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APPLICATION OF GENERATIVE ARTIFICIAL INTELLIGENCE FOR EPIDEMIC MODELING

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ABSTRACT

Epidemic models have become increasingly useful, especially in the wake of the recent COVID-19 pandemic, emphasizing the crucial role of human behavior in the spread of disease. There has been a recent rise in the usage and popularity of generative artificial intelligence (GenAI), such as ChatGPT especially with its ability to mimic human behavior. In this study, we demonstrate a novel application of GenAI for epidemic modeling. We employed GenAI for creating agents living in a hypothetical town in simulations and simulating their behavior within the context of an ongoing pandemic. We performed a series of simulations to quantify the impact of agent traits and the availability of information for health condition, virus, and government guidelines on the disease spread patterns in terms of peak time and epidemic duration. We also characterized the most influential factors in agents' decision-making using random forest model.

1 INTRODUCTION

Infectious diseases exemplified by notable outbreaks such as Influenza, SARS, and COVID-19 are illnesses that arise through transmission from an infected person to a susceptible host. Epidemic disease models, such as susceptible-infected-recovered (SIR) model, allow us to predict infectious disease spread patterns and help us to prepare response strategies. The recent COVID-19 pandemic, which swept across the globe, underscored the importance of epidemic disease modeling as nations grappled with an unprecedented public health crisis (Yadav and Akhter 2021).

Recognizing that infectious diseases are typically spread among the population through human-to-human contact, it has been emphasized the crucial role of human behavior in the spread of disease (Weston et al. 2020). Existing epidemic models have incorporated with various approaches such as using social contact networks (Chin and Bouffanais 2020) and human mobility data (Conlan et al. 2021) to better quantify how human behavior affects the spread of infectious diseases. However, the focus has been on human movement behavior, neglecting a crucial aspect incorporating feedback loops that capture changes in human behavior driven by perceived risks associated with rising cases (Rahmandad et al. 2022). These behavioral shifts could include an increase in the frequency of preventive behavior, such as avoiding social events or adopting mask-wearing in public, which in turn would lead to a decrease in transmission. The absence of such behavioral aspects in the current disease models underscores the pressing need to incorporate evolving human behavior (Nature Human Behaviour 2022). Nevertheless, integrating human behavior into disease models presents challenges, given the intricate and nuanced nature of human behavior (Weston et al. 2020).

In contrast, studies have demonstrated the success of generative artificial intelligence (GenAI) in generating believable human behavior (Park et al. 2023). There has been a recent rise in the usage and popularity of GenAI with large language models (LLMs) such as ChatGPT, being a popular form of GenAI. LLMs are trained using machine learning algorithms on large amounts of text, including books, news articles, and websites (Cooper 2023). Since LLMs have encoded a wide range of human behavior from their training data, this shows the potential of using LLMs to simulate nuanced human behaviors and interactions in the face of epidemics which current disease modeling methods lack.

The remainder of this paper is organized as follows: Section 2 gives a literature review on related work. Section 3 describes our experiment design including agent generation, epidemic modeling, and random forest model. Section 4 presents the numerical experiments and discusses the results. Section 5 summarizes our work and provides possible research directions for the future.

2 RELATED WORK

2.1 Generative Artificial Intelligence (GenAI)

Large language models (LLMs) are a form of GenAI that produces human-like language. OpenAI trains its text-generating models, such as ChatGPT, using machine learning algorithms on large amounts of text, including books, news articles, websites, and Wikipedia. This process, involving the analysis of terabytes of data, enables these models to grasp language patterns, empowering them to deliver relevant and meaningful content in response to user queries (Cooper 2023).

From the vast amounts of training data, it can be observed that LLMs have encoded a wide range of human behavior, so if prompted with a narrowly defined context, the models can be used to generate believable behavior (Park et al. 2023). In the work of Park et al. (2023), they created agents based on the LLM, and then produced believable emergent social behaviors such as making new acquaintances and hanging out. Another work of Williams et al. (2023) conducted on the usage of ChatGPT for epidemic modeling to empower each agent's reasoning and decision-making. They successfully demonstrated the generative agents were able to mimic real-world behaviors such as quarantining when sick and self-isolation when the cases rise.

