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Understanding terror states of online users in the context of COVID-19: An application of Terror Management Theory

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ABSTRACT

The COVID-19 pandemic has provided psych challenges for many in society. One such challenge is the anxiety that is created in many people faced with the risk of death from the disease. Another issue is understanding how individuals cope psychologically with the threat of death from the disease. In this study we examine the manifestation of death anxiety and various coping mechanisms through the lens of terror management theory (TMT) and online platforms. We take a novel approach to testing the theory using big data analytics and machine learning, focusing on the user-generated content of Twitter users. Based on a sample of all tweets in the UK mentioning COVID-19 terms over a 5-month period, we evaluate dictionary mentions of anxiety and death, and various TMT defense mechanisms, and calculate the pattern of latent death anxiety or 'terror' states of Twitter users via Hidden Markov Models. The research identifies four online 'terror' states, with high death and anxiety mentions during the peak of the pandemic. Further we examine various TMT defense mechanisms that have been proposed in the literature for coping with death anxiety and find that online social connection, achievement and religion all play important roles in improving the model and explaining movement between states. The paper concludes with various implications of the study for future research and practice.

1. Introduction

COVID-19, declared a pandemic by the World Health Organization on the March 11, 2020, created and continues to create severe impacts on governments, business and society (Barnes, 2020). COVID-19 has created a major public health incident in countries around the world, not least due to its suddenness, uncertainty, unpredictability, high death rate (estimated at around 1 %; van Elsland, 2020), enormous social media attention (e.g. Google Trends Index of 100), chain reaction, and need for evasion and preventative measures (Jia et al., 2020). As of the 7th of September 2020, there were 27,032,617 confirmed cases, and 881,464 confirmed deaths, over 216 countries areas or territories, led by the US (187,541 deaths), Brazil (126,203 deaths), India (71,642 deaths), Mexico (67,326 deaths) and the UK (41,551 deaths) (World Health Organization, 2020).

The coupled contagion (Epstein et al., 2008) of COVID-19, a combination of physical and psychological (fear) threats, has created a significant impact on the wellbeing of citizens. Terror Management Theory, with its roots in the work of Becker (1974), and later developed by Greenberg et al. (1986), provides some explanations for human behavior related to the fear of death (i.e. death anxiety). TMT suggests that death anxiety will increase with the threat source, including that of COVID-19 (Courtney et al., 2020). Further, there is a significant body of research that has examined the defensive tactics employed by people to cope with death anxiety, including via meaning derived through socio-cultural frameworks, such as those of a religious nature, and from affiliations and linkages to particular social groups (Burke et al., 2010). Research on TMT and defense mechanisms, often referred to as "anxiety buffers", has been replicated across many countries and contexts (Pyszczynski et al., 2015).

In the context of the pandemic, social media and online information sources provide potential influences on individual behavior. Social media can support coping processes, offer sources of support, and enable individuals to reach out in times of social distancing and isolation. Platforms such as Twitter facilitate, invite and shape contributions and their spread in the digital community in a way that may influence attitudes and real-life behaviors. Talbot et al. (2020) found that people with dementia are using Twitter to further a social movement that is helping to improve the lives of those with the illness. In particular, social media provided positive messages for social support. Similarly, Berry et al. (2017) identified mental health benefits from Twitter through the provision of support and information for self-management. In the context of

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the #MeToo movement, Hosterman et al. (2018) found that informational support messages were the most popular content tweeted on the platform. In the context of the pandemic, Farooq et al. (2020) found that sharing information about COVID-19 online could contribute to individual coping perceptions and to their intention to self-isolate.

In this study, we aim to understand the change in terror states of online users due to the death anxiety caused by COVID-19 and the role of social media in facilitating coping mechanisms. To do this, we use a big data set of online tweets mentioning COVID-19-related terms from the UK and employ an advanced machine learning method, Hidden Markov Models. Moreover, we determine the coping strategies of online users as they move from one terror state to another during the pandemic, examining the role of social connection, religion, achievement and affiliation, using text analytics. In addition, we assess the role of public information provision on the number of COVID-19 cases on the terror state transition. The research question for this study is: How do social media and online information shape death anxiety buffers and the transition between 'terror states' during the COVID-19 pandemic?

The research uses a combination of text analytics and Hidden Markov Models that has been used in a number of recent studies (Chen et al., 2020; Ng et al., 2020; Reece et al., 2017; Roy & Hasan, 2021; Suh, 2015; Wang et al., 2016). This answers a recent call for the use of more advanced methods including text analytics to produce theoretical insights in business research. The approach has particular strengths with respect to the relevant treatment of social media data, particularly data from Twitter. The modelling outcome allows for some psychological inference based on social media data that typically lack one crucial aspect: the possibility to analyze data at the level of the individual user.

The paper makes a contribution to theory and our understanding of the role of social media in coping with death anxiety mechanisms. TMT is a long-standing theory that has been tested and extended in many contexts. However, although various conceptual models and discussions based on TMT have been proposed during the COVID-19 era (e.g. see Courtney et al., 2020), there has been no large-scale test of the applicability of TMT in this context using available data. This study tests the application of TMT in explaining different, latent death anxiety 'terror' states and online-facilitated coping behaviors or defenses during the pandemic via user-generated big data from social media and official Government data. We extend TMT by examining the impact of government information regarding COVID-19 cases on death anxiety during the pandemic.

The structure of this manuscript is as follows. In the next section, the underlying theory is discussed, hypotheses are presented, and a research model is proposed. Section three details the various steps in the research process used in the investigation. The fourth section provides the results of the statistical analysis, including the states and important transition variables. Finally, the last section discusses the results and concludes with implications for research and practice.

2. Theory and hypotheses

The sophisticated intelligence of humans renders us different from all other animals; while human intelligence provides behavioral flexibility and adaptation helps us to solve problems, it also makes us realize that death is inevitable, and can be unpredictable and uncontrollable (Pyszczynski et al., 2015). Terror Management Theory (TMT) posits that awareness of death creates primal fear or terror. Such death anxiety can hamper aspects of behavior and survival unless alleviated. Death awareness can be managed via ideas, beliefs, values and concepts (Greenberg et al., 2004). An important defense are cultural worldviews, defined as: "(1) a theory of reality that gives life meaning, purpose, and significance; (2) standards by which human behavior can be assessed and have value; and (3) the hope of literal or symbolic immortality to those who believe in and live up to the standards of their cultural worldview." (Pyszczynski et al., 2015, p. 7).

