Curse or Cure: Exploring Responses to Mental Health Related Posts in Reddit and ChatGPT Using Terror Management Theory

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Abstract

In our paper, we investigate the responses that individuals with mental illnesses receive on their posts on Reddit and ChatGPT. Using terror management theory (TMT), we propose that the level of empathy of the comments is a function of the mortality salience of the commenter and the technical platform. To test our proposed effects empirically, we extracted a sample of posts and their comments from the "mental illness" and "mental health" subreddits along with responses generated from those posts on ChatGPT. In our statistical analyses, we found a significant main effect for mortality salience in relation to empathy consistent with the TMT, but this effect was qualified by the technical platform. We found that higher mortality salience favored ChatGPT over Reddit and lower mortality salience had the opposite effect.

Keywords: Mental health, Terror management theory, Social media, ChatGPT, Empathy

1. Introduction

In the last decade, the number of individuals who have experienced mental health related conditions such as depression and prolonged emotional distress has risen dramatically (Bommersbach, Rosenheck, & Rhee, 2022; Chau, Li, Wong, Xu, & Yip, 2020). Arguably, the COVID-19 pandemic and the use of stress-inducing technologies have increased the prevalence of mental health issues (Golin, 2022; Salo, Pirkkalainen, Chua, & Koskelainen, 2022; WHO, 2022). In the United States, for instance, roughly 1 in 5 adults experience mental illness each year (NAMI, 2021). Mental health conditions adversely impact the lives of millions of individuals from all socio-economic demographics and regions of the world (Twenge et al., 2021).

As a result, there has been increased discussion of mental health in worldwide health forums, mainstream media, social media, and academic communities. Even still, however, social- and self-stigmas associated with individuals identifying as mentally ill persist (Fernández, Grandón, López-Angulo, Vielma-Aguilera, & Peñate, 2022). That is, many societies treat mentally ill individuals differently, which may result in further isolationism and depression (McKenzie, Oliffe, Black, & Collings, 2022). Mentally ill individuals often have death and suicidal thoughts (Alexander, Haugland, Ashenden, Knight, & Brown, 2009). Unfortunately, the suicidal warning signs are not always obvious and probably vary by individual.

It is difficult for mentally ill individuals to seek help from family and friends due to cultural norms and the uncomfortable nature of those conversations (Winterheld, 2017). Furthermore, individuals tend to have the least tolerance for the negative qualities of close acquaintances, which may result in individuals not admitting their mental weaknesses to family and friends. Instead, they may keep their illness to themselves or, possibly, seek an empathetic audience from a community of strangers on social media platforms (Chau et al., 2020; Hussain et al., 2020). Often, it is easier for individuals to share their mental challenges with strangers as opposed to risking the personal awkwardness that may come from sharing their issues with their real-life close acquaintances.

Discussions on social media platforms, however, are not always welcoming to marginalized groups such as those who are mentally ill (Chan, Cheung, Benbasat, Xiao, & Lee, 2022; Giumetti & Kowalski, 2022). The anonymity and other technical features make them rife for cyberbullying. The positive benefits of these social media platforms (e.g., sense of belonging and social bonds) may be mitigated by the cruelty associated with a portion of the virtual community of commenters (Chan, Cheung, & Lee, 2021). For mentally ill individuals, these potentially nasty online discussions might lead to further isolation and suicidal thoughts. As a result, they may seek an alternative platform outside of social media and real-life close acquaintances to share their mental illness stories.

One such alternative is artificial intelligence conversational agents (chatbots) such as ChatGPT, Tako, and Bard even though they were not specifically designed to offer emotional support. These chatbots may provide a platform that is judgment and cyberbullying free (Xue, Lei, & Cho, 2023). In theory,

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chatbot responses should not be influenced by unpredictable human emotions. By using algorithmically generated responses from text-based inputs using large language models (LLMs), chatbots may be able to respond with calculated feedback having the appropriate level of empathy. Yet, there is a lack of community support and social bonding associated with these chatbots, which might weaken some of their potential positive effects.

