Harnessing Digital Data for Outbreak Management: A Generative Agent-Based Policy Formulation and Assessment

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Abstract

Extant literature has rarely considered the cognitive aspects of an outbreak. Social psychology literature suggests that the mental construal of a specific event depends on psychological distance, i.e., the perceived distance from the event. Consequently, psychological distance can potentially influence (or even distort) the linguistic content of deliberations during outbreaks, making policy formulation based on such data problematic. Hence, we employed the theoretical lens of Construal-level Theory to understand the cognitive aspects of social media data during the 2014 Ebola outbreak and used these insights as input for our proposed generative agent-based policy formulation. The **core contribution** of this study is *leveraging social media data for policymaking through generative agents* and assessing the same by comparing the suggested policies with the original policy documents.

Introduction

An efficient outbreak management framework needs to collect, analyze, and interpret crisis-related data needed for the planning and implementation of public health policies. Thus, extant literature has considered various online contents, such as web search queries or microblogging data, as a crucial source of information for outbreak management (Ginsberg et al. 2009; Khatua, Khatua, and Cambria 2019; Liang et al. 2019; Cinelli et al. 2020; Xue et al. 2020; Loitz et al. 2023; Mao et al. 2024). For instance, initial studies have observed that web search query volume can predict an outbreak (Achrekar et al. 2011; Ginsberg et al. 2009). Literature has also probed the linguistic contents of social media posts for extracting relevant and actionable information during an outbreak (Cinelli et al. 2020; Miller et al. 2017; Khatua, Khatua, and Cambria 2019; Kouzy et al. 2020; Gao et al. 2023). However, the role of underlying emotions and cognitive aspects of social media users in extracting relevant information from online platforms has been relatively underexplored (Cambria 2024; Susanto et al. 2020; Cambria et al. 2024, 2026). We employ the lens of **Construal Level Theory (CLT)** from the social psychology literature and aim to address this research gap by *leveraging social media data as input for generative agent-based policy formulation.*

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CLT argues that the mental construal of a specific event, such as an outbreak, depends on the **psychological distance** between the event and the observer (Trope and Liberman 2010; Van Lent et al. 2017; Wong, Yang, and Liu 2022; Sharples et al. 2022). For instance, increased psychological distance (between an event and observer) on social media platforms can potentially "include difficulty in relating to each other or sharing a deep level of interaction" (Lim et al. 2012). Also, the psychological distance with an outbreak depends on the transmission probability of an epidemic from the epicenter to other parts of the world (Van Lent et al. 2017). Thus, emotional involvement and risk perceptions depend on psychological distance (Bhatia and Walasek 2016; Wong, Yang, and Liu 2022; Tan and Hsu 2023). Psychological distance also impacts the linguistic usage of social media users. Hence, the linguistic content of a social media user closer to the crisis will differ from that of distant users (Sharples et al. 2022; Wong, Yang, and Liu 2022).

We study the 2014 Ebola outbreak in this work. In the initial phase, the 2014 Ebola outbreak mainly affected West African countries. Subsequently, it reached the Western world, which immediately pressed the panic button in advanced economies. A few cases in developed economies created a sudden surge of Ebola-related discussion on the $\mathbb{X}$ platform. Hence, the 2014 Ebola outbreak became a global concern after the initial phase, and this unique context enables us to investigate the contrasting characteristics of social media deliberations. Besides, compared to advanced economies, internet penetration was significantly low in West Africa during the crisis (Khatua, Khatua, and Cambria 2019). Thus, the relative presence of Africa-related concerns on social media platforms was significantly low compared to advanced economy-related problems due to the **digital divide** in conjunction with the psychological distance.

Using the psychological distance framework, we have identified two types of concerns for the 2014 crisis as follows: **low-level construal**, such as concerns directly related to African nations and advanced economies; and **high-level construal**, such as generic Ebola-related concerns and administrative concerns (like racial or hate comments or propagation of medical misinformation and rumors). Figure 1 illustrates our **proposed research framework**. Our study elucidates that policy formulation is a context-specific task.

