IS THERE DISCOURSE AFTER BANDWAGON?

Analysing mechanisms of change in #Mentalhealth discourse through the prism of cultural power.

Master Thesis

Student: Alina Pavlova, 429002
Supervised by: Dr. Alex Van Venrooij

Research Master Sociology of Culture, Media and The Arts

Erasmus School of History, Culture and Communication
Erasmus University Rotterdam

25th of July, 2018

Abstract

The global burden of mental health disorders on society increased steadily during the past decade. To date mental illness is the leading cause of total years lived with disability. Future projections of positive shifts in overall mental health measures are bleak. Global mental health policies and budgets fall short of addressing the societal burden as mental health discourse languishes in the shadows due to stigma. Bringing awareness to stigmatized topics for which the funding is scarce can be challenging. Online social movements can provide an answer to this challenge. The internet creates a safe environment for marginalized members of society to voice their discontent and create awareness. Social media activism can also drive offline activism and shape traditional media discourse. This thesis' objective is then (1) to map the mental health discourse online and, consequently, (2) to analyse the mechanisms through which cultural power emerges online in the context of mental health narratives. To achieve these goals, this research employs innovative methods of topic modelling, sentiment and panel data regression analyses, and combines, in a multidisciplinary fashion, concepts such as emotional energy and cognitive focus from sociology and bandwagon effects from economics. The evidence shows that low-cost attention mechanisms are ineffective in fostering online mental health discourse, whereas emotional energy and discursive variability have positive influence by engaging the audiences, creating online solidarity and speaking to worldviews of audiences from different walks of life.

Mental health, discourse analysis, topic modelling, social media, stigma

Acknowledgments

- *To Whom It May Concern* -

Table of Contents

Introduction

- Mental illness is nothing to be ashamed of, but stigma and bias shame us all -

Bill Clinton

One in four people in the developed world are affected by a mental illness. The global burden of mental health disorders on society has increased steadily during the past decade (MHA, 2016; WHO, 2016; Eurostat, 2017), making mental health the leading cause of disability (Whiteford et al., 2015). However, the percentage of healthcare budget spent on mental illness prevention and treatment falls short of addressing the societal burden that mental illness causes (IMHE, 2010). More than 40% of countries worldwide either have limited or no mental health policy (WHO, 2011). Failure to treat mental illness not only diminishes individuals' health and wellbeing but also negatively affects the economy: evidence finds a four-fold return on every dollar spent on mental health (Chisholm et al., 2016). Despite the potential benefits of treatment, issues related to mental health continue to linger in the shadows due to both the associated stigma and lack of awareness (Leonard, 2016; Whitley and Wang, 2017; Thornicroft et al., 2013).

Raising awareness of the benefits of funding stigmatised topics, such as mental health, can be challenging. In my research, I consider potential solutions within the theory of social movements, specifically online environments. People increasingly socialise in online environments, which have become a major source of information[1] (Perrin, 2015; Shearer & Gottfried, 2017; Barthel et al., 2015; Agosto & Hughes-Hassell, 2005). Empirical evidence suggests online and offline lives are fundamentally interwoven (De Koster, 2010) and that social media activism drives offline activism (Fisher & Boekkooi, 2010; Leung & Lee, 2014; Vasi et al., 2015) and shapes the traditional media discourse (Zhou & Moy, 2006)[2].

According to Bail (2012), the environment of online social networks can be understood as discursive fields, i.e. the "public battlegrounds where collective actors compete to give meaning to an issue" (p. 857). As such, the online realm provides a social setting for the discovery of societal problems (Bail, 2016) and sustains interactions capable of creating such collective identity, "transforming individual actions into collective ones […] even without the presence of organizers"

[1] nearly two-thirds of the US population (90% of young adults aged 18-28) use social media and 78% of the population aged 18-49 access news online.

[2] The nature of media and the behaviour of the audiences in the realms of social media networks change as information is persistently built up upon the bottom-up user-generated content and, consequently, implies different narratives, discourses, criteria, and viewpoints (Van Dijck, 2009; Livingstone, 2009, 2013). For marginalized members of society, moreover, the internet creates a place where individuals can voice their discontent, express frustration and create awareness about an issue at hand as it provides a safe place characterised by anonymity and online solidarity (McKenna et al., 2002; De Koster, 2010).

(Brunsting & Postmes, 2002, p.126). Moreover, online environments can magnify and significantly speed up (De Koster, 2010; Brunsting & Postmes, 2002; McDonnell, Bail & Tavory, 2017) the process of "formulating grievances, defining a common identity, developing solidarity and mobilizing action"[3] (Swidler, 1995) and thereby create cultural change. The success of several online movements can only confirm these theses (e.g. Anonymous, ALS Ice Bucket Challenge, the "Alt-Right").

In this thesis, using theories of "culture in action", I will analyse *through which mechanisms online mental health discourse develops*. Specifically, my research studies how certain topics and discursive frames within the online mental health discourse come to life, fall behind or prosper by triggering two different forms of audience engagement: (1) meaningful and emotionally charged online conversations, or (2) low-cost engagement such as liking and re-tweeting posts, re-posting. Theoretically, I draw upon mechanisms at the macro-level such as cultural power, as well as more micro-level theories concerning emotional energy, bandwagon effect, and cognitive focus. Examining the mechanisms of online cultural power generation through the prism of macro-micro theories of cultural change not only serves as a novel contribution to academic discourse, but also is socially relevant.

This analysis will employ innovative research methods such as (1) a topic modelling analysis to map mental health discourse on Twitter, one of the major online social networks, and analyse its evolutionary dynamics, (2) semantic analysis of the discourse' sentiment to understand how mental health is communicated, perceived and how can it be compared to the discourse analysis of mental health in traditional media discussed in the existing academic literature and (3) panel regression to analyse dynamic mechanisms of mental health discourse. Mixed methods design provides both a more comprehensive view on cultural power than any methodology alone and a better understanding of the contextual meaning behind these cultural power mechanisms.

This thesis is organised as follows. First, I review the academic literature on mental health media discourse, which will allow me to situate the thematic analysis of online discourse within previous studies. Second, from the perspective of 'culture in action' I theorise the manifestation of cultural power by way of the concepts of emotional energy, cognitive focus and bandwagon behaviour. Third, I discuss my Twitter and sentiment data collection process, the topic modelling technique employed in the analysis and the fixed effects panel regression model. Fourth, I present the descriptive statistics, thematic and sentiment analysis, and the regression results. Finally, I conclude by outlining the implications of my findings for the domains of public health and health advocacy and note the potential contribution to the field of cultural sociology.

---

[3] a process which defines a social movement.

Theoretical Framework

(Online) media mental health discourse

Since the aim of this research is to analyse why some mental health (MH) online discourses prevail over others, it is important to understand the general structure of online MH discourse. While several studies on mental illness discourse in traditional media have been published, to date no studies analysing MH discourse on social media were conducted[4,5]. A number of studies on traditional media have shown that media discourse can have a negative effect on public opinion towards people who suffer from mental illness (Wahl, 1995; Angermeyer et al., 2005; Stuart, 2006). The dominant media often frames people with mental illness negatively, with scepticism and relates mental illness to criminality, danger and violence, using popular derogatory terms ('crazy', 'psycho', 'nutter'), negative emotional states ('disturbed', 'confused'), disabilities ('disabled', 'demented'), alienation and victimisation vocabulary ('hopeless victim', 'lonely', 'strange'), and psychiatric categories ('schizophrenic') to describe mentally ill (Whiltey & Berry, 2015; Rose et al., 2007; Thornicroft, 2013). Such portrait of mental illness can lead to discrimination and marginalization of these vulnerable populations (Whiltey & Berry, 2015). This issue becomes especially important when factually, people with mental illness are significantly more likely to be victimized rather than engage in violent behaviours and criminal activity than the general population (Teplin et al., 2005; Stuart, 2003).

On the other hand, media can also influence the perception of mental health positively. Positive, anti-stigmatising themes usually discuss the causes of mental illness (i.e. socio-economic, genetic, psychosocial), treatment solutions and MH awareness promotion (anti-stigma advocacy, prevalence discussion, problematizing injustice and lack of funding/services) (Thornicroft, 2013, Whitley & Hickling, 2007; Francis et al., 2004; Stuart, 2003). A narrative can also be considered de-stigmatising when sympathetic portrayal of mental illness is used (i.e. public figure) or a person with mental illness or a mental health expert is quoted (Whiltey & Berry, 2015; Thornicroft, 2013). Yet, an increase in positively framed MH-related media narratives is more an exception rather than

[4] As observed by analysing the body of work on MH discourse on Web of Science and Scopus (2018, April 30). Web of Science and Scopus are the two largest abstract and citation databases for peer-reviewed research. To search for works related to mental health discourse in (social) media a Boolean search of Titles/Abstracts/Keywords for ("mental health" OR "mental illness") AND ("portray*" OR "discourse") AND ("Media" OR "online")) was implemented.

[5] The social media studies with respect to MH are currently dedicated to analysing self-disclosure and social support (De Choudhury, 2014, Balani & De Choudhury, 2015), predicting users mental illness (i.e. depression, suicidal ideation) based on natural language processing (De Choudhury et al., 2013), analysing mental illness related online communities (Pavalanathan & Choudhury, 2015), implementing the impact studies (O'Keeffe & Clarke-Pearson, 2011), and analysing professional online mental health support (Hawn, 2009, Schepherd et al., 2015).

the rule, and the evidence of any decrease in negative, stigmatizing media narratives is inconclusive (Whitley & Berry, 2015; Whitley & Wang, 2017; Thornicroft, 2013) [6].

Studies on MH discourse within traditional media mainly focus on (1) the aspect of stigma and negative/positive framings of MH discourse, (2) the impact of contextual factors by which the MH discourse is framed (i.e. specific events reporting) and, (3) the representations of specific disorders (i.e. depression, schizophrenia) (Prikis & Francis, 2012). However, these studies generally do not perform a broader frame analysis to study the appearance of stigma in its discursive context. According to Gamson and Modigliani (1987) frames stipulate a "central organising idea" that specifies the meaning for given phenomena or event (p.143). Therefore, it is important to know which topics or topic combinations (discursive frames) are used to portray certain issues (i.e. stigma).

Only one study analyses different thematic discursive frames of MH discourse. The qualitative analysis employed by Paterson (2007) labelled the following topics as related to MH: foreign, legal, drug, feature, trauma, 'community, care, tragedy', social policy, inquiry report, and sports/celebrity stories. Within these topics the author further identified discursive frames. For example, the 'community, care, tragedy' topic usually revolves around a story where person with mental illness has committed homicide. While focusing on misconduct, it also problematizes the inadequacy of care and support received by the perpetrator, calling for change in policy implementation. Although it is a topic associated with stigma, it can actually be stigma-neutral as, although it depicts danger, it also builds awareness with regards to insufficient support a perpetrator received. Consequently, Paterson (2007) claims that media frames "remain a significant and important element of the discourse on mental illness because they can affect the day to day lives of people with mental illness, public opinion, and in some instances, perhaps even the priorities of social policy" (p. 1099).

What MH discourse looks like on social media is yet unknown. As we can see from the MH discourse studies in traditional media, stigmatization of mental illness remains one of the main concerns. As such, the issue of stigma should also be at the forefront of researching MH discourse online. Agreeing with Paterson (2007), this thesis will look at the aspect of stigma in social media MH discourse from the perspective of discursive frames, aiming to provide a more nuanced view

[6] The studies related to how MH is portrayed in (traditional) media show contradictory results. While some studies show an increase in positively-framed de-stigmatizing MH health discourse (Whitley & Wang, 2017; Thornicroft, 2013), there is little evidence of any decrease in stigmatizing media narratives (only confirmed by Whitley & Wang, 2017). Related to stigma MH discourse was observed in 46% of English newspaper articles (Thornicroft, 2013), 40% of Canadian newspapers during from 2005 to 2010 (Whitley & Berry, 2013) and 28% of Canadian newspaper articles from 2010 to 2015 (Whitley & Berry, 2013). Anti-stigmatising discourse was of a lower proportion and is observed 35%, 20% and 35% of printed press respectively. While all authors claim that anti-stigmatising articles in printed media increased, for some authors the proportional stability of stigmatising material is visible (Thornicroft, 2013), while for others the trend appears more positive (Whitley & Wang, 2016).

on how and where the stigmatisation takes place. In other words, the goal of the first, explorative part of this research will be to answer two questions: (1) what are the general discursive frames that dominate MH discourse in online social media and (2) how the issue of stigma manifests itself within these themes. Contrary to the traditional media MH discourse studies characterised by a relatively small-scale qualitative research design, this research will rely on big-data, employing quantitative topic modelling methods, letting us analyse far greater amounts of data, catch up with traditional media research and minimise the chance of human error.

CULTURAL POWER OF ONLINE DISCOURSE

Theorizing cultural power: 'Culture in action' perspective

The second part of this research will try to explore why certain discursive frames prevail over others. We rely on the 'culture in action' perspective which helps to understand how cultural symbols (here discursive frames)[7] can influence perceptions and actions, and argues that discursive prevalence, or the availability of one discursive frame over another, is one of the main prerequisite for the emergence of cultural power, or "the ability of culture[8] to shape one's actions and beliefs" (Swidler, 1986).

The culture in action perspective emphasizes how the cultural power of an object does not rely on the strength of "internalization" – as in the traditional cultural sociological perspective of Parsons – but should be positioned "outside of the head of the actor" (Lizardo, 2016, p. 114; DiMaggio, 1997; Sewell, 2005; Shepherd, 2011). The internalization of culture, sometimes described as a cultural symbol's depth (as opposed to shallowness) was often considered a determining factor in whether a given cultural symbol will spark an action or not. More recent conceptualizations of culture, such as the "culture in action" approach developed by Swidler (1986), however argues that the emphasis on internalization is misleading as people tend to know much more culture than they use, and have a wide "repertoire" of cultural tools available. Therefore, internalization is not determinative of the culture-action link, but the *triggering* of certain schemas by the external environment needs to be taken into account to explain how culture works. Hence, the emphasis has shifted from the "internalization" to the interaction between the internal cognitive make-up of individuals and the external environment (such as social structures, institutions, but also the "cultural environment" of discursive fields). Studies on discursive framing

[7] In the scope of this thesis, where we speak of discourse which is a fluid whole, consisting of a number of continuously intertwining discussion themes or genres, the cultural symbols could be represented by the linguistic vocabularies which identify discursive frames.

[8] Culture is defined as "a system of inherited conceptions expressed in symbolic forms by means of which men communicate, perpetuate, and develop their knowledge about and attitudes toward life" (Geertz, 1973).

present an example of this new emphasis on "externality" as it shows how people's beliefs and opinions can be triggered by the use of certain frames and narratives in the public, external domain.

More recent conceptualizations of cultural power therefore emphasize that the cultural power of an object is external to the social actor (Lizardo, 2016, p. 114; DiMaggio, 1997; Sewell, 2005; Shepherd, 2011). It is the environmental cues, theorised as externalized cultural scaffoldings, which trigger actions as the actors seek to reconstruct "an environment in which tacit competences can be recreated and expressed" (Lizardo & Strand, 2010, p.211). In the words of Swidler (1986, p. 283): "culture does not influence how groups organise action via enduring psychological proclivities implanted in individuals by their socialization. Instead, publicly available meanings facilitate certain patterns of action, making them readily available, by discouraging others". As such, "cues embedded in physical and social environment" (Shepherd, 2011 as cited by Lizardo, 2016, p. 114) are sufficient to trigger one's action without having to assume that a social agent internalizes "the entire model of social world or a whole system of values or logically organized conceptual scheme" (Martin, 2010 as cited by Lizardo, 2016, p. 114). These "access points to conceptual content" can then be used as a "toolkit", or (subconscious) explanatory model, for a consequent action (Lizardo, 2016, p. 4). To trigger the action, therefore, the primary requirement that should be met for the cultural symbol, i.e. discourse, to have power is simply, for it to be available.

Schudson's theory of cultural power

Although the culture in action approach has argues that culture can operate "from the outside in" (Swidler, 2001), Schudson (1989) has asked the additional question why cultural symbols might vary in their degree of cultural power. Schudson (1989) has identified five interdependent dimensions of cultural power to answer this question, which are: *retrievability* (i.e. symbols outreach), *resonance* (i.e. alignment with audiences' worldviews), *rhetorical force* (i.e. symbol's contextual effectiveness), *resolution* (i.e. clarity), and *institutional retention* (i.e. degree to which institutions reinforce the symbol). In the scope of this paper, we will focus on retrievability and resonance.

In order for a cultural symbol to influence the actions of individuals it must be "retrievable" and reach a person. We will consider discursive prevalence as an important aspect of "retrievability", as a widely prevalent discursive frame is more likely to ensure that a given discursive frame is both more easily retrievable than others (diffusion) and can be sustained for longer periods of time (duration) (McDonnell's et al., 2017).

For a cultural symbol to have cultural power it must also, according to Schudson, "resonate" with the public: it should fit with an audience's worldview in order to be noticed and classified as 'relevant'. Although the concept of resonance is widely used in the literature on framing and discourse, McDonnell et al. (2017) have criticized it's use in research as often tautological as scholars frequently assume that "successful" symbols resonate and unsuccessful do not. Explaining the success of cultural symbols through its resonance therefore becomes circular as those symbols that work are considered to resonate, and they resonate because they work. McDonnell et al. (2017) therefore theorize the concept of "resonance" as an emergent process which develops through interactions between individuals and cultural symbols. Their notion of resonance then, as opposed to a more passive form explained by Schudson, focuses attention to the interactional construction of resonance rather than simply assuming that it is there or not.

In the scope of this research I argue that "resonance" and "retrievability" are not independent, but that resonance can increase the retrievability (diffusion and duration) of a discursive frame by charging the discourse with meaning and increasing its retrievability: the more a discursive frame resonates the more available it becomes (McDonnell et al. 2017). Moreover, I argue that resonance, as an interactional process, can be observed in the form of three processes, or symbol-actor interactions: emotional energy, bandwagon behaviour and cognitive focus.

Emotional Energy (EE)

Emotional involvement can be considered as an observable indicator of the resonance of a discursive frame. Emotional energy is crucial for providing a discursive frame with momentum, transforming this discourse into a "sacred object", ritualizing the action encoded in it and sustaining the discourse.[9] Emotional energy can be defined as both positive or negative affectivity, which can arise from problem-solving interactions by either deep engagement with something (Tomko, 2007; Csikszentmihalyi, 1975; Im, Park & Storey, 2013) or in interaction through arriving at consensus, leading to feelings of solidarity and collective effervescence (Durkheim, 1973). Characterised by intense involvement and commitment, emotional energy is associated with greater confidence, morality, resilience, influence, attractiveness and the shared feeling of conviction. We therefore argue that this form of resonance might lead to more continuous

[9] Manifestation of emotional energy online has often been problematized due to the fact that physical aspect of experience is considered important as it presents the actors with multi-sensory cues which help to orient one's behaviour (Collins, 2004). However, according to Bakhtin's (1953) theory of speech genres, each form of communication, including online communication, represents a distinct speech genre which possesses its own norms and conventions by which emotions can be analysed. Based on this premise, DiMaggio et al. (2017) analysed the multi-user online discussions and found that the emotional energy can be produced online depending on context.

discourse and action, and therefore to higher degrees of retrievability and cultural power (DiMaggio et al., 2017).

Bandwagon Behaviour (BW)

On the other hand, and especially in the online field, resonance might not always take the form of emotional engagement. As Levina & Arriaga (2014) argued, social networks' designers rely on instruments such as Favourites and Retweets to attract users to generate online content. These instruments of attention often result in bandwagon behaviour, or low-cost, extrinsically-motivated form of engagement arising from either a need for social distinction or a need to fit in (Stigler & Beker, 1977, Van Herpen et al., 2009, Shiller, 1995). We argue that bandwagon behaviour could result in so-called "slacktivism" – a low-cost form of participation characterized by short-lived attention (Wicks, 2014) which does not have sufficient momentum to generate social change (Bail et al., 2017).

It is also worthwhile to note that, although we predict that bandwagon will cause both sudden rise and quick demise, which would then point at a lack of cultural power, this assumption should be tested. Additionally, within this thesis the definition of bandwagon intents to suit the online realm and assumes active bandwagon behaviour. Namely, it does not include previous levels of attention which reflect mimicry (i.e. when "popularity breeds popularity"), for it is inactive, can not be influenced by an actor and, additionally, can create bias in regression analysis outcomes as it breaches strict exogeneity assumption[10]. However, it includes low-cost attention-generating mechanisms which are practiced online (i.e. 'Likes', 'Shares', duplicates).

Cognitive Focus (CF)

The interaction between an actor and a discursive frame can also be facilitated by a cognitive focus. When discursive frames are matching worldviews of the audiences (Schudson's definition of resonance), the retrievability of a discursive frame might also be hindered if this frame is incoherent and an actor can not engage with it (Bail, 2016; Boone et al., 2012). On the contrary, when a discursive frame is aligned with the worldviews of the audiences, without being too narrow or overly-diversified, it can be said that this discursive frame is at optimal *cultural carrying capacity* (Bail, 2016), allowing the actor to cognitively focus on or interact with this discursive frame. In other words, either too many ideas at once in general (inter) or within a discursive frame (intra) can create discourse competition where messages with a similar goal will compete with and within each other's' discourse, compromising the resonance.

---

[10] According to strict exogenous assumption of FE model it is not advised to include autoregressive variables (i.e. lagged dependent variables) within covariates as it leads to serial correlation of errors which can result is biased test outcomes (Schmidheiny & Basel, 2011).

Additionally, clarity of a discursive frame to the public or when the discourse is issuing a call for action, or gives someone a direction for what to do, can enhance cognitive focus even when discursive frames are in competition between and within themselves. As such, Schudson's concept of *resolution*, or discursive clarity, will be a part of the operationalization of the cognitive focus, which is one of three ways (besides emotional energy and bandwagon behaviour) in which actor-to-symbol engagement, or resonance, happens.

To summarise, by theorising three mechanisms of resonance – as an actor's interactions with the discursive frames - the research question this paper will try to answer can be stated as follows:

"To what extent can resonance in form of emotional energy, bandwagon behaviour or cognitive focus predict future retrievability of mental health discursive frames?"

The general expectations in answering this question, moreover, will translate into the following hypotheses:

H1: Emotional energy in a previous period has a significant positive effect on the retrievability of a discursive frame in current period.

H2: Bandwagon behaviour in a previous period has a significant negative effect on the retrievability of a discursive frame in current period.

H3: Cognitive focus in a previous period has a significant positive effect on the retrievability of a discursive frame in current period.

External factors affecting the discourse

Although in this thesis we theorise emotional energy, bandwagon and cognitive focus as the primary meaning-making mechanisms which drive the retrievability of discourse, there are other factors which may have effects and which should be controlled for. Those are echo chambers, rhetorical force arising from influencers and institutional discourse or retention.