Mentally ill individuals often disclose deeply personal narratives on these platforms. These personal issues may involve their suicidal thoughts or less severe issues related to their mental struggles. These posts may trigger the community of commenters to have different thoughts related to their own mental struggles and their own life experiences. It is an open theoretical and empirical question whether the pattern of responses (comments) from posts from mentally ill individuals will vary within and between the two platforms. As a result, we address the following research question:

RQ: Do the comments from mental illness posts vary within and between chatbots and social media?

To address this research question, we apply terror management theory (TMT) (Becker, 1973; Greenberg, Pyszczynski, & Solomon, 1986). TMT posits that mortality thoughts conflict with one's inherent desire for immortality, which can potentially create existential terror if left unmanaged (Pyszczynski, Lockett, Greenberg, & Solomon, 2021). Individuals manage their death cognitions using anxiety-buffers such as building self-esteem, pursuing relationships, and defending their cultural worldviews (Hart, Shaver, & Goldenberg, 2005; Pyszczynski et al., 2021).

We suggest that mental illness posts will prime certain members of the virtual community to think about mortality (consciously or subconsciously), which impacts the level of empathy in their responses. We further argue that chatbots trained using LLMs may also be able to detect death-language and be primed to respond using appropriate death-language, which impacts how empathetic their responses will be. We further suggest that the effect on chatbots will be less pronounced than on social media platforms due to the inanimate nature of artificial agents.

2. Literature Review

In this section, we review relevant and selected literature on social media, artificial intelligence conversational agents (chatbots), and TMT.

2.1. Social Media

Social media are virtual environments that allow users to generate and share content while making virtual connections to others (Kane, Alavi, Labianca, & Borgatti, 2014; Kumar, Mukherjee, Choi, & Dhamotharan, 2022). There are both benefits and risks associated with social media platforms (Labban & Bizzi, 2022; Twenge et al., 2021). For instance, the virtual social bonds and attachments formed on these platforms provide many psychological benefits (Ren et al., 2012). Contrarily, however, spending excessive time on these social media platforms has been linked with increased anxiety and depression (Braghieri, Levy, & Makarin, 2022; Valkenburg, 2022). Therefore, social media may be part of the problem of mental struggles but also part of the solution when used to foster social bonds and attachments.

Popular social media platforms include Facebook, Instagram, Twitter (X), Threads, and Reddit. These platforms have been extensively studied across many disciplines using a variety of theories such as social exchange theory, social capital theory, and social attachment theory (Kane et al., 2014). This research includes different units of analysis – individual, organizational, and societal levels. At the individual level, scholars have applied many different economic, linguistic, communication, psychological, and sociological theories to explain posting patterns, forms of expression, and other social dynamics (Chen, Baird, & Straub, 2022; Faraj & Johnson, 2011; Kitchens, Johnson, & Gray, 2020). At the organizational level, scholars have investigated the impact that posting patterns have on firm performance, business-to-consumer engagement, and business-to-business exchanges (Dwivedi, Ismagilova, Rana, & Raman, 2023; Tajvidi & Karami, 2021). At the societal level, scholars have explored the impact that social media use has on public health and misinformation (Kim, Moravec, & Dennis, 2019; Olan, Jayawickrama, Arakpogun, Suklan, & Liu, 2022).

Particularly related to mental health and social media use, scholars have constructed models using machine learning algorithms to predict distress. For instance, Chau and colleagues (2020) developed a model using a combination of rule-based classification from experts and machine learning algorithms to identify bloggers who experienced prolonged emotional distress. Kumar et al. (2022) further used natural language processing and computational intelligence to find factors that influenced depressive and suicidal thoughts. Other research in this space has investigated the financial impact of social media use for mental health care workers and online marketplaces (Yan, Kuang, & Qiu, 2022; Zhou, Kishore, Amo, & Ye, 2022).