2.2 Human Behavior and COVID-19

There are several common preventive behaviors towards COVID-19 including maintaining social distance, staying at home if one is feeling unwell, and avoiding the crowds and close contacts (World Health Organization 2023). It has been shown that knowledge of COVID-19 led to a practice of preventive behavior (Lee et al. 2021). The practice of preventive behavior was associated with reductions in Covid-19 (Talic et al. 2021). Public health interventions recommending preventive behavior were also effective in decreasing the transmission of COVID-19 (Ayouni et al. 2021).

Many global research surveys have sought to understand the correlation between the practice of preventive behavior and the traits of a person. Traits of a person could include their gender, age, and their big five personality traits which includes (1) openness to experience, (2) conscientiousness, (3) extraversion, (4) agreeableness, and (5) Neuroticism (Soto 2018). Openness to Experience denotes intellectual curiosity, aesthetic sensitivity, and imagination, with open individuals being receptive to new ideas and experiences. Conscientiousness involves organization, productivity, and responsibility, with conscientious individuals displaying persistence and commitment to their goals. Agreeableness pertains to compassion, respectfulness, and acceptance of others, contrasting with disagreeable individuals who may show less concern for others' well-being. Neuroticism measures the frequency and intensity of negative emotions, with high levels indicating susceptibility to anxiety and mood swings. Extraversion reflects tendencies towards social engagement, assertiveness, and energy, with extroverted individuals enjoying social interactions and exhibiting enthusiasm.

The big five personality traits play a crucial role in shaping behavior and influencing various life outcomes across the lifespan, as supported by extensive research in the field of personality psychology (Soto 2018). In Australia, a study determined that those who practiced preventive behavior were those who mostly employed full- or part-time or retired, university-educated, female and had relatively low psychological distress, and relatively high trust in others (Oldmeadow et al. 2023). Another study in Australia determined that older adults (> 65 years) and women as more inclined towards preventive behaviors (Khalesi et al.

2021). In Korea, a study looked into the correlation between the big five personality traits and their correlation with preventive behavior which determined that those who had the traits of high openness, high conscientiousness, high agreeableness, and low neuroticism were more likely to practice preventive behavior (Han et al. 2021). A similar study conducted in Japan which also focused on the big five personality traits also produced similar results with more females and older adults, and those with high conscientiousness and high agreeableness practicing preventive behavior, while those with high extroversion were more likely to not follow COVID-19 preventive behaviors (Muto et al. 2020).

Based on the above mentioned studies, it can be summarized that the traits of a person who is more likely to exhibit preventive behavior against COVID-19, which can be extended to other infectious diseases, are those of the older generation, are female and individuals possessing the following big five personality traits where they have high openness, high conscientiousness, low extraversion, high agreeableness, low neuroticism. This summary forms the basis for investigating the effectiveness of GenAI, specifically ChatGPT, in replicating such human behaviors at the individual personality level during epidemic periods.

2.3 Epidemic Modeling

A predominant approach in disease transmission studies involves the use of compartment models (Tolles and Luong 2020). The compartment models simplify disease transmission processes and divide a population into labeled compartments. One of the simplest compartment models is the SIR model, where compartments S, I and R represent susceptible, infected, and recovered individuals in the population. This model, which was used in this study, simulates the transition of individuals from susceptible to infections, then to recovered, accounting for states of individuals at each time step. Recent developments in agent-based modeling and network-based approaches have expanded the scope of epidemic models, allowing for a more nuanced understanding of interactions within communities.

One notable advancement in epidemic modeling is the integration of social contact matrices. These matrices capture the intricate patterns of interactions between individuals within a population, offering a realistic depiction of how diseases spread through social networks. Social contact surveys can greatly help in quantifying the heterogeneous patterns of infectious disease transmission, as they can account for the heterogeneity in contact patterns across age groups, socioeconomic status and geographic locations.

Typically, social contact matrices are generated through surveys where individuals report their daily interactions and details of those interactions (Munasinghe et al. 2019). This approach has been valuable in understanding the transmission dynamics of infectious diseases, where close-contact interactions play a pivotal role.