TMT provides explanations for mechanisms to cope with death awareness via the hope for literal or symbolic immortality (Solomon et al., 1991). Literal mortality refers to life after death in an existential form, typically informed by religious aspects of cultural worldviews, including the promise of heaven, afterlife, reincarnation and so on. Alternatively, symbolic immortality refers to "being part of something greater than oneself that continues to exist after one's own death and on into eternity." (Pyszczynski et al., 2015, p. 8). Symbolic immortality can be developed through creation a valued contribution to the worlds they inhabit and reminders of existence, such as families, friends, group affiliation, fortunes or other signifiers of achievement. Such value derived from living up to the standards of a cultural worldview refers to the development of self-esteem. Self-esteem provides a defense for individuals against their death anxiety, which in turn leads them to think about their own mortality (or mortality salience), and defending their self-esteem more ardently, working harder to prove worthiness (Burke et al., 2010).

The research model tested in this study is provided in Fig. 1. The hidden online 'terror' states will be measured through the prevalence of anxiety-related and death-related terms in user-generated content. Further, we examine five factors facilitated by social media and online information provision that provide defense or coping mechanisms that can potentially explain the transition between terror states: online social connection (Social), religious beliefs (Religion), Achievement, group affiliation (Affiliation), and online information on COVID-19 cases. Let us examine the hypotheses for the study in more detail.

There is no doubt that COVID-19 creates death anxiety and can affect mental health through mortality salience – reminders of death (Jungmann & Witthöft, 2020). Previous research has found that more than half of individuals exhibit anxiety during virus-induced epidemics or pandemics (Bults et al., 2011; Goulia et al., 2010). Based on TMT, we would expect death anxiety online to peak during the height of the pandemic, when knowledge of the extent of the contagious, deadly nature and impact of the disease on mortality becomes known more fully. Thus, we posit:

H1: The online 'terror' state will peak during the height of the pandemic (i.e. highest death anxiety).

TMT has found numerous anxiety-buffering solutions used by people as psychological coping mechanisms to reduce anxiety. Self-esteem is a general anxiety buffer and elevating self-esteem reduces anxiety related to thoughts of death (Pyszczynski et al., 2015). Reminders of death increase individuals desire to build self-esteem in order to reduce death anxiety. A key aspect of developing self-esteem is through building social connections to friends, family, and partners. Cox et al. (2008) found that death awareness was linked to more positive associations with parents. Mikulincer et al. (2003) found that individuals' mortality salience was linked with greater attraction to partners, while Wisman and Goldenberg (2005) found a greater desire for children. In general, we would expect social connection to provide an important coping strategy in the context of the pandemic.

In the context of the pandemic, social media can support coping processes, offer sources of support, and enable individuals to reach out in times of social distancing and isolation. Various studies examining the role of the social media platform Twitter as a source of social support have found that it offers an important conduit for social connection, mutual support and self-help. One prevalent context for many studies is health and illness, including social support to help those suffering from dementia (Talbot et al., 2020) and provision of support and information for self-management of mental illness (Berry et al., 2017). However, the role of social media in social support may be mixed. Pittman and Reich (2016) found that while image-based social media such as Instagram may attenuate loneliness due to increased social presence, text-based social media such as Twitter appeared ineffectual. Nevertheless, text-based social media has had an impact in offering social support in a broad range of contexts. Hosterman et al. (2018) found that informational support messages were an important source of help offered through Twitter in the context of the #MeToo movement. Thus, in the

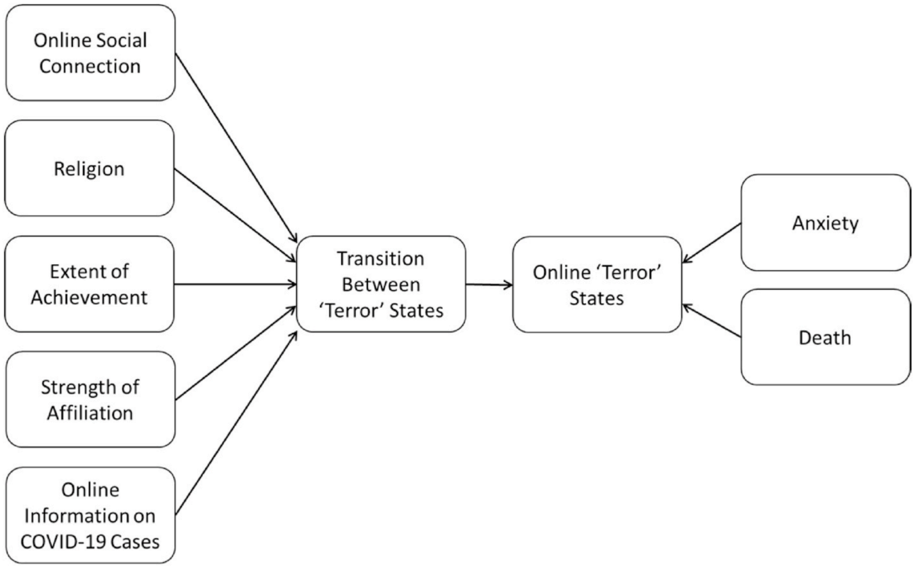


Fig. 1. Research model.

context of our research model, we hypothesize that:

H2: Online social connection will facilitate the transition between online 'terror' states during the pandemic.

Religion has been found to be an important defense mechanism within TMT (Greenberg et al., 1986). Religion has been argued to function to manage death-related fear (Kirkpatrick & Navarrete, 2006). In particular, religion helps to manage the terror associated with death awareness via the anticipation of immortality and provision of psychological security. However, religion can also be divisive, with mortality salience leading to more positive views of in-group members (own religion) and negative views of out-group members (other religions) (Greenberg et al., 1990). Religious beliefs have the benefit, from a defense mechanism perspective, of being not easily disconfirmed, all encompassing, and promising literal immortality (Vail et al., 2010). Moreover, research has shown that death reminders heighten beliefs in spirits, deities and an afterlife (Pyszczynski et al., 2015). Consistent with TMT research, we hypothesize in the context of online terror states that:

H3: Religion will facilitate the transition between online 'terror' states during the pandemic.