Despite all this research, our scholarly community still does not know whether the individuals interacting on social media platforms will respond empathetically to distressing posts from mentally ill individuals. Empathy is an understudied outcome variable. On the one hand, the literature explicating cyberbullying might suggest that these social media platforms would provide minimal empathy (Chan et al., 2021; Giumetti & Kowalski, 2022). On the other hand, however, posts about suicide might prime the virtual community to think about mortality, which may promote self-esteem building responses that include a level of empathy.

Empathy refers to the internal processes that help individuals share the emotional states of others (Cuff, Brown, Taylor, & Howat, 2016). The isomorphic definition of empathy is “I feel what you feel.” Empathy is a response that stems from the apprehension, comprehension, and communication of another individual’s emotional state (Cuff et al., 2016; Decety, 2021; Yaden et al., 2023). Unlike emotional contagion, empathy is a “self-focused process in which the target’s states are internalized and then become the focus of the empathizer’s attention” (Yaden et al., 2023, p. 2). That is, individuals experience empathy regardless of whether others also respond empathetically. Individuals exhibit empathy for many reasons, but it is highly situational and context dependent (Decety, 2021). For instance, individuals are more empathetic towards in-group versus out-group members, biased towards friends and family members, and socially driven (Decety, 2021; Zaki, 2014).

On social media, many individuals are unknown to one another, which makes the interactions depersonalized (Mattson, 2017). Therefore, it is unclear whether individuals have the ability to determine the affective and cognitive states of others through only text-based discourse. However, specialized social media platforms such as www.patientslikeme.com or subreddits designed to discuss specific illnesses might make it possible for such an understanding. For instance, a recovering addict interacting on an addiction subreddit probably will find an audience of other addicts who have had similar experiences. Those similar life experiences may help them understand the plight of a poster, which has the potential to lead to empathic responses. Similarity of common experiences between the empathizer and the individual seeking empathy is important even if the two individuals are not close acquaintances (Preston & Hofelich, 2012).

Interestingly, empathy benefits both parties (i.e., the seeker and the provider). For the individuals providing empathy, they may increase their reputation and self-esteem, which enhances their overall positive psychological well-being (Ferguson, 2016). For the individuals seeking empathy, empathetic responses provide social support that buffers negative spillover events (Ferguson, Carlson, Zivnuska, & Whitten, 2010). In our context, death-related social media posts are from mentally ill individuals who can use the empathetic responses to help reduce their negative thoughts about death or suicide. For the commenters providing empathy, they can build their own self-esteem by providing empathy, which can be an anxiety-buffer.

2.2. Artificial Intelligence Conversational Agents (chatbots)

Chatbots simulate text-based conversations with human agents (Go & Sundar, 2019; Schanke, Burtch, & Ray, 2021). Technologically, chatbots range from simple (i.e., pre-programmed) to highly sophisticated (i.e., complex LLMs). ChatGPT and Bard are two popular generalized chatbots trained using LLMs that provide well-articulated responses related to a multitude of topics. They are popular even though the responses are not always factually correct. For empathy, however, the factual accuracy of the response is not as important as understanding the feelings inferred by the text-based input. That is, a response may be empathetic while having factual inaccuracies and inconsistencies.

Chatbots have many human-like qualities, traits, and emotions (Pizzi, Scarpi, & Pantano, 2021), which is referred to as anthropomorphism. Effective anthropomorphism creates a sense of social presence (i.e., “realness” of others) (Schuetzler, Grimes, & Giboney, 2020). Creating social presence may involve embodied (physical representation of the object utilizing non-verbal cues) or disembodied (text representation) anthropomorphism (Araujo, 2018). Particularly on social media, chatbots most commonly represent disembodied anthropomorphism. With disembodied anthropomorphism, Ki, Cho, and Lee (2020) suggest that individuals have the ability to form para-friendships with and get social support from chatbots. Empathy is a core component of social support (Yaden et al., 2023).

