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Unravelling Collective Social Media Affordance Dynamics During Crises: An Analysis of Online Mental Health Discourse

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Research-in-progress

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Abstract

Social media can serve as a platform for collective engagement with diverse affordances during crises. We explore how social media served this role by focusing on how online mental health discourse evolved during the COVID-19 pandemic. Specifically, we examine shifts in collective affordance dynamics within the online mental health community using Twitter. A comprehensive dataset of mental health-related tweets from 2018 to 2021 was collected (N = 3,953,836) and analysed using Data-Driven Computationally Intensive Theory Development as a guiding methodology. A subset of 757 representative tweets were manually categorised into a cascading set of actor groups. Analysis uncovers that collective engagement transitioned from decentralised actor utilisation (pre-crisis) to centralised organisational utilisation (early-crisis), culminating in centralised actor utilisation (late-crisis). The study contributes theoretically to collective affordance knowledge by integrating dynamics in an online setting and practically by revealing key actors' evolution in shaping online discourse across crisis phases.

Keywords: Social media; collective affordances; dynamics; actors; crisis stages; computationally intensive theory development

1   Introduction

Social media can serve as a platform for collective engagement with various types of affordances during crises (Nan and Lu 2014; Vaast et al. 2017). One such crisis was the COVID-19 pandemic. With prevalence of anxiety and depression increasing by more than 25% during the initial phase of the pandemic (World Health Organization 2022a, 2022b), our study examines how social media served as a platform for collective engagement across different phases of the crisis within the online mental health community.

The features of social media platforms, such as its cost-effective reach to large audiences, continuous accessibility and enablement of anonymity allow individuals to seek social support at any time (Yan and Tan 2014). With the onset of the pandemic leading to a 61% increase in social media use (Holmes 2020), understanding the dynamic effects of the crisis on collective online mental health discourse becomes increasingly important. One approach to examining this phenomenon is to examine the dynamics of social media feature utilisation at an abstracted level through the concept of affordances.

Affordances represent the potential actions and opportunities that emerge when individuals interact with an IT artifact (Faraj and Azad 2012; Leonardi 2011, 2013; Volkoff and Strong 2017). While affordances are typically envisioned as individualised affordances realised to fit the specific needs of an individual (Karahanna et al. 2018), multiple actors can utilise technology in a manner that invokes shared or collective affordances. Shared affordances are realised when actors with similar needs utilise technology in a comparable manner, whereas collective affordances are actualised through different actors using technology according to their distinct needs, which, in turn, generates a collective outcome (Leonardi 2013; Sæbø et al. 2020). Social media, particularly during crises, serves as a technological platform where collective affordances can be activated as multiple actors interact with the same topic, driven by a diverse sets of needs (Vaast et al. 2017).

While collective affordances have been examined in the context of crises in the past (Nan and Lu 2014; Vaast et al. 2017), little research to date has examined the dynamics of collective affordance activation over time. Therefore, the purpose of this research is to explore the dynamics of collective social media affordance activation during crises within the context of mental health discourse on social media. This motivates our overarching research question: *How does the activation of collective social media affordances evolve throughout different crisis phases?*

2   Theoretical Background

The concept of affordances originated in Gibson's (1977) work in ecological psychology. Affordances refer to the potential actions and opportunities that emerge when interacting with an object (Faraj and Azad 2012). When humans interact with objects, they perceive the possibilities these objects offer (Gibson 1977). In the field of IS research, scholars have embraced the concept of affordances to better understand technology in a way that acknowledges its materiality without adopting a technologically deterministic view (Strong et al. 2014; Vaast et al. 2017). Human interaction with IT artifacts is driven by their perception of positive affordances (Leonardi 2011). However, affordances are distinct from IT artifacts, instead emerging when humans interact with IT artifacts (Faraj and Azad 2012; Markus and Silver 2008; Volkoff and Strong 2017).

Within the realm of Twitter, now X, the act of retweeting enables the affordances of meta-voicing and content sharing (Karahanna et al. 2018). Content sharing involves distributing content unrelated to the individual user (Karahanna et al. 2018). Conversely, meta-voicing involves engaging in online conversations by reacting to other users and observing other user's reactions in the context of presence, profiles, content, and activities (Majchrzak et al. 2013). Affordances are inherently relational, defined by the interplay between users with their specific intentions and social context, and the material features of the technology (Faraj and Azad 2012). Due to the relational nature of affordances, the same technology and features may support different affordances (Leonardi 2011, 2013). The dynamic nature of social media interactions influences how users engage with the platform's features, creating a reciprocal relationship between features, affordances and the users' needs (Karahanna et al. 2018). In this research, we focus on microblogging, which enables users to exchange short content elements like sentences, images, and video links (Harrigan et al. 2021; Oh et al. 2015). This implies that specific social media platforms, such as the microblogging platform Twitter, may allow different actors motivated by different needs to engage with distinct affordances (Vaast et al. 2017). Thus, when examining the dynamics of retweets, we can also explore the dynamics of affordance activation.

Affordances are frequently analysed at an individual level (Strong et al. 2014). Leonardi (2013) differentiates between individualised affordances, shared affordances, and collective affordances.

Moving beyond the individual level, multiple actors may utilise technology in a way that actualises shared or collective affordances. Shared affordances are realised by actors who share similar needs and usage patterns of the technology. On the other hand, collective affordances emerge when various actors use a technology to fulfil their unique needs, resulting in an aggregate collective outcome (Nan and Lu 2014; Sæbø et al. 2020). Collective affordances are especially relevant in the context of crises as different actors engage with social media for different purposes, but their actions in combination result in a collective outcome (Vaast et al. 2017).