Firstly, increased attention, even in the presence of emotional energy, could also be characterised by an *echo chamber* which will restrict the retrievability of new ideas beyond a certain restricted network (Kretschmer et al., 1999). Secondly, and as implied by Schudson's *rhetorical force,* a discourse is effective within a certain context. Such contexts might result from, for example, the use of discourse by *influencers* (i.e. users with high online social capital), who publicise them. Thirdly, *institutional retention*, or rather theme-related institutional discourse running in parallel in mass media, can have an effect, driving the retrievability of discourse on Twitter. Last but not least, we should be careful regarding the possibility of *saturation effects* for emotional energy (Bail et al., 2017). Although we predict the emotional energy to positively influence retrievability, there might be a tipping point after which the retrievability will subside.

Data and methods

The research uses a combination of (1) topic modelling analysis to map the discourse, (2) regression analysis to identify the effects of meaning-making resonance mechanisms on the retrievability of the discursive frames. My chosen methodology is unobtrusive quantitative content analysis, which draws statistical inferences from large amounts of data collected at a macro level. For the same reasons, the larger amounts of data are also needed to implement the inductive quantitative thematic analysis. As compared to surveys, unobtrusive methods can be advantageous as they avoid participant bias by reactivity (i.e. Hawthorne Effect), since data is being collected in a more natural environment, plus they are proven to be the most useful in analysing patterns of communication and inferring about aspects of culture and cultural change (Berelson, 1952). Longitudinal research design, moreover, allows for the possibility of causal inferences.

DATA SOURCES

Twitter data

I use time-series data derived from Twitter. Twitter was used for the following reasons. Firstly, as one of the biggest microblogging services Twitter allows people to engage in an open conversation with others (Weij et al., 2015), providing a great empirical avenue to study MH discourse. Secondly, unlike Facebook, which might have had a community more representative of the public, Twitter allows researchers to download texts or tweets produced by virtually any user, while Facebook users' posts might not be publicly available (Bail, 2012). Concerning data privacy issues, Twitter's public availability of data implies that users agree to forgo some confidentiality and anonymity by signing Twitter terms and conditions, which justifies this research from an ethical perspective.

The data was scraped via GetOldTweets software (Lee, 2018) which is based on Jefferson-Henrique script which by-passes some limitations of the Twitter API.[11] The search terms of "Mental Health" and #mentalhealth was used to derive the data for the last 10 years (2007-2017). Additionally, the tweets were restricted to English language tweets.

Since the download of the tweets is a lengthy process (approximately 0.15sec per tweet, averaging 9000 tweets per day), it was decided to take a cross-sectional sample of time-series data. Tweets were gathered on one single day in the middle of the month/middle of the week for each month, avoiding holidays and weekends.

[11] GetOldTweets allows for collection of historical data as far back as the inception of the Twitter platform. The Twitter API caps the download of the tweets to 10% of the daily tweet volumes. Limiting downloading of the tweets to MH discourse, therefore, allows for download of the entire related tweets universe per day. When setting the maximum amount of tweets per day to 100,000, the number of tweets have never exceeded this amount.

In total, 695,414 tweets posted by 339,493 unique users (2.05 tweets per user) were collected. The collected tweets contain the following data/variables: date (YYYYMMDD), username (account which posted a tweet), text of the tweet, number of replies (that is, comments in a discussion thread related to a single tweet), retweets (number of times a tweet was shared) and favourites (number of times a tweet was 'liked'), hashtags (#), mentions (@), tweet ID and tweet hyperlink. While for the topic modelling the original data is used, for the regression analysis the data is mean-aggregated per topic per quarter, resulting in a sample of 1,320 observations (30 topics/44 time periods). [12]

Additionally, for rhetorical force, users' meta-data per tweet, namely the number of followers, was collected. As downloading of meta data takes from 1 to 4 seconds per tweet, we only took a sample of data (1 year, 2015) for the reference.

Textual sentiment

In addition to Twitter data, sentiment characteristics of tweets were automatically derived using LIWC – *Linguistic Inquiry and Word Count* software (Pennebakker et al., 2014). LIWC is a dictionary-based, automated text analysis software which accounts for language cues or proportions of the text associated with certain dictionaries to assign sentiment characteristics to texts (Tausczik & Pennebaker, 2010). I focused specifically on the emotionality of the tweets (derived by measuring what proportion of either positive or negative emotions does a tweet display), confidence of the text (derived from LIWC composite variable 'Clout'[13,14]) and the use of 1st person plural personal pronouns to denote solidarity. Additionally, to describe the discourse we look at what negative emotions precisely are more prominent (i.e. anxiety, anger, sadness). We also use LIWC software to create custom dictionaries to quantify stigma-related vocabularies (see p. 17) in tweets or such measures as resolution (for operationalisation of resolution see p. 18).

---

[12] It is worth to mention that, although some variables presented skewed distribution (i.e. replies, retweets, hashtags mentions). However, referring to the central limit theorem, if higher volumes of variables data were available, the distribution would tend towards normal. When mean-aggregated per topic per quarter, variable distributions are within within acceptable range of +/- 2 (Field, 2009; Gravetter & Wallnau, 2014).

[13] Clout in text is operationalizaed by a lesser use of first person singular and higher use of first person plural and second person singular pronounce; additionally, auxiliary words and use of questions contribute to 'Clout' composite negatively (Kacewicz et al., 2012). LIWC Clout Thinking is a standardized composite measure ranging from 0 (low status, low confidence) to 100 (high status, high confidence).

[14] One limitation of using LIWC composite variables (note, we only use one composite variable 'clout' to operationalize confidence) is that they are are not transparent. All we know is that they were derived from previously published findings from LIWC lab converted to percentiles based on standardized scores from large comparison samples (LIWC, 2018). Saying that, the LIWC composite variables are widely used in peer-reviewed academic literature, especially in the field of linguistics and psychology (Pennebaker et al., 2014, Kacewicz et al., 2012, Newman et al., 2003, Cohn et al., 2004, Bail, 2017).

TOPIC MODELLING

To map the MH discourse, Latent Dirichlet Allocation (LDA) topic modelling technique was used to discover main themes related to mental health in the last 10 years[15]. Latent Dirichlet Allocation (Blei, Ng & Jordan, 2003) explores latent structures in texts by clustering words that 'occur in documents together more frequently than one would expect by chance' (DiMaggio et al., 2013: 578). In other words, topic modelling allows quantification of vocabularies which is a more efficient way to look at discourse when dealing with big data. The topics derived by this method are cross-checked with the most frequent hashtags (#), an online user-generated taxonomy used for information classification and retrieval (see Appendix 10).

Prior to analysis, the textual data of the tweets was cleaned (i.e. stopwords, corpus specific and rare words were removed, stemming[16] and lowercasing implemented)[17,18] to ensure better topical coherence. To run LDA analysis[19], the number of topics was set to 30, based on 20 top words, for the following reasons.[20] Considering that a tweet has a maximum length of 140 characters (approximately 50 words) 2 assumptions can be made. [21] First, the author should be concise, therefore many topic-relevant words would be expected to appear in a short text of a tweet. Secondly, removing the stopwords and the like will shorten the number of words within tweet.

Since a 30 topics solution, although methodologically optimal, is too extensive to analyse in the scope of this thesis, I cluster the topics into greater themes for better contextual comprehension. I do so by performing an LDA analysis again, now with the decreasing number of topics. Choosing a lower number of topics would identify themes which would be implicit in the higher number of topics. I have looked at the topic composition of 5, 7 and 10 topics (see Appendix 3) and selected a 7 topics solution which provided to be most logical (the logic will be explained in the results). Throughout the paper, we will call the topics from the 7 topics solution

---

15 A Python based Mallet software was used for the analysis (McCallum, 2002).

16 Abridging words to their morphemes.

17 Stop words here include such parts of speech as prepositions and conjunctions (i.e. and, or, that, then), punctuation, numbers, links and other special characters. Corpus specific stop words are the words encountered in > 80% of the text and rare words are words which appear in less than 200 documents. Additionally, an attempt to create bi- and trigrams was made to analyse topics including most frequent 2 and 3 words phrases. However, given the diversity and short size of tweets only a few were meaningful (i.e. mental_health_day, learning_disability) whereas the majority of bigrams and trigrams were irrelevant (i.e. day_today, already_feel) and resulted in worsened topic model (qualitatively assessed).

18 Implemented in Python, a free open-source programming language, which is an efficient method to handle big data.

19 I decided to analyse the entire corpus at once, as opposed to dynamic topic model which could give a more refined vocabulary representing the topics semantic changes in time (Blei & Lafferty, 2006). I made this decision for two reasons: (1) our timeline is relatively small (10 years) and looking at vocabulary change of topics is beyond the scope of this paper and, (2) regressing dynamic vocabularies could potentially affect the sentiment analysis performed on topics, which complicates the comparison.

20 For the method used to assess the optimal number of topics, refer to Appendix 2.

21 Changed to 280 characters in 2017, although mean word count per tweet is 20 (see Table 1).

'themes' and topics from 30 topics solution 'topics'. As such, by qualitative matching of keywords the topics (t=30) are attributed to the broader themes (t=7).

In addition to topic modelling of MH discourse, the discursive frames are grouped according to two criteria. Firstly, the themes which express higher levels of stigma are grouped into stigma-related category, remaining themes, will be grouped into stigma-neutral category. Stigma-related category is derived by either of (1) qualitative thematic assignment (i.e. if a topic clearly relates to violence, criminalisation or danger, frames mental health as madness or looks at mental illness with scepticism) or (2) above the mean levels of stigma-related vocabularies.[22]

Secondly, we group discursive frames by their trend patterns (by analysing them graphically). We compare the discursive frames which express a 'pick and through pattern' (i.e. indication of short-lived attention or "slacktivism"), with discursive frames which display more usual trend pattern either representing a flat pattern, growth or decline trends of the retrievability of a topic (operationalization of retrievability is explained on the next page).

STATISTICAL ANALYSES

In this thesis, 2 statistical techniques are used to analyse the dynamics of the discourse. Firstly, when looking at the MH discourse in general, I assess trend patterns of discourse characteristics by using Mann-Kendall trend test (McLeod, 2005), which indicates whether or not the trend observations are significant. Mann-Kendall trend test has been performed in R by using *Kendall* package. Secondly, I look at the differences in discourse characteristics (i.e. sentiment, mechanisms of online attention generation such as 'Favourites' and 'Replies') between stigma-related and stigma-neutral, and short-lived attention versus stable trend retrievability pattern by comparing means with independent samples t-test by using R *t.test* function.

Regression analysis

I use regression analysis to analyse the predictive power of either emotional energy, bandwagon behaviour of cognitive focus on the retrievability of the discourse. Since my goal is to test how either of the predictors affect the discourse both per topic and in time, the transformation of data is performed by mean-aggregating variable per topic per quarter, which constitutes a panel data structure. The model variables are operationalized as follows (for an extended operationalization table, please refer to Appendix 4):

---

22 The latter, quantitative measure of level of stigma within a discursive frame is calculated as the mean-average proportion of stigma-related vocabularies in tweets per theme derived via LIWC. Stigma-related vocabulary is defined by an average22 of LIWC in-house dictionaries of Risk ("danger", "beware", "fear"), Power (only when related to victimisation, submission or domination such as "criminal", "pitiful", "hopeless", "victim" – see Appendix 7) and Swear (i.e. such as "moron", "idiot", "psycho") words, and a custom LIWC dictionary created from inappropriate words or phrases used to describe mental illness as identified by Rose et al. (2007) (i.e. "crazy", "dumb", "freak"). However, to avoid bias we have excluded words which can also be used in non-stigmatising way depending on the context (i.e. "ill", "schizophrenia", "mental illness") or imply polysemy (i.e. "pray" can be used to describe a victim or as a verb "to pray") (see Appendix 7).

Operationalization of variables

Dependent Variable

In this analysis the dependent variable is retrievability as a dimension of *cultural power*. Retrievability is operationalised by the number of documents in which a specific theme from the topic modelling analysis occurs. The document is attributed to a specific topic and counted if it exceeds a cut off value of 20% as a proportion of the document.

Independent Variables

Emotional Energy will be operationalised, similarly to DiMaggio et al. (2017), by assessing whether communication is emotionally engaging and expresses solidarity indicated by the tweet characteristics of (1) *emotional intensity* (high intensity sentiment, either positive or negative calculated as the square root of the sum of squares of positive and negative emotions proportions (as adapted from Lee & Nerghes, 2017)), (2) *high expression of confidence* (clout, see p. 15, footnote 13), (3) high levels of *solidarity* expressed by an increased use of 1st person plural <u>personal pronouns</u> (i.e. we, us, ours) and (4) high *level of engagement of a tweet* expressed by the <u>number of replies</u> a tweet attracts. The emotional energy variable will be represented by a composite variable which averages the normalized[23] values of replies, emotional intensity, confidence and solidarity.

Bandwagon Behaviour has been defined by the use of low-cost attention generating mechanisms and will be operationalized by the average of the normalised values of *favourites* and tweet *duplication rate* variables[24].

Cognitive focus is operationalised as a normalised average of intra-topic focus, inter-topic focus and resolution. *Intra topic focus* is calculated as a median value of proportional split of 30 topics discovered by topic modelling within a single tweet (intra-tweet). *Inter-topic focus* is operationalised as a median value of proportional split of 30 topics discovered by topic modelling aggregated per period. A higher inter-topic focus indicates that the discourse per given period is more concentrated, which means that it possesses a lower number of discursive frames of high prominence. *Resolution*, has been operationalized in accordance with the notion of illocutionary force in speech-act theory, namely, that particular linguistic composition of speech can display an urgency and call for action (Austin, 1962). Speech will usually imply action by either making use of imperative verbs (usually present tense 2nd person verbs "Come here", "Read this", "Let us…") or indirectly via modal auxiliary verbs ("Could you pass me…?") or, sometimes, performative

---

23 $\frac{(x-MIN)*10}{RANGE}$

24 Due to the high correlation between retweets and favourites (0.96, $p<0.05$), it has been decided to only focus on favourites in general analysis and as a covariate and leave the retweets (both were operationalized as bandwagon) within the data as retweets also contribute to overall discourse and appear in searches.

verbs which convey warnings, for example ("I advise you to…") (Allen & Core, 1997). Since LIWC allows us to detect verbs and present focus, I composed a proxy to reflect resolution in text by averaging the proportions of verbs, present focus and modal auxiliary verbs (using a custom-made dictionary, see Appendix 5).

Control Variables

Echo chamber is operationalized via inverse *Krackhardt's E/I Ratio:*

$$E - I\ Index = \frac{(EL - IL)}{(EL + IL)} \times (-1)$$

where *EL* represents the number of edges that are external to a given topic per time period (quarter) and *IL* is the number of edges internal to or between vertexes within that topic. This measure varies on a scale from -1 to 1 with -1 representing a perfectly open community and +1 representing an absolute echo chamber (Krackhardt & Stern, 1988). Internal Edges are calculated as total number of users minus unique number of users per topic per period while the External Edges are calculated by a difference of a total number and unique number of users of all topics per quarter minus Internal Edges of the topic.

Institutional Retention, defined as parallel mass media discourse, will be operationalized by current attention to the topic of the discourse in the media which can be derived from the Google Trends.[25] [26]

Additionally, I control for the influence of hashtags and mentions which could also potentially influence the retrievability of discursive frames. Hashtags (#) are used to "index keywords or topics on Twitter. This function […] allows people to easily follow topics they are interested in […] or categorize those Tweets and help them show more easily in Twitter search" (Twitter, 2018a). Mentions (@) are used to "tag other users in the discourse for either acknowledgement or engaging these users in conversation" (Twitter, 2018b). I use these two variables as controls as neither of them represents purely emotional energy, bandwagon behaviour or cognitive focus because it implies a degree of rational argumentation and the use of these symbols is not limited. In other words, neither the use of hashtags or mentions is emotional

[25] Google Trends represent "a time series index of the volume of queries users enter into Google in a given geographic area. The query index is based on query share: the total query volume for the search term in question within a particular geographic region divided by the total number of queries in that region during the time period being examined. The maximum query share in the time period specified is normalised to be 100, and the query share at the initial date being examined is normalised to be zero. The queries are 'broad matched' in the sense that queries such as [used automobiles] are counted in the calculation of the query index for [automobile]. Note that Google Trends data is computed using a sampling method, and the results therefore vary a few per cent from day to day. Furthermore, due to privacy considerations, only queries with a meaningful volume are tracked." (Choi & Varian, 2011, p.3)

[26] It was only possible to download data for certain topics which display more specific keywords (i.e. topics related to Substance Abuse, Trump, Guns/Violence – will be explained in greater detail later in text). The Worldwide trends were used for the analysis.

(although mentions could reflect solidarity to a certain extent), rational (does not imply extrinsic motivation for instant gratification) and does not influence cognitive focus (hashtags may, but they are not limited to a single hashtag and are already accounted by topic modelling analysis and intra-focus as a cognitive focus measure).

Other variables

Rhetorical force can be assessed using the number of followers of an account posting a tweet in question. Although the number of followers of an account is related to the account and not the message, according to Schudson (1989) when a message is spread by the parties with high influence it can drive up the discourse. It was only possible to derive the number of followers for a small sample of data due to the time-intensity of the scraping task (see p. 14). I therefore only use rhetorical force in the descriptive analysis. Additionally, and as described within the theoretical framework, the saturation effect of the emotional energy (Bail et al., 2017) is considered by lagging multiple periods.

Model

For the panel data, the most appropriate regression model would be the econometric panel linear model (R[27] plm package Croissant & Millo, 2017) for the following reasons. First, this panel data is a time series data where the goal of the analysis is to scrutinize the relationships between covariates and the dependent variable taking into consideration two dimensions – topics and time. To rule out the use of simpler methods, such as pooled OLS, it is important to note that econometric panel model allows me to account for individual-specific effects implied by the data, while pooled OLS does not (Baltagi, 2008). Furthermore, since the dependent variable is represented by count data and the mean of the dependent variable is tending towards its variance, it would also be reasonable to consider Poisson regression (as done by Van Venrooij, 2015). However, Poisson regression model ignores the trend pattern which is rather pronounced in the time-series (see interactive graphs – Appendix 10)[28,29]. The econometric model solves for non-stationarity by differencing both dependent and independent variables (Schmidheiny & Basel,

---

[27] R is an open-source dialect which is based on S statistical computing language allowing for statistical analysis and visualisations. The code has been implemented in an online environment by using Jupiter Notebooks, which is an open source web-based "software for interactive computing across dozens of programming languages" (Kluyver et al., 2016). Both R language and Jupiter Notebooks software are free and contain contributions from top computational statisticians (Ihaka & Gentleman, 1996). Code within Jupiter Notebooks can be saved for future reference.

[28] For similar reasons I have decided not to use Structural Topic Model, a Python-based topic model which allows for inclusion of meta data and a consequent analysis of these as covariates (Roberts, Stewart & Tingley, 2018). While STM accounts for covariates it does not take both time and topic dimensions into consideration.

[29] Although models to undertake Poisson panel regression do exist in R (see the pglm package for example), they are a relatively recent development and the theoretical statistical properties are not fully understood. This can be an area for future research.

2011). Another motivation of my choice of a continuous model specification is that at large sample sizes the discrete Poisson model approaches the continuous exponential model.

Based on the Hausman test[30] (p <0.05) (Hausman, 1978), a diagnostic for the assumption of whether individual-specific effects are more or less likely to be correlated with explanatory variables, the Fixed Effects (FE) model is chosen (for model assumption checks, please refer to Appendix 6). As opposed to the Random Effects[31] model, FE model allows for 'individual-specific effect to be correlated with the explanatory variables' (Schmidheiny & Basel, 2011). As such it controls for omitted variables by controlling the variables against each other (unobserved effect).

The FE model can be written as follows:

$$\ddot{y}_{it} = \beta_{EE}\ddot{x}'_{(EE)it} + \beta_{BW}\ddot{x}'_{(BW)it} + \beta_{BW}\ddot{x}'_{(CF)it} + \beta_{CV}\ddot{x}'_{(CV)it} + \ddot{u}_{it}$$

,where $\ddot{y}_{it}$ is a count of documents representing retrievability, from which time averages have been subtracted ($\ddot{y}_{it} = y_{it} - \bar{y}_{it}$, where $\bar{y}_{it} = 1/T \sum_t y_{it}$) per subject i per time t.

$\ddot{x}'_{it}$ is an independent variable calculated in a similar manner (where EE stands for Emotional Energy operationalization, BW - Bandwagon Effect, CF – Cognitive Focus operationalization and CV - a control variable(s)),

β coefficients which measure the effect of the explanatory variables (x's) on the dependent variable (y),

$\ddot{u}_{it}$ is an idiosyncratic error term which is, likewise, time-adjusted.

The logic behind the FE model, therefore, entails the subtraction of time averages from both sides of the initial model (equals first differencing for 2 period model), which yields a "within model" solution for heterogeneity bias by "cancelling out the time-related individual specific effect, the intercept and time-invariant regressors". This also means that the coefficients derived by the FE model can be used to describe the independent variables effects autonomously from other covariates (Schmidheiny & Basel, 2011).

[30] This is done via a Wald test of the difference between the vector of coefficient estimates of FE and that of RE (Torres-Reyna, 2008)

[31] Random Effect model assumes that (1) 'the individual-specific effect is a random variable that is uncorrelated with the explanatory variables of all past, current and future time periods of the same individual' and (2) that 'individual specific effect is of constant variance'

Results[32]

THEMATIC ANALYSIS

The following 30 topics (Table 3) emerged via topic modelling analysis. The topics have been sorted by prominence and represent 48.7% of the MH discourse on Twitter. The remaining 51.3% of discourse consists of topics which are more fragmented (represent <0.5% of discourse) and, hence, could not be meaningfully identified by an LDA model. The topics were labelled according to their keywords and qualitative assessment looking at the tweets they represented. For instance, the topic called 'Feelings' was labelled as such because the tweets which represent this topic are feeling-related, where the author of the tweet speaks about how he or she feels about one's self, one's mind or other people. The topic called 'Problematisation' speaks about mental health as an 'issue', 'problem' or 'illness'. It also notes the importance of solving this 'issue' and talking about the subject, and so on.