Generalized chatbots are only as good as the data that are used to train them. With the "right" training data, they have the potential to provide empathetic responses. With the "wrong" training data, however, they may provide coarse or abrasive responses. The first and second generations of these generalized LLM chatbots have been trained with between 250 and 350 billion words sourced from blogs, Wikipedia, news articles, and books. The sheer volume and variety of text and model parameters used to train these generalized chatbots enable all types of responses. ChatGPT demonstrated that machines can learn the complexities of human language and social interactions.

Creative individuals continue to come up with new and innovative use cases for these generalized chatbots (particularly ChatGPT) such as providing emotional and social support even though that was not their original purpose. Other chatbots such as Inflection's Pi are being trained and validated specifically for anxiety or emotional distress. However, these specialized chatbots do not have the widespread adoption as generalized chatbots like ChatGPT. Currently, individuals are using ChatGPT for social and emotional support instead of the more specialized chatbots even though ChatGPT was not designed to offer such support.

Many individuals interact with chatbots as if they were interacting with actual people such that they become friends with chatbots (Brandtzaeg & Følstad, 2018). In this manner, chatbots are social agents or social actors more so than mere technical agents. Human-to-machine communication poses a unique challenge for scholars because artificial intelligence, communication, social, and psychological theories have generally been separate research streams. However, chatbots have automated both the communication and the social processes dependent on it (Guzman & Lewis, 2020). These technologies have the ability to adjust their responses to individual users and the context of the message. Even though individuals generally recognize that they are communicating with machines instead of humans, they still perceive them as social interactions (Brandtzaeg & Følstad, 2018; Ki et al., 2020). These social aspects have resulted in scholars using social and communication theories to explain interaction patterns with chatbots (Peter & Kühne, 2018).

2.3. Terror Management Theory (TMT)

The existing social media and chatbot literature does not adequately explain how communities or artificial chatbots respond to posts about death or suicide. Existing theories such as social presence theory, social exchange theory, social capital theory, and others do not specifically address death-related posts and their associated comments. Posts about death have the potential to prime the community to think about mortality, which makes TMT an ideal fit to explain the variance of posting patterns. TMT is a theory that focuses on death-related cognitions and the implications that those thoughts have on a variety of behaviors (and attitudes thereof) (Becker, 1973; Greenberg et al., 1986). Individuals' cognitive ability to think about the inevitability of death coupled with their inherent desire for self-preservation (immortality) are the central tenets of TMT. According to TMT, the interplay between inevitable mortality and the quest for literal or symbolic immortality lead to existential terror (Pyszczynski, Solomon, & Greenberg, 2015). Left unchecked, existential terror may lead to unwell psychological states (Pyszczynski et al., 2021).

According to TMT, individuals use anxiety-buffers such as defending their cultural worldviews, increasing their self-esteem, and creating close interpersonal relationships to manage their death thoughts (Pyszczynski et al., 2015; 2021). Cultural worldviews are shared beliefs and values based on an individual's group or cultural affiliations. Self-esteem refers to a sense of satisfaction for living up to the standards and values defined by their cultural worldviews. For instance, certain cultural worldviews may value compassion and benevolence. Therefore, individuals subscribing to that cultural worldview may increase their own self-esteem by living up to those altruistic values. The final primary anxiety-buffer is maintaining close relationships to provide a degree of security from their death thoughts. These anxiety-buffers mitigate the potential for existential terror by creating cognitive thoughts that their actions contribute meaningfully to society (Pyszczynski et al., 2021).

There are three core TMT hypotheses (Pyszczynski et al., 2015; Schimel, Hayes, & Sharp, 2019). The first hypothesis is the mortality salience hypothesis, which proffers that reminding individuals of their own mortality results in actions that increase their self-esteem, defend their cultural worldviews, and foster close personal relationships. That is, individuals who are primed to think about their own mortality demonstrate a strengthened commitment to and defense of their three anxiety-buffering mechanisms. The second hypothesis is the death-thought accessibility hypothesis, which is the inverse of the mortality salience hypothesis. This hypothesis states that if cultural worldviews, self-esteem, and close relationships buffer individuals from death-related thoughts, then weakening these buffers should increase death-related cognitions. The third hypothesis is the anxiety-buffer hypothesis, which states that individuals need self-esteem to shield themselves from death-related anxiety. Self-esteem buffers anxiety because being benevolent signals emotional closeness to others and serves to meet cultural worldviews.