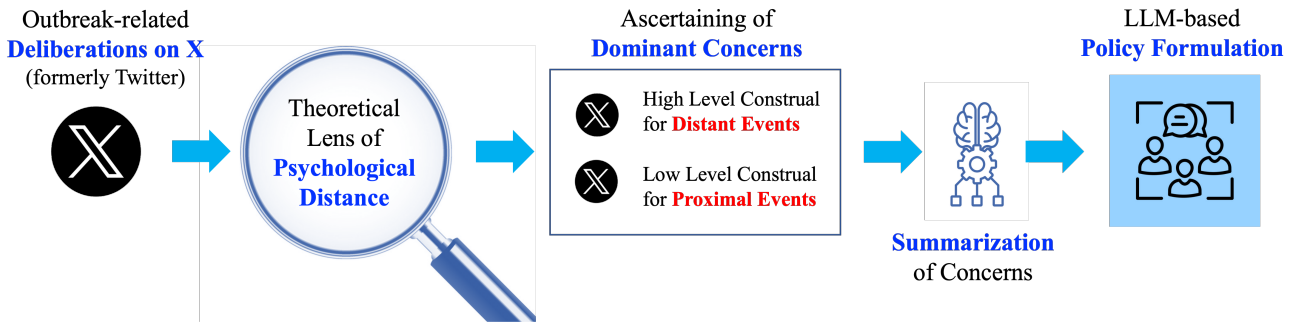

Figure 1: Proposed Research Framework

For instance, there were around 10 Ebola cases in advanced economies, whereas reported cases were more than 10,000 in Guinea, Sierra Leone, and Liberia during the 2014 outbreak. However, we note that one of the shortcomings of social media platforms is the under-representation of concerns due to the **digital divide and psychological distance**. Hence, an effective policy formulation must consider the cognitive aspects to have a nuanced understanding of the potential and pitfalls of social media data. The core contributions of our study are as follows: 1) An innovative dataset on the 2014 Ebola crisis to highlight the cognitive aspects of social media deliberations. 2) Generative agent-based policy formulation using different personas from various backgrounds. 3) Assessment of suggested policies with respect to original policy documents.

Related Works on Outbreak Management

As mentioned above, search query data was widely explored for outbreak management, such as prediction of crisis (Ginsberg et al. 2009; Loitz et al. 2023; Ma et al. 2025). For example, initial studies based on 𝕏 mainly involved **volumetric analyzes** of social media posts to predict the propagation of the outbreak (Achrekar et al. 2011; Culotta 2010; Singh et al. 2020). However, this approach has been critiqued as *big data hubris* (Lazer et al. 2014). Subsequently, NLP-based approaches explored the **linguistic content** of social media discussions. 𝕏 data around the 2014 Ebola and Zika outbreaks effectively captured time-specific public concerns (Glowacki et al. 2016; Kim et al. 2016; Khatua and Khatua 2016; Miller et al. 2017). **Informative tweets** have been categorized into health risks, prevention, symptoms, transmission, and treatment (Ghosh et al. 2016; Miller et al. 2017; Khatua, Khatua, and Cambria 2019) and used for cognitive analysis during Covid-19 (Mao et al. 2026). Prior studies also classified disaster-related tweets into direct, indirect, and vulnerable eyewitnesses, noting that direct eyewitnesses use sensory language, while indirect ones express emotions and prayers (Zahra, Imran, and Ostermann 2020). However, literature also found that "91% of retweets were directly retweeted from the initial message", highlighting the role of influential users (Liang et al. 2019). 𝕏 is also a major source of **medical misinformation** (Oyeyemi, Gabarron, and Wynn 2014; Hickmann et al. 2015; Cinelli et al. 2020; Kouzy et al. 2020; Sharma et al. 2020; Ortiz-Martínez et al. 2022), and misinformation spreads rapidly across borders (Sharma et al. 2020). Alarmingly, during Covid-19 24.8% of tweets propagated misinformation, with unverified accounts and less regulated platforms like Reddit and Gab playing a key role (Cinelli et al. 2020; Kouzy et al. 2020). Beyond misinformation, outbreaks also trigger **hatred** on digital platforms (Alshalan et al. 2020; Uyheng, Bellutta, and Carley 2022). For instance, racially charged tweets blamed the African population for Ebola's spread in 2014, underscoring the need for hate speech detection and sentiment regulation (Kouzy et al. 2020). In short, the outbreak management literature has evolved from volumetric analyses to NLP-based inquiry. Despite extensive research, especially after Covid-19, no prior study has leveraged social media data for generative agent-based policy formulation - to the best of our knowledge.

Construal Level Theory (CLT): We argue that considering the cognitive aspect of digital data can be an efficient approach to identifying informative tweets. However, outbreak management literature has rarely employed this cognitive lens - except for a few studies (Johnson 2018; Kim 2019; Craig et al. 2021; Craig, Ma, and Karabas 2021). Social psychology literature emphasized the role of psychological distance on our mental construal of an event (Liberman and Trope 1998). This stream of literature has conceptualized psychological distance as the "subjective experience that something is close or far away from the self, here, and now" (Trope and Liberman 2010). The perceived psychological distance depends on the event's proximity (Trope and Liberman 2003, 2010; Van Lent et al. 2017). Consequently, the mental construal or "the meaning of the same social event changes depending on whether it is believed to occur at a spatially near or distant location" (Fujita et al. 2006). Therefore, the psychological distance can impact, or even distort, social media discussions during a crisis or disaster. We argue that all four dimensions of psychological distance, i.e., *spatial, temporal, social, and hypothetical distance or probability*, are relevant in the context of outbreak management (Trope and Liberman 2010; Van Lent et al. 2017). For instance, the mental construal depends on the spatial distance, i.e., whether the specific event is located nearby or at a distant location. Proximal events are represented with "rich, complex, concrete, and contextual" information, known as low-level construal (Snefjella and Kuperman 2015).

