aimed to apply and test a psychological model that is set up in the project MPICE by Lilian Kojan and André Calero Valdez [6] on an ABM-based environment.

II. Methods and Materials

In this study, we simulated the spread of a COVID-19-like contagious infectious disease in a fictitious population of $N = 10{,}000$ individuals over a time frame of 120 days within the simulation environment provided by the German Epidemic Modeling System (GEMS) [7]. GEMS is a flexible, individual-based infectious disease modeling framework that is able to represent a realistic synthetic population, including factors such as age, gender, health conditions, household composition, and assignments to schools and workplace. Within this framework, the structural model MPICE [6] was applied to a simulated pandemic to investigate the influence of predictive factors for adherence on the behavioral outcome "self-isolation". This model contains the following predictors for adherence: Attitude towards interventions ($\beta = .505$), Intervention Habit ($\beta = .116$), Perceived Risk ($\beta = .107$) and Subjective Norm ($\beta = .231$). The infectious outcomes were modulated as a consequence of self-isolation.

To analyze the spread of infections, we determined the cumulative number of infections as the target value. Two principal scenarios were investigated. The first scenario served as a baseline to assess how epidemic outcomes might evolve when adherence for self-isolation is entirely random - referred to as the “random model”. This model assumed that individuals decide to self-isolate with a fixed probability of 50 % and remain isolated for a specified duration of 14 days whenever symptoms occur. The second scenario, called the “psychological model”, incorporated the application of MPICE‘s factors. Each individual’s adherence intention was calculated as a weighted sum of these factors. Throughout the simulation, perceived risk and subjective norm were updated at every time step based on the fraction of infectious household contacts and the observed adherence of those contacts, respectively.

In the Random Model, the simulation proceeded without additional modifications, while in the psychological model these psychological variables were updated at every time step. At the end of each run, results were processed to generate result data that held the time-resolved progression of infection numbers and adherence. For statistical analysis, data was obtained through running the simulation 10 times, since this remains within the technical resources. Lee et al. [8] suggest that the minimum sample size is reached when the variance of the results reaches a certain stability. This was realized by analyzing the variability of the results across different sample sizes prior to measurement.

The data sets obtained were further processed in R. The primary objective was to determine whether there was a statistically significant difference in cumulative infection counts between the two models. To achieve this, several steps were carried out. In the data preprocessing, the cumulative infection counts for each batch run were extracted from both datasets. After this, through a Two-Sample t-test the mean cumulative infection counts between the random behavior and psychological behavior models were compared. The null hypothesis assumed no significant difference between the means of the two groups, while the alternative hypothesis posited that the means were different. A significance level of 0.05 was used to determine statistical significance. To test how variation of the model's parameters influence the infectious cases, we implemented a sensitivity analysis with the goal of factor prioritization (relative importance of alternative model elements), direction change (whether they increase or decrease the quantity of interest) and robustness analysis (whether conclusions drawn from the model are robust with respect to variations in the inputs) [9]. Through that, we varied the model's predictors for adherence in the range from 0 to 1 over 10 runs, while the other parameters are scaled to keep the overall effect constant.

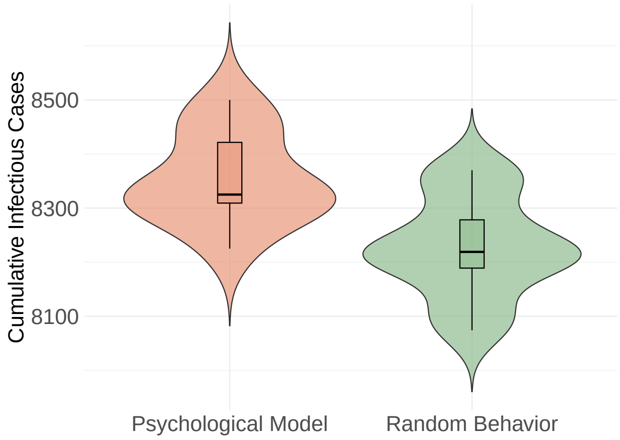

Figure 1: Comparison of cumulative infectious cases over 10 runs in use of a psychological model and random behavior, using a violin plot.