Fischer-Preßler, Schwemmer, and Fischbach (2019) applied the mortality salience TMT hypothesis to Twitter responses related to the Berlin bombings. During discussions of the bombings (mortality prime), they found that individuals reinforced their cultural worldviews and sought to increase their self-esteem. Part of their self-esteem building was showing sympathy for the victims and calling for tolerance. These insights are helpful in the context of mentally ill individuals sharing their suicidal thoughts on social media, especially for commenters whose cultural worldviews include being kind to strangers. With chatbots, however, it is unclear whether they are intelligent enough to think about mortality given their human-like qualities but technical existence.

3. Hypotheses

Figure 1 displays our research model. We hypothesize about how mortality salience and the technical platform impact responder empathy.

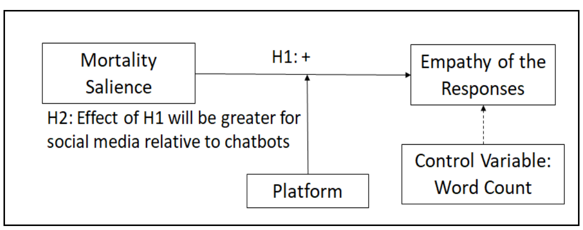

Figure 1. Research Model

On social media platforms, we suggest that mortality salience has the potential to prime at least a portion of commenters to be empathetic. Death reminders may lead to socially constructive responses (Fischer-Preßler et al., 2019; Schimel et al., 2019; Vail et al., 2012). These socially constructive responses partially stem from cultural worldviews that value compassion, sympathy, empathy, tolerance, and general benevolence (Vail et al., 2012). The TMT mortality salience hypothesis suggests that mortality primes will result in individuals defending their worldviews. If worldviews value pro-social or benevolent actions, it would be logical to expect these individuals to respond empathically to individuals who post about their mental health challenges. The mortality salience hypothesis also expects individuals to act in manners that increase their self-esteem (Pyszczynski et al., 2015). One way to increase self-esteem is by being empathetic.

On the surface, it may seem odd to apply the mortality salience hypothesis to artificial chatbots that do not have a finite life expectancy like humans. However, generalized LLMs have been demonstrated to perform as well or better than humans on a variety of emotional tasks. For instance, a group of scientists demonstrated that ChatGPT was able to outperform the general population on the Level of Emotional Awareness Scale (LEAS) across twenty different scenarios.[1] That same study demonstrated that ChatGPT performed even better after one month, which suggests that with more data generalized chatbots trained using LLMs can become highly emotionally aware just like humans. ChatGPT's ability to recognize emotions and articulate emotionally aware responses suggests that it can demonstrate an appropriate level of empathy in response to mentally ill posts and death language. As a result, we hypothesize the following main effect:

H1: Mortality salience of the responders (i.e., chatbot or social media commenters) will be positively associated with empathy.

We further suggest that the aforementioned effect of mortality salience will be less pronounced on generalized chatbots relative to social media platforms due to the inanimate nature of artificial agents. The artificial agents only have text-based cues to determine whether and how to display their empathy. The humans can use their own emotional states and prior life experiences to determine the appropriateness of their responses. Additionally, the ability to integrate emotional intelligence (i.e., self-emotional awareness and awareness of others emotions) into generalized chatbots like ChatGPT is still in its infancy, despite positive results in initial tests. Mortality salience is a specialized emotional state that might still be more prevalent in humans relative to machines (at least currently). This proposed stronger effect for humans in social media may change as LLMs become more sophisticated in the coming months and years. However, we presently propose the following:

[1] https://neurosciencenews.com/chatgpt-emotion-awareness-23231/

H2: The technical platform will moderate the effect of mortality salience on empathy favoring social media over chatbots.