TMT suggests that individuals maintain self-esteem by maintaining faith in worldviews and living up to the standards of these worldviews (Greenberg et al., 1986). This requires people to establish themselves as valuable participants in a meaningful universe (Pyszczynski et al., 2015). One way to do this is through consensual validation of worldviews and self-esteem via affiliation with certain groups. Empirical research has found that affiliation with groups can indeed shield against death awareness (Dechesne et al., 2000). Dechesne et al. (2000) found that sports fan affiliation can provide an effective buffer against death concerns. Thus, in affordance with the above, we hypothesize:

H4: Affiliation will facilitate the transition between online 'terror' states during the pandemic.

As mentioned above, individuals seek symbolic immortality as a buffer towards death anxiety. Such symbolic immortality can be reached by personal achievement that creates a significant reminder of existence after death (Greenberg et al., 1986). This includes amassing financial wealth, building families, tangible artefacts such as monuments, books, pictures or music, and intangible artefacts, such as ideas or memories (Pyszczynski et al., 2015). Perach and Wisman (2019) found that creativity (related to idea generation) was associated with lower death-thought accessibility and mortality salience. Some authors have suggested that terror management theory can be used to explain consumer behaviour, such as conspicuous displays of wealth through consumption (Arndt et al., 2004; Maheswaran & Agrawal, 2004; Rindfleisch & Burroughs, 2004). In line with previous research, we posit that:

H5: Achievement will facilitate the transition between online 'terror' states during the pandemic.

Public information provision in the context of terror management theory has received very little attention in the information systems literature. A recent study by Wang et al. (2019) suggests that online provision of cancer information provides a potential buffer to death fear, through the provision of hope. Fischer-Preßler et al. (2019) found that, in the context of the Berlin terrorist attack, Twitter was used for sense-making, to validate worldviews and to maintain self-esteem. In general, TMT suggests that online provision of information that would remind individuals about mortality (mortality salience) would engender greater death anxiety. In the context of the pandemic, Farooq et al. (2020) found that sharing information about COVID-19 online could contribute to individual coping perceptions and to their intention to self-isolate, but also to cyberchondria and information overload. Thus, in this study, we would expect information on newly diagnosed, daily COVID-19 cases at the national level to be associated with greater death anxiety. Therefore, we posit that:

H6: Online public information provision on new COVID-19 cases will increase death anxiety (i.e. contribution to fit in the transition model).

3. Methodology

In this section, the research process and statistical methods are outlined. The study employs a LIWC dictionary analysis of social media data from Twitter in the UK, combined with advanced machine learning to detect terror states via Hidden Markov Models. The research process is described in Fig. 2. Data were downloaded from Twitter, preprocessed, a LIWC dictionary was applied, the data was prepared and examined, and then the research model was tested using Hidden Markov Models. The approach has particular strengths in analyzing large amounts of user-generated content over a period of time to make psychological inferences where it is difficult to analyze data at the level of the individual user. We now look in more detail at the steps in the research process.

3.1. Data collection, preparation and exploration

This study focuses on existing public data from Twitter users in the UK. We focus on tweets referring to the COVID-19 pandemic during the

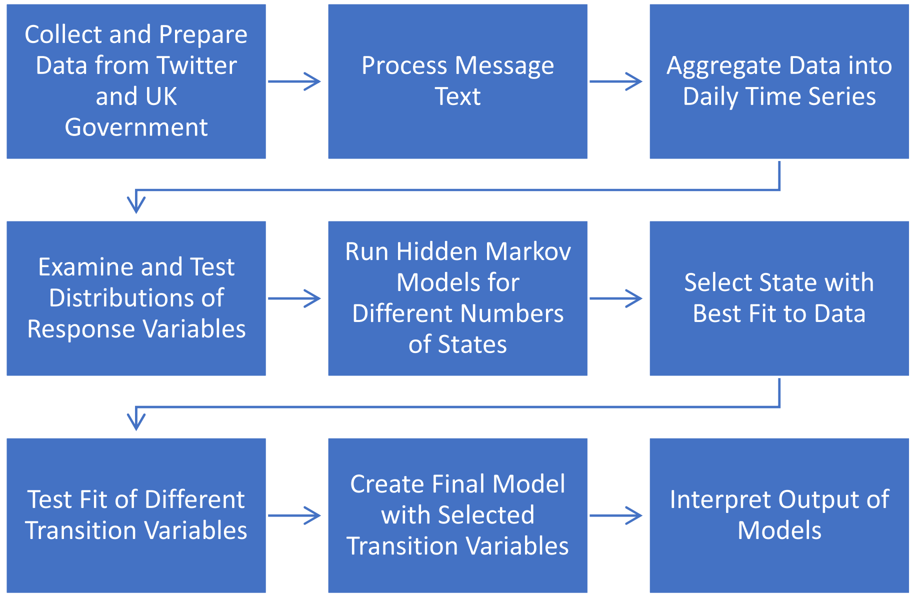


Fig. 2. Research process.

period from the 1st of March to the July 31, 2020. In order to identify these tweets, we used the dataset provided by Banda et al. (2020), who collected post data including the terms: COVD19, Coronavirus Pandemic, COVID-19, 2019nCoV, Corona Outbreak, coronavirus, Wuhan Virus, covid19, coronaviruspandemic, covid-19, 2019ncov, coronaoutbreak, and wuhanvirus. The data was downloaded and filtered for UK tweets. A total of 152,331 tweets were downloaded (the remainder were presumably not attributed to the UK or no longer available for download). The tweets downloaded were pre-processed and screened for non-English content, resulting in 125,218 English tweets. Public Health England data on the number of daily diagnosed COVID-19 cases in the UK was downloaded from the UK Government (Public Health England, 2020). The data on new COVID-19 cases is shown in Fig. 3. This shows a peak between April (day 32 = 1st April) and May (day 62 = 1st May).