Table 1: A few annotated tweets of the 2014 Outbreak with Construal Level (CL)

Sl.No.	Sample Tweets	Concern (CL)
1	Ebola symptoms start as malaria or cold then vomiting, joint pain, muscle ache,and lack of appetite.	GEN (High)
2	Ebola is 3rd outbreak ever to get 'public health emergency' status.	GEN (High)
3	From body bags to goggles, Liberia is short on supplies in the fight against #Ebola.	AFR (Low)
4	Hospital in #SierraLeone is eerily deserted. 22 hospital workers died from #Ebola. Locals afraid to visit.	AFR (Low)
5	The president should consider a temporary ban on travel to the U.S. from countries afflicted with #Ebola.	DEV (Low)
6	#Ebola: The risk to people in the U.K. is still very low.	DEV (Low)
7	EBOLA has entered Zaria Kaduna, so everyone should add salt to their bathing water this morning.	ADM (High)
8	I'm the only black person in my business class. Imagine when I sneezed, someone whispered "Ebola".	ADM (High)

Table 2: Total Number of Annotated Tweets

Event	GEN	AFR	DEV	ADM	TOT
2014 Outbreak	398	269	405	155	1227

The low-level construal of events in a spatially nearby location is the function of the direct experience (Fujita et al. 2006). Similarly, temporal distance can be defined "as the perceived proximity of an event in time", influencing individuals' perceptions of an event (Kim 2019). Social distance is the result of socioeconomic differences between different groups within society. Increased social distance can potentially lead to racial attitudes. Finally, propensity matters because the possibility of an event is an essential factor for psychological distance. For example, social media users from developing economies might be more sensitive to malnutrition or infant mortality than those from advanced nations.

Research Gap: Only a handful of prior studies have considered the effects of psychological distance in the context of outbreak management (Van Lent et al. 2017; Johnson 2018; Kim 2019; Blauza et al. 2021; Craig et al. 2021; Craig, Ma, and Karabas 2021; Sharples et al. 2022; Wong, Yang, and Liu 2022). For instance, literature probed "how individuals' psychological distance toward a disease influences the effectiveness of health campaign messages related to the disease" (Kim 2019). Similarly, another study explored the effects of psychological distance on Americans' risk views and behavioral intentions in the context of the Zika outbreak (Johnson 2018). However, to the best of our knowledge, none of the prior studies employed this lens for generative agent-based policy formulations. Thus, our **research question** is: *How does the perceived psychological distance impact social media deliberations and, subsequently, policy formulation?* Additionally, we also need to assess *the quality of these policies in comparison to the actual policy measures* adopted by the WHO and the government agencies.

Research Context

On August 08, 2014, the World Health Organization (WHO) declared Ebola an international health emergency, and it became a serious health concern in African countries over the next few months (Van Lent et al. 2017). In early September 2014, the number of infected cases was more than 4000 in five West African countries. On September 30, 2014, Thomas Duncan became the first confirmed case of Ebola in Dallas, US (and he died on October 8, 2014). A Spanish nurse, the case of the first human-to-human transmission outside West Africa, was detected on October 6, 2014. The above two instances triggered a series of preventive measures by the Western world, such as temperature screening for passengers arriving at airports from Ebola-hit nations. But, the African nations remained the epicenter of the crisis.

Digital Data

We have extracted and pre-processed English tweets containing either the word *Ebola* or the hashtag *#Ebola*. We have considered 2.2 million tweets from August 01, 2014, to November 15, 2014. Interestingly, we note a significant surge of $\mathbb{X}$ deliberations, with concerns related to advanced economies, immediately after the first confirmed case in the USA. For the sake of robustness, we also explored **Google Trend** and noted that the sharp spike in early October 2014 (as a response to the first confirmed case in the USA) was significantly higher than the initial spike in early August 2014 (as a response to the crisis in African countries). This pattern indicates the cognitive aspects in conjunction with the digital divide.

Dominant Themes of 2014 Crisis: CLT suggests that psychological distance leads to high-level construal, where abstract and decontextualized features represent events. On the contrary, proximal events will be represented by concrete and contextualized details, i.e., low-level construal. For the 2014 Ebola crisis, we have categorized decontextualized $\mathbb{X}$ deliberation related to the symptoms or precaution or prevention of the Ebola outbreak or tweets that disseminate information, such as WHO or CDC announcements, as *Generic Ebola-related concern* **(GEN)**. These tweets are high-level construal. Notably, these tweets **are not a relevant source of information for policy formulation.**

Next, we find low-level construal where tweets are concrete, contextual, and rich in information. We have categorized these contextual tweets into two categories. If tweets mention concrete facts or figures or the severity of the Ebola outbreak in West African nations or discuss contextual challenges faced by health workers, such as shortage of medical equipment, in these nations, then they are categorized as *Africa-related concerns* **(AFR)**. Similarly, tweets expressing contextual concerns about cases (or suspected cases) in the USA or European nations or discussing the need to implement a stringent travel ban policy to control the prolif-

Table 3: Committee Members: Affiliations, Roles and Expected Contributions

Member	Affiliation	Roles	Expected Contributions
POLICY STRATEGISTS	WHO	Policy Strategist & Crisis Manager	Global coordination, ethical policymaking
EPIDEMIOLOGIST	Europe (ECDC)	Data Analyst & Scientific Collaborator	Disease modeling, research collaboration
MEDICAL EXPERT	Africa (AU/CDC)	Clinical Advisor & Capacity Builder	Treatment protocols, vaccine distribution
COMMUNICATION EXPERT	USA (CDC/FEMA)	Public Engagement & Misinformation Mgmt.	Transparent messaging, community trust

eration of Ebola outbreaks in these countries are labelled as *Concerns for Developed Economies* **(DEV)**. Intuitively, **these tweets will be more relevant for policy formulation**.