4. Research Design & Methods

We tested our hypotheses using Reddit and ChatGPT. Reddit is a social media platform containing discussion forums (subreddits) regarding many different topics. We used the Pushshift repository and the Reddit application programming interface to download a sample of posts and comments from the "Mental Health" and "Mental Illness" subreddits. These two subreddits are among the most popular for mental health discussions. In these subreddits, the topics are personal narratives about mental health challenges, suicidal or death-related thoughts, and general information seeking. Each post may generate zero or more comments.

For our chatbot, we used ChatGPT. We picked ChatGPT over a specialized mental health chatbot such as Inflection's Pi due to ChatGPT's popularity. Currently, ChatGPT is the most widely adopted generalized chatbot. Unfortunately, the specialized mental health chatbots have not been widely adopted. As validation, we polled a sample of students about what chatbot they would use to discuss anxiety or emotional distress. They almost all mentioned ChatGPT. None of the students in our small poll had even heard of any specialized mental health chatbots. Hopefully, this awareness changes over time, but ChatGPT is the go-to chatbot for anything and everything including mental health issues at this point.

Even though individuals are using it for social and emotional support, ChatGPT was not originally developed for this purpose. As a result, ChatGPT may respond to an input such as "I want to commit suicide" with a response similar to "I am not qualified to help you. Please seek professional help." However, when ChatGPT is given inputs similar to the posts in the "Mental Health" and "Mental Illness" subreddits, it offered a wide variety of valid (non-reductionist) responses with varying levels of empathy. We had three posts in our sample where ChatGPT had this type of "I am not qualified" response. We removed them from our sample.

After downloading the sample of posts and their respective comments from the two subreddits, we used the LIWC 2015 dictionary to determine the death language of the comments along with other linguistic characteristics of the posts and comments. The LIWC 2015 dictionary contains roughly 6400 words, word stems, and emoticons, which are organized hierarchically in categories and subcategories. For instance, words in the negative emotion category are rolled up into the affect category. The death category contains 74 words such as bury, coffin, or kill. We then used the same LIWC 2015 library to determine the emotional tone, positive emotion, and negative emotion of both the post and the responses. We next determined the responses from ChatGPT (version 3.5) by manually entering each subreddit post in our sample in ChatGPT. After getting all of the responses from ChatGPT, we used the LIWC 2015 library to determine the death language, emotional tone, positive emotion, and negative emotion of the ChatGPT responses. LIWC uses its dictionary library to score each text-based input as a percentage between 0 and 100. For instance, "I want to die, but maybe not" will get a LIWC death score of 14.29 (i.e., 1/7=14.29%) and "death death death" will get a LIWC death score of 100 (i.e., 3/3 = 100%).

Mortality salience of the responders is challenging to operationalize using archival data because many different factors may cause an individual to think about their own mortality depending on their past life experiences. It is context specific and may vary by individual. Instead of assuming that all commenters reading a post about death had the same mortality prime similar to the approach taken by Fischer-Preßler, Schwemmer, and Fischbach (2019), we used the language of the responders to make this estimation. If a responder (ChatGPT or individuals on Reddit) used death language in the comment, then they were thinking about mortality. The more they mentioned death in their responses, then the greater their mortality salience. Table 1 displays a few sample comments across the two platforms.

Table 1. Examples Responses

Platform	Mortality Salience Greater than Zero	Mortality Salience Equal to Zero
Reddit	Fear of Death: I dont wanna die. I mean, I don't wanna live forever but I'm hella scared of death. […] I don't want it to end that soon. […] I will die.	Is numbness a sign of severe depression?: same as title
ChatGPT	I understand that the fear of death can be a daunting and unsettling thought. […] The experience of death itself is a	Other common symptoms of depression include persistent sadness, loss of interest or pleasure in activities,

	mystery because it is beyond our conscious	changes in appetite or weight, sleep disturbances, fatigue […]

In our study, we used an isomorphic definition of empathy (i.e., "I feel what you feel"). To do so, we calculated a similarity score between the affect-related features of the post and responses using a Euclidean distance metric, which is displayed in Equation 1.