The text in each tweet was analyzed using the Linguistic Enquiry and Word Count software (Pennebaker et al., 2015). We applied the dictionaries for Anxiety, Death, Religion, Reward, Affiliation and Social. This resulted in scores for each tweet, according to word dictionary. The construct data and data on COVID-19 cases was then aggregated into a daily time series format using SPSS, adding daily LIWC scores. Descriptive statistics on the sample are shown in Table 1. The time series for the two response variables used in the analysis, Anxiety and Death,

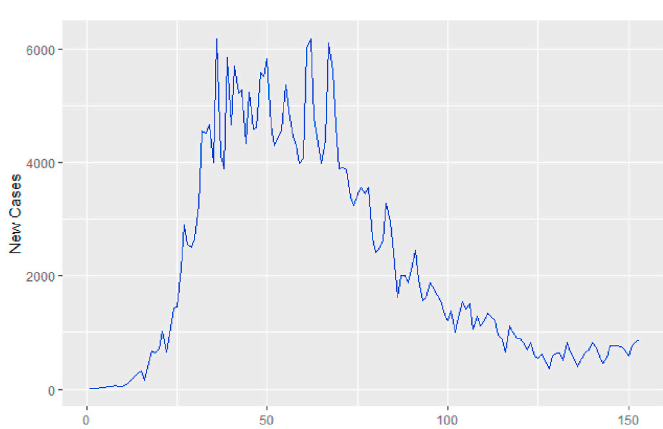


Fig. 3. New cases of COVID-19 in the UK (1st March to July 31, 2020).

Table 1
Descriptive statistics on sample.

Variable	Days	Min.	Max.	Mean	Std. Dev.
New Cases of COVID-19	153	5	6201	2181.25	1831.46
Anxiety	153	0	772.68	274.58	129.38
Death	153	0	789.15	277.50	161.87
Social	153	0	13911.37	5410.83	2451.48
Religion	153	0	500.28	183.94	101.12
Achievement	153	0	2602.40	1026.47	463.54
Affiliation	153	0	4757.57	1690.75	763.99

are shown in Fig. 4. This provides some interesting insights. Although, anxiety and death mentions are high during the peak of the pandemic, anxiety is elevated in mid-March, well before cases begin to rise sharply, while both anxiety and death mentions continue to be high well beyond the peak.

Correct determination of the distribution of response variables is important for Hidden Markov Models. Initial examination of the distribution of the response variables, anxiety and death, appeared to suggest that they were not Gaussian (see Fig. 5). These variables appear to display an Inverse Gaussian distribution. In order to confirm the Inverse Gaussian distribution of the response variables, the fit for Inverse Gaussian distributions with unknown parameters were tested (Gonzalez-Estrada & Villasenor-Alva, 2018). The test transforms observations into an approximately normal distribution before applying the Shapiro-Wilk test to examine univariate normality (Villasenor et al., 2019). For both anxiety and death, the test confirmed an Inverse Gaussian distribution ($W = 0.339$, $p < .001$ and $W = 0.557$, $p < .001$ respectively).

3.2. Analysis and model testing

Latent or Hidden Markov Models (e.g. see Frühwirth-Schnatter, 2006; Zucchini & MacDonald, 2009), sometimes referred to as regime-switching models in economics (e.g. Kim, 1994), have many potential applications in the social sciences (Cappe et al., 2005), including a number of existing applications in business, such as forecasting municipal waste generation (Jiang & Liu, 2016), measuring earnings quality (Du et al., 2020), measuring business cycle turning points (Gregoir & Lenglart, 2000), forecasting on-shelf out-of-stock products (Montoya & Gonzalez, 2019), and ascertaining stages of mobile

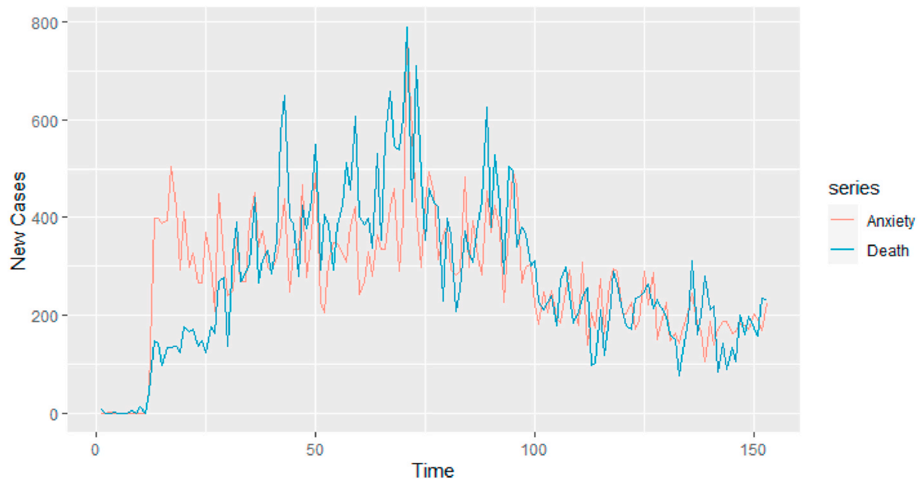


Fig. 4. Anxiety and death mentions on twitter (1st March to July 31, 2020).

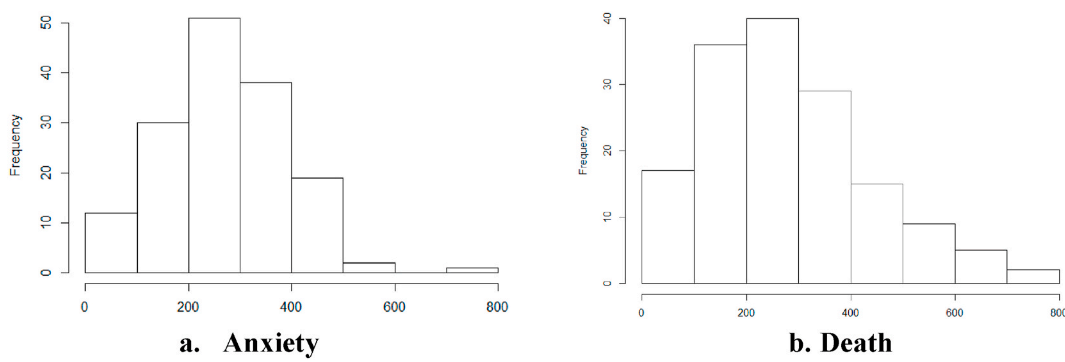


Fig. 5. Histograms of response variables.

user engagement (Zhang et al., 2019).

