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Short communication

Utilizing large language models in infectious disease transmission modelling for public health preparedness

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ABSTRACT

Introduction: OpenAI's ChatGPT, a Large Language Model (LLM), is a powerful tool across domains, designed for text and code generation, fostering collaboration, especially in public health. Investigating the role of this advanced LLM chatbot in assisting public health practitioners in shaping disease transmission models to inform infection control strategies, marks a new era in infectious disease epidemiology research. This study used a case study to illustrate how ChatGPT collaborates with a public health practitioner in co-designing a mathematical transmission model.

Methods: Using natural conversation, the practitioner initiated a dialogue involving an iterative process of code generation, refinement, and debugging with ChatGPT to develop a model to fit 10 days of prevalence data to estimate two key epidemiological parameters: i) basic reproductive number (Ro) and ii) final epidemic size. Verification and validation processes are conducted to ensure the accuracy and functionality of the final model.

Results: ChatGPT developed a validated transmission model which replicated the epidemic curve and gave estimates of Ro of 4.19 (95 % CI: 4.13- 4.26) and a final epidemic size of 98.3 % of the population within 60 days. It highlighted the advantages of using maximum likelihood estimation with Poisson distribution over least squares method.

Conclusion: Integration of LLM in medical research accelerates model development, reducing technical barriers for health practitioners, democratizing access to advanced modeling and potentially enhancing pandemic preparedness globally, particularly in resource-constrained populations.

1. Introduction

From the 2003 Severe Acute Respiratory Syndrome epidemic (SARS) in Hong Kong to the 2009 influenza pandemic and recent continued clusters of Middle-East Respiratory Syndrome (MERS) in the Middle East and South Korea, mathematical modelling has become increasingly influential in informing infectious diseases transmission mitigation strategies in recent years [1–3]. The coronavirus disease 2019 pandemic highlighted the widespread adoption of data-driven intervention strategies and resources management informed by modelling results such as the adoption of non-pharmaceutical interventions and border control measures in many populations including United Kingdom [4], the United States [5], and Hong Kong [6,7]. Chat Generative Pre-trained Transformer (ChatGPT), a large language model (LLM) powered chatbot developed by OpenAI, has generated significant interest in the medical research community [8–10].

With their sophisticated natural language processing capabilities, LLM-powered chatbots can serve as a comprehensive resource for

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infectious diseases for essential disease-related information [11,12]. Aside from understanding and generating natural language, LLM-powered chatbots are also adept at creating, refining and debugging computer code spontaneously through natural conversational interaction [13]. The naturalistic interaction of LLM-powered chatbots accommodate researchers who are less competent in computer programming to construct transmission models with fewer technical barriers. Unlike traditional chatbots that rely on predefined rules and scripts, LLM-powered chatbots like ChatGPT employ advanced natural language processing, machine learning, and deep learning techniques to mimic human conversation based on information from its knowledge domains [14]. These technologies enable LLM-powered chatbot to handle complex queries, engage in context-aware conversations and maintain follow-up conversations.

What distinguishes LLM-powered chatbots from other AI-chatbots, such as Siri and Alexa, is its profound ability to conduct detailed and context-sensitive dialogues across various domains of knowledge. Trained on an extensive corpus of text that includes books, articles, and websites, ChatGPT can draw from a vast range of contexts, mirroring human conversational patterns more closely than ever before. This capability allows LLM-powered chatbots to provide nuanced responses that include relevant background information, use appropriate terminology, and engage in a way that is contextually appropriate for the conversation. As a result, the interactions with ChatGPT are not only more natural and human-like but also more engaging and effective in delivering information.

The adoption of LLMs holds transformative potential for public health science by expanding the pool of health practitioners and researchers who can efficiently implement these modelling methods. For epidemiologists and clinicians, especially those deeply familiar with specific diseases, LLM-powered chatbots offer assistance in building practical computational models for disease transmission. For experienced researchers in disease modeling, LLM-powered chatbots can accelerate the development process, enabling the rapid construction and comparison of diverse model scenarios. The ability to quickly iterate and refine models empowers researchers to respond more agilely to emerging health crises, optimizing interventions in real-time based on evolving data and insights. The integration of LLM-powered chatbot in modeling infectious diseases could revolutionize how we manage disease outbreaks globally.

Our study aims to investigate the potential of LLM-powered chatbots in enhancing the process of developing infectious diseases models for public health professionals. Specifically, we are interested in their role in resource-constrained settings where access to advanced analytical tools and expert consultation may be limited. By evaluating these aspects, we aim to provide comprehensive insights into the potential benefits and challenges of adopting LLM technologies in the field of infectious disease management.