However, there are challenges when conducting surveys, especially during an ongoing pandemic such as the phenomenon of survey fatigue, characterized by decreased response rates and reducing the quality of data (De Koning et al. 2021). This necessitates an alternative approach. Therefore, one objective of this study is to emulate realistic social contact matrices using responses from ChatGPT. This innovative approach aims to provide a practical solution for swiftly generating contact matrices, ensuring flexibility in studying disease transmission dynamics.

3 EXPERIMENT DESIGN

3.1 Agent Generation

In this study, we considered two key questions in exploring agent characteristics and their impact on disease transmission dynamics. The first question (Q1) is “How many people would you interact with in a day?” and the second question (Q2) is “Would you stay 1.5m away from others (i.e., maintain social distance) when outside?”

For the simulation of epidemic dynamics, we generated agents using ChatGPT 3.5 by taking into account nuanced human behavior towards disease transmission as found in previous research (Lee et al. 2021; Talic et al. 2021; Ayouni et al. 2021; Fazio et al. 2021).

Table 1: A summary of experiment prompt inputs.

Experiment	basic info	health info	virus info	contact info	gov. guideline	Q1	Q2
1	✓					✓	
2	✓	✓				✓	
3	✓	✓	✓			✓	
4	✓	✓	✓	✓		✓	
5	✓	✓	✓			✓	✓
6	✓	✓	✓		✓	✓	✓

Firstly, for every experiment, we included basic information regarding the hypothetical person such as age, gender, personality traits, the fact that they go to work to earn a living, the town they live in, and the virus name. We included the big 5 personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) as binary variables (i.e., high or low), so 32 possible personalities were reflected. An example combination of personalities would be high openness, high conscientiousness, low extraversion, low agreeableness, and high neuroticism. According to Park et al. (2023) and Williams et al. (2023), here we postulated that ChatGPT 3.5 had been trained with a wide range of literature in human behavior, so it understands what the big five personality traits represent. There are 3 categories for the age of the hypothetical person: young adult (18–33), early middle-aged (34–49), and late middle-aged (50–65). A random number will be decided from within the range to decide the age of the hypothetical person. There are 2 genders, male and female. Everyone is defined as a working adult who needs to go to work to earn a living. The town that the hypothetical people live in is called Skystead and their hypothetical virus is called Nazria to avoid bias towards known cities and viruses.

Next, for selected experiments, some additional information such as health condition, virus, contact, and government guidelines is included. The health condition is encoded 3 ways: (1) “Feels normal” denoting either immune, uninfected, or asymptomatic, (2) “Has a light cough” indicating mild symptoms, and (3) “Has a fever” signifying heavy symptoms. Regarding the virus information, we added the context of the Nazria virus which is an infectious disease spread via an airborne virus. About the contact, the agents were informed that contact was defined as an interaction lasting 15 minutes or longer. Information of government guidelines is relevant to the recommendations such as maintaining social distance when the agents are in the public places in their town.

For each experiment, we created and fed a prompt to ChatGPT including basic information and some additional information. In every ChatGPT prompt, an example of the desired response from ChatGPT is given, so that ChatGPT generates its responses in a desired format. Furthermore, for every question given to ChatGPT, the reasoning behind every response is also asked, so that ChatGPT spends more tokens thinking about the question and gives us a deeper understanding as to why ChatGPT responds in such a way.

According to the above-mentioned setups, we conducted 6 experiments by varying available information for the agents and questions asked them. Table 1 shows a summary of experiment prompt inputs and Figure 1 presents flow diagram describing the various steps taken for the experiments shown in Table 1. Appendix A shows an example of ChatGPT prompt.

3.2 Epidemic Dynamics

The experiment setups relevant to epidemic dynamics were determined based on the previous study (Williams et al. 2023). Each experiment utilized a consistent set of parameters to reduce the complexity. The town population was defined as 5000 with an initial infected population of 2%, an infection rate was 0.1.