We also came across another category of decontextualised tweets (i.e., high-level construal) spreading rumours or conveying sarcastic or racial views about the outbreak. We labelled them as *Administrative Concerns* **(ADM)**. WHO categorically mentioned (in 2014) that "decades of scientific research have failed to find a curative or preventative agent" to tackle the Ebola virus, but during the 2014 crisis, a rumour of bathing and drinking salt water as a treatment for Ebola became viral. Consequently, at least two people have died after drinking excessive salt water in Nigeria.

One of the aspects of psychological distance is social dominance orientation, which leads to group hierarchies (Hardy et al. 2010; Pratto, Sidanius, and Levin 2006). Social dominance orientation can lead to racial comments. This category of tweets can have a disastrous effect on the psychological well-being of the concerned person. Although these tweets are high-level construals, **effective policy formulation must address these false or racially charged narratives** and condemn these tweets stringently. Table 1 reports a few sample tweets from our corpus for all four concerns and the associated construal level (CL) for the 2014 Ebola outbreak.

Annotation: We have selected 1600 tweets from our corpus, and approached student annotators, but we realized this task requires deep insights regarding the research context and CLT. Hence, one of the authors, with another senior colleague, performed the annotation task. The inter-annotator agreements were 0.84. For our final analysis, we discarded tweets when two annotators failed to reach a consensus. Table 2 reports the distribution of these annotated tweets.

Classification Accuracy: This paper is not focused on text classification; however, to test the applicability and scalability of our approach, we examined the accuracy of both basic neural models and Bidirectional Encoder Representations from Transformers (BERT)-embedded models. For robustness, we used multiple batch sizes (16 and 32), hidden layer sizes (256 and 512), and dropout rates (0.3 and 0.5). In this study, we adopted an 80/10/10 split for training, validation, and testing, consistent with standard practices in NLP research. We observed that BERT-embedded neural models significantly outperformed models without word embeddings. For example, the average accuracy of the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models (across various hyperparameter combinations) without BERT embedding was around 85%. In contrast, the average accuracy improved substantially to approximately 95% after incorporating BERT. This **high accuracy** confirms the real-time applicability of our proposed policy formulation approach.

Summarization of Concerns

Policymaking needs to extract relevant and actionable insights from social media discussions to create effective policies. Using text summarization, we can remove redundant and repetitive content, allowing generative agents to focus on the most essential information related to the crisis. Text summarization can be of three types: Extractive, Abstractive, and Hybrid. The Extractive approach scores sentences and selects the most important ones based on the desired summary length. Conversely, the Abstractive approach rephrases sentences, generating new ones that convey the same meaning. Hybrid summarization combines both Extractive and Abstractive methods, along with other factors such as output length and consistency. The BART (Bidirectional and Auto-Regressive Transformers) model is a denoising autoencoder that is pre-trained to recover original text corrupted by various noising functions. This makes it effective for abstractive summarization by reducing redundancy and noise in data. T5 (Text-to-Text Transfer Transformer) frames all NLP tasks as text-to-text tasks, including summarization, by using a unified model, loss function, and hyperparameters for tasks like translation and classification.

In this work, we focus on **abstractive summarization**, which allows for the automatic generation of concise and clear representations of tweets while preserving key information. Abstractive summarization condenses content and retains contextual knowledge, which is especially helpful when dealing with a large number of tweets on a given topic. This approach reduces redundancy and noise in the data. Thus, we used the GPT-4 model for our summarization task and limited the output to 500 tokens to maintain consistency across simulations from different perspectives.

The highlighted summaries in this section present abstract summaries of various concerns based on our annotated corpus. Since this paper focuses primarily on the agent-based simulation, we are not conducting a rigorous evaluation or reporting detailed metrics here. We note that the generated summary achieved a high BERTScore F1 (0.8151), indicating strong semantic similarity, while the Distinct-1 score (0.6270) reflected high lexical diversity. However, relatively low ROUGE-1 (0.1452) and ROUGE-L (0.1276) scores sug-

gest limited surface-level overlap, highlighting the abstract nature of the generated text. Additionally, both of our annotators have confirmed that these summaries effectively capture the concerns expressed by social media users.

Summary of AFR-related Concerns:*The Ebola outbreak in West Africa has led to a severe strain on healthcare systems, particularly in Liberia and Sierra Leone ... there is a critical shortage of healthcare workers and facilities, with every hospital in Monrovia, Liberia ... WHO has reported that the epidemic has been contained in Nigeria and Senegal ... various international responses ... 700 British troops are to be deployed to Sierra Leone to assist in combating the disease ... a British cargo plane carrying medical equipment and ambulances has landed in Sierra Leone ... Nigeria's president has declared a national state of emergency ... the Nigerian Medical Association has called off a month-long doctors' strike ... Liberia's health system is collapsing ,,, In Sierra Leone, the situation is also dire, with a report of 140 Ebola deaths in a single day...*

Summary of DEV-related Concerns: *... spread of the Ebola virus in various regions, including the United States and Europe ... report cases of suspected and confirmed Ebola patients, particularly focusing on instances of the disease in Dallas and Madrid ... concern over the handling of Ebola cases by health officials, with reports of health workers becoming infected and questions raised about safety protocols, particularly in the context of air travel ... strikes by airport workers due to fears of exposure, protests calling for travel bans from affected regions, and a case of potential public endangerment where NYPD were allegedly seen improperly disposing of Ebola-related waste ... changes in guidelines for protective gear following the infection of health workers ... Nina Pham, a nurse who was infected with Ebola, treated, and later declared Ebola-free.*