Table 3 *LDA-derived MH discourse topic model (N=695,414, T=30)*

TOPIC	WEIGHT	Top Words (10)
PROBLEMATIZATION	5.37%	issues people problems care important good life talk feel illness
FEELINGS	3.03%	day good issues bad love people shit break feel lol care head mind
COMMUNITY, AWARENESS, EVENTS	2.97%	event conference support awareness aid training join community group meeting
EDUCATION, RESEARCH, SCHOOLING	2.93%	care services students support research school education training community social childrens youth improve
ANTI-STIGMA AWARENESS	2.51%	stigma talk awareness people lets change campaign conversation support open
EVERYDAY LIFE	2.42%	day time good important work days school lives today bad risk taking put feel back year
DEPRESSION, ANXIETY, BPD, PTSD (#)	2.08%	#depression #anxiety #mentalillness disorder #bipolar #ptsd illness #bpd #stigma #suicide
ACCESSIBILITY OF MH CARE	2.07%	care services system treatment state coverage access veterans substance abuse addiction insurance program
HEALTHY LIFESTYLE, PHYSICAL EXERCISE	1.93%	physical improve important exercise body mind benefits stress healthy life positive care
SOCIAL MEDIA, SHARING	1.89%	blog #mhsm stories read post share news social story chat
SUBSTANCE ABUSE	1.76%	abuse substance addiction study risk drug women treatment teens poor
FUNDING CUTS, CRISIS	1.73%	services funding support cuts minister crisis government budget call reform money
WELLBEING AND MINDFULNESS, SELFCARE, LOVE	1.69%	#mindfulness #wellness #wellbeing #recovery #therapy #love #happiness #selfcare #inspiration #motivation
STRESS AND PHYSICAL SYMPTOMS	1.53%	depression study brain risk research anxiety linked stress sleep eating
YOUNG PEOPLE, LEARNING DISABILITY	1.46%	people young children support adults experience parents struggling learning disabilities
GUNS AND VIOLENCE	1.37%	gun control violence laws people checks background shootings school reform bill mass ban
NURSING JOBS, WORKING AT A HOSPITAL	1.34%	nurse worker services registered job community therapist care manager hospital
ENGLAND, NHS SYSTEM, CRISIS	1.24%	care services crisis nhs patients beds england provide staff system
CHARITY AND HELPING	1.12%	support charity online follow interested send resources love people helping
MH AWARENESS MONTH, CAMPAIGNING	1.11%	awareness week #mhaw month raise facts support campaign everybodys video
DEATH AND MURDER	0.99%	death hospital stabbed experts police murder facility patient people worker
MEN, VETERANS, PTSD, SUICIDE, MILITARY	0.89%	suicide military crisis veterans #suicide #ptsd ptsd #veterans men care
DONALD TRUMP	0.89%	donald trump president doctor exam physical journalists america expert cognitive
WORK AND MH	0.80%	workplace work employees conditions benefits wear apps wristbands employers candidate
DONATING TO MH PROGRAMS	0.75%	#bellletstalk tweet awareness donate canada programs raise money initiatives support
PSYCHIATRIC PROFESSION, PSYCHIATRIC NURSING	0.71%	nurse psychiatric job practitioner position counselor psychiatry therapist counseling
WORLD MH DAY	0.60%	day world #wmhd depression global october happy #depression link theme
AUTISM, ADHD, CHILDREN	0.55%	children #parenting #autism #asd #adhd sciences autism crisis adhd syndrome
POLICE TRAINING, PRISONS	0.52%	police raises million training aid officers spending people boosts budget reform cells
PARENTING	0.46%	american parenting baby monitor exmobabybychkov visit receive medication assistance coddling
Σ	48.7%	

Because it is difficult to analyse the discourse consisting of as many as 30 topics, these topics were clustered in themes. The following 7 themes (Table 4), sorted by prominence, can be

[32] For descriptive statistics please refer to Appendix 1.

said to be representative of the MH discourse. Recalling that 5, 7 and 10-topics LDA solutions were looked at, the 7 topic solution appeared most plausible as (1) 5-topics solution provided too general (clustering distinct themes such as 'Funding', 'Service' and 'Youth'[33]) (2) 10-topics solution created less meaningful categories. For instance, topics which in 7-topics solution related to the same theme ('Guns and Violence', 'Death and Murder' and 'Donald Trump' clustered in Stigma) in 10 topic solutions were split ('Guns and Violence', 'Death and Murder' as one theme, and 'Donald Trump' as a separate theme) (for 5 and 10-topic solutions refer to Appendix 3).

Table 4 *LDA-derived MH discourse topic model (N=695,414, T=7)*

TOPIC	WEIGHT	Top Words (10)
FEELINGS AND PROBLEMATISATION	7.64%	day issues people good #mentalhealth important time life care work make feel bad talk physical today days problems things world love back issue taking school depression break
AWARENESS	6.79%	#mentalhealth awareness week support day today stigma issues talk people work great #mhaw month charity world raise join check campaign share event community youth aid free blog supporting conference stories
FUNDING	5.46%	care services #mentalhealth crisis support funding cuts treatment system news people nhs patients access service report act community children lives state risk police budget veterans call issues million put plan
YOUTH	5.38%	#mentalhealth issues problems people depression physical children study disorders #mhsm social work stress young risk care treatment anxiety illness research improve benefits disorder #health women impact linked kids life abuse
CLASSIFICATION	3.66%	#mentalhealth #depression #anxiety #bellletstalk #mentalillness #health #psychology tweet #mhsm today disorder cents #bipolar #ptsd donate bell #recovery #mindfulness #wellness #mental programs depression awareness anxiety #stress canada #wellbeing day #suicide
STIGMA	2.78%	gun issues trumps trump guns people issue control problem checks violence care problems facility history laws police law man ban news jones treatment mentally ill president test bill shootings woman
SERVICE	2.19%	nurse #jobs #health #job #mental worker job services psychiatric center care jobs hospital therapist practitioner registered counselor nursing social community manager team professional specialist position time unit program counseling technician
∑	33.9%	

The topics from the 30-topics model were then assigned to the 7 themes by qualitative judgement and keyword matching. This procedure enables one to better understand the general discourse and contextual meanings of the themes. The matching uses the original 30-topics model topic proportions. Hence, the themes proportions differ from the 7-topic model proportions as derived from LDA (see Table 5). As a result, 'Awareness' becomes the most prominent theme in Twitter MH discourse (14.7%). The discourse within 'Awareness' theme on Twitter goes beyond social media itself (only 1.9% of 14.7%) and also focuses on creating community and organising events, research and education, anti-stigma awareness, MH campaigning (i.e. World MH day, MH month) and even awareness with regards to MH at a workplace. Additionally, within the 'Awareness' theme, 1.9% out of 14.7% is dedicated to fundraising. The second most prominent theme in Twitter MH discourse is the theme labelled 'Feelings and Problematisation' (further referred to as 'F&P'), representing 10.8% of the discourse. This theme problematizes MH ('issue', 'problem', 'bad', 'shit'), expresses feelings ('feel', 'lol') and speaks about MH in context of everyday life ('day', 'today', 'work', 'life', 'time', 'things').

[33] The meanings behind these themes will be explained in greater detail below.

‘F&P’ theme is followed by the ‘Classification’ theme (10.4% of the discourse). The ‘Classification’ theme was labelled as such, because it speaks about distinctive disorders, similar to DSM-5 mental illness categories. The ‘Classification’ theme refers to disorders such as Anxiety, Depression, Bipolar Personality Disorder (BPD), Post Traumatic Stress Disorder (PTSD). It also speaks about physical symptoms (stress, sleep disorders) and MH-illness related maladies such as substance abuse or risk of suicide. Additionally, ‘Classification’ theme also frames certain disorders. For instance, PTSD is often referred to in a context of gender (male) and occupation (military trauma and veterans) and is linked to substance abuse and suicide. ADHD and autism is mainly spoken about in relation to children. It can also be said that with regards to diagnostic categories Twitter MH discourse is more detailed than traditional media discourse. It differs from the traditional media discourse in a way that it barely discussed schizophrenia (18% of traditional media discourse (Paterson, 2007), whereas Twitter MH topic modelling output did not even identify ‘Schizophrenia’ as a keyword). Additionally, ‘Classification’ theme features positively oriented topics of healthy lifestyle, self-care and well-being.

On the other hand, it is worthwhile to note that the disorder categories discussed in ‘Classification’ theme are rather general. In other words, it mainly focuses on ‘culture-bound syndromes’ (i.e. depression, often followed by a hashtag #depression, stress) and popularized mental health disorders (i.e. anxiety, depression, ADHD, Autism, bipolar) (Dowrick, 2013; Timimi, 2014). These disorders are often seen as controversial and the classification of such within DSM-5 (American Psychiatric Association, 2013) is commonly debated due to the fact that these type of mental health disorders are characterized by vague diagnostic procedures and have “no sound evidence for a discrete pathophysiological basis” (Dowrick, 2013, p.229; Cohen, 2016). Furthermore, physiological disorders such as eating disorders, sleeping disorders or learning disabilities are frequently used within the discourse, which reflects Rose et al. (2007) stigma-inducing association of physical illness with mental disability. With regards to non-popularized mental health disorders (i.e. neurocognitive diseases such as Alzheimer’s and Parkinson disease) there was virtually no discourse discovered during the analysis of Twitter data. As such, it could be assumed that these disorders are rarely popularly contextualized in relation to mental health.

Finally, the contextual theme of ‘Stigma’ emerged from topic modelling. The ‘Stigma’ theme, comparable to previous literature on MH discourse on media (Thornicroft, 2013; Whitley & Berry, 2013; Whitley & Wang, 2017) and revolved around risk, danger and violence (topics of ‘Guns and Shooting’ and ‘Death and Murder’) and the connection of mental illness to madness and insanity as portrayed by its contextual use within ‘Donald Trump’ topic. The contextual theme of 'Stigma', however, only represented 3.2% of the discourse which is, again, much lower in comparison to traditional media discourse.

It is worthwhile to note that the only stigma-related words related to mental health, as can be seen from the topic modelling output, were the words 'violence', 'murder' and 'abuse'. The majority of stigma-related words associated with mental health (i.e. 'criminal*', 'schizophren*', 'mad' (Whitley & Berry, 2017; Rose et al., 2007)) did not appear, indicating that the stigma-related vocabulary in relation to MH on Twitter is more of exception than a rule. This corresponds with the finding that only 0.3% of the discourse has been associated with stigma-related vocabulary (Appendix 1). By looking at the tweets of the 'Stigma' theme, it can also be said that, unlike other themes, the 'Stigma' theme can be characterised by sensationalism and fluidity (i.e. not a continuous discourse, but stories of a similar theme replacing each other overtime). Oftentimes these type of tweets come from actual media outlets such as news channels and press, but also (which is rather surprising) from MH advocacy organisations. Few examples are provided below:

Consequently, Twitter MH discourse can be characterised by its high focus on building awareness, problematizing mental health and a more diversified discussion of MH disorders categories (even if the majority of such categories can be seen as popularised). Stigma-related discourse, at least contextually, features on social media to a lower extent and is driven by sensationalism. Additionally, as compared to the traditional media discourse, Twitter MH discourse explores societal issues associated with MH more closely as exemplified by the themes 'Funding' (5.6%), 'Service' (2%) and 'Youth' (1.9%) which problematize MH budgets, funding, policy and accessibility, the cons of MH (psychiatric) professions, and MH of children, youth and parents respectively.

Table 5 *MH discourse themes categorisation (N=695,414, T=7)*

THEME	SUB-THEME	AVERAGE TOPIC PROPORTIONS	LABEL	KEYWORDS
AWARENESS [14.7%]	*AWARENESS GENERAL [12.8%*	3.0%	COMMUNITY, AWARENESS, EVENT	*#mentalhealth awareness day week support today #bellletstalk stigma talk world issues people tweet great work #mhaw month raise charity join*
		2.9%	EDUCATION, RESEARCH, SCHOOLING	
		2.5%	ANTI-STIGMA AWARENESS	
		1.9%	SOCIAL MEDIA, SHARING	
		1.1%	MH AWARENESS MONTH, CAMPAIGNING	
		0.6%	WORLD MH DAY	
		0.8%	WORK AND MH	
	CHARITY [1.9%]	1.1%	CHARITY, HELPING	
		0.7%	DONATE	
FEELINGS AND PROBLEMATISATION [10.8%]		5.4%	PROBLEMATIZATION	*day issues people good #mentalhealth important time life care work make feel bad talk physical today days problems things world love back issue taking school depression break lot week shit*
		3.0%	FEELINGS	
		2.4%	EVERYDAY LIFE	
CLASSIFICATION [10.4%]	*CLASSIFICATION [6.8%]*	2.1%	DEPRESSION, ANXIETY, BPD, PTSD (#)	*#mentalhealth #depression #anxiety #health #mentalillness #psychology #mhsm disorder depression #bipolar #ptsd anxiety #mental #mindfulness #wellness #recovery #stress life #wellbeing #parenting #suicide #mentalhealthawareness blog #stigma #addiction post #mentalhealthmatters read illness #therapy*
		1.8%	SUBSTANCE ABUSE	
		1.5%	STRESS AND PHYSICAL SYMPTOMS	
		0.9%	MEN, VETERANS, PTSD, SUICIDE, MILITARY	
		0.5%	AUTISM, ADHD, CHILDREN	
	WELLNESS [3.6%]	1.9%	HEALTHY LIFESTYLE, PHYSICAL EXERCISE	
		1.7%	WELLBEING AND MINDFULNESS, SELFCARE, LOVE	
FUNDING [5.6%]		1.7%	FUNDING CUTS, CRISIS	*care services #mentalhealth crisis support funding cuts treatment system news people nhs patients access service report act community children lives state risk police budget veterans call issues million put plan*
		1.2%	ENGLAND, NHS SYSTEM, CRISIS	
		0.5%	POLICE TRAINING, PRISONS	
		2.1%	ACCESSIBILITY OF MH CARE	
STIGMA [3.2%]		1.4%	GUNS AND VIOLENCE	*gun issues trumps trump guns people issue control problem checks violence care problems facility history laws police law man ban news jones treatment mentally ill president test bill shootings woman*
		1.0%	DEATH AND MURDER	
		0.9%	DONALD TRUMP	
SERVICE [2.0%]		1.3%	NURSING JOBS, WORKING AT A HOSPITAL	*nurse #jobs #health #job #mental worker job services psychiatric center hospital care jobs therapist practitioner registered counselor nursing community social*
		0.7%	PSYCHIATRIC PROFESSIONS, PSYCHIATRIC NURSING	
YOUTH [1.9%]		0.5%	PARENTING	*issues problems people depression physical children study disorders #mhsm social work stress young risk care treatment anxiety illness research improve benefits disorder #health women impact linked kids life abuse teens*
		1.5%	YOUNG PEOPLE, LEARNING DISABILITY	

To conclude the thematic analysis, the topic modelling shows that there is a more nuanced discussion on mental health than previously discussed in the literature. When previous academic attempts to analyse MH discourse were mainly focused on the aspect of stigma (Pirkis & Francis, 2012), it can be seen from this analysis, that the issue of stigmatization of mental health in online media and, particularly, on Twitter, has lower prominence than other themes. Additionally, the quantitatively analysed labels differ from the qualitatively derived categories proposed by Paterson

(2007) (i.e. foreign, legal, drug, feature, trauma, tragedy, 'community, care, tragedy', social policy, inquiry report, and sports/celebrity stories), which can be either be a result of different type of media analysis or, in fact, the LDA technique might be a more refined method for categorizing themes in discourse.

Discursive trends and comparative analysis

Together, the themes of 'Stigma' (contextual) and, 'Feelings and Problematisation' and 'Service'[34] (quantitative, based on the levels of stigma-related vocabularies[35]) have been assigned to stigma-related discourse[36]. In sentiment analysis and afterwards as a part of regression analysis, stigma-related discourse is compared to stigma-neutral discourse.

Looking at the trends of thematic prominence (Figure 3 and 4) [37], we can note that stigma-related discourse grew, whereas stigma-neutral discourse stagnated. This can be considered contradictory to the traditional media trends described by Whitley and Wang (2015) which indicated that stigmatizing articles were decreasing in prominence. It is worth to mention that stigma-related discourse growth resulted from the growth of 'Stigma' and 'F&P' themes (Figure 4). On a bright side, 'Awareness' theme, although not related to stigma, has also experienced a slight increase in retrievability. The themes which discuss MH in a more nuanced way and relate to discussion of MH categories ('Classification') and societal concerns ('Service', 'Funding', 'Youth') plummeted[38].

[34] It is interesting to note that the theme of 'Service' displayed above average stigma-related vocabularies which points at a potential problem of MH-related professions being stigmatised in social media online.

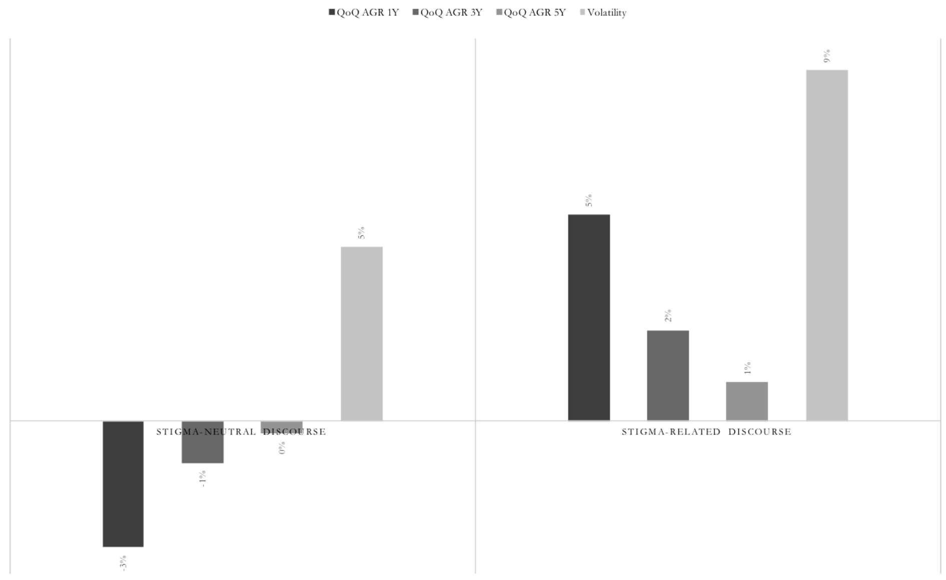
[35] An average tweet within these themes displays >0.3% of stigma-related vocabularies (Appendices 5, 7), which is an average for general MH discourse (see Appendix 1).

[36] See 'Data and Methods' section (p. 17, para 1) for a more detailed procedure.

[37] Calculated based on the document proportions as compared to other themes/topics, thus should be interpreted as relative to other topics/themes, whichever unit is concerned. The percentage change of document proportions per theme/topic is calculated per period, the results are then summed at 1,3 and 5 Years to derive the Average growth rates. I argue that the average growth rate is a better alternative as trend analysis as it accounts for fluctuations in attention.

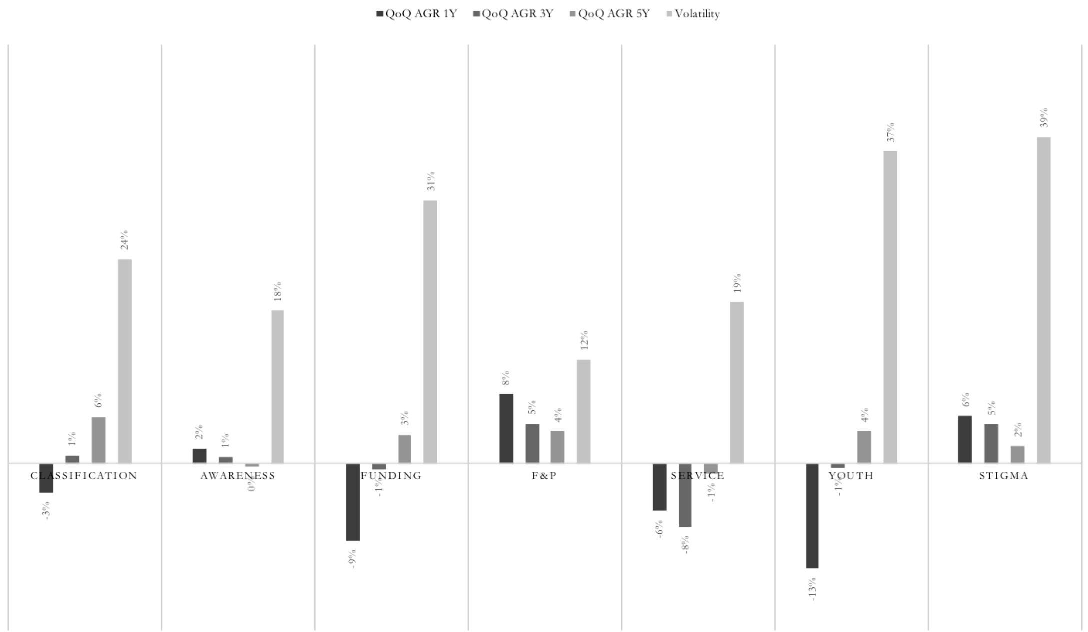
[38] For topical trends consult Appendix 8.

Figure 3: *MH discourse Trends [Stigmatisation categories]*



QoQ - quarter on quarter; AGR - average growth rate

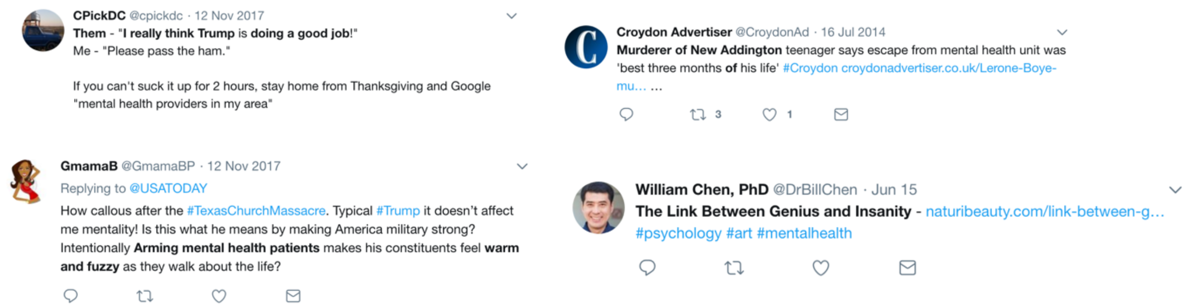
Figure 4: *MH discourse Trends [Themes]*



QoQ - quarter on quarter; AGR - average growth rate

Assessing the differences in the discourse characteristics between stigma-related and stigma-neutral discourse (independent sample t-test, see Table 6), it shows that stigma-related discourse is on average more retrievable (p<0.001). Stigma-related discourse also displays higher levels of emotional intensity[39] (p<0.001) and higher levels of negativity (p<0.001). However, paradoxically, stigma-related discourse has significantly higher levels of positive emotions (p<0.001), which makes stigma-related discourse sentiment higher than that of stigma-neutral, even though not significantly.

Considering that the themes of 'Stigma' and 'F&P' grew, this contradictory finding, in fact, could align with Whitley and Wangs (2015) results indicating that articles with a positive tone have gained more attention in recent years. Upon closer investigation, filtering tweets which display positive emotions within stigma-related discourse, a number of examples emerged which indicated that positivity of stigma-related MH discourse could emerge from sarcasm, which is probably not the case in traditional media[40]. Below, examples are provided.