The disease model uses the SIR Model, where the disease has a duration of 6 days. For the first two days of infection, the agents would be asymptomatic but infectious, while on days three and six, the agents

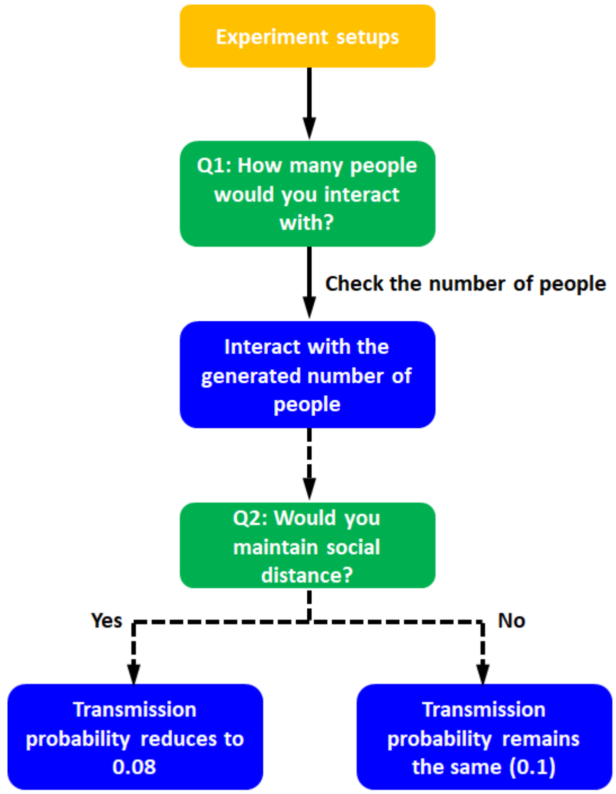

Figure 1: Flow diagram describing the various steps taken for the experiments shown in Table 1.

would feel a light cough, and finally on days four and five, the agents would have a fever. Throughout the six days of infection, whenever they interact with other susceptible agents, they have the possibility of infecting them with the virus. After 6 days of infection, the agents will recover, and they will feel normal and will be immune to the virus.

At the start of the experiment, when the world is built and initialized, each agent has a personality combination randomly assigned to them which assigns to them their age, gender, and big 5 personality traits. The health conditions of the agents are initialized with a percentage of the population, equal to the initial infected population, assigned the "Infected" health condition on the first day of infection while the rest of the population is "Susceptible".

The transmission model is dependent on the social contact and transmission probability. The number of people they would interact with is dependent on each experiment. The other agent they would interact with is randomly selected from the other agents found on the grid. For every agent interaction, if a susceptible agent interacts with an infected agent, a float from 0 to 1 would be randomly generated and if this float is above the infection rate, then the susceptible agent will be infected with the virus. It is assumed that each household is only the agent, so there will be no transmission within the household and there will only be transmission if they go on the grid.

Other defined factors in the experiment include that a simulation step size is defined as 1 day and each simulation will run for at most 100 days, however, if there are no infected agents for 2 days consecutively, the model will end prematurely. For each experiment, we generated 576 agents by factoring 2 gender types (male, female), 32 possible combinations of personality traits, 3 age groups, and 3 possible health conditions ($576 = 2 \times 32 \times 3 \times 3$). The model underwent 10 runs for each experiment and the same prompt was given to each run. We determined the average of results based on the number of interactions at the end of the day computed by ChapGPT (see the example answer in Appendix A).

Table 2: The features used to characterize the most influential factors in agents' decision-making

Feature	Note
age group encoded	basic information
gender encoded	basic information
health condition encoded	additional information
health condition info	additional information
virus info	additional information
government guidelines	additional information
15 min contact info	additional information
extraversion	big five personality traits
agreeableness	big five personality traits
conscientiousness	big five personality traits
openness	big five personality traits
neuroticism	big five personality traits

3.3 Random Forests

Random forests offer a powerful tool for identifying the most influential factors within a dataset. By leveraging the collective predictive power of numerous decision trees, random forests can effectively discern patterns and relationships among variables. In addition, random forests provides valuable insights into variable importance, ranking features based on their contribution to predictive accuracy (Biau 2012). Through thorough analysis of feature importance scores generated by random forests, we can identify the key factors driving the observed outcomes, facilitating a deeper understanding of the underlying mechanisms generating the observed results. Table 2 shows the features that we used to characterize the most influential factors in agents' decision-making. The random forests were implemented by using scikit-learn package of python. For experiments 1–6, we use the number of interactions as an evaluation metric for the random forest model, we focus on predicting the number of interactions. To assess the effectiveness of the random forest model, a five-fold cross-validation was conducted by dividing the data into five equal parts and then training and evaluating the model on different combinations of these subsets.