Summary of ADM-related Concerns: *... reflects the widespread misinformation, panic, humor, and cynicism surrounding the outbreak ... a range of emotions - from despair to disbelief, and even ridicule - towards various so-called 'cures' such as saltwater baths or bleach ... the perceived racial inequalities in healthcare ... referencing Spongebob or adding cooking ingredients to bath water ... express frustration over the circulation of false information, demonstrating the dangers of misinformation during a public health emergency. Some even reflect a religious undertone, suggesting the belief of divine retribution ...*

Summary of GEN Concerns: *... concern of Ebola's spread globally and the urgent need for a solution ... disproportionate attention given to Ebola cases in first-world countries ... death toll continues to rise, and an effective response requires international coordination ... importance of education in curbing panic ... factual information regarding its transmission and symptoms ... the severity of the Ebola crisis ... mourn the loss of healthcare workers who succumbed to the disease and applaud the bravery of those on the front lines ... potential experimental vaccine... funding allocation for research ... pointing out the dire need for a global response... fact-based information to counter fear and misinformation ... criticize sensationalist media coverage.*

Multiagent Persona Simulation

We have employed Microsoft's open-source **Multi-agent Persona Simulation Environment**, i.e., TINYTROUPE (Salem et al. 2024). It offers a powerful simulation framework that allows researchers to create multiple LLM-powered personas and observe how these personas interact with each other. Broadly, it provides a platform where human-like agents' interactions, dialogues, and actions can be simulated under defined conditions. In other words, this open-source platform, powered by GPT-4 for generating realistic simulated behaviour, creates a TINYPERSON and pushes them into an environment to simulate interactions. Notably, this framework allows one to specify the situation, context, and a detailed persona based on their profile. This framework can help us replicate real-life conversations between different people.

Policy Strategist: To address the concerns about the spread of Ebola in the US and Europe, we should focus on enhancing protective measures for healthcare workers and ensuring clear communication with the public. This includes updating guidelines for protective gear and providing training to healthcare staff. Additionally, we should work with airlines to implement effective screening and isolation protocols to minimize the risk of transmission during air travel. Clear and transparent communication will help alleviate public fears and ensure that people are informed about the measures being taken to control the outbreak.

Epidemiologist: Data analytics can play a crucial role in enhancing protective measures and communication strategies. By analyzing data on healthcare worker infections, we can identify patterns and potential gaps in protective measures, allowing us to update guidelines and training programs effectively. Additionally, data-driven insights can help tailor communication strategies to address public concerns and misinformation, ensuring that messages are clear, accurate, and impactful. This approach will help build trust and confidence in the measures being taken to control the outbreak.

Medical Expert: I support the focus on enhancing protective measures for healthcare workers and ensuring clear communication with the public. By using data analytics to identify gaps in protective measures and tailor communication strategies, we can effectively address public concerns and build trust in the measures being taken to control the outbreak. Collaborating with airlines to implement effective screening and isolation protocols will also be crucial in minimizing the risk of transmission during air travel.

Communication Expert: Building on these suggestions, I propose we also focus on developing a comprehensive public awareness campaign that emphasizes the importance of following health guidelines and dispels common myths about Ebola. This campaign can utilize various media channels, including social media, to reach a wide audience and ensure that accurate information is accessible. By addressing misinformation and promoting preventive measures, we can help reduce fear and encourage responsible behavior among the public.

Figure 2: Conversation Instance from our Multi-Agent Persona Simulation: The colored dialogue boxes represent the viewpoints of TINYPERSON during their multi-round discussion. This Figure illustrates the interaction among the members or personas of TINYWORLD, and their conversation aims at managing the crisis. The simulation begins with the POLICY STRATEGISTS. Subsequent interactions showcase how the EPIDEMIOLOGIST, MEDICAL EXPERT, and COMMUNICATION EXPERT engage, exchange perspectives to address the crisis.

Social Simulation: Simulation aims to replicate various social activities, encompassing a wide range of applications (Gilbert and Troitzsch 2005; Bratley, Fox, and Schrage 2011). One key advantage of social simulation is its potential to create pseudo-worlds to test expected outcomes (Khatua 2025). While societal reactions are not always predictable, such simulations can assist in understanding underlying mechanisms (Gilbert and Troitzsch 2005; Bratley, Fox, and Schrage 2011). A prior study discovered that LLMs can replicate some classic experiments in economics (Aher, Arriaga, and Kalai 2023). Another study substituted human participants with LLM agents, providing them with various personas - such as information, preferences, and other parameters - through prompts and then used this environment for economic simulations (Horton 2023). Another study created a virtual town populated with 25 LLM-powered agents within a video game environment, where these agents can plan and schedule their daily activities (Park et al. 2023). Drawing insights from this stream of work, we aim to simulate how a task force, comprised of a team with diverse back-

grounds, discusses and arrives at policy-level recommendations. As a background to their discussion, we are providing them with a summary of social media deliberations - as reported in the previous section.

TINYPERSON: In this framework, a TINYPERSON represents an agent in the experiment. This representation includes participants' common attributes and behaviours, such as their name, personality traits, occupation description, interests, skills, relationships, age, education, country, and the environment these agents use to generate messages (Salem et al. 2024) - allowing the replication of a social role. "As each such simulated agent progresses through its life, it receives stimuli from the `environment` and acts upon them. The stimuli are received through the `listen`, `see`, and other similar methods, and the actions are performed through the `act` method. Convenience methods like `listen_and_act` are also provided" (Salem et al. 2024).