2. Method

To assess ChatGPT's utility in developing disease transmission models, we conducted a case study focusing on the collaborative model design process between a human health practitioner and ChatGPT. The public health practitioner initiated a dialogue with ChatGPT, outlining the objective to develop a classic disease transmission model using the susceptible-exposed-infected-recovered (SEIR) framework. Using 10 days of prevalence data which exhibits expoential charcteristics, the health practitioner aimed to estimate two important epidemiological parameters: i) the basic reproductive number (Ro): the average number of secondary cases generated by an infectious individual in a totally susceptible population [15] with its 95 % confidence interval (CI) and ii) the final epidemic size [16] based on prevalence data from the first ten days of an outbreak. Through natural language conversation, the practitioner and ChatGPT engaged in an iterative process of code generation, refinement, and debugging to enhance accuracy. This process included clarifying the objectives, discussing the fitting methods, refining the code structure such as standard variable naming conventions, and exploring alternative estimation techniques. The generated codes underwent thorough validation with the prevalence data of influenza outbreak in British boarding School in 1978 [17] to ensure technical correctness, consistency with epidemiological expectations, and readability. This step was crucial to confirm the reliability of the model developed with ChatGPT's assistance.

3. Result

We have included four application scenarios of a case study (Supplementary Material) demonstrating how ChatGPT can be employed to assist public health practitioners and researchers in developing and validating disease transmission model. In these scenarios, the public health practitioner and ChatGPT collaborated in a progressive refinement process, with discussions focusing on understanding the existing code, seeking clarity on the model development, refining the code structure, and exploring alternative fitting techniques. In the initial scenario, ChatGPT successfully developed a SEIR transmission model and was then fitted to the prevalence data (Prompt 1.5), resulting in an estimated Ro of 4.18. Additionally, the model also predicted that by the end of the 60-day period, 9836 out of population size of 10,000 (approximately 98 %) will have been infected (Prompt 1.6). We further examine the epidemiological characteristic of the model using the code provided in Prompt 1.7 and adjusting the β values, where $Ro = \frac{\beta}{\gamma}$. This allows us to observe that: when Ro > 1, it triggers the exponential growth; Ro $= 1$ yields a flat epidemic curve, and Ro < 1 results in a decline in the epidemic curve. Subsequently, we constructed plots to depict the time series of individuals in different disease states (Prompt 1.8). During the second scenario, the human collaborator and ChatGPT engaged in an iterative refinement process to clarify the details of the least squares method (LSE) in Scenario 1 along with the newly introduced approach by the human practitioner, involving the maximum likelihood estimation (MLE) with a Poisson distribution. ChatGPT highlighted the shortcomings of LSE and clarified the advantages of the latter approach over the former. The revised code based on the latter estimation approach provided a revised but similar R_0 estimate of 4.19 from the Poisson MLE method (Prompt 2.7). A plot of the observed data and the fitted models employing both the least squares and Poisson MLE methods suggested that both fitting approaches demonstrated good ability to reproduce the prevalence data (Fig. 1B). In Scenario 3, we demonstrated how epidemiologists co-work with ChatGPT to construct 95 % CI for Ro (4.13- 4.26). In Scenario 4, the validation of the model constructed by ChatGPT indicated that our MLE estimate of R_o at 3.78 (Prompt 4.2), based on British boarding school influenza outbreak prevalence data, aligned with the estimate reported in [18].

4. Discussion

Our exploration of simple disease transmission model development with ChatGPT through natural conversation yielded results comparable with a small team of health practitioners and researchers with experience in these techniques working on a problem for several days. LLMs' natural language interface allows public health practitioners and researchers with less experience in computer programming to construct transmission models with fewer technical barriers**.** In this collaborative process, LLMs act as co-pilots in assisting public health practitioners, epidemiologists and clinicians to swiftly construct functioning initial transmission models and potentially develop a wide range of model variants for experimentation, selection, and comparison. LLMs drastically reduce the time required for development of complex models that characterize heterogeneous social mixing patterns [19] or utilize individual-based approaches [20] , thereby potentially transforming the