A Hidden Markov Model (HMM) is a dual stochastic process containing an unobservable, latent or 'hidden' stochastic process that can only be observed via an alternative set of stochastic processes and the symbols they produce (Murphy, 2012; Rabiner & Wang, 1986). In simple terms, we observe changes in state of a hidden process (say bull or bear market states in the stock market) via data from observable variables (such as stock prices), typically as a time series. The structure of an HMM is illustrated in Fig. 6. Here, $S_{1:T} = (S_1, S_2, S_2, \ldots, S_T)$ denotes a hidden sequence of states for a time-series of length T. Further, $X_{1:T} = (X_1, X_2, X_2, \ldots, X_T)$ represents a time-series of observations of m variables in each time-period that will be used to infer the hidden states. Everything behind the dashed line in Fig. 6 is 'hidden'. The progression by which the hidden process moves from one state to another is described by the stochastic matrix A, which provides the state transition model – the probability of moving from any one state to any other state. The matrix B is used to infer particular states in the model. Matrix B is a stochastic matrix that gives the probability of making a particular observation at time t via the m observed variables, given state particular state at time t.

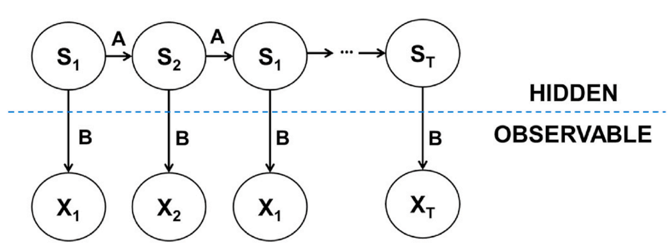


Fig. 6. Hidden Markov model.

More generally, the Hidden Markov Model can be developed to include covariates (Visser & Speekenbrink, 2010), $z_{1:T} = (z_1, z_2, z_2, \ldots, z_T)$, represented by:

$$P(X_{1:T}, S_{1:T}|\theta, z_{1:T}) = \pi_i(z_1) b_{S_1}(X_1|z_1) \prod_{t=1}^{T-1} a_{ij}(z_t) b_{S_t}(X_{t+1}|z_{t+1}) \tag{1}$$

where S_t is an element of $S = \{1 \ldots n\}$, a set of latent states; θ is a general parameter vector consisting of sub-vectors for the prior model, transition model and response (observation) model; $\pi_i(z_1) = P(S_1 = i|z_1)$ refers to the probability of state i at time $t = 1$ via covariate z_1; matrix A refers to $a_{ij}z_t = P(S_{t+1} = j|S_t = I, z_t)$, the probability of transition from state i to state j via covariate z_t; and matrix B refers to b_{S_t}, the conditional densities of observations of variables associated with state j and covariate z_t.

The marginal log-likelihood of observations, which is required to calculate the maximum likelihood of model parameters in equation (1), is determined using Lystig and Hughes (2002) adaption of the forward-backward algorithm (Baum & Petrie, 1966; Rabiner, 1989), which enables the calculation of both gradients and log-likelihoods concurrently. Parameters are estimated via the expectation-maximization algorithm by iteratively maximizing the expected joint log-likelihood of parameters for the states and observations (Visser & Speekenbrink, 2010). The log-likelihood is used to calculate various fit metrics, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). In this study, we used the BIC and AIC to choose among models, which is standard practice. Hidden Markov Models were calculated using the approach of Visser and Speekenbrink (2010).

4. Results

In this section we provide the results of HMM testing to examine the number of online terror states, contribution of variables to the transition between terror states, and a test of the contributory variables in an overall research model.

4.1. Number of model states

In order to determine the number of states in the Hidden Markov Model, we tested five models, testing and then fitting the models for one to five states. The models tested used the time-series response (observation) variables for anxiety and death, such that $X^1_{1:T} = Anxiety$ and $X^2_{1:T} = Death$ in equation (1). The length of the time-series is T = 153 days. The models used no transition or other covariates, $z_{1:T}$, in the model shown in equation (1).

To test the models, the initial probabilities were set at state one. The results of model testing are shown in Fig. 7. As we can see, the BIC and AIC declines steadily from the one state model through to the four-state model, at which point it begins the increase. Since the nadir occurs at the four-state model (AIC = 3616.3, BIC = 3710.2) we select this as the best-fitting solution and will use four states in our future models.

Tables 2 and 3 provide the results of testing the baseline four-state model. As we can see, the levels of anxiety and death extracted from the tweets differ significantly between the four terror states, which appear well separated. We will refer to these states as “baseline” (state 1), “low” (state 2), “moderate” (state 3) and “high” (state 4). In the “baseline” state, state 1, death and anxiety mentions are at the lowest level. The baseline for anxiety is higher (intercept = 164.7) and with greater variability (S.D. = 196.8) than that of death (intercept = 60.0; S.D. = 66.8). Both anxiety and death increase by a sizeable proportion to state 2 (the “low” state); anxiety increases by a little under 50 and has tighter spread than the baseline (S.D. = 55.1), while death increase by a massive 134, again with a closer spread (S.D. = 55.6). Anxiety increases in steps of approximately 100 up to state 3 (“moderate”, intercept = 316.0) and further up to state 4 (“high”, intercept = 420.8), with similar levels of spread to the low state. Death increases in much bigger steps of approximately 146–177 up to the moderate and high states, with a higher standard deviation for state 4 (S.D. = 108.8).

The probability of transition between states is shown in Table 3. As we can see, there is a small chance of moving from the baseline state to the low state of 4.9 %. Once in the low state, there appears to be an even smaller chance of 2 % for moving into the moderate state. However, once in the moderate terror state, there is a large probability of moving into the high state of 19.8 %, with a 2.6 % chance of falling back to the low state, with a 77.5 % probability of stating within state 3. Similarly, once in the high terror state, around a third of the time the terror state will move back to the moderate level (31.3 %), holding at the high state approximately two-thirds of the time (68.7 %). This appears to suggest a clear upward path in terror states to the moderate state, but significant variability (high probability of switching) between states 3 and 4.

Table 2
Response parameters for hidden Markov model: Baseline model.