Effects of Persona: Generally, a person's background plays a significant role in their thought process (Zhu et al. 2023, 2024a,b; Xie and Mao 2025; Khatua 2025). Hence, we anticipate that diverse backgrounds of personas will enrich the discussion and offer holistic policy-level recommendations. Prior studies suggest that having multiple personas or agents in a discussion adds value (Chen et al. 2023). However, including more personas introduces randomness and adversely affects the richness of deliberations. Therefore, we have considered an optimal size of four personas, each with distinct qualities and capabilities, as described in detail in Table 3. In other words, four different types of personalities can play four distinct but complementary roles, such as POLICY STRATEGISTS, EPIDEMIOLOGIST, MEDICAL EXPERT, and COMMUNICATION EXPERT. Each agent is expected to bring their own experience, knowledge, and diverse viewpoints for outbreak management. We find that POLICY STRATEGISTS tends to initiate the discussion. We also note that the characteristics or technical expertise of agents significantly influence these discussions or viewpoints of these personas.

TINYWORLD: TINYWORLD comprises TINYPERSON, reflects the environment. To elaborate on the process, a representative example of a conversation between POLICY STRATEGISTS, EPIDEMIOLOGIST, MEDICAL EXPERT, and COMMUNICATION EXPERT is illustrated in Figure 2. TINYWORLD enforces minimal constraints on possible interactions. As noted, personas can interact with each other to simulate complex scenarios (Salem et al. 2024). To initiate the simulation, i.e., the discussion between agents, we have considered the following system prompt:

```
 Committee Members, we need to develop actionable
strategies to address the Ebola outbreak
collaboratively. In your recommendations, consider
the critical issues based on the information
provided. [Here, we have provided one of the four
summaries reported in Section 5.] Avoid generic
solutions and focus on practical, innovative, and
sustainable approaches to the crisis. Let's leverage
our diverse expertise to craft comprehensive,
effective policy recommendations. Please start the
discussion now.
```

Policy Formulation and Assessment

Our analysis indicates that using psychological distance as a lens for policy formulation has enhanced the context sensitivity and applicability of policy recommendations during the Ebola 2014 crisis. For instance, suggestions such as deploying mobile health units, combating misinformation through social media, and ensuring equitable vaccine distribution were valuable but lacked region-specific considerations and did not highlight the differential nature of crises across African countries and developed countries like the USA and Europe.

Conversely, in our proposed approach, policy formulation became more targeted and actionable. For example, Africa-specific recommendations emphasized strengthening local healthcare infrastructure, fostering international collaborations, and incorporating traditional medicine practices - strategies reflecting the region's resource constraints and the severity of the crisis. In contrast, policies for developed economies prioritized advanced technological tools like predictive modeling, geographic mapping, and enhanced airport screenings to prevent the virus's spread.

LLM-as-a-Judge: To assess the effectiveness of agent-based policy generation, we adopted the LLM-as-a-Judge evaluation approach, as demonstrated in prior work by Zheng et al. (Zheng et al. 2023). Specifically, we used this method to evaluate the quality of the policies generated by the TINYTROUPE framework. Although human evaluation remains the gold standard for assessing accuracy and completeness, it is highly resource-intensive (Gu et al. 2024; Gao et al. 2025). Therefore, we adopted LLM-as-a-Judge techniques as a scalable alternative. Our evaluation process begins by collecting policy-focused PDF documents from the WHO and extracting their raw text to assess the quality of the generated policies.

Next, the extracted text is partitioned into overlapping chunks (4,000 characters with a 200-character overlap) to ensure each segment remains within LLM token limits. These chunks are then each encoded into dense vector representations via OpenAI's embedding API and indexed in a FAISS vector store to support efficient semantic retrieval (Douze et al. 2024). Policies generated by TINYTROUPE were assessed for their similarity to the original policy documents, such as the WHO's roadmap for addressing the crisis. Most policy recommendations are multi-line entries submitted against an indexed collection of source materials to retrieve the top-k semantically relevant excerpts. For each recommendation, we construct a combined prompt that includes both the generated policy and the excerpts retrieved from WHO policy documents. GPT-4 is then instructed to assign an assessment score—Strong, Moderate, Weak, or None—along with a brief explanation supporting the evaluation. The resulting ratings and explanations are compiled into a structured table to visualize the correctness of policy generation using the TINYTROUPE framework. This quantitative comparison highlights how well multiple documents support each policy recommendation across different categories in Tables 4, 5, 6, and 7. The details of these documents are provided in Appendix .

Conclusion

Outbreak management literature is trying to extract actionable insights from online data, but the real-life applicability of this approach is still a subject of debate. This study employs CLT to analyze the impact of cognitive aspects on social media deliberations during a crisis. We highlight that it is essential to apply the cognitive lens to identify rich, context-specific insights. Furthermore, we propose using text summarization techniques to process a large corpus and tease out the informational content. We can generate more precise and contextually relevant policy recommendations by considering these summarized insights. For effective policy formulation, collaboration between AI researchers, policymakers, and health organizations is crucial to tackle the cognitive and contextual aspects of online data for policy formulation.