While mean level of solidarity projected by stigma-neutral discourse was higher, it did not differ significantly as compared to the levels of solidarity in stigma-related discourse. Confidence, engagement (replies), and other measures of emotional energy did not significantly differ between stigma-neutral and stigma-related discourse either. As such, the significantly higher levels of emotional energy displayed by stigma-related discourse (p<0.01) would probably stem from the intensity of the discourse.

With respect to bandwagon behaviour, stigma-related discourse is associated with significantly higher levels of bandwagon behaviour than the discourse which is stigma-neutral. Since higher bandwagon for stigma-related discourse neither relates to higher favourites per tweet nor duplication rate as compared to the discourse which is stigma-neutral, this effect must be

[39] To review the levels of discourse characteristics per themes and topics, please refer to Appendix 9.
[40] Journalistic codes of conduct include 'Truth and Accuracy' (ASNE, 2015), which can be compromised and misunderstood when sarcasm or satire is used.

synergetic. The mean of cognitive focus for stigma-related discourse is also higher (not-significantly), possibly due to significantly higher resolution in stigma-related discourse (*p*<0.001).

Lastly, tweets belonging to stigma-related discourse use significantly less hashtags (*p*<0.001) and mentions (*p*<0.001), and are initiated by users with significantly lower social capital (*p*<0.001). Moreover, stigma-related discourse is tending towards higher polarisation (higher echo-chamber) at 99% confidence level.

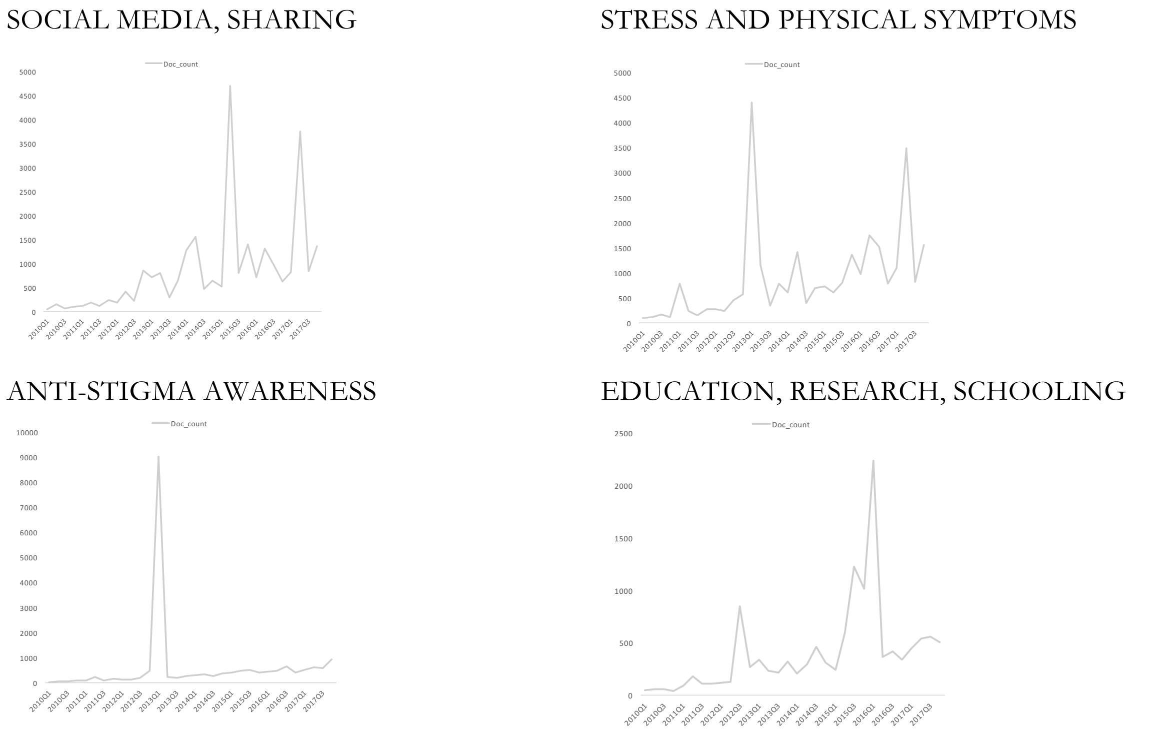
Table 6: *Descriptive Statistics [Stigma] with t-test (N=1320)*

	Stigma-Related Discourse (N=352)		*Stigma-Neutral Discourse (N=968)*		*All MH Discourse (N=1320)*		
Variable	*Mean*	*StDev*	*Mean*	*StDev*	*Mean*	*StDev*	*Sig.*
Twitter Characteristics							
Retrievability	1,061	1,153	741	892	826	978	***
Replies per tweet	0.11	0.12	0.12	0.13	0.13	0.34	
Favourites per tweet	1.12	6.80	0.86	2.75	0.93	4.22	
Duplication rate	1.06	0.31	1.07	0.41	1.07	0.39	
Tweets per user	1.09	0.33	1.09	0.44	1.09	0.41	
User social capital	5,315	3,535	12,060	13,049	10,261	11,707	***
Hashtags per tweet	0.17	0.20	0.35	0.62	0.30	0.55	***
Mentions per tweet	0.16	0.27	0.25	0.47	0.23	0.43	***
Echo chamber	- 0.16	0.43	- 0.23	0.36	- 0.21	0.38	**
Sentiment Characteristics							
-positive	2.86	1.62	2.24	1.70	2.41	1.70	***
-negative	1.93	1.47	1.35	1.34	1.51	1.39	***
Sentiment	0.93	2.10	0.89	2.15	0.90	2.14	
Intensity	4.43	2.06	3.40	2.03	3.67	2.09	***
Confidence	57.40	17.80	57.14	19.65	57.21	19.17	
Solidarity	0.38	0.30	0.40	0.44	0.40	0.42	
Discourse Characteristics							
-Intra Focus	2.57	0.83	2.63	0.93	2.61	0.90	
Resolution	4.57	2.79	3.97	2.60	4.13	2.67	***
Resonance Mechanisms							
Emotional Energy	3.48	1.32	3.20	1.37	3.28	1.36	**
Bandwagon	4.09	1.57	3.61	1.77	3.74	1.73	***
Cognitive Focus	3.94	1.14	3.88	1.15	3.89	1.15	

p<0.05;p<0.01;***p<0.001 (two-sided tests)*

Looking at retrievability trends overtime, the following 3 topics from the 'Awareness' theme were identified as having relatively short-lived attention spikes: 'Social Media and Sharing', 'Anti-stigma awareness' and 'Education, Research, Schooling', and one topic from the 'Classification' theme - 'Stress and Physical symptoms' (see Figure 5).

Figure 5: *Topics with short-lived retrievability pattern*



When we look at these topics with short-lived attention (Table 7), what stands out is that these topics are of significantly lower emotional energy (p<0.05) and bandwagon behaviour (p<0.001) than topics with continuous attention patterns, but higher cognitive focus (p<0.05). The short-lived attention topics also display less negative vocabulary (p<0.01) and more solidarity (p<0.001). Perhaps the combination of being less intense and less confident (both non-significant) could explain lower emotional energy. Again, significantly lower levels of bandwagon effect must be synergetic. Discourse characterised by hype, moreover is initiated by users with significantly less social capital (lower rhetorical force, p<0.001) and significantly higher use of hashtags and mentions (p<0.001).

Table 7: *Descriptive Statistics [Retrievability Patterns] with t-test (N=1320)*

	Short-lived attention (N=176)		*Stable attention pattern (N=1114)*		*All MH Discourse (N=1320)*		
Variable	*Mean*	*StDev*	*Mean*	*StDev*	*Mean*	*StDev*	*Sig.*
Twitter Characteristics							
Retrievability	503	953	876	973	826	978	***
Replies per tweet	0.12	0.16	0.12	0.12	0.13	0.34	
Favourites per tweet	1.02	3.00	0.91	4.39	0.93	4.22	
Duplication rate	1.11	0.61	1.06	0.34	1.07	0.39	
Tweets per user	1.04	0.43	1.06	0.41	1.09	0.41	
User social capital	7,706	1,560	10,655	12,516	10,261	11,707	***
Hashtags per tweet	0.88	0.82	0.21	0.43	0.30	0.55	***
Mentions per tweet	0.68	0.60	0.16	0.34	0.23	0.43	***
Echo chamber	- 0.22	0.31	- 0.21	0.39	- 0.21	0.38	
Sentiment Characteristics							
-positive	2.42	1.86	2.40	1.68	2.41	1.70	
-negative	1.25	1.32	1.55	1.40	1.51	1.39	**
Sentiment	1.17	2.28	0.86	2.11	0.90	2.14	
Intensity	3.47	2.13	3.70	2.08	3.67	2.09	
Confidence	55.23	21.55	57.52	18.77	57.21	19.17	
Solidarity	0.54	0.49	0.37	0.38	0.40	0.42	***
Discourse Characteristics							
-Intra Focus	2.86	1.12	2.57	0.86	2.61	0.90	***
Resolution	5.10	2.95	3.98	2.59	4.13	2.67	***
Resonance Mechanisms							
Emotional Energy	3.04	1.38	3.32	1.35	3.28	1.36	*
Bandwagon	2.60	1.83	3.91	1.65	3.74	1.73	***
Cognitive Focus	4.10	1.17	3.86	1.14	3.89	1.15	*

$*p<0.05$;$**p<0.01$;$***p<0.001$ (two-sided tests)

REGRESSION ANALYSIS

The Fixed Effect panel regression model was run for 30 topics for 10 years, quarterly (1320 observations) to assess which resonance mechanisms affect the retrievability of the discourse. For Model 1 (Table 8), the Fixed Effect regression results explained 41.9% of variance in discursive retrievability, which is statistically significant [$F_{(6,1254)}=150.56$, $p < 0.001$]. The results indicate that we can reject the H_0 for H1 (*emotional energy in a previous period has a significant positive effect on the retrievability of a discursive frame in current period)* since topics with high EE are persistently driving the discourse ($p < 0.001$), mostly by engagement ($p<0.001$) and to a lesser extent by high confidence and solidarity ($p<0.01$). H_0 for H2 shall be accepted as the *bandwagon behaviour does <u>not</u> have significant negative influence on the retrievability of discourse* ($p >0.05$). However, we can observe that duplicates within the discourse have a significant negative effect on discursive retrievability, with levels of significance increasing with time ($p_{lag2,3}<0.05$, $p_{lag4}<0.001$). Interestingly, although not significant, the sign of bandwagon effect indicates negative, rather than positive effect of the bandwagon behaviour on the discourse.

Cognitive focus has a significant <u>negative</u> effect on the discourse retrievability (p<0.05), as such we accept the H_0 for H_3 since *cognitive focus in a previous period has <u>no</u> significant <u>positive</u> effect on the retrievability of a discursive frame in current period.* However, it is only applicable within a short timeframe (lag1). Negative effect of cognitive focus on the discourse comes from the significant negative effect on the discourse by intra-topic focus (p<0.001). In other words, tweets that can feature more topics/are more thematically diverse, drive more attention. On the other hand, inter-topic focus has a significant positive affect on the discourse (p<0.001). This means that when the discourse in general is concentrated on fewer topics, it lowers discursive competition and drives the retrievability up. Resolution, while appearing to have a negative effect on the discourse (β=-4.42), does not have a significant influence (p>0.05).

Looking at controls, using hashtags to thematically tag the discourse has a significant positive effect on the continuation of this discourse (p<0.01). It is also worthwhile to note that with time, *ceteris paribus*, explained variance of Model 2 is increasing. This can mean that the mechanisms affecting the discourse work long term.

Table 8: *Model summaries of Fixed Effect Panel Regression assessing the mechanisms of retrievebility of MH discourse (N=1290)*

	Model 1				Model 2			
	Lag1 B (SE)	*Lag2* B (SE)	*Lag3* B (SE)	*Lag4* B (SE)	*Lag1* B (SE)	*Lag2* B (SE)	*Lag3* B (SE)	*Lag4* B (SE)
Emotional Energy	388.603 (73.57)***	355.939 (65.87)***	302 (68.84)***	367.814 (66.12)***				
replies					1.83 (0.47)***	1.805 (0.54)***	2.623 (0.33)***	2.966 (0.38)***
intensity					-0.243 (7.72)	-12.64 (9.26)	-4.027 (10.58)	1.505 (6.76)
confidence					8.059 (2.64)**	8.503 (2.49)***	6.122 (1.51)***	6.265 (1.58)***
solidarity					219.711 (76.33)**	226.792 (62.38)***	86.398 (83.41)	202.212 (62.73)**
Bandwagon Behaviour	3.838 (52.41)	-18.33 (48.76)	-5.156 (42.33)	-45.892 (43.57)				
favourites					-0.005 (0)	-0.004 (0)	-0.001 (0)	0.031 (0.03)
duplication rate					-125.195 (82.56)	-207.98 (81.01)*	-157.213 (63.09)*	-123.34 (36.94)***
Cognitive Focus	-56.157 (27.42)*	22.857 (31.78)	52.864 (36.66)	42.654 (28.85)				
Inter_focus					82.724 (10.07)***	123.334 (12.31)***	102.329 (9.36)***	84.415 (5.57)***
intra_focus					-141.644 (34.05)***	-154.381 (29.07)***	-102.05 (25.66)***	-92.87 (24.75)***
Resolution					-4.415 (8.47)	-12.417 (8.14)	-4.974 (6.04)	-7.93 (5.25)
Controls								
Echo chamber	9.845 (69.2)	63.081 (72.3)	25.84 (71.79)	69.484 (68.07)	33.661 (44.19)	75.309 (51.38)	26.87 (48.59)	50.504 (42.68)
Hashtags	0.571 (0.19)**	0.626 (0.2)**	0.602 (0.24)*	0.41 (0.28)	0.414 (0.15)**	0.429 (0.15)**	0.472 (0.14)***	0.218 (0.16)
Mentions	0.081 (0.46)	-0.051 (0.49)	0.216 (0.56)	0.379 (0.65)	-0.066 (0.26)	-0.234 (0.24)	-0.279 (0.2)	-0.136 (0.24)
N	1290	1260	1230	1200	1290	1260	1230	1200
df	6/1254	6/1224	6/1194	6/1164	12/1248	12/1218	12/1188	12/1158
R^2	41.87%	39.82%	39.01%	38.29%	59.00%	58.68%	63.24%	64.24%
F-test	150.56***	134.98***	127.69***	120.35***	181.07***	144.168***	170.33***	173.32***

*^p<0.1;*p<0.05;**p<0.01;***p<0.001 (two-sided tests)*

Secondly, we looked at the potential differences in stigma-related, stigma-neutral and short-lived attention discursive mechanisms (Table 9). Interestingly, the mechanisms driving stigma-related and stigma-neutral discourse are very similar to the mechanisms which drive MH discourse in general and in between themselves. For instance, emotional energy has a significant positive effect on both stigma-related and stigma neutral discourse, while bandwagon behaviour has no significant effect on the retrievability of either of the discursive themes. Cognitive focus, once again, did not exhibit a significant effect on either stigma-related nor stigma-neutral discursive retrievability.

Some differences can still be noted. Although the sign of the effect is not surprising, as it mimics the general discourse, high level of emotional arousal and high levels of a bandwagon-related, low investment online currency of 'Favourites' seem to affect the discourse related to stigma negatively. Additionally, at a 90% confidence level we can observe that stigma-neutral discourse is positively affected by echo-chambers (recall, that stigma-neutral discourse had significantly lower presence of echo chamber), while stigma-related discourse is negatively affected by resolution.

What is, however, more peculiar is that discourse characterised by short lived attention works by a different logic. Firstly, we find (with caution, at 90% of confidence level only) that *for discursive frames characterised by short-lived attention bandwagon behaviour in a previous period has a significant negative effect on the retrievability of a discursive frame in current period.* Additionally, high emotional intensity (p<0.001) and duplication rate (p<0.05) can be considered the main drivers of the more volatile discursive themes. Nevertheless, a given model only explains 20% of variance in what drives the short-lived attention up, meaning that the themes characterised by short-lived attention cannot be assessed in a similar fashion as the rest of the themes and are probably driven by other unobserved exogenous factors.

Table 9: *Model summaries of Fixed Effect Panel Regression assessing the mechanisms of retrievability of MH discourse [thematic] (N=1290)*

	Stigma-related *B (SE)*	*Stigma-neutral* *B (SE)*	*Short-lived attention* *B (SE)*	*Stigma-related* *B (SE)*	*Stigma-neutral* *B (SE)*	*Short-lived attention* *B (SE)*
Emotional Energy				296.959 (117.91)*	343.635 (73.41)***	170.351 (55.46)**
replies	2.253 (0.16)***	1.989 (0.37)***	0.153 (0.52)			
intensity	-47.805 (19.53)*	6.63 (8.89)	35.71 (6.65)***			
confidence	9.632 (3.58)**	7.654 (2.65)**	-4.346 (2.5)^			
solidarity	563.429 (109.68)***	181.94 (81.18)*	403.808 (170.56)*			
Bandwagon Behaviour				42.105 (104.16)	12.568 (52.98)	-152.092 (78.91)^
favourites	-0.003 (0)*	-0.039 (0.03)	-0.012 (0.02)			
duplication rate	-65.01 (161.26)	-111.391 (85.05)	89.815 (36.28)*			
Cognitive Focus				-87.057 (71.33)	-45.375 (27.86)	19.739 (30.77)
Inter_focus	85.539 (15.65)***	74.809 (10.64)***	-19.322 (37.84)			
intra_focus	-157.912 (47.8)**	-132.324 (35.66)***	44.136 (46.7)			
Resolution	-20.788 (11.55)^	-3.046 (10.54)	5.112 (16.7)			
Controls						
Echo chamber	-83.839 (98.67)	67.988 (35.65)^	-107.204 (133.24)	-496.64 (174.85)**	97.197 (57.81)^	-76.395 (78.75)
Hashtags	1.122 (0.58)^	0.531 (0.15)***	1.027 (0.53)^	3.853 (0.6)***	0.641 (0.18)***	1.12 (0.57)*
Mentions	-0.524 (0.47)	-0.358 (0.31)	-0.442 (1.03)	-0.893 (0.56)	-0.436 (0.39)	-0.405 (1)
N	352	968	176	352	968	176
df	12/324	12/912	12/156	6/332	6/920	6/164
R^2	82.40%	50.52%	20.00%	56.62%	45.88%	11.17%
F-test	135.38***	77.60***	3.24***	108.37***	206.52***	5.16***

*^p<0.1;*p<0.05;**p<0.01;***p<0.001 (two-sided tests)*

With regards to emotional energy we mainly looked at the intensity of emotions in a tweet (both positive and negative). The literature suggests that sentiment (the sign of emotion) might also matter (Whitley & Berry, 2015; Whitley & Wang, 2017; Thornicroft, 2013). As such, we tested if sentiment levels could affect the MH discourse as well (Table 10). Although not significant (possibly due to low levels of the sentiment) it is interesting to observe the sign of the potential sentiment effect, which indicates that positive sentiment would be more likely to increase the discourse. This can explain why stigma-related discourse has been growing (characterised by positive discourse) and contradicts the assumption that negative information drives the discourse, at least in relation to mental health.

Table 10: *Model summaries of Fixed Effect Panel Regression assessing the mechanisms of retrievability of MH discourse [sentiment] (N=1290)*

	Model 3 - sentiment (lag1) B (SE)	*Stigma-related* B (SE)	*Stigma-neutral* B (SE)	*Short-lived attention* B (SE)
Emotional Energy				
replies	1.831 (0.46)***	2.252 (0.16)***	1.989 (0.37)***	0.1 (0.52)
intensity	-1.271 (7.99)	-48.965 (20.42)*	5.396 (8.8)	54.221 (19.17)**
sentiment	5.498 (6.43)	8.378 (19.09)	6.071 (7.01)	-40.051 (22.56)^
confidence	8 (2.6)**	9.503 (3.48)**	7.594 (2.62)**	-3.672 (2.56)
solidarity	217.824 (75.23)**	556.036 (110.71)***	180.289 (80.29)*	392.901 (161.68)*
Bandwagon Behaviour				
favourites	-0.005 (0)	-0.003 (0)*	-0.039 (0.03)	-0.01 (0.02)
duplication rate	-119.031 (80.18)	-53.131 (172.71)	-104.742 (82.53)	53.818 (34.38)
Cognitive Focus				
Inter_focus	82.402 (9.89)***	85.281 (16.24)***	74.37 (10.28)***	-21.09 (40.57)
intra_focus	-142.36 (34.52)***	-159.63 (49.28)**	-132.958 (36.06)***	46.452 (49.54)
Resolution	-4.546 (8.55)	-20.922 (11.48)^	-3.205 (10.7)	5.236 (14.95)
Controls				
Echo chamber	33.918 (44.06)	-79.949 (94.45)	67.436 (35.6)^	-78.498 (112.54)
Hashtags	0.415 (0.15)**	1.131 (0.6)^	0.532 (0.15)***	0.971 (0.49)^
Mentions	-0.069 (0.26)	-0.527 (0.48)	-0.363 (0.31)	-0.361 (0.99)
N	1290	352	968	176
df	13/1247	13/323	13/911	13/155
R^2	59.01%	83.38%	50.54%	23.47%
F-test	138.09***	124.65***	71.59***	3.07***

*^p<0.1;*p<0.05;**p<0.01;***p<0.001 (two-sided tests)*

Finally, we controlled for institutional retention (Table 11) by selecting a number of topics[41] for which it is possible to approximate the general online attention trend. Regressing the retrievability of the discourse by the EE, BW, CF and institutional retention, it can be seen that EE is still the predominant driver of the discourse and institutional retention does not have a causal effect on the retrievability of the discourse on social media.[42]

[41] Donald Trump; Guns and Violence; Stress; ADHD; Substance Abuse; Anti-stigma awareness; Veterans/PTSD.
[42] Considering graphical representation, however, indicates that some topics attention closely correlates with general online discourse (i.e. 'Guns/Violence', 'Veterans/PTSD' – see Appendix 11 to review the graphs)

Table 11: *Model summaries of Fixed Effect Panel Regression assessing the mechanisms of retrievability of MH discourse [Institutional Retention] (N=307)*

	Institutional Retention (Model 1) *B (SE)*	*stitutional Retention (Model 2)* *B (SE)*
Emotional Energy	407.661 (110.15)***	
replies		0.629 (0.68)
intensity		-7.911 (13.53)
confidence		7.659 (4.01)^
solidarity		391.808 (178.64)*
Bandwagon Behaviour	-221.133 (90.32)*	
favourites		0 (0)
duplication rate		-621.028 (258.72)*
Cognitive Focus	-43.51 (135.14)	
Inter_focus		49.481 (132.96)
intra_focus		-3.674 (29.18)
Resolution		78.69 (39.26)*
Controls		
Echo chamber	-43.51 (135.14)	-63.58 (119.61)
Hashtags	0.997 (0.69)	0.612 (0.59)
Mentions	-0.011 (0.74)	0.491 (0.66)
Institutional Retention	-5.484 (7.87)	-7.046 (12.7)
df	7/293	13/288
R^2	29.84%	29.27%
F-test	17.79***	9.93***

*^p<0.1;*p<0.05;**p<0.01;***p<0.001 (two-sided tests)*

Discussion

THEMATIC OBSERVATIONS

The results of the thematic analysis of online MH discourse show that, while the discourse is growing in both absolute and relative to total Twitter discourse terms, it can be characterized as being timid, of low emotional intensity, high anxiety, but also high solidarity. Although over the years the discourse became characterised by more confident, more personal and more emotionally charged tweets, especially with regards to positive emotions, the general discourse is still heavily tilted towards negative sentiment, problematising mental health, whereas positive sentiment often masks sarcasm.