State	Anxiety Intercept	Anxiety std. dev.	Death Intercept	Death std. dev.
State 1. Baseline.	164.688	196.806	60.000	66.768
State 2. Low.	213.257	55.084	193.592	55.994
State 3. Moderate.	315.936	60.477	339.824	67.766
State 4. High.	420.797	97.227	517.100	108.826

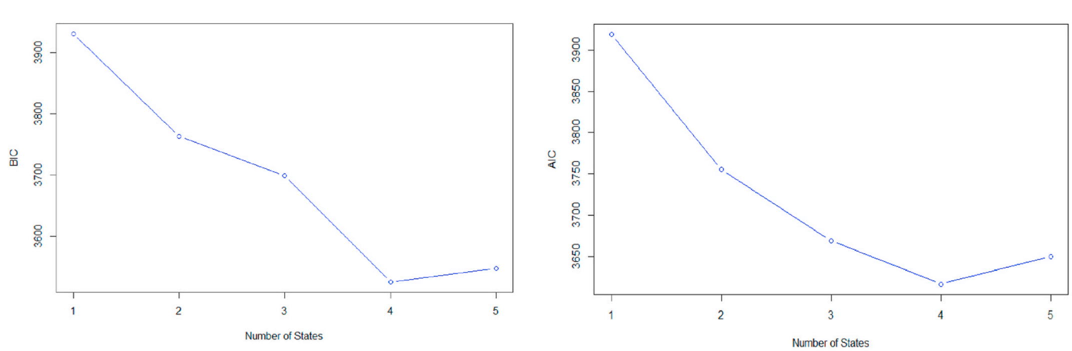
Table 3
State transition matrix: Baseline model.

From/To	*State 1*	*State 2*	*State 3*	*State 4*
State 1. Baseline	0.951	0.049	0.000	0.000
State 2. Low.	0.000	0.980	0.020	0.000
State 3. Moderate.	0.000	0.026	0.775	0.198
State 4. High.	0.000	0.000	0.313	0.687

4.2. Testing the fit of transition variables

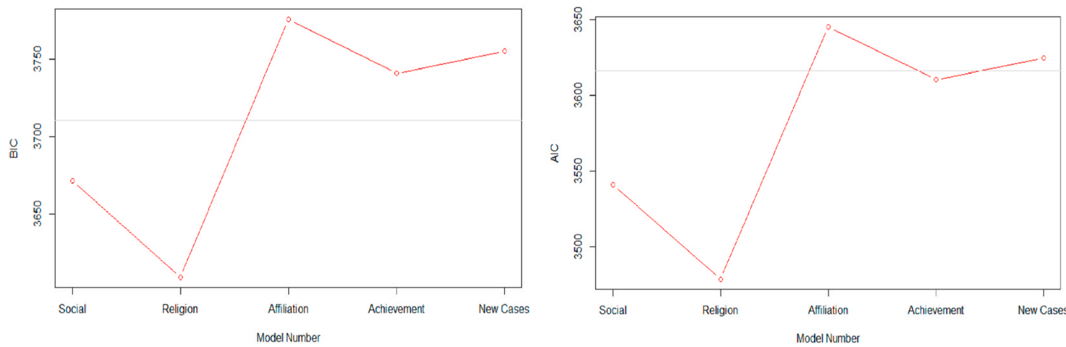
To test the fit of specific variables in explaining the transition between online terror states in the baseline four-state model specified above, we tested an additional five HMM models. In each of the five models, a single transition variable covariate, $z_{1:T}$, was tested in the model shown in equation (1). The transitional model variables corresponded to the individual concepts required to test hypotheses to H2 to H6: Social, Religion, Affiliation, Achievement, and New COVID-19 Cases. To test the models, the initial probabilities were set at state one (baseline). In order to assess the contribution of variables to the transition model, we compared them to the fit indices for AIC and BIC in the baseline four-state model. The results of model testing are summarized in Fig. 8.

Fig. 8(a) examines the fit of models with transition variables using the BIC. The horizontal line denotes the BIC for the baseline four-state model (BIC = 3710.2). As we can see, the results indicate that both Social (BIC = 3671.2) and Religion (BIC = 3609.0) make a notable contribution to the transition between online terror states in the data set. Similarly, Fig. 8(b) examines the fit of models with transition variables using the AIC. The baseline model had an AIC of 3616.3. Here, the pattern is similar for Social (AIC = 3540.9) and Religion (AIC = 3540.9), but Achievement also appears to make a small contribution to the transition between terror states (AIC = 3610.7). The results offer support for hypotheses H2, H3 and H5, but not for H4 or H6. We will test the final model using the contributory transition model variables.



(a) Bayesian Information Criterion. **(b) Akaike Information Criterion.**

Fig. 7. Model comparison: Number of states.



(a) Bayesian Information Criterion. **(b) Akaike Information Criterion.**

Fig. 8. Model comparison: Contribution of transition variables.

4.3. Testing the final model

To test the final research model, we employed a four-state model with the response parameters $X^1_{1:T} = Anxiety$ and $X^2_{1:T} = Death$ in equation (1), T = 153 days and scaled covariates $z^1_{1:T} = Social$, $z^2_{1:T} = Religion$ and $z^3_{1:T} = Achievement$ (the variables were subject to the scale procedure in Visser & Speekenbrink, 2010, to enable easier interpretation of state probabilities). The initial probabilities were set at state one, the baseline state.

The response parameters for the four terror states are summarized in Table 4. The levels of the intercepts and standard deviations are very similar to those of the baseline model in Table 2, but most are very slightly smaller, particularly the standard deviations for state 3 ("moderate" terror state), and the levels of Anxiety and Death for state 4 ("high" terror state).

Fig. 9 graphically depicts the changes in terror states over the time series, along with the response variables, Anxiety and Death, and the transition model variables, Social, Religion and Achievement, while Table 5 examines the transition models of different states. As we can see from Fig. 9, the "high" terror state, at which point Anxiety and Death are elevated, does appear to coincide with the height of the pandemic, shown by the number of new cases diagnosed in Fig. 3. However, this does appear to alternate between the "high" and "moderate" states, perhaps in relationship to spikes in the number of new cases diagnosed. A Spearman's rank correlation coefficient test was used to confirm the significance of the relationship between online terror states and the height of the pandemic (number of new cases of COVID-19). The result showed a significant relationship ($\rho = 0.858$, $p < .001$), confirming *H1: The 'terror' state will peak during the height of the pandemic.*

Fig. 9 also displays the covariates for the transition model. Religion appears to be very active during the peak of the pandemic, where there are sharp spikes in mentions on Twitter between 30 and 90 days. The other transition model covariates, Social and Achievement, although elevated during the peak of the pandemic, appear most active, with sharp spikes in mentions, between 60 and 90 days.