Contributions to AI for Social Good: Our study points out that regional under-representation can distort reality. Hence, an effective policy formulation framework needs to **overcome the regional under-representation on digital platforms** – especially for countries or locations where internet penetration is low. On theo-

Policy Recommendation	Assessment	Explanation
Increase medical resources in affected regions by deploying mobile health units and partnering with local community leaders	Strong	The excerpts provide strong support for the policy recommendation, highlighting the importance of partnerships, capacity development, and the role of WHO in supporting affected regions.
Combat misinformation through targeted communication campaigns and leverage social media for broader reach.	None	The excerpts do not provide any evidence or mention of combating misinformation through targeted communication campaigns or leveraging social media for broader reach.
Ensure equitable distribution of vaccines and treatments, prioritizing the most vulnerable populations. Establish a robust monitoring and evaluation framework to track intervention effectiveness and make data-driven adjustments.	Moderate	The excerpts show evidence of WHO's efforts in research, development, and preparedness for health emergencies, but they do not directly address the equitable distribution of vaccines or the establishment of a robust monitoring and evaluation framework.
Develop a centralized platform for real-time data sharing and coordination among stakeholders, enhancing transparency and collaboration.	Moderate	The excerpts mention collaboration, data sharing, and transparency in the context of health emergencies, but do not directly address the development of a centralized platform for real-time data sharing among stakeholders.
Integrate digital tools for real-time data collection and analysis to improve decision-making processes. By implementing these strategies, we aim to create a comprehensive and effective response to the Ebola outbreak.	Moderate	The excerpts mention the use of tools for preparedness and response, progress tracking, and research and development. However, they do not directly address the integration of digital tools for real-time data collection and analysis.

Table 4: Policy Formulation for Generic Concerns(High-level Construal) and Assessment

Policy Recommendation	Assessment	Explanation
Strengthening local healthcare systems with training and resources	Strong	The excerpts provide evidence of training and resource provision in local healthcare systems, including infection prevention, data management, and contact tracing. This supports the policy recommendation strongly.
Enhancing international collaboration for medical supplies and personnel.	Strong	The excerpts highlight the need for foreign medical teams, international preparedness strengthening teams, and international collaboration for training and managing EVD outbreaks.
Implementing community engagement programs to reduce stigma and misinformation. Developing rapid response teams for outbreak containment.	Strong	The excerpts provide strong evidence of community engagement programs reducing stigma and misinformation, and the use of rapid response teams for outbreak containment.
Utilizing disease modeling to predict trends and allocate resources	Moderate	The excerpts provide some evidence of disease tracking and response, but do not directly address the use of disease modeling to predict trends and allocate resources.
Creating equitable vaccination programs and integrating traditional medicine practices.	None	The excerpts discuss community engagement and education about Ebola, but do not provide evidence supporting the integration of traditional medicine practices or creating equitable vaccination programs.
Establishing a comprehensive communication plan to build trust and ensure compliance with health interventions.	Strong	The excerpts provide multiple instances of comprehensive communication plans being implemented and their effectiveness in health interventions, supporting the policy recommendation strongly.

Table 5: Policy Formulation for Africa-related Concerns (Low-level Construal) and Assessment

retical fronts, a few prior studies employed CLT to probe outbreaks like the 2014 Ebola outbreak (Van Lent et al. 2017) or the COVID-19 crisis (Craig et al. 2021; Craig, Ma, and Karabas 2021; Blauza et al. 2021). Hence, a handful of studies have established the importance of CLT in the context of outbreaks and pointed out that social distance is inversely related to the emotions and risk perception of social media users (Wong, Yang, and Liu 2022). However, to the best of our knowledge, this is the first study that has considered **cognitive aspects for policy formulation**. For instance, a prior study explored Dutch tweets and noted that public attention or fear was a function of psychological distance in the Netherlands and neighboring countries. Specifically, they explored the fear for self and fear for others when Ebola crossed the Mediterranean Sea and the Atlantic Ocean (Van Lent et al. 2017).

Generally, prior studies employed qualitative research design, such as interviews (Sharples et al. 2022), or considered survey data (Wong, Yang, and Liu 2022; Craig et al. 2021; Craig, Ma, and Karabas 2021). For instance, a prior study conducted an online survey in the German context and observed the participants' affective, cognitive, and behavioral attitudes depending on psychological distance (Blauza et al. 2021). Interestingly, this study pointed out that psychological distance also depends on the knowledge and awareness of participants. Notably, *our proposed approach was rarely employed in the AI for Social Good research stream.* Therefore,

Policy Recommendation	Assessment	Explanation
Implement enhanced airport screenings and quarantine protocols for travelers from affected regions.	Strong	The excerpts provide substantial evidence of enhanced airport screenings and quarantine protocols being implemented, including specific measures, locations, and procedures.
Ensure healthcare workers have access to adequate protective equipment and training.	Strong	The excerpts provide evidence of improvements in protective equipment, rigorous training for healthcare workers, and coordination efforts at various levels, strongly supporting the policy recommendation.
Develop predictive models to identify potential hotspots for Ebola transmission.	Moderate	The excerpts provide evidence of preparedness plans, training, and infrastructure for Ebola response, but do not directly address the development of predictive models for identifying Ebola hotspots.
Strengthen healthcare infrastructure in underserved areas and deploy mobile health units.	Strong	The excerpts provide evidence of efforts to strengthen healthcare infrastructure, deploy mobile health units, and train healthcare workers in underserved areas, supporting the policy recommendation.
Integrate advanced data visualization and geographic mapping tools to track the virus.	Moderate	The excerpts mention data gathering, monitoring, and response to the virus, which indirectly supports the recommendation. However, there is no explicit mention of integrating advanced data visualization and geographic mapping tools.
Create offline resources and partner with local radio stations to reach underserved communities.	Strong	The excerpts provide evidence of successful use of traditional media like radio for public outreach and the call for cost-effective innovations to combat Ebola, supporting the policy recommendation.