Equation 1. Empathy Equation

$$d(x,y) = \sqrt{\sum_{i}^{n} (x_i - y_i)^2}$$

In Equation 1, x is the feature of the post, y is the feature of the responses (Reddit and ChatGPT), and i is the feature (emotional tone, positive emotion, and negative emotion). With this operational definition, the lower the number means greater empathy.

Our initial sample contained 1000 posts from the "Mental Health" subreddit with 1537 associated comments and 1000 posts from the "Mental Illness" subreddit with 2029 associated comments. Certain posts were deleted or removed in Pushshift or Reddit, so we could not download the full text. We removed those from our sample. Our final sample contained 493 posts from the "Mental Health" subreddit with 1493 associated comments and 617 posts from the "Mental Illness" subreddit with 1998 associated comments. Each of the 1110 remaining comments were manually entered into ChatGPT to get the ChatGPT responses.

The Reddit responses (mean of 38.28 and standard deviation of 31.74) had more empathy relative to ChatGPT (mean of 56.92 and standard deviation of 31.34) on our reverse scaled empathy variable. The average mortality salience for ChatGPT responders was 0.09 (standard deviation of 0.42) and for Reddit responders was 0.29 (standard deviation of 1.48). We controlled for the word count of the post because post length may influence the empathy level of the responses. The average word count was 191.9 (standard deviation of 250.0).

5. Results

We analyzed our data with an ordinary least squares (OLS) regression. We ran these models with post-level fixed effects and post-level random effects. In both cases, the results and associated conclusions were the same. Therefore, we only report the more parsimonious OLS models without either the fixed or random effects.

Table 2 displays the results of a few of our regression models. We first tested the main effect of mortality salience for all of the data across both platforms in a single model (Model 1 in Table 2). In this model, we have a significant main effect for mortality salience. When commenters have an increased mortality salience, they show more empathy in their responses in our reverse scaled empathy variable. Therefore, Model 1 provides support for our H1. Model 2 shows the main effect of platform. This model shows that responses on Reddit are more empathetic than responses from ChatGPT regardless of mortality salience. This model helps to contextualize the strong platform effect when interpreting the interaction effect.

Table 2. Regression Results

	Model 1	Model 2	Model 3
R^2	0.01	0.06	0.06
Root Mean Squared Error	32.6	31.6	31.6
Intercept	41.6 (0.6) ***	55.6 (1.0) ***	56.2 (1.0) ***
Mortality Salience	-1.02 (0.4) **		-6.1 (2.3) **
Platform (Reddit)		-18.5 (1.1) ***	-19.0 (1.1) ***
Platform (Reddit) * Mortality Salience			5.7 (2.3) *
Word Count	0.01 (0.6) ***	0.01 (0.002) ***	0.001 (0.002) **

Note: The standard error is in parentheses.

*<0.05, **<0.01, ***<0.001, NS is not significant

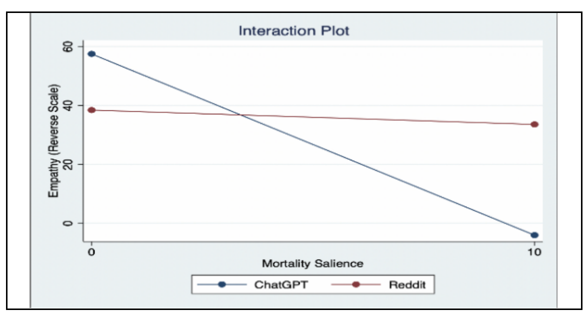

Figure 2. Interaction Plot

Model 3 and Figure 2 display the interaction effect between the technology platform and mortality salience. We see an interesting pattern of results, which supports our H2 moderating hypothesis. On both technology platforms, greater mortality salience results in significantly more empathy (reverse scaled) in responses, which means mentally ill individuals may elicit more empathy in responses by priming the Reddit responders or the LLM chatbot to think about mortality. The effect of ChatGPT is stronger (i.e., steeper negative slope) than Reddit. ChatGPT becomes more empathetic than Reddit as mortality salience increases. The trained LLM associated with ChatGPT seems to recognize the appropriateness of empathy as its responses demonstrate greater mortality salience. The logic of the TMT seems to be able to be trained in the generalized ChatGPT model.