Compared to MH discourse in traditional media, firstly, online discourse is more diverse, as it includes such themes as 'Youth' and 'Service' and such topics as 'Workplace', 'Parenting' and other important topics rarely discussed in traditional media due to stigma ('Veterans, PTSD' or 'Substance Abuse'). As a part of this discursive diversity, MH discourse on Twitter also addresses a larger range of mental disorders and associated problems. That said, Twitter discourse is still mostly comprised of more general, often popularised MH categories (i.e. Depression and Anxiety) which only make up a limited proportion of MH disorders as compared to DSM-V. For instance, schizophrenia, or neurocognitive diseases such as Alzheimer's or Parkinson's are rarely mentioned in the context of online MH discourse. Unlike Alzheimer or Parkinson, which could benefit from increased attention, the absence of schizophrenia from MH discourse on Twitter can indicate lowering of stigma in relation to this particular disease, as it often used in stigmatized context (represents 18% of the discourse in traditional media).

Secondly, in online social media discourse the issue of stigma is less pronounced. On the contrary, online MH discourse is more oriented towards creating awareness about mental health, talking about feelings and encouraging conversation. However, these findings should be taken with caution, because even while stigma-related discourse on Twitter is low, relative to stigma-neutral discourse it is more retrievable and growing.

MENTAL HEALTH DISCOURSE AND CULTURAL POWER

With regards to cultural power mechanisms, bandwagon behaviour can be considered futile, only negatively affecting the themes characterised by short-lived attention. Only tweet duplicates affect the discourse negatively. Perhaps filtered out through Twitter algorithms (Gillespie, 2014), either as an ecological density problem (Van Venrooij, 2015) duplicate tweets dilute the discourse, leaving the audiences uninterested in reading copy-past tweets and, hence, losing interest in a discursive frame.

Emotional energy, on the other hand, can be seen as a driving force behind increased discourse. Emotional energy increases the discourse by engagement ('Replies') and featuring tweets which display higher levels of solidarity and confidence. The emotional intensity of the discourse, or arousal, usually contributes to increased levels of attention for topics for which the attention is short-lived. For stigma-related discourse high emotional intensity of discourse has a significant negative effect. Therefore, it can be said that high emotionality relates to short-termism, whereas emotional neutrality can make the discourse more sustainable.

As for the cognitive focus, the evidence of its effect on discursive retrievability is conflicting. On a macro level, lower number of topics discussed within the general MH discourse (inter-topic), which is in accordance with the theory of cultural carrying capacity as theorised by Bail (2016). On a micro level, however, higher discursive variability (intra-topic) within a tweet can be considered more cognitively engaging, driving the retrievability up. It seems that the global nature of online social networks, which entails high geographical and cultural diversity will require discourse which encompasses a broader range of themes within a single tweet. Hence, it is the tweets which speaks to worldviews of larger audiences (Benford, 1997; Collins, 2001) which contribute to the cultural power of a discursive frame. To second that, when the content is too specific for the majority of the audience to engage with, greater levels of intra-topic focus could play a role in fast demise of a discursive frame as exemplified by the short-lived attention topics. Finally, resolution had a negative effect on retrievability[43], indicating that audiences might not like being told what to do or how to act.

What is more puzzling, however, is that while stigma-related discourse is growing, it does not seem to stand out by the same attributes which contribute to the retrievability. Displaying significantly higher than stigma-neutral topics bandwagon behaviour, emotional intensity and resolution is not what contributes to the growth of MH-stigmatising narrative. Some of the control variables, as well as the theory of cognitive-emotional currents (Bail et al., 2017) can lend a hand in understanding of this dilemma.

Firstly, looking at the control variables, stigma-related discourse had higher echo-chamber. More often than not the users active in creating and disseminating stigma-related topics engaged in a conversation within a closer community. Simultaneously, higher levels of echo-chamber affected the retrievability of stigma-neutral discourse positively. This could mean that a certain

[43] Note, only for stigma-related discourse at 90% confidence level, for other discursive frames resolution had the same sign but was not significant.

level of communal closeness is necessary to positively affect the retrievability of a discourse. Moreover, when institutional retention did not show to have an effect on the retrievability, the retrievability of some discursive frames on Twitter correlated with, rather than preceded, Google Trends[44], and themes with higher prominence (i.e. stigma-related) were initiated by users with significantly lower social capital, it is safe to assume that engagement of users with lower levels of social capital might be instrumental to ensure the continuity of the discourse. Finally, hashtags affected the discursive retrievability positively by helping the audiences to (1) better classify a tweet or assign it to a certain cognitive category, making it more (consciously or subconsciously) retrievable for a consequent action, and (2) make certain discursive frames more searchable.

Secondly, in combination with the findings that high emotional intensity drives up the attention of short-lived topics, the theory of cognitive-emotional currents (Bail et al., 2017) indicate that fast-rising emotions may reach a saturation point (Bail et al., 2017) and, if the content of the discourse is not strong enough to induce cognitive process, the retrievability of the topic will suffer. How the 'cognitive-emotional currents' work to maintain the discourse, can be exemplified by stigma-related discourse driven by sensationalism. Stigma-related MH discourse arises from many different emotional ever-changing dramatic news stories (i.e. a mass shooting perpetrated by a psychologically disturbed individual, a murder at a psychiatric hospital etc.), usually coming from traditional media outlets (i.e. news channels, press). As the stories in question are both emotional and constantly renewing, neither emotional nor cognitive content of a discursive frame is ever able to reach a peak. The discourse then rolls over resulting in an increased attention and sustainability.

LIMITATIONS AND AVENUES FOR FUTURE RESEARCH

This research is not without limitations. First, operationalizing emotional energy online we relied on easily available data of tweet texts, online attention (i.e. 'Replies') and sentiment characteristics. However, it would also be desirable to analyse the conversation threads and interaction rituals between users (i.e. how fast some Tweets elicit the replies, what is the speed of interaction etc.). Additionally, taking a longer timeframe we had to forgo some of the micro-elements of this research. Although our models have a significant predictive power, increasing with longer lags which shows that mechanisms of online attention work long-term, comparison of how these mechanisms work over a shorter timescale (i.e. on a day-to-day basis) is requered.

Methodologically, this research could benefit from cross-checking between different topic modelling algorithms. Future research could scrutinize the findings by running a Biterm Topic Model, a topic modelling technique specifically designed for short texts which helps to avoid data

[44] Assessed graphically, see Appendix 11.

sparsity in the documents of limited word count (Yan et al., 2013)[45]. Secondly, looking in depth at how topics develop and interact with each other can be implemented in future research by applying Dynamic Topic Models (Blei & Lafferty, 2006). Lastly, improving the search term optimisation to derive the corpus of tweets could further fine tune the research. The current research, however, is instrumental to derive these search terms.

Another limitation is the restriction of this research to the empirical topic of mental health and the single platform of Twitter. Future research can relate our findings to a different empirical reality to assess whether the mechanisms driving the retrievability differ across contexts. Furthermore, juxtaposing online to traditional media discourse in relation to mental health thematically and cross-cultural and different languages analyses could contribute to the mapping of media mental health discourse. Lastly, considering that online social media platforms are run by algorithms, the question might be whether we are really analysing the meaning making, contestation mechanisms which can evoke cultural power or do we just discover the mechanics of Twitter? In other words, can social media participants indeed influence discursive development or, in reality, does the discretion with regards to discourse remain under control of the online platforms?

[45] I only learned about BTM in later stages of this thesis which made it was not feasible to use.

Conclusion

This research is the first big-data-based attempt to map online mental health discourse. Using social movement theory and 'culture in action' perspective, it bridges the macro-and micro-levels by analysing how the online mechanisms of attention generation can affect cultural power, also comparing these mechanisms across subsets of the discourses (i.e. stigmatising vs stigma-neutral discourse). In short, the results show that emotional energy created by connectedness and inclusiveness, while cost-effective extrinsically motivated attention generating mechanisms and emotional intensification are ineffective.

Furthermore, this research potentially holds important societal implications. The discovery of factors which positively contribute to discourse can find use in MH advocacy and outreach by helping to guide the relevant parties when engaging via social media and, perhaps, conventional media. Considering the theory of cultural carrying capacity (Bail, 2016) and resource competition (Van Venrooij, 2015), actively engaging in stigma-reducing MH discourse and making it more personal and confident would drive the stigma-producing topics away. Engaging in discourse, even individually, will not be futile even for less influential users with little followers as we observed that prominent MH related discourse is really initiated from the bottom-up. Moreover, closer online communities and thematic dedication, as opposed to spreading ones attention, could also positively affect stigma-neutralising discourse, stemming from connectedness and solidarity.

Focusing on content, content diversification and keeping it up-to-date, could provide additional positive contribution to stimulating the discourse since emotions can reach saturation and only meaningful or novel topics can sustain attention. Although intensifying emotions can lead to discursive growth it does not translate to continuity. It is also advisable to use hashtags to classify the discourse as it helps the audiences to discover the themes which matter. Although providing resolution, or telling people how to act, might not be a good idea.

Importantly, policy work in relation to traditional media channels and their contributing to stigma-associated discourse through sensationalism should be considered, especially when traditional media channels are increasingly becoming a part of online social media discourse. The use of sarcasm with respect to mental health by prominent and engaged online users should be observed insomuch as detecting accounts (possibly bots) which use tweet-duplication technique to inflate stigmatising MH discourse.

On the whole, although Twitter MH discourse seems to be oriented towards stigma-neutral discourse, we should be cautious not to idealise this discourse as there can be danger of misinformation by uninformed parties providing inaccurate information, perpetuating myths and therefore having a negative influence on audiences.

References

Agosto, D. E., & Hughes-Hassell, S. (2005). People, places, and questions: An investigation of the everyday life information-seeking behaviours of urban young adults. *Library & information science research*, *27*(2), 141-163.

Allison, P. D. (2009). *Fixed effects regression models* (Vol. 160). SAGE publications.

Anderson, C. (2007). *The long tail: How endless choice is creating unlimited demand*. Random House.

Angermeyer, M. C., Dietrich, S., Pott, D., & Matschinger, H. (2005). Media consumption and desire for social distance towards people with schizophrenia. *European Psychiatry*, *20*(3), 246-250.

ASNE (2015). Statement of Principles. *The American Society of News Editors*. Retrieved from: https://www.asne.org/content.asp?pl=24&sl=171&contentid=171

Austin J.L. 1962: *How to do things with words*. University Press, Oxford.

Bail, C. A. (2012). The fringe effect: Civil society organizations and the evolution of media discourse about Islam since the September 11th attacks. *American Sociological Review*, *77*(6), 855-879.

Bail, C. A. (2016). Combining natural language processing and network analysis to examine how advocacy organizations stimulate conversation on social media. *Proceedings of the National Academy of Sciences*, *113*(42), 11823-11828.

Bail, C. A., Brown, T. W., & Mann, M. (2017). Channeling Hearts and Minds: Advocacy Organizations, Cognitive-Emotional Currents, and Public Conversation. *American Sociological Review*, *82*(6), 1188-1213.

Balani, S., De Choudhury, M. (2015) Detecting and characterizing mental health related self-disclosure in social media. In Begole, B., Kim, J., Inkpen, K., Woo, W. (Eds.) *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems, Seoul, CHI 2015 Extended Abstracts*; Republic of Korea. April 18 – 23, 2015; ACM; 2015. pp. 1373–1378.http://doi.acm.org/10.1145/2702613.2732733

Bakhtin, M. (1953). (English translation 1986). "The Problem of Speech Genres." Translated by Vern McGee. Pp. 60-102 in *Speech Genres and Other Late Essays*. Trans. By Vern McGee and ed. By Caryl Emerson and Michael Holquist. Austin: University of Texas Press.

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons.

Barthel, M., Shearer, E., Gottfried, J. & Mitchell, A. (2015). The evolving role of news on Twitter and Facebook. *Pew Research Centre*. Retrieved from: http://www.journalism.org/2015/07/14/the-evolving-role-of-news-on-twitter-and-facebook/

Barthes, R. (1999). *Mythologies*. New York, NY: Hill and Wang, pp. 109-130, 148-156. ('Myth today')

Bénabou, R., & Tirole, J. (2006). Incentives and prosocial behavior. *American economic review*, *96*(5), 1652-1678.

Benford, R., Snow, D., (2003). Framing processes and social movements: an overview and assessment. *Annual Review of Sociology, 26*: 611-639.

Berger, J. (2011). Arousal increases social transmission of information. Psychological science, 22(7), 891-893.

Berelson, B. (1952). Content analysis in communication research.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research*, *3*(Jan), 993-1022.

Blei, D. M., & Lafferty, J. D. (2006). Dynamic topic models. In *Proceedings of the 23rd international conference on Machine learning* (pp. 113-120). ACM.

Boone, C, C. H. Declerck, H. Rao, en C. Van den buys. (2012). Out of tune: The rise and fall of modernistic music in Brussels, 1919–1939. *Poetics 40:* 44–66.

Brienza, C., & Revers, M. (2016). The field of American media sociology: Origins, resurrection, and consolidation. *Sociology Compass, 10* (7), 539-552. http://onlinelibrary.wiley.com/doi/10.1111/soc4.12384/epdf

Brunsting, S., & Postmes, T. (2002). Social movement participation in the digital age: Predicting offline and online collective action. *Small group research*, *33*(5), 525-554.

Byrne, P. (2001). Psychiatric stigma. The British Journal of Psychiatry, 178(3), 281-284.

Carroll, W. K., & Hackett, R. A. (2006). Democratic media activism through the lens of social movement theory. *Media, culture & society*, *28*(1), 83-104.

Chisholm, D., Sweeny, K., Sheehan, P., Rasmussen, B., Smit, F., Cuijpers, P., & Saxena, S. (2016). Scaling-up treatment of depression and anxiety: a global return on investment analysis. *The Lancet Psychiatry*, *3*(5), 415-424.

Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. *Economic Record*, *88*(s1), 2-9.

Cohen, B. M. (2016). Psychiatric Hegemony: Mental Illness in Neoliberal Society. In *Psychiatric Hegemony* (pp. 69-96). Palgrave Macmillan, London.

Cohn, M. A., Mehl, M. R., & Pennebaker, J. W. (2004). Linguistic markers of psychological change surrounding September 11, 2001. Psychological Science, 15, 687-93. doi: 10.1111/j.0956-7976.2004.00741.x

Collins, R., (2001). Social movements and the focus of emotional attention. In: *Passionate Politics: Emotions and Social Movements*, pp. 27-46. Chicago: University of Chicago Press.

Collins, R. (2014). *Interaction ritual chains*. Princeton university press.

Core, M. G., & Allen, J. (1997, November). Coding dialogs with the DAMSL annotation scheme. In *AAAI fall symposium on communicative action in humans and machines* (Vol. 56).

Croissant, Y. and Millo, G. (2008). "Panel Data Econometrics in R: The plm Package." *Journal of Statistical Software, 27*(2), pp. 1-43. doi:
10.18637/jss.v027.i02

Crossley, N. (2009). The man whose web expanded: Network dynamics in Manchester's post/punk music scene 1976-1980. *Poetics 37* (1): 24–49. doi:10.1016/j.poetic.2008.10.002.

Csikszentmihalyi, M. (1996). *Flow and the psychology of discovery and invention*. New York: Harper Collins.

Durkheim, E. (1973). *Emile Durkheim on morality and society*. University of Chicago Press.

De Choudhury, M., Counts, S., & Horvitz, E. (2013). Social media as a measurement tool of depression in populations. In *Proceedings of the 5th Annual ACM Web Science Conference* (pp. 47-56). ACM.

De Choudhury, M. (2014). Mental health discourse on reddit: Self-disclosure, social support, and anonymity. In Adar, E., Resnick, P., Choudhury, M.D., Hogan, B., Oh, A., (Eds.): *Proceedings of the Eighth International Conference on Weblogs and Social Media, ICWSM 2014*; Ann Arbor, Michigan, USA. June 1–4, 2014; The AAAI Press; 2014. Retrieved from: http://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/view/8075

De Koster, W. (2010). *'Nowhere I Could Talk Like That': Togetherness and Identity on Online Forums.* EUR (248 pag.) Prom./coprom.: Prof.Dr. D. Houtman & Dr. S.D. Aupers.

De Saussure, F. (1964). *Course in general linguistics.* New York, NY: McGraw-Hill, pp. 6-17, 65-78.

DiMaggio, P. (1997). Culture and cognition. *Annual review of sociology*, *23*(1), 263-287.

DiMaggio, P., Nag, M. & Blei, D. (2013) Exploiting affinities between topic modelling and the sociological perspective on culture: application to newspaper coverage of U.S. government arts funding. *Poetics*, 41, 570–606.

DiMaggio, P., Bernier, C., Heckscher, C., & Mimno, D. (2017) Interaction Ritual Threads: Does IRC Theory Apply Online? *CSSO Working Paper #16*. Retrieved from: https://www.princeton.edu/csso/working-papers/WP16-DiMaggio.pdf

Dowrick, C. (2013). Depression as a culture-bound syndrome: implications for primary care. *British Journal of General Practice, 63*(610): 229–230. doi: 10.3399/bjgp13X665189

Elberse, A., & Oberholzer-Gee, F. (2006). Superstars and underdogs: An examination of the long tail phenomenon in video sales (p. 43). Division of Research, Harvard Business School.

Eurostat. (2017). *Mental health and related issues statistics*. Retrieved from:

http://ec.europa.eu/eurostat/statisticsexplained/index.php/Mental_health_and_related_issues_statistics

Field, A. (2009). *Discovering statistics using SPSS*. London: SAGE.

Fisher, D. R., & Boekkooi, M. (2010). Mobilizing Friends and Strangers: Understanding the role of the Internet in the Step It Up day of action. *Information, Communication & Society*, *13*(2), 193-208.

Gamson, W. A., & Modigliani, A. (1994). The changing culture of affirmative action. *Equal employment opportunity: labor market discrimination and public policy*, 373-394.

Geertz, C. (1973). *The interpretation of cultures* (Vol. 5019). Basic books.

Gillespie, T. (2014). The relevance of algorithms. *Media technologies: Essays on communication, materiality, and society*, *167*.

Goffman, E. (1963). Stigma: Notes on a spoiled identity. *Jenkins, JH & Carpenter.*

Gravetter, F., & Wallnau, L. (2014). *Essentials of statistics for the behavioral sciences* (8th ed.). Belmont, CA: Wadsworth.

Hogan, B. (2010). The presentation of self in the age of social media: Distinguishing performances and exhibitions online. *Bulletin of Science, Technology & Society*, *30*(6), 377-386.

Horsfall, J., Cleary, M., & Hunt, G. E. (2010). Stigma in mental health: Clients and professionals. Issues in Mental Health Nursing, 31(7), 450-455.

IHME (2010). *Financing Global Health 2010: Development assistance and country spending in economic uncertainty*. Seattle, WA: Institute for Health Metrics and Evaluation, 2010.

Ihaka, R., & Gentleman, R. (1996) R: A language for data analysis and graphics. *Journal of Computational and Graphical Statistics, 5*(3): 299–314.

Im, G., Park, E., & Storey, V. (2013). The effects of cognitive and emotional contagion on repurchase intentions of information technology.

Internet Live Stats (2018). Twitter Usage Statistics. Retrieved in May, 2018 from: http://www.internetlivestats.com/twitter-statistics/

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 1251-1271.

Hawn, C. (2009). Take two aspirin and tweet me in the morning: how Twitter, Facebook, and other social media are reshaping health care. *Health affairs*, *28*(2), 361-368.

Hipel, K. W., & McLeod, A. I. (1994). *Time series modelling of water resources and environmental systems* (Vol. 45). Elsevier.

Kacewicz, E., Pennebaker, J. W., Davis, M., Jeon, M., & Graesser, A. C. (2013). Pronoun use reflects standings in social hierarchies. Journal of Language and Social Psychology, doi: 0261927X13502654

Kendall, M.G. (1976). Rank Correlation Methods. 4th Ed. Griffin.

Kluyver, T., Ragan-Kelley, B., Pérez, F., Granger, B. E., Bussonnier, M., Frederic, J., ... & Ivanov, P. (2016, May). Jupyter Notebooks-a publishing format for reproducible computational workflows. In *ELPUB* (pp. 87-90). doi: 10.3233/978-1-61499-649-1-87

Konrath, S., Ho, M. H., & Zarins, S. (2016). The strategic helper: Narcissism and prosocial motives and behaviors. *Current Psychology*, *35*(2), 182-194.

Krackhardt, D., & Stern, R. N. (1988). Informal networks and organizational crises: An experimental simulation. *Social psychology quarterly*, 123-140.

Kretschmer, M., Klimis, G. M., & Choi, C. J. (1999). Increasing returns and social contagion in cultural industries. *British journal of management*, *10*(s1), 61-72.

Lee, J. S., & Nerghes, A. (2017, July). Labels and sentiment in social media: On the role of perceived agency in online discussions of the refugee crisis. In *Proceedings of the 8th International Conference on Social Media & Society* (p. 14). ACM.

Lee, J. (2018) GetOldTweets Graphical User Interface software. Code retrieved from: https://github.com/Jefferson-Henrique/GetOldTweets-java

Leonard, K. (2016). WHO: Ignoring Mental Health Causes Countries to Lose Money.

U.S. News. Retrieved from: https://www.usnews.com/news/best-countries/articles/2016-04-12/who-makes-economic-argument-for-mental-health-treatment

Leung, D. K., & Lee, F. L. (2014). Cultivating an active online counterpublic: Examining usage and political impact of Internet alternative media. *The International Journal of Press/Politics*, *19*(3), 340-359.

Levina, N., & Arriaga, M. (2014). Distinction and status production on user-generated content platforms: Using Bourdieu's theory of cultural production to understand social dynamics in online fields. *Information Systems Research*, *25*(3), 468-488.