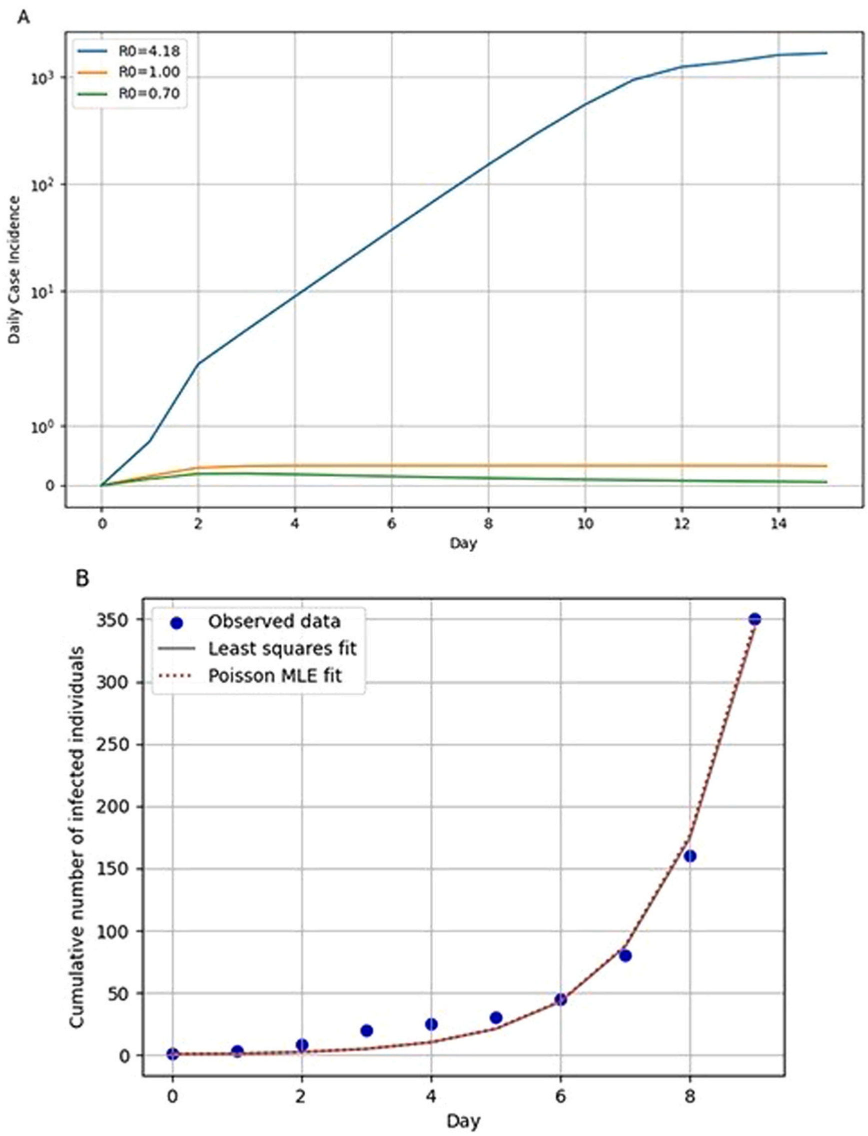

Fig. 1. **A.** Daily case incidence (in log scale) under different values of Ro. The model exhibits important epidemiological characteristics: when Ro > 1, it triggers exponential growth; Ro = 1 yields a flat epidemic curve, and Ro < 1 results in a decline in the epidemic curve. **B**. Comparison of two fitting methods: Least Squares vs. Poisson Maximum Likelihood Estimation for reproducing observed prevalence data. Both fitting approaches demonstrated good ability to reproduce the prevalence data.

entire modelling workflow. The integration of LLMs into the public health sector plays a pivotal role in bolstering pandemic preparedness. Rapid response is crucial when facing potential outbreaks, and LLMs can significantly expedite the preliminary analysis and understanding of a novel pathogen's transmission dynamics. By providing instantaneous modeling support, these systems allow for real-time scenario analysis, facilitating faster and more informed decision-making. Also, the code displayed a high level of consistency with our expectations in terms of functionality, structure, and included valuable comments. It was well-organized and accompanied by explicit explanations of programming logic, ensuring good readability.

Like any new technology, LLMs have limitations. Rigorous verification of the technical correctness of the code and information produced by LLMs is critical, as bugs or logic errors may have inadvertently crept in. Also, while LLMs can provide a variety of technically correct designs to any request, human practitioners must be able to understand subtle differences between these variations and are ultimately responsible for making the final choices. While engaging in interactive conversations with LLMs and presenting follow-up questions and/or instructions is an effective approach to address uncertainties in the generated results, at this stage, human practitioners must also establish a line-by-line understanding of the results. Somewhat counter-intuitively, user expertise in understanding the nuances of alternate transmission models becomes even more important to effectively manage the rapid model development using LLMs.

The proliferation of LLMs reduces technological and financial barriers across a range of domains, facilitating the localization of modelling, particularly in low-income populations. This may have the potential to bridge the gap for countries and areas with limited resources, as it democratizes access to advanced modeling techniques, catering especially to healthcare facilities in low-income regions. This approach can also apply to mitigating nosocomial transmissions, an area often overlooked by researchers due to a scarcity of resources and a dearth of modelling expertise. With sufficient safeguards against model misspecification, this could potentially promote more equitable preparedness measures and responses across diverse populations, ultimately strengthening global resilience in the face of future pandemics [21] and prompting us to assess potential bias in LLM-independent advanced analytics and modeling.

Declaration of Generative AI and AI-assisted technologies in the writing process

No AI and AI-assisted technologies are involved in the writing process.

CRediT authorship contribution statement

Kin On Kwok: Writing – review & editing, Writing –original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tom Huynh:** Writing – review & editing, Investigation, Data curation. **Wan In Wei:** Writing – review & editing, Methodology, Investigation, Formal analysis. **Samuel Yeung Shan Wong:** Writing – review & editing, Supervision, Resources. **Steven Riley:** Writing –review & editing, Validation, Supervision, Methodology. **Arthur Tang:** Writing – review & editing, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

None.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.csbj.2024.08.006.

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