4 SIMULATION RESULTS

4.1 Epidemic Dynamics

Figure 2 shows temporal evolution of the spreading process in terms of susceptible-infected-recovered (SIR) curves. From all the panels, it can be observed that the number of infected cases increases and then decreases in the course of time. From Figure 2(a) to (f), the peak value of infected cases (i.e., y-axis value) tends to decrease while the peak time is increasing, suggesting that the making the agents have more information can results in flatten the curve. Especially, in Figure 2(f), the infected case curve is significantly lower than in other cases, seemingly because of social distancing.

From Figure 3, one can see graphs of new infections broken down by health condition of infecting agents for experiments 2, 3, and 4. The majority of infected agents were infected by asymptomatic infecting agents in experiment 2, but this is less pronounced in experiments 3 and 4, suggesting that virus information contributes to reduce the asymptomatic infections.

Analyzing the top 20 words and top 30 phrases provides additional insights on the reasoning from the ChatGPT results. In experiment 1, the words and phrases that appeared quite often attributed to the personality traits of the agents such as "low extraversion", "high conscientiousness", "low conscientiousness", and "high extraversion" all appearing in the top 5 most frequent phrases. For experiment 2, health condition

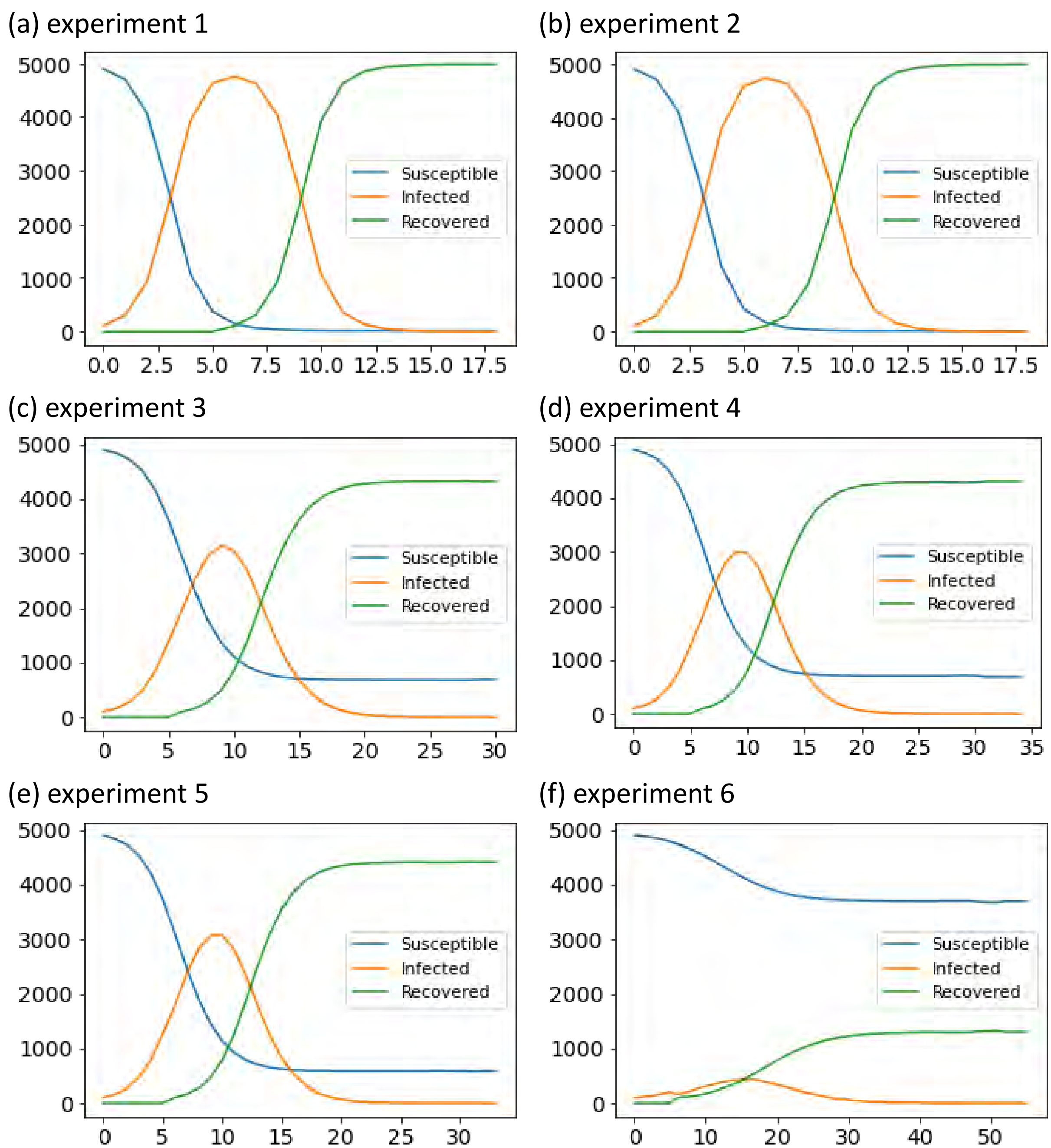

Figure 2: Temporal evolution of the spreading process in terms of susceptible-infected-recovered (SIR) curves: Blue, orange, and green curves indicate susceptible, infected, and recovered cases respectively.

played a significant role in its reasoning as "light cough" was the most frequent phrase that appeared in its reasoning while "fever" and "cough" appeared in the top 7 words. In experiments 3 and 4, the phrases "low extraversion", "high neuroticism", "high conscientiousness", and "high agreeableness" appeared in the top 5 phrases, inferring that the reasoning from ChatGPT is more associated with agents' personality traits. Both experiments 5 and 6 have their top phrase as "potential danger" so the agents would maintain