Lizardo, O., & Strand, M. (2010). Skills, toolkits, contexts and institutions: Clarifying the relationship between different approaches to cognition in cultural sociology. *Poetics*, *38*(2), 205-228.

Lizardo, O. (2013). Rethinking Cultural Depth. *Orgtheory.net*. Retrieved from: https://orgtheory.wordpress.com/2013/01/06/rethinking-cultural-depth/

Lizardo, O. (2016). Cultural symbols and cultural power. *Qualitative Sociology*, *39*(2), 199-204.

Lizardo, O.(2016) Cultural Theory. In Abrutyn, S. (Ed.). (2016). *Handbook of contemporary sociological theory*. Springer.

Livingstone, S. (2009). On the mediation of everything: ICA presidential address 2008. *Journal of communication*, *59*(1), 1-18.

Livingstone, S. (2013). The participation paradigm in audience research. *The Communication Review*, *16*(1-2), 21-30.

Loewenstein, J., Ocasio, W., & Jones, C. (2012). Vocabularies and vocabulary structure: A new approach linking categories, practices, and institutions. *Academy of Management Annals*, *6*(1), 41-86.

Ma, W. W., & Chan, A. (2014). Knowledge sharing and social media: Altruism, perceived online attachment motivation, and perceived online relationship commitment. Computers in Human Behavior, 39, 51-58.

Martin, J. L. (2010). Life's a beach but you're an ant, and other unwelcome news for the sociology of culture. *Poetics*, *38*(2), 229-244.

McCallum, A.K. (2002). MALLET: A Machine Learning for Language Toolkit. Available at: http://mallet.cs.umass.edu./

McDonnell, T. E., Bail, C. A., & Tavory, I. (2017). A Theory of Resonance. *Sociological Theory*, *35*(1), 1-14.

McDonnell, T. E., Jonason, A., & Christoffersen, K. (2017). Seeing red and wearing pink: Trajectories of cultural power in the AIDS and breast cancer ribbons. *Poetics*, *60*, 1-15.

McKenna, K. Y., Green, A. S., & Gleason, M. E. (2002). Relationship formation on the Internet: What's the big attraction? *Journal of Social Issues*, *58*(1), 9-31.

McLeod, A.I. (2011). Kendall: Kendall rank correlation and Mann-Kendall trend test. R package version 2.2. Retrieved from: https://CRAN.R-project.org/package=Kendall

MHA. (2016). *Mental Health America.* Retrieved from 2016 State of Mental Health in America - Report Overview Historical Data: http://www.mentalhealthamerica.net/issues/2016-statemental-health-america-report-overview-historical-data#Key

Murphy, E. J. (2013). Transnational ties and mental health. In *Cultural psychology of immigrants* (pp. 95-108). Psychology Press.

Murphy, N. A., Fatoye, F., & Wibberley, C. (2013). The changing face of newspaper representations of the mentally ill. *Journal of mental health*, *22*(3), 271-282.

Newman, D., Lau, J. H., Grieser, K., & Baldwin, T. (2010, June). Automatic evaluation of topic coherence. In *Human Language Technologies: The 2010 Annual Conference of the North American*

Chapter of the Association for Computational Linguistics (pp. 100-108). Association for Computational Linguistics.

O'Keeffe, G. S., & Clarke-Pearson, K. (2011). The impact of social media on children, adolescents, and families. *Pediatrics*, *127*(4), 800-804.

Parsons, T., & Shils, E. A. (1951). Values, motives, and systems of action. *Toward a general theory of action*, *33*, 247-275.

Paterson, B. (2007). A discourse analysis of the construction of mental illness in two UK newspapers from 1985–2000. *Issues in mental health nursing*, *28*(10), 1087-1103.

Pavalanathan, U., & De Choudhury, M. (2015, May). Identity management and mental health discourse in social media. In *Proceedings of the 24th International Conference on World Wide Web* (pp. 315-321). ACM.

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The Development and Psychometric Properties of LIWC2015. *UT Faculty/Researcher Works.* Retrieved from: https://repositories.lib.utexas.edu/bitstream/handle/2152/31333/LIWC2015_LanguageManual.pdf

Perrin, A. (2015). Social Network Usage 2005-2016. *Pew Research Centre.* Retrieved from: http://www.pewinternet.org/2015/10/08/social-networking-usage-2005-2015/

Pirkis, J., & Francis, C. (2012). Mental illness in the news and the information media. *A critical review.* Retrieved from: http://www.mindframe-media.com/__data/assets/pdf_file/0013/6322/mental-illness-in-the-media-critical-review-2012.pdf

Putman, S. (2008). Mental illness: diagnostic title or derogatory term? (Attitudes towards mental illness) Developing a learning resource for use within a clinical call centre. A systematic literature review on attitudes towards mental illness. Journal of psychiatric and mental health nursing, 15(8), 684-693.

Rehurek, R., & Sojka, P. (2010). Software framework for topic modelling with large corpora. In *In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks.* Retrieved from: http://is.muni.cz/publication/884893/en

Roberts, E.M., Stewart, B.M.,& Tingley, D. (2018). stm: R Package for Structural Topic Models. Retrieved from: http://www.structuraltopicmodel.com.

Röder, M., Both, A., & Hinneburg, A. (2015, February). Exploring the space of topic coherence measures. In *Proceedings of the eighth ACM international conference on Web search and data mining* (pp. 399-408). ACM.

Rose, D., Thornicroft, G., Pinfold, V., & Kassam, A. (2007). 250 labels used to stigmatise people with mental illness. *BMC Health Services Research*, *7*(1), 97.

Saxena, S., Thornicroft, G., Knapp, M., & Whiteford, H. (2007). Resources for mental health: scarcity, inequity, and inefficiency. *The Lancet*, *370*(9590), 878-889.

Sengers, Frans, Rob PJM Raven, and A. H. T. M. Van Venrooij. "From riches to rags: Biofuels, media discourses, and resistance to sustainable energy technologies." *Energy Policy* 38.9 (2010): 5013-5027.

Sewell Jr, W. H. (1992). A theory of structure: Duality, agency, and transformation. *American journal of sociology*, *98*(1), 1-29.

Shearer, E. & Gottfried, J. (2017). News Use Across Social Media Platforms 2017. *Pew Research Centre*. Retrieved from: http://www.journalism.org/2017/09/07/news-use-across-social-media-platforms-2017/

Shiller, R. J. (1995). Conversation, Information, and Herd Behavior. *The American Economic Review*, *85*(2), 181–185.

Shepherd, A., Sanders, C., Doyle, M., & Shaw, J. (2015). Using social media for support and feedback by mental health service users: thematic analysis of a twitter conversation. *BMC psychiatry*, *15*(1), 29.

Schmidheiny, K., & Basel, U. (2011). Panel data: fixed and random effects. *Short Guides to Microeconometrics*, 2-7. Retrieved from: https://www.schmidheiny.name/teaching/panel2up.pdf

Schudson, M. (1989). How culture works. *Theory and Society*, *18*(2), 153-180.

Stigler, G. J., & Becker, G. S. (1977). De gustibus non est disputandum. *The american economic review*, *67*(2), 76-90.

Stuart, H. (2003). Stigmatisation. Leçons tirées des programmes visant sa diminution. *Santé mentale au Québec*, *28*(1), 54-72.

Stuart, H. (2006). Media portrayal of mental illness and its treatments. *CNS drugs*, *20*(2), 99-106.

Swidler, A. (1995). Cultural power and social movements. In *Culture and Politics* (pp. 269-283). Palgrave Macmillan, New York.

Swidler, A. (1986). Culture in action: Symbols and strategies. *American sociological review*, 273-286.

Swidler, A. (2001). What anchors cultural practices. *The practice turn in contemporary theory*, 74-92.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of language and social psychology*, *29*(1), 24-54.

Teplin, L. A., McClelland, G. M., Abram, K. M., & Weiner, D. A. (2005). Crime victimization in adults with severe mental illness: comparison with the National Crime Victimization Survey. *Archives of general psychiatry*, *62*(8), 911-921.

Thompson, E. R. (2007). Development and validation of an internationally reliable short-form of the positive and negative affect schedule (PANAS). *Journal of cross-cultural psychology*, *38*(2), 227-242.

Thornicroft, A., Goulden, R., Shefer, G., Rhydderch, D., Rose, D., Williams, P., ... & Henderson, C. (2013). Newspaper coverage of mental illness in England 2008-2011. *The British Journal of Psychiatry*, *202*(s55), s64-s69.

Timimi, S. (2014). No more psychiatric labels: Why formal psychiatric diagnostic systems should be abolished. *International Journal of Clinical and Health Psychology*, *14*(3), 208-215.

Tomko, Michael. 2007. "Politics, Performance and Coleridge's `Suspension of Disbelief'." *Victorian Studies 49*(2): 241-49.

Torres-Reyna, O. (2007). Panel data analysis fixed and random effects using Stata (v. 4.2). *Data & Statistical Services, Priceton University*. Retrieved from: https://www.princeton.edu/~otorres/Panel101.pdf

Torres-Reyna, O. (2010). Getting started in fixed/random effects models using R. *Data & Statistical Services. Princeton University*.Retrieved from: https://www.princeton.edu/~otorres/Panel101R.pdf

Trussler, M., & Soroka, S. (2014). Consumer demand for cynical and negative news frames. *The International Journal of Press/Politics*, *19*(3), 360-379.

Twitter, (2018a). How to use hashtags. Retrieved from Twitter Help Centre on 10 July from https://help.twitter.com/en/using-twitter/how-to-use-hashtags

Twitter, (2018b). About Replies and Mentions. Retrieved from Twitter Help Centre on 10 July from https://help.twitter.com/en/using-twitter/mentions-and-replies

Van Dijck, J. (2009). Users like you? Theorizing agency in user-generated content. *Media, culture & society*, *31*(1), 41-58.

Van Herpen, E., Pieters, R., & Zeelenberg, M. (2009). When demand accelerates demand: Trailing the bandwagon. *Journal of Consumer Psychology*, *19*(3), 302-312.

Van Venrooij, A., & Schmutz, V. (2010). The evaluation of popular music in the United States, Germany and the Netherlands: A comparison of the use of high art and popular aesthetic criteria. *Cultural Sociology*, *4*(3), 395-421.

Van Venrooij, A. (2015). A community ecology of genres: Explaining the emergence of new genres in the UK field of electronic/dance music, 1985–1999. *Poetics*, *52*, 104-123.

Vasi, I. B., Walker, E. T., Johnson, J. S., & Tan, H. F. (2015). "No fracking way!" Documentary film, discursive opportunity, and local opposition against hydraulic fracturing in the United States, 2010 to 2013. *American Sociological Review*, *80*(5), 934-959.

Yan, X., Guo, J., Lan, Y., & Cheng, X. (2013, May). A biterm topic model for short texts. In *Proceedings of the 22nd international conference on World Wide Web* (pp. 1445-1456). ACM.

Zhou, Y., & Moy, P. (2007). Parsing framing processes: The interplay between online public opinion and media coverage. *Journal of communication*, *57*(1), 79-98.

Wahl, O. F. (1997). *Media madness: Public images of mental illness.* Rutgers University Press.

Ward Jr, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American statistical association*, *58*(301), 236-244.

Weij, F., Berkers, P., & Engelbert, J. (2015). Western solidarity with Pussy Riot and the Twittering of cosmopolitan selves. *International journal of consumer studies*, *39*(5), 489-494.

Whiteford, H. A., Ferrari, A. J., Degenhardt, L., Feigin, V., & Vos, T. (2015). The global burden of mental, neurological and substance use disorders: an analysis from the Global Burden of Disease Study 2010. *PloS one*, *10*(2), e0116820.

Whitley, R., & Berry, S. (2013). Trends in newspaper coverage of mental illness in Canada: 2005–2010. *The Canadian Journal of Psychiatry*, *58*(2), 107-112.

Whitley, R., & Wang, J. (2017). Good news? A longitudinal analysis of newspaper portrayals of mental illness in Canada 2005 to 2015. *The Canadian Journal of Psychiatry*, *62*(4), 278-285.

Wicks, P. (2014). The ALS Ice Bucket Challenge–Can a splash of water reinvigorate a field? *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration 15* (7-8)*:* 479-480.

WHO. (2011). Mental health atlas 2011. *Mental health atlas 2011*.

WHO. (2016). *Data and Statistics.* Retrieved from World Health Organization Europe:
http://www.euro.who.int/en/health-topics/noncommunicable-diseases/mentalhealth/data-and-statistics

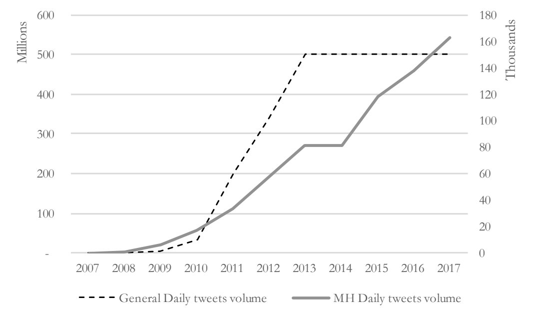
Appendices

Appendix 1

Descriptive statistics

Overall the Twitter data shows growing interest in mental health discourse. MH discourse on Twitter not only grew in absolute numbers, but also continued to grow after the general tweets volumes stabilized (Figure 1). Current MH discourse represents 0.003% of all twitter discourse, which is rather small. However, the average five-year growth rate of 25% (or 15% if we look at the proportion of MH discourse to total discourse) indicates growing interest in the subject.

Figure 1: *Daily Tweet Volumes*



Source (general daily tweets volumes): Internet Live Stats (2018)

25% of the tweets collected (171,799) are duplicate tweets. 12% of the duplicates (or 2.9% of all tweets, 19,908 tweets), in turn, can be classified as retweets (RT-labelled)[46], with the rest being an exact text posted by the same or different users, which entails contributions to the discourse by minimal investment by the user.

While only 19% of the tweets elicit conversation in terms of replies, an average tweet is "liked" and retweeted 1.6 and 2.6 times respectively. On average 44% of tweets use hashtags as classification symbols and 28% of tweets "tag" or mention other users. On average, users who tweet about mental health have high social capital (median = 1026 followers[47]). However, if we look at the absolute numbers, 55% of the discourse is initiated by users with less than 1000 followers (usually private individuals), 30% by accounts with the number of followers ranging from 1000 to 5000 (usually small enterprises, consultants), and the remaining 15% comes from the influencers, who are media outlets, celebrity influencers (also doctors, consultants, researchers)[48], and businesses.

[46] Total number of corpus tweets classified as retweets. Note, this is not the same as the number of retweets associated with a tweet, but an actual tweet classified as retweet and which, consequently, can also be retweeted.
[47] The distribution is highly skewed by few high players (i.e. @HuffPost, @mental_health, @BostonGlobe, @vicenews)
[48] See Appendix 12 for examples.

With regards to discourse characteristics, average tweet focus (intra-focus) on a 0-10 scale is 3.75[49] (0 being very dispersed/ 10 very thematically focused) and a proportion of directedness of an average tweet (resolution) is 5.29%. Texts are on average of a moderate confidence (65.01/100), which is close to and slightly higher than the general Twitter level of confidence (63.02/100). The tweets sentiment is tilted slightly towards positive (a proportion of positive sentiment in an average tweet is 3.04% and of negative sentiment is 1.88%), however it is lower than Twitter sentiment in general (positive/negative sentiment proportions are 5.48% and 2.14% respectively). The level of perceived anxiety, as a negative emotion, in MH discourse is more pronounced in Twitter MH discourse than in general (0.40/0.24%), however, the levels of anger and sadness are lower (0.40/0.75% and 0.39/0.43% respectively). Additionally, solidarity is more pronounced in MH-related tweets than in general Twitter discourse (0.62/0.47%).

Table 1: *Descriptive Statistics All Tweets (N=695,414)*

Variable	*Mean*	*Min*	*Max*	*StDev*	*Mean [Twitter]**
Tweet Characteristics					
Replies	0.20	-	817	2.6	
Retweets	1.64	-	52,980	126	
Favourites	2.62	-	116,239	257	
User social capital	10,028	-	11,562,825	184,594	
Hashtags	0.44	-	402		
Mentions	0.27	-	247		
Word count	20.76	1.00	143	7.08	
Sentiment Characteristics					
Sentiment	1.17	-66.67	72.22	5.96	3.34
-positive	3.04	-	72.22	4.40	5.48
-negative	1.88	-	68.42	3.62	2.14
--anxiety	0.40	-	50.00	1.58	0.24
--anger	0.40	-	60.00	1.63	0.75
--sad	0.39	-	37.50	1.54	0.43
Intensity	4.58	0.00	72.22	4.93	5.88
Confidence	65.01	1.00	99.00	25.75	63.02
Solidarity	0.62	-	47.06	1.95	0.47
Discourse Characteristics					
Intra Focus	3.75	0.03	10.00	2.17	
Resolution	5.29	-	41.67	4.57	
Stigma	0.30	-	18.00	0.75	

**(Pennebaker et al., 2015)*

Relying on graphical analysis (Figure 2) and using the Man-Kendall test (Table 2), over time we can observe that levels of emotional intensity in MH discourse have risen (p_{10y}<0.001), mainly due to the rise in negative sentiment (slope=0.48, p_{10y}<0.001) and to a lesser extent positive (slope=0.256, p_{10y}<0.05). Nevertheless, in the last 5 years the level of emotional intensity was insignificant to display a trend pattern. The discourse displayed higher levels of solidarity, exhibiting upward trend (p_{10y}<0.001, p_{5y}<0.05). Additionally, the level of confidence in talking about MH was steadily growing ($p_{10y, 5y}$<0.001).

[49] In absolute numbers the average of intra-focus is 0.27, min and max 0.03 and 0.65 respectively and standard deviation is 0.13.

The inter-focus of discourse in the last 10 years became more pronounced, making MH discourse more concentrated on a lower number of topics (p_{10y}<0.01). However, in the last 5 years the discourse, on the contrary, started to become more diverse, and possibly also more competitive (slope=-0.35, p_{5y}<0.05). The intra-topic competition has been less volatile, but has also been showing a declining pattern (p_{10y}<0.01, p_{5y}<0.05), meaning that single tweet would cover a greater number of themes. It is imaginable that the discourse became less focused due to increase in the number of people participating in it, however this assumption would only apply to the inter-topic focus. The call to action, or resolution in the discourse, has become more prominent as well (p_{10y}<0.001).

With regard to online tweet characteristics, we can see that the use of favourites and replies, also per tweet, grew (p_{10y}<0.001). The use of hashtags and mentions also increased during the 10 years' period ($p_{\#}$<0.001, $p_{@}$<0.01), however in the last 5 years the use of hashtags and mentions was in decline (slope$_{\#}$=-0.05, p_{5y}>0.05, slope$_{@}$=-0.63, p_{5y}<0.001). Replies per tweet grew faster than the number of replies (see Figure 2), which indicates an increase in engagement. This is also confirmed by the fact that the duplication rate decreased (slope=-0.37, p_{5y}>0.05) while the tweets per user ratio remained stable (p_{5y}>0.05). Perhaps, users began to engage in more conversation rather than in tweet-copying or tweeting just once in a while. With regards to echo chamber, we can observe that users who engage in MH discourse are doing so across a variety of topics (echo-chamber is negative). Although, in recent years, the discourse was tending towards polarisation, there was a correction in 2017 (Mann-Kendall results insignificant, see Figure 2).

Stigmatisation of MH discourse on Twitter have been increasing in the last 10 years (can only be seen graphically (Figure 2), $p_{10y,\ 5y}$>0.05; moreover, in 2014 we can see a correction to stigma-related vocabularies growth). Yet, stigma-related vocabularies were not often used. Only 0.3% of the discourse features word and phrases associated with stigma, as compared to almost 28% in press (Whitley & Wang, 2016). Such big difference might stem from two facts. First, quantifying stigma-related vocabularies runs a risk of missing stigmatising content which does not feature stigma-related words and is contextual (that is why we later include contextual 'Stigma' theme, see pp. 23, 40)[50]. Second, tweet text is limited to 140 characters in comparison with much larger newspaper articles, hence tweets have a lower probability to include as many stigma-related words.

With regards to resonance mechanisms, indicators of bandwagon have been growing at highest pace (slope$_{5y}$=0.863, p_{5y}<0.001) followed by emotional energy (slope$_{5y}$=0.747, p_{5y}<0.001)

[50] Later in the analysis I split the corpus into stigma-related and stigma-neutral discourse, adding the context-dependent stigma-related theme to the analysis besides the themes which display above average stigma-related vocabularies.

(particularly from engagement as operationalized by replies, solidarity and positive tone). Cognitive focus of the discourse has been stable (p_{5y}>0.05). These findings indicate that the increases in both emotional energy and bandwagon characteristics of discourse could contribute to the growth in discursive retrievability ($p_{10y,5y}$<0.001) and hence, which could aid MH discourse on social in projecting cultural power.