Table 6: Policy Formulation for Developed Economy-related Concerns (Low-level Construal) and Assessment

Policy Recommendation	Assessment	Explanation
Implementing a robust data-driven approach to track and model the spread of Ebola, integrating real-time data from local health teams and global networks	Weak	The excerpts mention the severity of Ebola and the need for public health interventions, but do not directly support the implementation of a data-driven approach to track and model the spread of the disease.
Develop a culturally sensitive communication strategy that leverages technology, such as mobile platforms and social media, to counter misinformation and engage communities.	Weak	The excerpts discuss the importance of communication and community engagement in healthcare settings, but they do not specifically address the use of technology or social media to counter misinformation.
Ensuring equitable vaccination programs and healthcare access, prioritizing high-risk areas and vulnerable populations.	Moderate	The excerpts provide some support for the policy recommendation by discussing the establishment of Ebola Care Units and Community Care Centres, which can help in ensuring healthcare access. However, there is no specific mention of prioritizing high-risk areas and vulnerable populations.
Establishing partnerships with international health organizations and NGOs to leverage additional resources and expertise.	Strong	The excerpts show evidence of successful collaborations between WHO, NGOs, and other partners in managing health crises, supporting the policy recommendation.
Training local healthcare workers in outbreak management and data collection to ensure sustainability and empower communities.	Strong	The excerpts highlight the role of trained health aid workers and community workers in managing ECUs/CCCs, indicating the importance of training local healthcare workers in outbreak management and data collection.

Table 7: Policy Formulation for Administrative Concerns (High-level Construal) and Assessment

the contribution of this study is to offer a generative agent-based framework for policy formulation to mitigate the dual challenges of psychological distance and the digital divide on digital platforms.

Future Research: The obvious follow-up question is – *can we employ this policy formulation framework for other crises*, such as the Covid-19 outbreak? We believe that the answer is *Yes*, but the prerequisite is contextual understanding. For instance, Covid-19 was a distant outbreak just for the initial few months, and online deliberations were high-level construal. Then, the psychological distance came down drastically for the entire world. 𝕏 deliberation during the Covid-19 second wave reflected the *fear, stigma, and psychological concerns of social media users* (Xue et al. 2020). Thousands of tweets reported *context-specific concerns* and posted queries about the availability of medical infrastructure, i.e., low-level construal. 𝕏 deliberation aptly captured that the intensity and nature of the crisis in Italy were different from that of Germany during the first wave. Similarly, 𝕏 deliberation elucidates India's sufferings during the second wave – mostly, these tweets were low-level construal. Hence, we need to consider these nuances when formulating context-sensitive policies.

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GenAI Usage Disclosure

In our experiments, we used OpenAI's GPT-4 model to generate the conversation using the TINYTROUPE framework. ChatGPT was employed at the sentence level for tasks such as grammar correction and rewording to enhance clarity and readability.

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Appendix

TINYPERSON: Medical Expert

We have reported here the characteristics of the Medical Expert, i.e., one of the committee members or TINYPERSON in our simulation framework.

Age: 48

Nationality:African (affiliated with African CDC)

Occupation: Medical Expert and Clinical Advisor

Routine: You start by reviewing patient care data and addressing challenges in vaccine distribution logistics.

Occupation Description: You are a Medical Expert and Clinical Advisor affiliated with the African CDC. Your focus is on developing clinical guidelines for outbreak management, leading vaccination campaigns, and ensuring healthcare systems in resource-limited settings are prepared for crises.

Personality Traits:

- You are empathetic and patient-focused.
- You are resourceful, finding innovative solutions in constrained settings.
- You strongly advocate for health equity.
- You can be assertive when advocating for underserved populations.

Professional Interests:

- Developing equitable vaccination programs.
- Enhancing healthcare infrastructure in underserved areas.
- Training healthcare workers in outbreak management.

Personal Interests:

- Volunteering at local health camps.
- Exploring traditional medicine practices.
- Mentoring young medical professionals.

Skills:

- You are an expert in virology, with significant contributions to vaccine development.
- You are experienced in vaccine campaign logistics.
- You are skilled at creating practical, evidence-based treatment protocols.
- You are adept at training healthcare workers for crisis situations.

Professional Relationships:

- **Dr. Aisha:** A fellow scientist specializing in public health surveillance who frequently collaborates with you on outbreak investigations.
- **UN Health Teams:** partners in vaccine distribution efforts.
- **UNICEF Africa Team:** A group of professionals you work with to ensure vaccination campaigns reach remote communities.

Policy Documents for Assessment

- WHO: Ebola Response Roadmap Situation Reports. Sources:
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