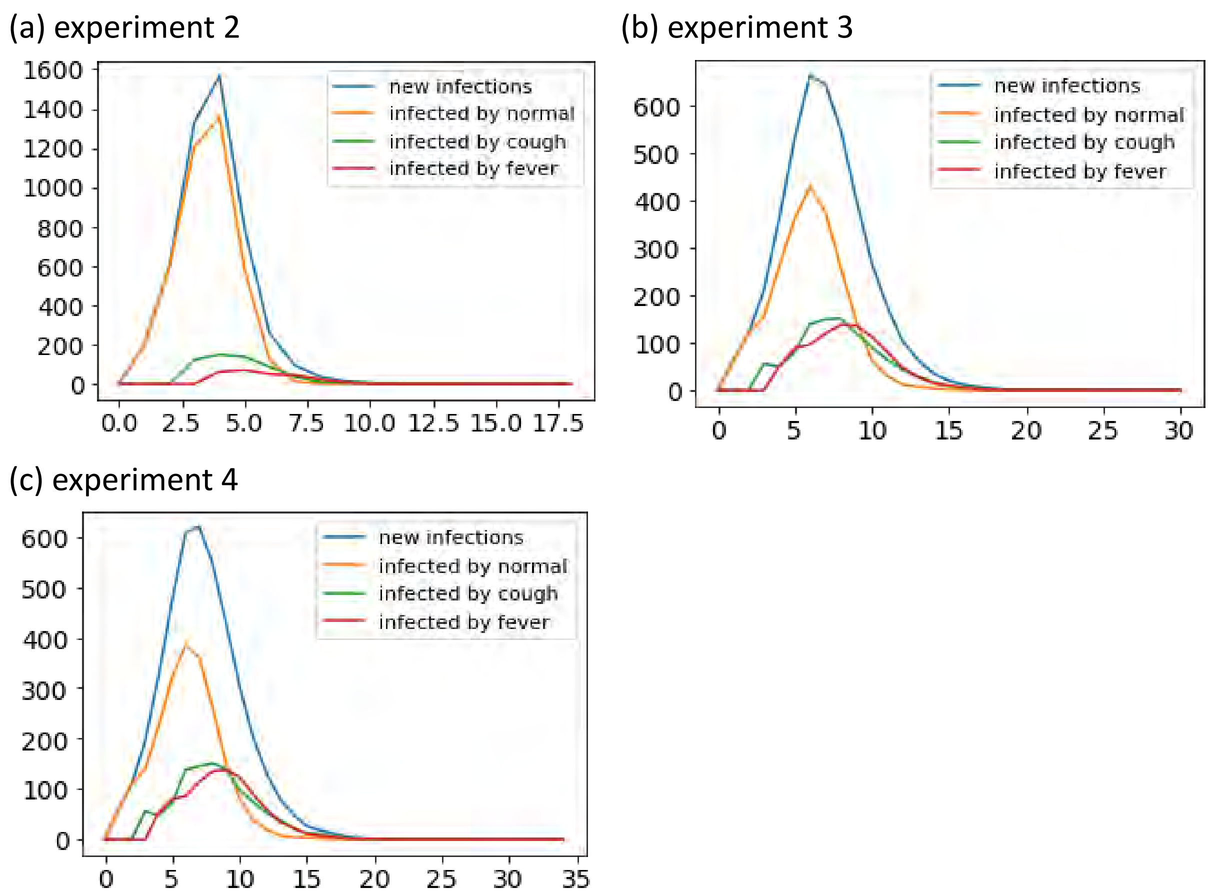

Figure 3: Graph of new infections broken down by health condition of infecting agents. Blue curves show the number of new infections. Orange, green, and red curves indicate the number of cases infected by agents feeling normal, having cough, and having fever respectively.

social distance as a precaution behavior. For experiment 6, the word “government” is the 3rd most frequent word which shows how the addition of the government guidelines contributed to the agents largely social distancing behavior.

4.2 Feature Importance

Figure 4 illustrates the feature importance computed by random forest model. The encoded health condition seems to be the most important feature, followed by virus information, extraversion, and health condition information. Therefore, it is suggested that the agent’s health condition and extraversion level are the most influential features for predicting the number of interactions in