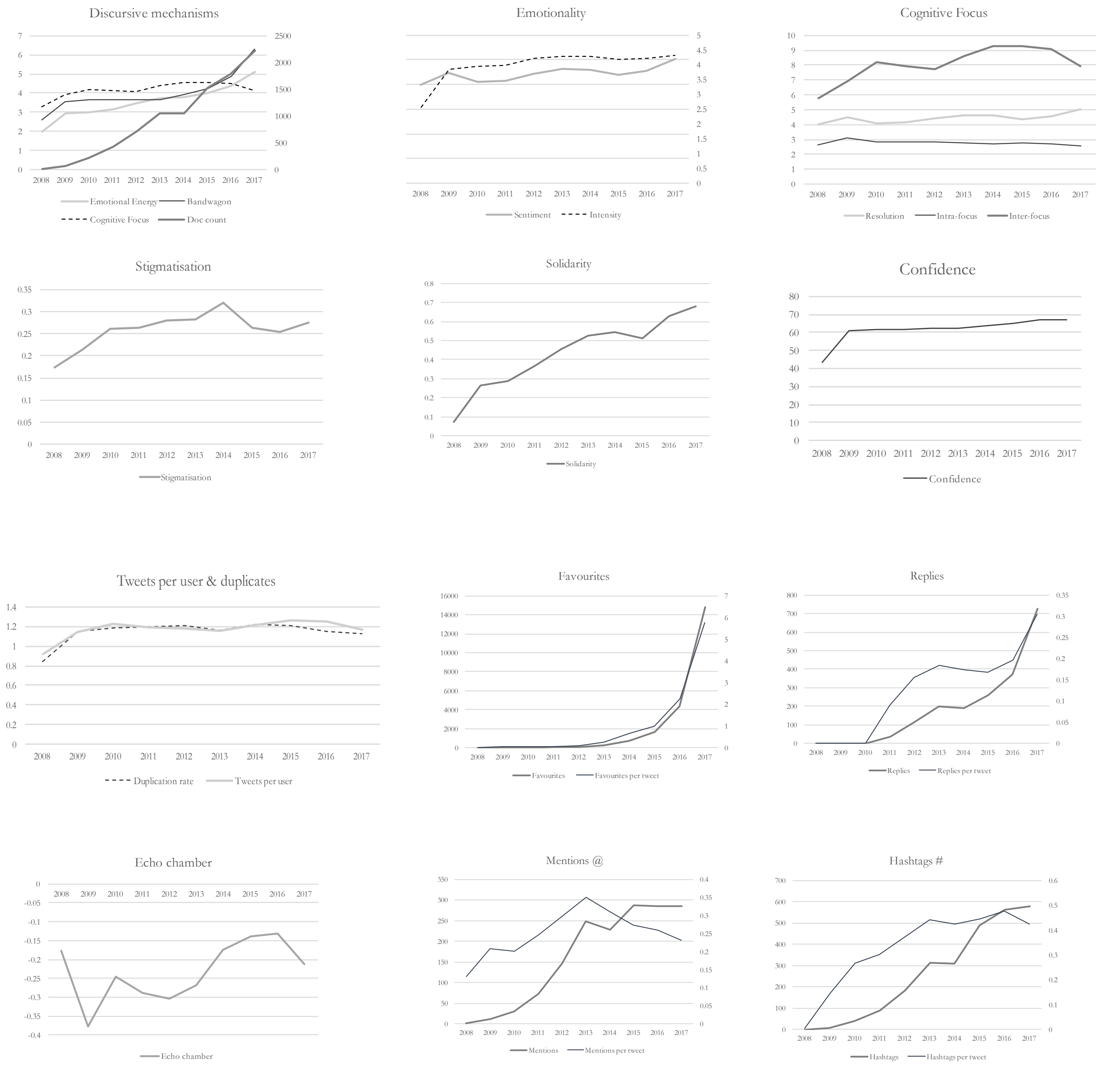
Table 2:*Mann-Kendall Trend Test (N=44)*

	Slope (10 years trend)	*Slope (5 years trend)*
Mental Health discourse	**0.925*** **	**0.737*** **
Stigma vocabularies	**0.071**	**0.05**
Emotional Energy	**0.896*** **	**0.747*** **
Replies	0.875***	0.726***
-Replies per tweet	0.734***	0.354*
Sentiment	0.556***	0.179
-Positive emotions	0.256*	0.01
-Negative emotions	0.48***	0.021
Intensity	0.882***	0.021
Confidence	0.592***	0.653***
Solidarity	0.78***	0.442*
Bandwagon Behaviour	**0.801*** **	**0.863*** **
Favourites	0.961***	0.905***
-Favourites per tweet	0.897***	0.926***
Duplication rate	0.228*	-0.37*
Cognitive Focus	**0.490*** **	**-0.316**
Inter-topic focus	0.606**	-0.35*
Intra-topic focus	-0.29**	-0.36*
Resolution	0.433***	0.158
Controls		
Echo chamber	0.09	0.189
Hashtags (#)	0.878***	0.516**
-Hashtags per tweet	0.687***	-0.06
Mentions (@)	0.831***	0.305
-Mentions per tweet	0.333**	-0.63***
Other		
Followers	0.191	0.52**
Tweets per user	0.368***	0.073

p<0.05;p<0.01;***p<0.001 (two-sided tests)*

Note: A slope of >0 indicates an increasing trend, while a slope of <0 indicating a decreasing trend. The larger the value is, the more degree of slope for the trend line.

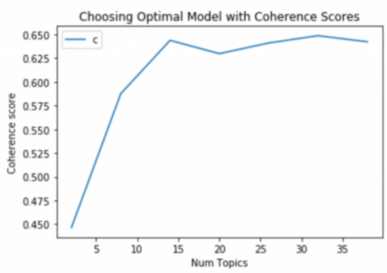
Figure 2: *Tweet characteristics trends (N=695,414)*



APPENDIX 2

Optimal number of topics selection process

The number of topics of 30 was decided based on coherence score change when testing for different number of topics at one period. In simple terms, coherence score can be defined as the ease of topics interpretability by taking a median of pairwise word-similarity scores within a given topic for a group of topics (Newman et al., 2010; Röder et al., 2015). I approach it by building many LDA models in one algorithm[51] with the different topic numbers (k) and picking the topic number with the highest value or when coherence growth stabilizes (see below). In other words, I run and LDA model per a sample period per year (November of each year) and checked what the optimal number of topics per year would be.



Year	*Topic Number*	*Coherence Score*	*New Topics*
2007	5	44	
2008	6	43	1
2009	10	55	4
2010	10	59	0
2011	12	59	2
2012	15	61	3
2013	14	58	-1
2014	28	61	14
2015	29	59	1
2016	31	60	2
2017	30	60	-1
Average	17.3	56	2.5

As the maximum optimal number of topic per period was 30, the number was selected for the analysis. Of course, in the beginning of the dataset the topic number was much lower (2007 – 5 topics optimal). However, the maximum was still chosen upon an assumption that, if the topic did not exist in a previous period, the prominence, or proportion of such, would tend to zero. Once the topic and keywords numbers were defined I implemented a Mallet-based topic analysis for the entire corpus of tweets.

[51] A Gensim (Python-based Software framework for topic modelling with large corpora) algorithm based on Gensim-wrapped MalletLda output and Gensim-based Coherence model (Rehurek & Sojka, 2012).

APPENDIX 3

TOPIC (N=5)	WEIGHT	Top Words (10)
FEELINGS	8.51%	issues people day good #mentalhealth time important problems care issue physical work make bad life feel talk problem days things
STIGMA/SERVICES	7.91%	care #mentalhealth services issues people problems crisis support treatment news children funding system patients young cuts gun risk access report
AWARENESS	6.97%	#mentalhealth awareness day week support today #bellletstalk stigma talk world issues people tweet great work #mhaw month raise charity join
CLASSIFICATION	5.32%	#mentalhealth #depression #anxiety #health #mhsm #mentalillness #psychology depression disorder anxiety life #mental #ptsd stress #bipolar physical #parenting illness brain improve
SERVICE	2.18%	nurse #jobs #health #job #mental worker job services psychiatric center hospital care jobs therapist practitioner registered counselor nursing community social
∑	30.9%	

TOPIC (N=10)	WEIGHT	Top Words (10)
AWARENESS	6.10%	#mentalhealth support today stigma people work issues awareness talk great services community day youth join week aid young event training conference students wellbeing free stories workplace share campaign talking check
FEELING	5.84%	day good #mentalhealth important time people work issues physical feel bad life love today days care make talk back things week break taking school world great year job happy mind
YOUTH	4.56%	#mentalhealth problems issues people children physical depression study disorders young care risk work social stress illness treatment anxiety research kids linked improve impact teens support women affect #mhsm life #health
STIGMA	4.39%	issues people gun issue care problem problems guns control make #mentalhealth stop violence life real illness system stigma ill man doesnt talk good laws country mentally time person suicide treatment
SYSTEM/POLICY/FUNDING/ACCESS	3.81%	care services #mentalhealth news treatment system crisis veterans access state funding bill county report hospital plan act abuse law million issues support court community police substance reform program center addiction
#/CLASSIFICATION	3.78%	#mentalhealth #depression #anxiety #health #mentalillness #psychology #mhsm disorder depression #bipolar #ptsd anxiety #mental #mindfulness #wellness #recovery #stress life #wellbeing #parenting #suicide #mentalhealthawareness blog #stigma #addiction post #mentalhealthmatters read illness #therapy
NHS	2.03%	services care crisis #mentalhealth cuts nhs funding people support patients lives risk news treatment problems children call police jones extra budget put conditions facility trust minister england young beds service
AWARENESS/CHARITY/CANADA	1.97%	awareness day week #bellletstalk world tweet #mentalhealth today raise donate month cents #mhaw bell support canada programs talk lets supporting stigma raising money depression priority donating spread campaign #wmhd issues
SERVICE	1.64%	nurse #jobs #job #health #mental job worker services psychiatric jobs therapist practitioner registered care counselor social center nursing community specialist position manager professional time hospital technician full unit medical program
TRUMP	1.02%	trumps trump #mentalhealth raises test startup president series donald check media million round lantern talking mind video doctor real question colleagues worried online gop journalists customers expert franken science public
∑	35.1%	

APPENDIX 4

Operationalisation of variables

Concept	Variable	Operationalization	Coding	Variable type and range
		DEPENDENT VARIABLE*		
RETRIEVABILITY	**Tweets count**	A count of documents (tweets) which represent a topic with higher than a cutoff point of 20% proportion of that tweet (in relation to other topics). A single document can be counted multiple times if it has more than one topic of more than 20% represented.	Open, discrete	Ratio [0;∞]
		INDEPENDENT VARIABLES: PREDICTORS* [RESONANCE}		
EMOTIONAL ENERGY	**Engagement**	A number of replies to a single tweet	Open, discrete	Ratio [0;∞]
	Solidarity	A proportion of 1st person plural personal pronouns in a tweet retrieved from LIWC (we, our, us, lets, let's etc.)	Open, continuous	Ratio [0;100]
	Confidence	LIWC Clout Thinking standardized composite ranging from 0 (low status, low confidence) to 100 (high status, high confidence)	Open, continuous	Ratio [0;100]
	Intensity	Square root of the sum of positive and negative emotions proportion squares	Open, continuous	Ratio [0;72]
BANDWAGON BEHAVIOUR	**Favourites**	Number of times a tweet is liked	Open, descrete	Ratio [0;∞]
	Duplicate tweets	Inverse proportion of unique to total tweets	Open, continuous	Ratio [0;1]
COGNITIVE FOCUS	**Intra-topic focus**	A median of a tweet topics proportions	Open, continuous	Ratio [0;1]
	Inter-topic focus	A median of all topics proportions per period	Open, continuous	Ratio [0;1]
	Resolution	A proportion of tweet represented by action associated vocabularly [an average of modal auxiliary verbs + verbs + present tense]	Open, continuous	Ratio [0;100]
		INDEPENDENT VARIABLE: CONTROL*		
ECHO CHAMBER	=	Krackhardt E/I Ratio E-I Index = (EL-IL)/(EL+IL), where EL represents the number of connections that are external to a user within a given topic and IL is the number of connections internal to or between vertexes within that topic.	Open, continuous	Ratio [-1;1]
INSTITUTIONAL DISCOURSE	**Parallel Mass Media Discourse**	Google Trends Popularity of the theme	Open, continuous	Ratio [0;100]
SYMBOLS	**Hashtags**	Presence of hashtags (#) in a tweet	1= TRUE I 0=FALSE	Ratio [0;∞]
	Mentions	Presence of mentions (@) in a tweet	1= TRUE I 0=FALSE	
		OTHER VARIABLES [NOT IN REGRESSION]*		
RHETORICAL FORCE	**Followers per user**	Number of followers per user who posted a given tweet	Open, discrete	Ratio [0;∞]
SENTIMENT	=	Proportion of positive emotions - Proportion of negative emotions	Open, continuous	Ratio [-100;100]

**All variables are mean-aggregated per topic per quarter*

APPENDIX 5

Modal Auxiliary Verbs Dictionary

can
could
may
might
will
would
shall
should
must
ought

APPENDIX 6

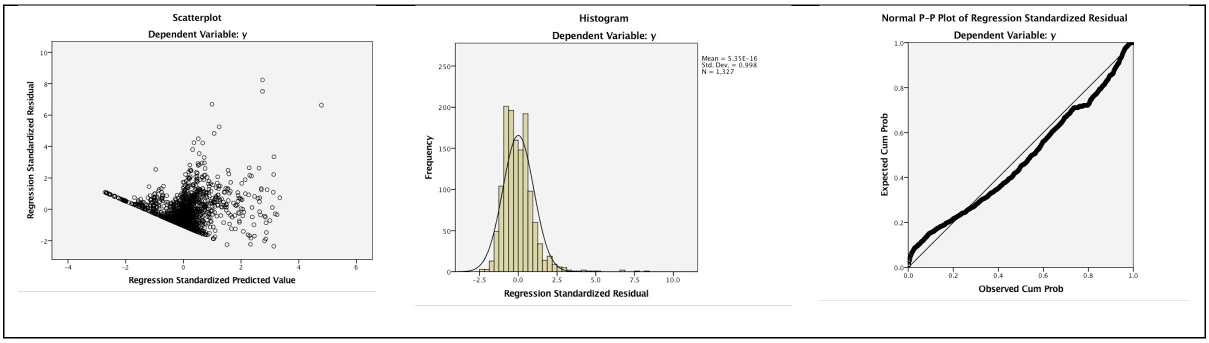
Assumptions Checks for Fixed Effects Panel Regression

The assumptions of linearity and homoscedasticity were assessed via scatterplot (see below). Although the linearity assumption was proved, the data displayed a pattern of heteroskedasticity. We control for heteroskedasticity by using a robust covariance matrix estimation by vcovHC R function (Croissant & Millo, 2017). Namelly we use "Arellano" method which controls for both heteroskedasticity and serial correlation (recommended for fixed effects models), reducing the significance bias described by Torres-Reyna (2008). Normality was assessed via histogram and P-P Plot (see below). No multicollinearity was detected (VIF<10; tolerance > 0.1). The panel data has not presented outliers across subjects (Mahal. Distance max (4) = 10.32<18.47), Cook's distance was also within the limits (max<1.0)[52]. Durbin-Watson test (0.64) indicated that the error terms are independent of each other.

Wooldridge's test for serial correlation in FE panels, which is frequently used in "short" panels (i.e. quarterly data) rejected null hypothesis (p<0.001) showing that serial correlation of errors is not a problem (Croissant & Millo, 2017). Augmented Dickey-Fuller Test confirmed that within FE model data stationarity was implied (p<0.001) (Croissant & Millo, 2017). The model has also been tested for cross-sectional dependence/contemporaneous correlation, which indicated the presence of thereof (p>0.05) (Breusch-Pagan LM test as cited by Croissant and Millo (2017)). Yet, according to Baltagi (2008), this should not substitute a problem/bias the results of micro panels (number of cases>periods) and should only be explored further in macro panels with long time-series. The assumption test for time-effect indicated significance (p>0.05) (using Lagrange Multiplier Test as cited by Croissant and Millo (2017)). Whereas it would be advisable to add a time-effect to the model, by doing so the model fit decreases[53]. As such, we decide to abstain from adding time-effect to the model and compare the initial model to a model with lagged covariates instead, which also makes more sense theoretically.

[52] To assess the presence of outliers in a panel across subjects, I selected a random single time period (2017Q1).

[53] I have also tried to test for time-effect for 2013-2017 time frame only, which presents with a more stable data; however, the time-effect assumption remained significant.



APPENDIX 7

Stigmatising vocabulary dictionary

abnormal
“not normal”
abusive
anti-social
asylum*
“attention seeker”
bewildered
bimbo
bonkers
“brain dead”
childish
“cola sweat”
“is confused”
crackers
crazy
“cushioned walls”
deformed
demented
depressing
deranged
dildo
disturbed
disturbing
“disturbing images”
div
dopy
downy
dribbling
drugged-up
dumb
embarrass*
“escaped from an asylum”
“feel sorry”
“few sandwiches short of a picnic basket”
flid
flip
“flip in the head”
freak
“fruit cake”
fucked
gay
“get lost”

"gone in the head"
goon
"green room"
halfwit
hallucinating
"hand fed"
handicapped
"happy club"
"head bang*"
"head case"
helpless
idiot
indecisive
infixed
insane
insecure
"intellectually challenged"
irrational
isolated
"joe from eastenders"
jumpy
lonely
loony
"loony bin"
loser
lunatic
mad
"made fun of"
"make fun of"
madness
manic
"mass murderer*"
"mental hospital"
bully
"mental institution"
"mentally challenged"
"mentally handicapped"
mong*
muppet*
nervous
non-caring
"none caring"
"no-one upstairs"
"not all there"
"not quite there"
"not the sharpest knife in the drawer"
numscull
nutcase
nutter
nuts
"nutty as a fruitcake"
odd
oddball
"off their rocker"
outcast
"padded cells"
paedophile
panic*
paranoid

"patch adams"
pervert*
pinflump
pive
plank
ponce
psycho
psychopath
retard
"sandwich short of a picnic"
"pepperoni short of a picnic"
scary
schizo
schizophrenia
schizophrenic
"screw loose"
"sick in the head"
simpleton
nutty
parano*
obsessed
reject*
rapist
murder*
screw*
"lack* brain"
spanner
spastic
spaz
"split personality"
spoone
"stiggy nutter"
"strait jackets"
"strange person"
thick
tiring
touchy
troubl*
twist*
ugly
unappreciated
unapproachable
unfortunate
unpredictable
unstable
veg
vegetable
victim*
violen*
voices
wacky
wally
"wheelchair jockey"
weird*
weirdo
"wheel chair"
"white coats"
wild
noises

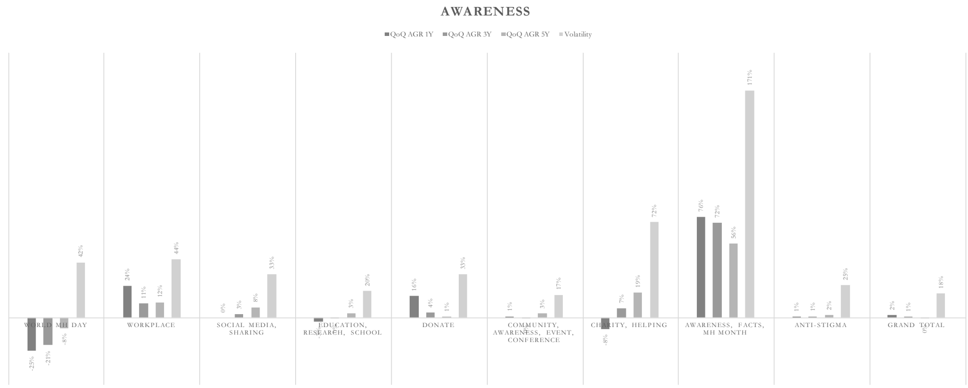
“window licker”
withdrawn
“world of their own”
“a home”
risk
rape
crim*
hooligan*

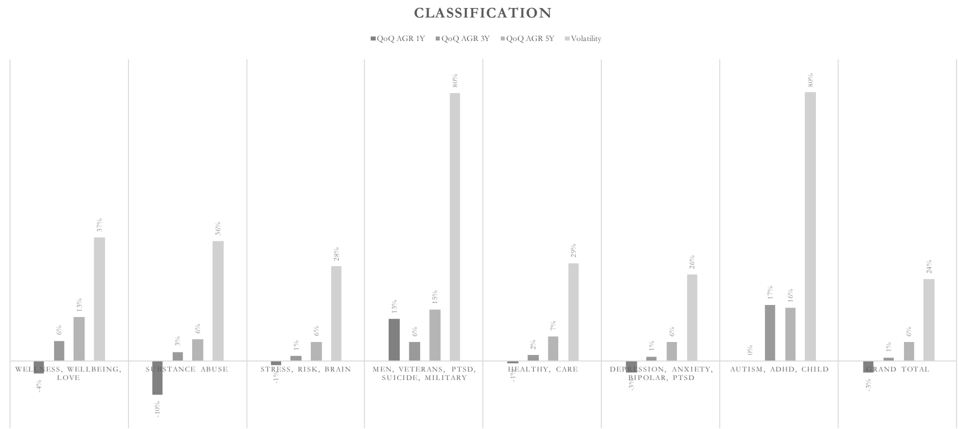
Power-low vocabulary dictionary
weak
underdog*
unqualified
unwanted
vunerab*
victim*
wimp
wuss
pity
pitiful*
poor
powerless
predator
punish*
probation*
rookie
shame*
scum
slave
submis*
terror*
threat
unaccept*
obey
moron
menial
meek
manipulat*
maid
loser*
inferior*
insecure*
incapab*
incompetent*
ignorant
humiliat*
hopeless*
hobo
helpless*
good-for-nothing
amateur*
apology*
asham*
assault*
attack*
beat
beats
beaten

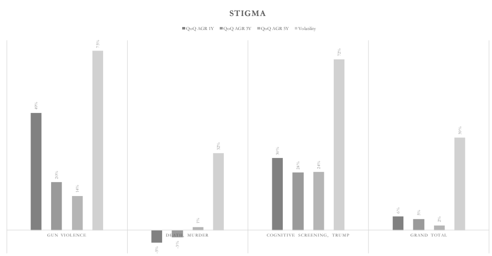
beating
abus*
beg
beggar
begging
bossy
bully
bullying
bum
bums
embarrass*
coward*
criminal*
crook*
degrade*
crushed
destroy*
destruction
dependent
disadvanteg*
disgac*
dishon*
disrepute*
dumb
failure
forbid*
doofus
dufus
powerless*

For the general power dictionary, please download LIWC dictionary via the following link.