Table 5 shows the probabilities at zero values of the covariates. Once in the baseline terror state (state 1), it appears to have a high probability of continuing (99.9 %), with only a very small chance of moving up to a more elevated state. The baseline state is the zero state, where other states are associated with higher Social and Achievement. However, once the low terror state (state 2) is reached, the situation changes. From the low terror state, there is a 7 % probability of moving to the moderate terror state (state 3) and a 93 % chance of staying in the low state. State 2 is associated with higher Religion and Achievement (0.942 and 0.826 respectively), but these are even higher for State 3 (1.923 and 1.576 respectively). From the moderate terror state, there is a 34.5 % chance of falling back to the low state and a 19.6 % probability of moving to the high terror state, with a 45.8 % chance of maintaining state. State 3 is associated with elevated levels of Religion (1.272), Achievement (1.629) and Social (1.642), with higher Achievement for State 4 (2.229), and lower Achievement and Social for State 2 (−5.429 and −9.123 respectively). Religion appears higher at State 2. Once in the most elevated terror state, state 4 or high terror state, the chance of moving back to the moderate state is more than a third (36.7 %), with the probability of maintaining state at just less than two-thirds (63.3 %). Both state 4 and state 3 appear to be associated with similar levels of all three transition variable covariates.

Table 4
Response parameters for hidden Markov model: Final model.

State	Anxiety Intercept	Anxiety std. dev.	Death Intercept	Death std. dev.
State 1. Baseline.	163.090	197.998	58.489	66.116
State 2. Low.	213.543	54.008	193.534	56.899
State 3. Moderate.	312.860	53.413	337.201	59.727
State 4. High.	416.466	96.489	505.408	109.279

5. Discussion and conclusions

The application of text analytics and Hidden Markov Models has afforded us significant insight into online user behavior during the COVID-19 pandemic. The research found that death anxiety does indeed peak during the height of the pandemic, as online users are reminded of their own mortality (support of H1). This finding supports the notion that knowledge of the extent of the contagious, deadly nature and impact of the disease on mortality is relate to death anxiety. In fact, research has even developed a Coronavirus Anxiety Scale in the journal *Death Studies* to assess the dysfunctional anxiety created by the pandemic, focusing on symptoms such as dizziness, problems sleeping, 'freezing' when thinking about the pandemic, lack of appetite, and stomach problems (Lee, 2020).

In terms of the death anxiety buffers that were effective in explaining the collective movement of online users between death anxiety states, we found mixed results. Three of the buffers mentioned in the literature were found to contribute to the transition between online terror states, Social, Religion and Achievement. Of these, Religion (H3) appeared to be the strongest. Religion is one of the most fundamental buffers in TMT, by virtue of its reference to symbolic immortality, a central aspect of the theory (Pyszczynski et al., 2015). This appears to spill over into religion cues mention in social media – Twitter in this case. Social connection (H2) was the second most important contributor to improved fit in the transition models. The supports the assertion that individuals attempt to create an anxiety buffer through building self-esteem via social connections to friends, family, and partners. Indeed, there is a rich stream of literature to support this (Cox et al., 2008; Mikulincer et al., 2003;