the sense of personality. In terms of context, the knowledge of the virus and the agents knowing their health condition are the most important features in determining the number of interactions. It can be understood that if an agent knows the virus spreading situation and their health condition whether feeling well or not can reduce the number of interactions among the agents, leading to a decrease in transmission. In contrast, other features including the encoded age group, agreeableness, government guidelines, conscientiousness, openness, gender encoded, neuroticism, and 15 min contact information show smaller feature importance value, indicating that those features are less pronounced in the random forest.

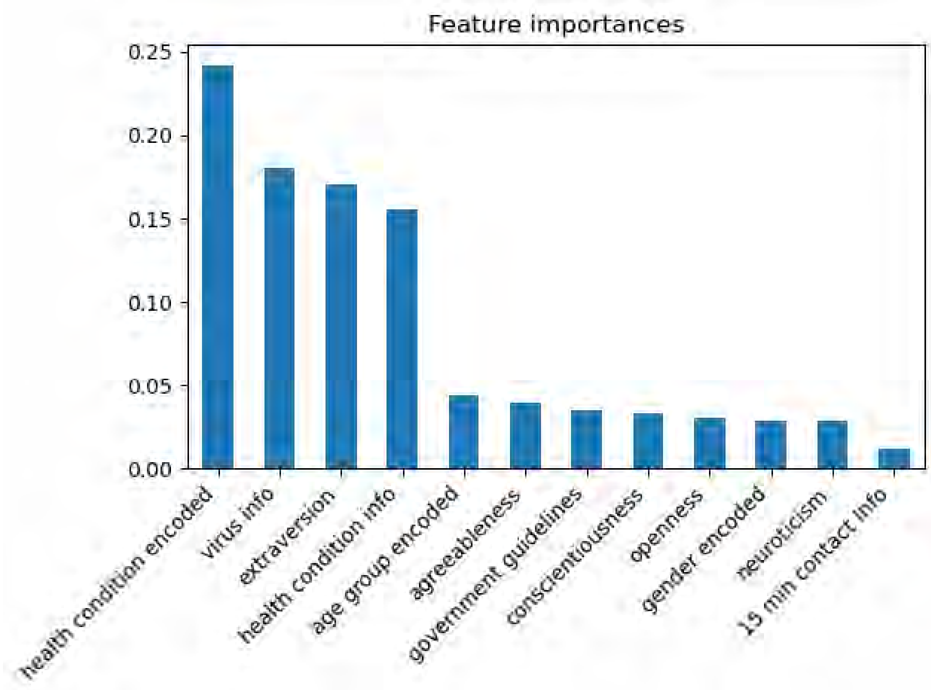

Figure 4: Feature importance computed by random forest model

Table 3: Comparison of average number of interactions between the ChatGPT generated results and the prediction by random forest model