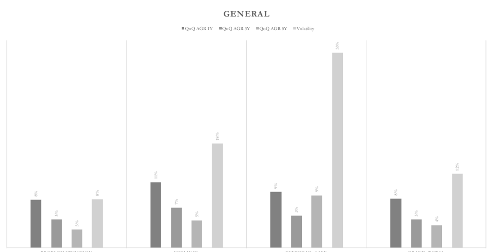
Appendix 8

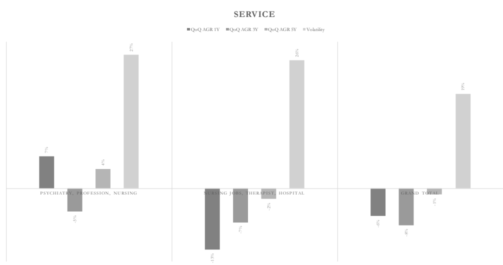

AWARENESS
QoQ AGR 1Y
QoQ AGR 3Y
QoQ AGR 5Y
Volatility
WORLD MH DAY
WORKPLACE
SOCIAL MEDIA, SHARING
EDUCATION, RESEARCH, SCHOOL
DONATE
COMMUNITY, AWARENESS, EVENT, CONFERENCE
CHARITY, HELPING
AWARENESS, FACTS, MH MONTH
ANTI-STIGMA
GRAND TOTAL


CLASSIFICATION
QoQ AGR 1Y
QoQ AGR 3Y
QoQ AGR 5Y
Volatility
WELLNESS, WELLBEING, LOVE
SUBSTANCE ABUSE
STRESS, RISK, BRAIN
MEN, VETERANS, PTSD, SUICIDE, MILITARY
HEALTHY, CARE
DEPRESSION, ANXIETY, BIPOLAR, PTSD
AUTISM, ADHD, CHILD
GRAND TOTAL


STIGMA


FUNDING


GENERAL


SERVICE


YOUTH

APPENDIX 9

Stigmatisation and emotional energy characteristics of MH discourse per thematic cluster

	Stigmatisation	Positive Emotion	Negative Emotion	Sentiment	Intensity	Solidarity	Confidence
CLASSIFICATION	0.27	2.2	1.2	1.1	3.3	0.4	56.1
AWARENESS	0.19	2.3	1.4	0.9	3.5	0.4	56.7
FUNDING	0.18	2.3	1.0	1.3	3.2	0.4	60.4
FEELINGS AND PROBLEMAT	0.33	3.0	2.6	0.4	5.1	0.4	55.6
SERVICE	0.34	1.7	2.2	-0.6	3.7	0.3	57.8
STIGMA	0.20	3.5	1.0	2.5	4.3	0.4	58.9
YOUTH	0.27	1.7	2.2	-0.5	3.7	0.3	55.8

Averages per theme per quarter

Bandwagon characteristics of MH discourse per thematic cluster

	Duplication rate	Favourites per tweet
CLASSIFICATION	1.05	0.9
AWARENESS	1.10	0.8
FUNDING	1.06	1.0
FEELINGS AND PROBLEMAT	1.04	1.0
SERVICE	1.03	0.6
STIGMA	1.09	1.6
YOUTH	1.02	0.6

Averages per theme per quarter

Cognitive focus characteristics of MH discourse per thematic cluster

	Resolution	Inter_focus	Intra_focus
CLASSIFICATION	3.8	7.5	2.7
AWARENESS	4.5	7.5	2.6
FUNDING	3.1	7.5	2.6
FEELINGS AND PROBLEMATESATION	5.6	7.5	2.7
SERVICE	3.6	7.5	2.5
STIGMA	4.2	7.5	2.5
YOUTH	3.8	7.5	2.6

Averages per theme per quarter

Control characteristics of MH discourse per thematic cluster

	Echo Chamber	Hashtags	Mentions	Followers
CLASSIFICATION	0	319	106	9,338
AWARENESS	0	269	199	12,958
FUNDING	0	155	113	11,764
FEELINGS AND PROBLEMATESATION	0	267	299	3,637
SERVICE	0	215	32	3,923
STIGMA	0	87	80	7,923
YOUTH	0	127	81	18,138

Averages per theme per quarter

Stigmatisation and emotional energy characteristics of MH discourse per topic

	Stigmatisation	Positive Emotions	Negative Emotions	Sentiment	Intensity	Solidarity	Confidence
PROBLEMATIZATION	0.5	5.5	2.8	3.4	5.5	0.5	56.3
MEN, VETERANS, PTSD, SUICIDE, MILITARY	0.4	3.3	1.8	1.8	3.3	0.5	61.3
CHARITY, HELPING	0.1	1.6	1.4	0.3	1.6	0.3	54.8
SOCIAL MEDIA, SHARING	0.1	3.0	2.4	0.7	3.0	0.4	55.7
YOUNG PEOPLE, CHILDREN, PARENTS	0.2	4.2	1.9	2.6	4.2	0.3	55.2
WELLNESS, WELLBEING, LOVE	0.4	4.0	1.7	2.6	4.0	0.3	52.2
AUTISM, ADHD, CHILD	0.2	3.2	2.3	1.0	3.2	0.3	59.6
PARENTING	0.3	3.1	1.5	1.9	3.1	0.3	56.5
ANTI-STIGMA	0.1	3.6	3.3	0.5	3.6	0.7	55.6
WORLD MH DAY	0.4	5.3	3.6	2.3	5.3	0.3	50.4
NURSING JOBS, THERAPIST, HOSPITAL	0.5	4.8	1.5	3.7	4.8	0.4	56.9
AWARENESS, FACTS, MH MONTH	0.1	3.5	3.1	0.4	3.5	0.7	60.9
DEPRESSION, ANXIETY, BIPOLAR, PTSD	0.2	4.6	4.3	0.5	4.6	0.8	59.5
STRESS, RISK, BRAIN	0.5	3.7	2.0	2.0	3.7	0.4	52.5
WORKPLACE	0.3	3.4	0.9	2.7	3.4	0.2	61.7
COGNITIVE SCREENING, TRUMP	0.3	3.3	2.5	1.0	3.3	0.4	56.7
DONATE	0.4	4.0	2.7	1.6	4.0	0.3	57.7
FEELINGS	0.3	5.3	3.4	2.4	5.3	0.3	47.4
SUBSTANCE ABUSE	0.1	1.5	0.8	0.7	1.5	0.2	47.4
COMMUNITY, AWARENESS, EVENT, CONFERENCE	0.2	2.0	0.9	1.1	2.0	0.4	54.2
GUN VIOLENCE	0.1	3.7	3.1	0.9	3.7	0.4	60.5
DEATH, MURDER	0.2	5.8	5.0	1.2	5.8	0.4	59.5
COVERAGE, ACCESS, INSURANCE, STATE	0.1	3.4	2.5	1.0	3.4	0.6	59.7
ENGLAND, NHS, SYSTEM, BEDS	0.3	3.2	2.7	0.6	3.2	0.6	59.5
EVERYDAY LIFE	0.2	4.4	2.7	2.1	4.4	0.4	63.3
PSYCHIATRY, PROFESSION, NURSING	0.2	2.6	1.9	0.8	2.6	0.2	58.8
POLICE	0.3	2.7	1.7	1.2	2.7	0.3	58.9
EDUCATION, RESEARCH, SCHOOL	0.1	3.5	2.0	1.8	3.5	0.7	57.2
HEALTHY, CARE	0.2	4.4	3.4	1.3	4.4	0.4	63.3
FUNDING, CUTS, CRISIS	0.0	3.4	2.5	1.1	3.4	0.0	63.3

Bandwagon characteristics of MH discourse per topic

	Duplication rate	Favourites per tweet
PROBLEMATIZATION	1.0	1.3
MEN, VETERANS, PTSD, SUICIDE, MILITARY	1.1	0.7
CHARITY, HELPING	1.0	0.3
SOCIAL MEDIA, SHARING	1.1	1.1
YOUNG PEOPLE, CHILDREN, PARENTS	1.0	0.6
WELLNESS, WELLBEING, LOVE	1.0	0.5
AUTISM, ADHD, CHILD	1.1	0.6
PARENTING	1.0	0.7
ANTI-STIGMA	1.1	0.8
WORLD MH DAY	1.0	1.2
NURSING JOBS, THERAPIST, HOSPITAL	1.1	0.7
AWARENESS, FACTS, MH MONTH	1.0	1.5
DEPRESSION, ANXIETY, BIPOLAR, PTSD	1.0	0.7
STRESS, RISK, BRAIN	1.0	1.3
WORKPLACE	1.2	0.6
COGNITIVE SCREENING, TRUMP	1.1	0.5
DONATE	1.1	0.6
FEELINGS	1.1	1.1
SUBSTANCE ABUSE	1.1	1.1
COMMUNITY, AWARENESS, EVENT, CONFERENCE	1.2	0.6
GUN VIOLENCE	1.0	3.4
DEATH, MURDER	1.1	0.8
COVERAGE, ACCESS, INSURANCE, STATE	1.1	0.7
ENGLAND, NHS, SYSTEM, BEDS	1.0	0.7
EVERYDAY LIFE	1.0	0.6
PSYCHIATRY, PROFESSION, NURSING	1.0	0.5
POLICE	1.1	1.7
EDUCATION, RESEARCH, SCHOOL	1.2	0.9
HEALTHY, CARE	1.0	1.0
FUNDING, CUTS, CRISIS	1.0	1.0

Control characteristics of MH discourse per topic

	Echo chamber	Hashtags	Mentions	Followers
PROBLEMATIZATION	-0.3	416.8	466.1	4912.
MEN, VETERANS, PTSD, SUICIDE, MILITARY	-0.3	133.1	75.0	6909.
CHARITY, HELPING	-0.2	158.3	146.3	64405
SOCIAL MEDIA, SHARING	-0.1	350.9	255.8	6917.
YOUNG PEOPLE, CHILDREN, PARENTS	-0.4	208.4	134.9	5509.
WELLNESS, WELLBEING, LOVE	0.0	527.0	106.7	5044.
AUTISM, ADHD, CHILD	-0.2	97.0	27.4	7607.
PARENTING	-0.2	44.9	26.3	30766
ANTI-STIGMA	-0.4	453.4	313.6	8642.
WORLD MH DAY	-0.3	68.1	58.0	2866.
NURSING JOBS, THERAPIST, HOSPITAL	0.4	262.7	41.7	1749.
AWARENESS, FACTS, MH MONTH	-0.3	161.4	106.3	2612.
DEPRESSION, ANXIETY, BIPOLAR, PTSD	0.0	642.3	156.8	13241
STRESS, RISK, BRAIN	-0.1	287.3	99.6	9656.
WORKPLACE	-0.4	114.0	67.1	12396
COGNITIVE SCREENING, TRUMP	-0.4	53.2	61.5	13945
DONATE	-0.1	204.1	150.5	3417.
FEELINGS	-0.4	217.3	274.7	2850.
SUBSTANCE ABUSE	-0.4	208.8	132.5	13681
COMMUNITY, AWARENESS, EVENT, CONFERENCE	-0.2	474.2	386.8	9755.
GUN VIOLENCE	-0.3	119.8	122.0	5459.
DEATH, MURDER	-0.1	86.6	55.7	4363.
COVERAGE, ACCESS, INSURANCE, STATE	-0.1	207.2	157.8	15409
ENGLAND, NHS, SYSTEM, BEDS	-0.3	131.3	97.7	20274
EVERYDAY LIFE	-0.5	165.5	156.6	3147.
PSYCHIATRY, PROFESSION, NURSING	0.4	166.4	21.3	6097.
POLICE	-0.2	51.1	29.7	4546.
EDUCATION, RESEARCH, SCHOOL	-0.3	433.3	304.3	5611.
HEALTHY, CARE	-0.3	339.4	147.5	9227.
FUNDING, CUTS, CRISIS	-0.3	231.2	165.1	6825.

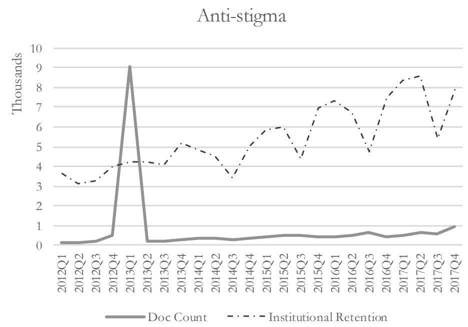
Cognitive focus characteristics of MH discourse per topic

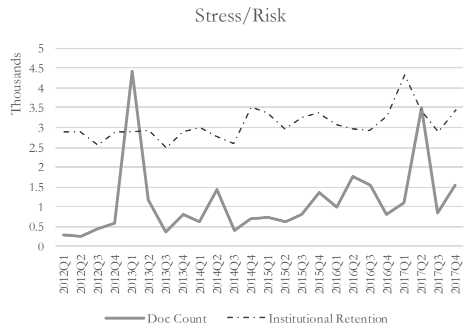
	Resolution	Inter_focus	Intra_focus
PROBLEMATIZATION	6.9	7.5	2.7
MEN, VETERANS, PTSD, SUICIDE, MILITARY	3.6	7.5	2.6
CHARITY, HELPING	2.0	7.5	2.4
SOCIAL MEDIA, SHARING	5.4	7.5	3.0
YOUNG PEOPLE, CHILDREN, PARENTS	3.3	7.5	2.4
WELLNESS, WELLBEING, LOVE	3.4	7.5	2.4
AUTISM, ADHD, CHILD	3.8	7.5	2.7
PARENTING	4.4	7.5	2.9
ANTI-STIGMA	5.6	7.5	2.9
WORLD MH DAY	6.4	7.5	2.7
NURSING JOBS, THERAPIST, HOSPITAL	4.2	7.5	2.4
AWARENESS, FACTS, MH MONTH	3.7	7.5	2.4
DEPRESSION, ANXIETY, BIPOLAR, PTSD	4.6	7.5	2.5
STRESS, RISK, BRAIN	4.4	7.5	2.6
WORKPLACE	3.2	7.5	2.6
COGNITIVE SCREENING, TRUMP	4.1	7.5	2.4
DONATE	6.2	7.5	2.5
FEELINGS	5.7	7.5	2.9
SUBSTANCE ABUSE	2.2	7.5	2.9
COMMUNITY, AWARENESS, EVENT, CONFERENCE	3.2	7.5	2.7
GUN VIOLENCE	4.5	7.5	2.4
DEATH, MURDER	4.1	7.5	2.8
COVERAGE, ACCESS, INSURANCE, STATE	4.5	7.5	2.6
ENGLAND, NHS, SYSTEM, BEDS	4.3	7.5	2.5
EVERYDAY LIFE	4.2	7.5	2.5
PSYCHIATRY, PROFESSION, NURSING	3.0	7.5	2.5
POLICE	2.9	7.5	2.8
EDUCATION, RESEARCH, SCHOOL	5.0	7.5	2.9
HEALTHY, CARE	4.8	7.5	2.5
FUNDING, CUTS, CRISIS	0.6	7.5	2.5

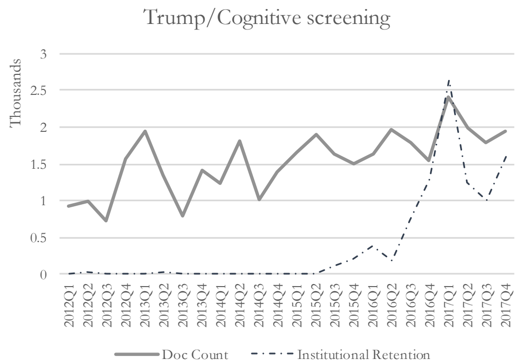
Appendix 10

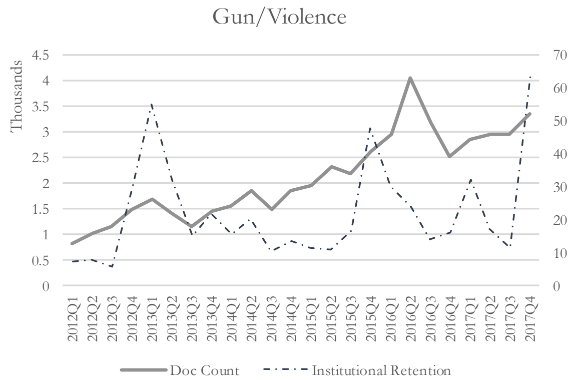
Link to an interactive tool.

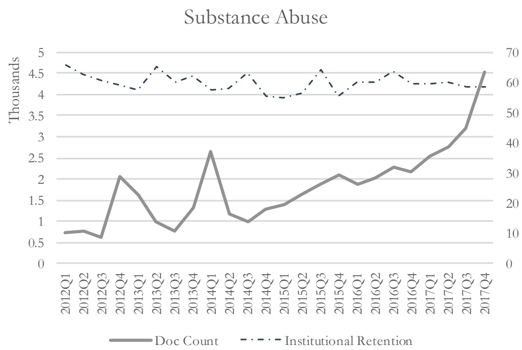
Appendix 11

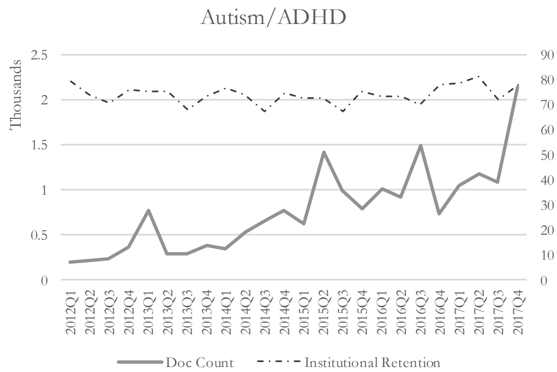

Anti-stigma
Thousands
Doc Count
Institutional Retention

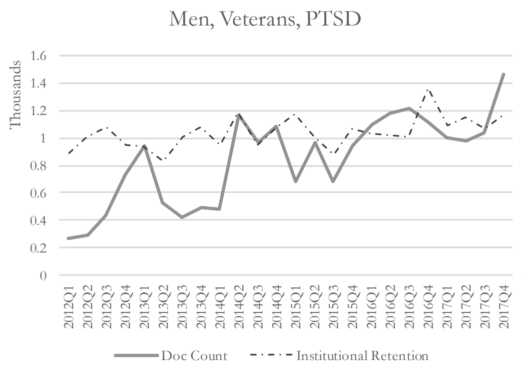

Stress/Risk
Thousands
Doc Count
Institutional Retention


Trump/Cognitive screening
Thousands
Doc Count
Institutional Retention


Gun/Violence
Thousands
Doc Count
Institutional Retention


Substance Abuse
Thousands
Doc Count
Institutional Retention


Autism/ADHD
Thousands
Doc Count
Institutional Retention


Men, Veterans, PTSD
Thousands
Doc Count
Institutional Retention

Appendix 12

Account	*Number of followers*	*Description*
mental__health	14232	Find mental health jobs today! #MENTAL#HEALTH#JOB#JOBS#WORK#CAREER#THERAPY#THERAPIST
itscubanyo	3827	(fan account)
marcuslisle	1848	Most known for 'Makeup with Marcus' on Facebook & 'Marcus's Autism Journey' | contact:
nhenews	14220	National Health Executive, the essential guide to health service management
Consultro_Com	107	Consultro is your dependable forum for #online_mental_health Online #therapy #counseling sessions from anywhere. An easy way to provide and receive MH services
ERMurray	6499	Author #TheBookOfLearning (Dublin UNESCO Citywide Read 2016), #TheBookofShadows (Shortlisted #BGEIBA 2016) & #CaramelHearts. I fish& grow veg! Rep: @Sallyanne_s
Miss_Grief	404	Girlguide Leader, Beginner Harpist and Charity Founder. My views are my
HealthyPlace	64844	Trusted information on psychological disorders and treatments, plus mental health support. Home to Stand Up for Mental Health campaign.
AuthorsTalk	9823	Supporting indie & self-published #authors. #books #bookpromotion #writingcoach #bookcontest #manuscriptcritique
iFredorg	1657	We shine a positive light on #depression and have a free program for youth to #teach #hope. 💛 #sharehope by planting
OfficialNIHR	45219	The NIHR is dedicated to improving the health and wealth of the nation through research. Retweets aren't necessarily endorsements.
olgaisthebest	6807	PhD Candidate in Psychology at the University of Toronto. A volunteer at CPPA. My interests are: #positivepsychology #mentalhealth #parenting #autism #ADHD
valenruizl	2536	@UBCJournalism alumna | Social media | Journalist
TheseLegs	224	One can never consent to creep when you feel the need to #soar - ,real jobs, grants, fellowships and educational opportunities etc. #soar
RachiieCohen	8311	Therapist in group practice. Married to Dr. David Cohen. Mother of 2 kids: one with #ADHD, another with #Asperger. Interested in #Parenting and #MentalHealth
Authors_Village	555	Tweeting tons of fantastic authors and books!
ReadersVillage	518	Bringing you new books and authors to explore!
WomenWorldNew	18773	#Women #News Worldwide #Feminism #LikeAGirl #LGBT #Islamophobia #DomesticViolence #UniteBlue #AnimalRights #Gunsense Powered by @AnimalRightsJen
dr_metzner	7085	Clinical psychologist in private practice. NYU graduate. Lecturer at Hunter college.
HeyDiddleDiddle	6175	Critically-acclaimed feature film centering around a person with Social Anxiety Disorder. https://itunes.apple.com/us/movie/hey-diddle-diddle-2009/id349283564 …
rehab_hotline	3525	Find Careers and Jobs in Rehabilitation at http://www.healthcarehiring.com ! #JOB #JOBS #CAREER #WORK #REHAB #RECOVERY #MONEY
Simply_Saila	326	#Wiccan woman who has #mentalhealth issues like #DID #BPD #depression ~just trying to make it through the day moment by moment.
barrypearman	14588	Empowering your #MentalHealth Writing to help you and others find #faith#hope#love#kiwi
hipmomjulie	8574	Down to earth Mom, Blogger, Love connecting, learning, growing, playing, singing, laughing and living. Cheers to you!
RachiieCohen	8311	Therapist in group practice. Married to Dr. David Cohen. Mother of 2 kids: one with #ADHD, another with #Asperger. Interested in #Parenting and #MentalHealth
PlusGuidance	8276	Improving the world's #MentalHealth with #OnlineTherapy.
Respect_Ability	6989	Fighting Stigmas. Advancing Opportunities. Jennifer Laszlo Mizrahi, president @HarrisC2, Chair
urfoodmedicine	6712	#health #greenliving #organic #food#juicing#rawfood#vegan #sustainable #detox#Superfoods #gmofree #glutenfree#Smoothies
Red__Rover	6577	The definitive mobile resource for parents on the go. Give your kids the best day ever.
Red__Rover	6577	
DrMBengtson	2111	#Author, #Speaker, Neuropsychologist, #Hope Instiller, #Encourager, #Joy Enthusiast, #MentalHealth Advocte, #tagtribes http://www.DrMichelleB.com
andrewzimmern	1270875	Chef, Writer, Traveler, TV Host
Surgeon_General	525212	U.S. Surgeon General VADM Jerome M. Adams.
theheraldsun	303697	Join in the conversation on all the news from Melbourne's Herald Sun.
TAMU	257057	The official Twitter account for Texas A&M University
getitoutnow	228203	Tweet Social News is the network of http://socialstartnow.com
HuffPost	11562825	HuffPost
atiku	1313961	Waziri Adamawa, former Vice President of Nigeria, a dad, businessman and philanthropist.
BostonGlobe	712868	
JohnsHopkinsSPH	440884	@JohnsHopkins Bloomberg School of Public Health. Together we're Protecting Health, Saving Lives—Millions at a Time
guardianeco	438818	News and comment on the world's most important environmental storie
StandardKenya	953479	Your Gateway | Related to @KTNKenya @Radiomaisha
vicenews	891390	
thinkprogress	853745	Moving news forward since 2005.
jilevin	584231	Marketing Programs Manager, social media, human rights, politics and news junkie, equality. #RESIST #FBR
GeorgeAylett	294535	Chair: @HullUniLabour. Founder: @LabourUBI. Used to be a 'Rotund Labourite'. Once ran for Parliament. Terrible at running. 🇬🇧 🌹
hnshah	224638	Started a few businesses. @CrazyEgg& KISSmetrics with@NeilPatel. Working on @ProductHabits &@usefyi with @MarieProkopets . I creating products people love.
JeffreyGuterman	203448	Mental Health Counselor and Author | #TheResistance | #BlockedByTrump | http://JeffreyGuterman.com
socialstartnews	156436	Social Start News is a network of http://socialstartnow.com 321 536-3485
PsychCentral	150823	The professional feed for Psych Central. For mental health professionals.

;

alina.pvlova@gmail.com

@AliPvlova