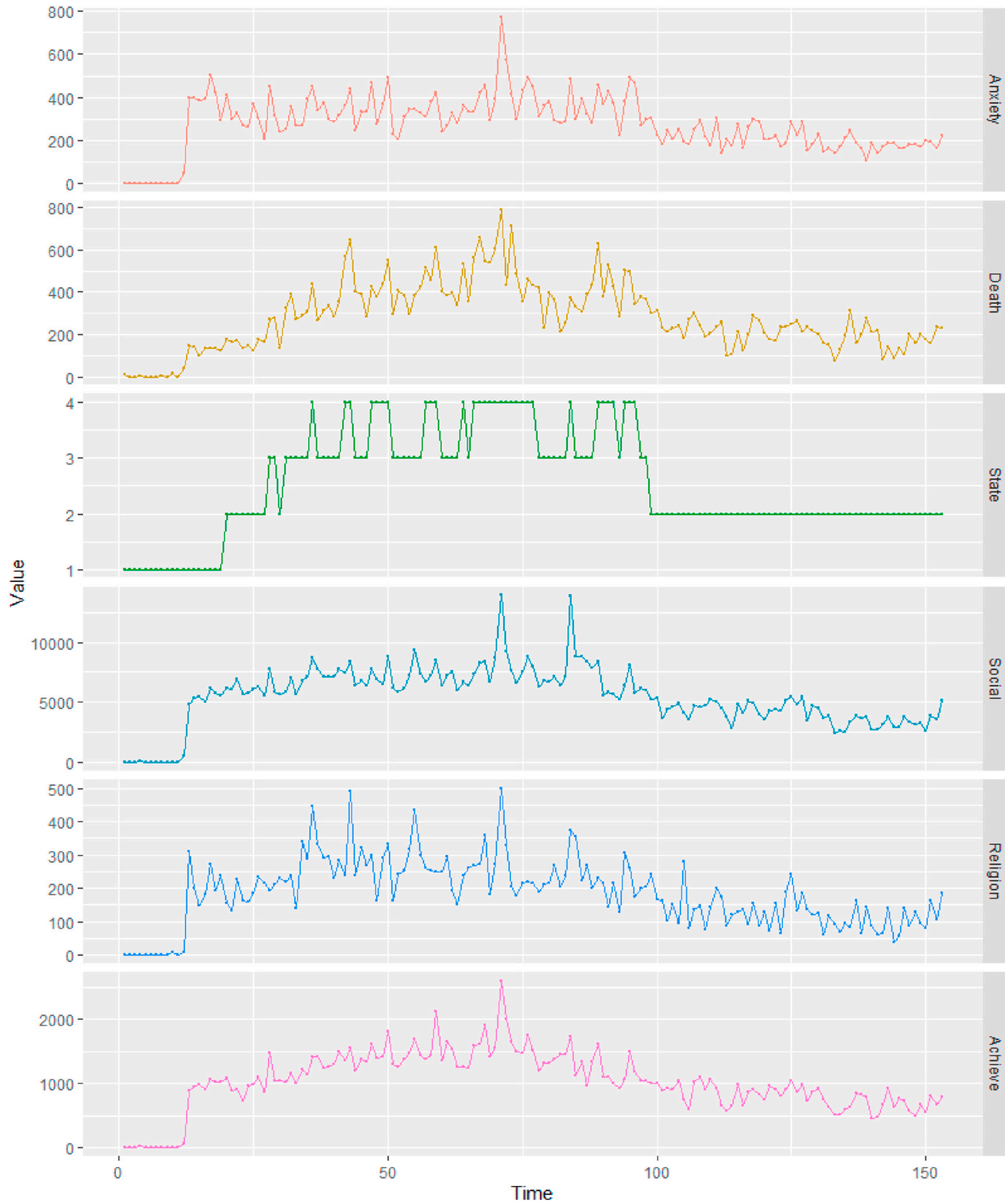


Fig. 9. 'Terror states' from final hidden Markov model.

Wisman & Goldenberg, 2005).

Our research confirms the extension of buffers in the social media context during the pandemic. This supports the importance of social media for social connection, mutual support and self-help. This is in line with research examining Twitter as a form of online social connection and support in the context of health (Berry et al., 2017; Talbot et al., 2020) and other contexts (e.g. Hosterman et al., 2018).

Third, the research supports the contribution of Achievement (H5) to the transition between online terror states, albeit more modest. The value of this concept was supported by AIC, but not by BIC, suggesting that it should perhaps be scrutinized in more detail in future research. Achievement is related to another central pillar of TMT, literal mortality (Pyszczynski et al., 2015), as people seek to establish a lasting presence in the world. In the context of this study, the lasting presence may be developed through achievements in family, wealth, and tangible or intangible artefacts. The research appears to suggest that this aspect is manifested in social media, but not very strongly.

In obverse, the study provides no statistical support for Affiliation (H4) in explaining the transition between online terror states. The affiliation concept in TMT suggests that people faced with death anxiety cling strongly to the worldview and values associated with particular groups. In the context of COVID-19, it appears that affiliation is not important as an anxiety buffer. This may be because the prevalence and impact of COVID-19 is so ubiquitous. Thus, the concepts of in-group and out-group are much less relevant, since the disease can potentially kill anyone. Social connection to family and friends (H2) is much more important in this context. Moreover, the study found no support for the provision of information on newly diagnosed COVID-19 cases to the transition between online terror states (H6). This is unexpected but may be as a result of the focus only on UK data. Thus, the Twitter users may already have been exposed and aware of the nature, impact and death risks associated with COVID-19 after following earlier information about the disease internationally, e.g. in China, South Korea, Italy and Iran. Such information may render further information, even if it is local,

Table 5
State transitions: Final model.

a. State 1. Baseline State.

Coefficients	State 1	State 2	State 3	State 4
Intercept	0	−22.210	−17.073	−17.947
Religion	0	−22.015	−5.8518	−5.711
Achievement	0	22.844	29.689	27.670
Social	0	72.285	8.105	12.319
Probabilities (at zero values of the covariates)	.999	<.001	<.001	<.001

b. State 2. Low Terror State.

Coefficients	State 1	State 2	State 3	State 4
Intercept	0	15.404	12.824	2.608
Religion	0	0.942	1.923	0.956
Achievement	0	0.826	1.576	−0.300
Social	0	−2.655	−1.545	−0.592
Probabilities (at zero values of the covariates)	<.001	.930	0.070	<.001

c. State 3. Moderate Terror State.

Coefficients	State 1	State 2	State 3	State 4
Intercept	0	11.188	11.471	10.622
Religion	0	6.062	1.272	0.783
Achievement	0	−5.429	1.629	2.229
Social	0	−9.123	1.642	1.242
Probabilities (at zero values of the covariates)	<.001	.345	.458	.196

d. State 4. High Terror State.

Coefficients	State 1	State 2	State 3	State 4
Intercept	0	3.238	11.322	11.868
Religion	0	11.087	−2.561	−3.386
Achievement	0	−14.154	5.075	6.683
Social	0	−32.088	14.202	13.498
Probabilities (at zero values of the covariates)	<.001	<.001	.367	0.633

less valuable or influential.

This study has several practical implications. First, the study demonstrates that the wellbeing of a population can potentially be evaluated using online social media sources. Death anxiety can have a significant effect on physical and mental wellbeing and must be managed appropriately by Governments and other institutions. Death anxiety is highest during the height of the pandemic and measures must be put in place to ameliorate the negative impacts on wellbeing. The study has shown that religious beliefs can provide an important anxiety buffer and thus vocal support by religious leaders and groups is particularly important during the pandemic. Further, during such a difficult time, self-esteem must continue to be developed through such mechanisms as personal achievement. Similarly, since social connection to families and friends is so important during the pandemic, this social connection must be maintained to ensure individual wellbeing. This includes ensuring the those on the 'wrong' side of the digital divide, such as the elderly and those on lower incomes, are assisted to ensure inclusive communication (Beaunoyer et al., 2020). Further, rules around social distancing should ensure personal safety from the spread of the disease but, where possible, should enable connectedness to friends and family cohesion.

This study has several limitations. First, at the time of writing, a cure for COVID-19 has not been found, and the pandemic continues. Thus, the research window of five months does not capture the whole of the pandemic period, and future research could extend the research window. Second, the research focuses on English language responses on Twitter in the UK. Further research could examine the application of TMT to changing terror states in other social media platforms, in other languages, and in other countries. Third, as we might expect for stochastic, probabilistic models of this kind, there is a random element in the creation of models. Thus, fitting the models on different occasions may result in varying results. Fourth, some of the tweets we wished to analyze were not attributed to the UK domain in the public data or not available for download retrospectively, limiting the current data set.

Credit author statement

Sole authored work: All aspects completed by the author.

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