6. Discussion & Conclusion

We found that ChatGPT and the community commenting on the mental health and mental illness subreddits responded to mental health posts empathetically, but the effect of mortality salience on ChatGPT was stronger than on Reddit. It may seem odd that TMT was more pronounced with an algorithm relative to a community of humans. However, one of ChatGPT's strengths is its ability to craft well-written prose, which was not necessarily the case for our sample of Reddit commenters who typically opted for short comments using informal language. Another possible explanation for this pattern of results is that it might be challenging for para-friends and virtual acquaintances in these two subreddits to experience empathy simply by reading the text-based posts. The common experiences between the posters and commenters may lead to compassion or sympathy but not necessarily empathy. The LLMs in ChatGPT may be able to share similar feelings due to their advanced text-mining capabilities.

It is also possible that empathy as operationalized using an isomorphic definition of empathy is not the best approach. Murphy, Lilienfeld, and Algoe (2022, p. 30) argue that isomorphic definitions of empathy are overly restrictive and suggest that empathy is an "unfolding process of imaginatively experiencing the subjective consciousness of another person, sending, understanding, and structuring the world as if one were that person." Main (2022) further argues that individuals must flexibly adapt their behaviors to the other person's emotions in order to be empathetic. In this manner, empathy is an interpersonal process that may not be captured with just isomorphic matching (Main, 2022). Empathy might be best studied using dynamic methods rather than in a static fashion as we did in our study. Our TMT explanation suggests internal processes of the empathizer and at least some interpersonal connection, but our archival data study and isomorphic definition of empathy did not explicitly measure those processes.

It is important to distinguish between empathy and compassion. Whereas empathy involves mirroring the feelings of others but not necessarily caring for others, compassion involves caring for others but not necessarily mirroring their feelings (Yaden et al., 2023). The two constructs are often (but not always) correlated. An individual, for instance, may not be able to share the feelings of a mentally ill individual who is suicidal (low empathy), but they can offer emotional support and caring words for them (high compassion). Contrarily, an individual may be able to share feelings with a mentally ill individual (high empathy), but they may offer a terse or abrasive response (low compassion). We investigated empathy in our paper. Future research may investigate whether mortality salience has a positive or negative relationship with compassion or other forms of social support.

Our paper makes several notable contributions to the literature. First, we contribute broadly to the social media literature by introducing TMT. TMT has the flexibility to explain a variety of discourse patterns, specifically related to conversations about death. Death conversations prompt unique cognitions and emotions from the posters and the commenters, which may not be adequately explained by the existing theories in the literature. Second, we contribute to the information systems literature investigating mental health issues by explaining the variance in comments. In this manner, we complement the mental health related work that built models identifying potentially suicidal community members. Finally, our paper is one of the first to compare social media responses and chatbots responses using ChatGPT. We show that under certain conditions ChatGPT may provide more empathy relative to the Reddit social media platform. Understanding which platform can provide more empathy is important to direct mentally ill individuals to an appropriate platform to provide a bit of assistance to hopefully help them seek professional help and to reduce their death-related thoughts.

Obviously, more empirical work is needed to make any claims of generalization beyond our sampling frame of mentally ill individuals on Reddit. Other social media platforms may have different interactive cultures and other chatbots such as Tako or Bard may have different LLMs, which may impact patterns of empathy provided to posts from mentally ill individuals. However, our results do provide a first step and a few important insights toward understanding discourse patterns on two important technical platforms.

7. References

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