III. Results and Discussion

III.I. Results

The statistical analysis revealed a weak but significant difference in cumulative infection counts between the random behavior model and the psychological behavior model. Fig. 1 reveals that behavior following the psychological model led to higher mean cumulative infections ($M = 8354.3$) than random behavior ($M = 8227.0$). A Two-Sample t-Test showed a significant difference between both models (*t(18) = -3.1937, p = .005, 95%-KI[-211.04, -43.56]*) with an effect size of Cohens' *d =1.4282*. The 95% confidence interval for the mean difference confirmed that the difference was statistically significant and unlikely due to random variation. Fig. 2 captures how varying the MPICE factors while holding other factors constant affects the mean cumulative infections over 10 runs for each variation. Sensitivity analysis showed that all four predictors for adherence have a significant influence on the cumulative number of infections. An ANOVA showed that variation of all predictors cause significant changes in infection outcomes ($p < 2e^{-16}$). Subjective Norm showed the strongest effect of *F(10, 99) = 1073*, followed by Attitude (*F(10, 99) = 381.3*) and Intervention Habit (*F(10, 99) = 339.9*). Perceived Risk (*F(10, 99) = 47.18*) showed smaller but still significant effects.

III.II. Discussion

This study aimed on testing the psychological model MPICE [6] on a simulated environment to gain direct insights into the dynamics between determinants of adherence and infectious outcomes. The significant findings demonstrate that psychological adherence factors substantially influenced pandemic dynamics, as evidenced by the higher cumulative infection counts in the psychological model compared to the random behavior model. The psychological model incorporated these factors, resulting in a more nuanced representation of individual decision-making processes compared to the random behavior model. The results of this study indicate that the inclusion of psychological adherence factors significantly influenced the spread of the pandemic, as evidenced by the higher cumulative infection counts in the psychological behavior model compared to the random behavior model. This finding highlights the complex interplay between individual decision-making and pandemic dynamics. Higher infection counts observed in the psychological model may stem from the variability and delays in adherence driven by perceived risk, social norms, and individual habits. Such variability is consistent with the idea that fear and stress can both promote and hinder adherence to public health measures, depending on the individual and social context [10]. The psychological model simulated these dynamics by embedding psychological mechanisms, including perceived risk and subjective norms, which influenced adherence to interventions. This approach aligns with Jager's (2017) [2] Enhanced Realism in Simulations (EROS) framework, which advocates for models that reflect underlying psychological and social processes [2]. The significant differences between the two models underscore the importance of integrating psychological and social dimensions into pandemic response strategies. For example, the variability in adherence observed in the psychological model suggests that public health messaging should address the factors that drive adherence, such as trust in health authorities, effective risk communication, and the minimization of stressors associated with preventive measures [1]. Sensitivity Analysis showed that all by the MPICE model postulated predictors play a significant role in modulating infectious outcomes. This means that behavioral factors play a central role in infection dynamics. As captured in Fig. 2, Intervention habit and Attitude have a preventive effect, with higher values of these vari-

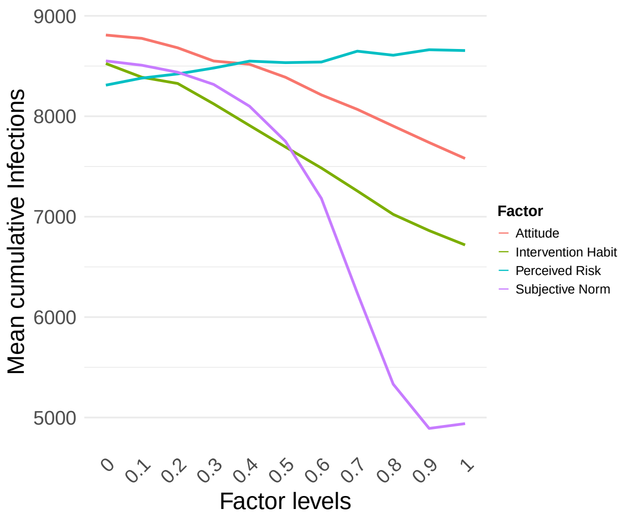

Figure 2: Mean cumulative infectious cases for different factor levels of postulated coefficients.

ables being associated with a significant reduction in infections. Increased Perceived Risk showed the weakest influence with a slight upward trend in infectious outcomes. Further examination of the interplay between Perceived Risk and infection dynamics within the GEMS framework is required. The influence of Subjective Norm varied from the other factors as it showed an interplay between caused adherence with the consequence of decreasing infections and increase in its own value.

IV. Conclusion

The findings of this study emphasize the use of intervention evaluation using simulation models. The significant results underscore the critical role of behavioral modeling in epidemic simulations and give insight into how different adherence mechanisms can influence outbreak trajectories and highlights the potential role of interventions targeting factors like risk perception and habit formation. This suggests that psychological adherence factors such as intervention habit or subjective norm must be carefully considered in policy planning to ensure effective pandemic control. Due to computing capacities, this study used a rather small number of runs and agents for data acquisition. Also, the population structure is still simplified. Further research could aim for an accurate representation of a real-world population by orienting on existing data about population sizes and structures, considering more diverse social settings where infection transmissions occur.

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Author's statement

Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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