Experiment	by ChatGPT (true value)	by random forest model (prediction)
1	10.85	8.20
2	4.71	4.80
3	2.38	2.31
4	1.84	1.85
5	2.17	2.31
6	0.23	0.26

Table 3 compares the average number of interactions between the ChatGPT generated results and the prediction by random forest model. Except for experiment 1, the average number of interactions predicted by the random forest model shows good agreement with the one from the ChatGPT generated results. The prediction for experiment 1 shows notable discrepancy in that health condition is not included for the agent generation in experiment 1.

4.3 Limitations

A major limitation of the study is that unintended biases might be introduced to the simulations mainly due to the ChatGPT's sensitivity to the prompt. This can be seen as a double-edged sword as there are some pros and cons regarding how sensitive ChatGPT is to the prompt especially when using ChatGPT to decide on the decision-making and behaviors of the agent. On one hand, we were able to observe that small prompt modifications enable nuanced responses. For example, ChatGPT was able to respond accordingly and imagine the scenario in the eyes of an older person with a simple number change from 33 to 64. On the other hand, previous studies have indicated that ChatGPT's responses may be influenced by the frequency of certain words in the prompt, introducing an additional consideration for precise prompt construction. For instance, Ghaffarzadegan et al. (2023) showed that given a Yes or No question, ChatGPT was more likely to answer "Yes" if the word "Yes" were to appear more than the word "No" in the prompt.

5 CONCLUSION

In this study, we applied GenAI for epidemic modeling to demonstrate potential in incorporating nuanced human behavior in epidemic models. Based on GenAI, we created agents living in a hypothetical town in simulations and then simulated their behavior in the context of a pandemic. From simulations, we observed that the availability of information for health condition, virus, and government guidelines impacts on the agent's decision in response to the ongoing pandemic. We were also able to see the impact of information availability on the disease spread patterns in terms of peak time and epidemic duration. Furthermore, we identified the most influential factors in agents' decision-making using random forest method.

As the application of Generative AI for epidemic modeling continues to evolve, future research in this domain could explore the incorporation of memory architecture into Generative AI for agents within the models. By allowing agents to remember past actions and make decisions based on this memory, the modeling of human behavior could reach new levels of realism and sophistication, the potential benefits of this approach were seen in the study by Park et al. (2023). It is essential to acknowledge the current computational challenges associated with GenAI, as it demands substantial resources. However, with the ongoing development and improvement of LLMs in terms of cost and speed, there is hope that more researchers can explore this new modeling approach and contribute to more realistic representations of nuanced human behavior.

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A APPENDIX A: CHATGPT EXAMPLE PROMPT FOR EXPERIMENT 1

Imagine the following scenario:
You are Diane, female, 18 years old.

Here are Diane's Big Five Personality Traits :
Low Openness, Low Conscientiousness, Low Extraversion, Low Agreeableness, Low Neuroticism

Diane lives in the town of Skystead. Diane likes the town and has friends who also live there.
Diane has a job and usually leaves the house to go to the office for work everyday to support Diane's self.

Based on the provided scenario, what would your day in the life schedule be like and why?
How many people would you physically interact, virtual interactions do not count, with at each point of time?

Please follow the following format when answering the question:
Explanation: [Reason why that is your day in the life schedule]
Morning: [Insert Activity here and number of interactions]
Afternoon: [Insert Activity here]
Night: [Insert Activity here]

End of day, number of interactions: [Sum of number of interactions]

Example Answer:
Explanation: I would go on about my usual day in the life.
Morning: Eat Breakfast with Family, Number of interactions: 2
Afternoon: Go to the Office for Work, Number of interactions: 8
Night: Rest at Home and watch TV, Number of interactions: 0
End of day, Number of interactions: 10

Please remember to keep the end of day, number of interactions to a single number.

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