3 Methodology

Digital trace datasets, such as social media trace data, represent digital records of activities and events occurring on digital technologies which offer a level of granularity that has the potential to revolutionise established paradigms (Berente et al. 2019; Grisold et al. 2023; Howison et al. 2011; Müller et al. 2016). However, developing theoretical insight from digital trace datasets can be a challenging task (Maass et al. 2018). Unlike surveys or interviews designed to produce research data, digital trace data is the by-product of other activities, and therefore must be adapted for research purposes (Howison et al. 2011, p. 769). To overcome these challenges, the Information Systems (IS) field has increasingly adopted computationally intensive approaches to generate, reformulate, replace, and extend through the analysis of digital trace data (Berente et al. 2019; Lindberg 2020; Miranda, Berente, et al. 2022). These approaches draw from computational theory discovery, computational social science, grounded theory methodology and mixed methods research, "but is not reducible to any one of them" (Miranda, Berente, et al. 2022, p. iv). At a high-level, we follow the four iterative phases of Data-Driven Computationally Intensive Theory Development (CITD): (1) data collection and sampling (i.e., iteratively develop dataset), (2) synchronic analysis (i.e., categorising data), (3) lexical framing (i.e., engaging and extending an existing scholarly discourse) and (4) diachronic analysis (i.e., generating and extending theory) (Berente et al. 2019).

3.1 Data Collection and Sampling (Phase 1)

3.1.1 Data Collection

Twitter was selected as the primary source of data. Notably, Twitter allows users to contextualise their tweets by using hashtags. Through hashtags, users can quickly take note of important information and participate in real-time dialogue as contextual information is created and disseminated (Rao et al. 2020). Our specific case focuses on the month of May which is known internationally for raising mental health awareness (Makita et al. 2021; Stupinski et al. 2022). May represents two major international mental health awareness campaigns, Mental Health Month (MHM) and Mental Health Awareness Week (MHAW). MHM and MHAW are US-based and UK-based campaigns, respectively. Both campaigns have run for over a decade and possess a strong social media presence (Mental Health America 2022; Mental Health Foundation 2022). Both MHM and MHW possess Twitter accounts and use them actively, particularly during the month of May (Kishore et al. 2022; Makita et al. 2021). These campaigns in combination with other factors make May the most popular month for mental well-being discourse on Twitter.

Data was collected from the month of May spanning 2018 to 2021. These four months in aggregate allow us to make precise comparisons before (2018 and 2019) and after (2020 and 2021) the pandemic commenced. We chose to focus on these time periods as they are distinct. For example, in May 2020 and 2021, travel restrictions and lockdowns were widely in place (Coccia 2022). In 2022 and 2023, these restrictions have eased in most countries, but not all (Taylor 2022). Further, this four-year time period provides us with sufficient detail to explore and answer the research question.

Parameter development focused on identifying a group of hashtags that were used consistently over the entire four-year period to ensure comparability. Hashtags that were specific to the pandemic, for example, were excluded from the development process. Focusing on hashtags concentrated parameter development and data collection on a specific community's discourse. Four seed hashtags related to the campaigns were initially adopted: #MentalHealthMonth, #MentalHealthAwarenessMonth, #MentalHealthWeek and #MentalHealthAwarenessWeek. We used a specialised toolkit to collect tweets using at least one of these hashtags during the month of May from 2018 to 2021 (Kishore et al. 2019). We then identified the most popular co-occurring hashtags over two iterations resulting in nine hashtags in total: #MentalHealth, #MentalHealthAwarenessWeek, #MentalHealthAwarenessMonth, #MentalHealthWeek, #MentalHealthMonth, #MentalHealthMatters, #LetsTalk, #TogetherWeCan and #EndTheStigma. The list of hashtags defined above was used to collect all English tweets across the specified time period. Data collection resulted in 3,953,836 tweets in total.

3.1.2 Sampling

Previous work analysing the entire dataset has identified that users engaged in retweeted behaviour significantly more during the initial phase of the pandemic (i.e., 2020) whereas tweeting behaviour did not change significantly across the time period (Kishore et al. 2022). To qualitatively analyse collective affordance dynamics in-depth, we extracted a sample of 200 of the most retweeted tweets per year (N = 800). The sample decreased slightly during the data cleaning process (N = 757).

3.2   Synchronic Analysis (Phase 2)

Synchronic analysis focuses on analysing multiple technologies at a specific point of time. In plain terms, "a synchronic analysis would compare technologies with each other, whereas a diachronic analysis would contrast earlier and later periods of a single technology's use" (Barley 1990, p. 223). For example, Barley et al. (1990) used synchronic analysis to analyse multiple technologies used within a radiology department (i.e., radiography, CT scanning and ultrasound), whereas diachronic was used to examine a single technology (i.e., CT scanning) over time. From a different perspective, synchronic analysis reveals cross-sectional patterns, static concepts, and static relationships amongst concepts, whereas diachronic analysis enables researchers to examine temporal patterns, dynamics, and change (Berente et al. 2019).

Our analysis focuses on manually categorising a sample of the most influential tweets (based on retweets) and qualitatively analysing actor groups longitudinally (Kotlarsky et al. 2022; Mirbabaie et al. 2020). The categorisation of users into actor groups allows us to differentiate between users with distinct characteristics and behavioural intentions. For instance, media organisations tend to be more active on social media platforms, and usually have a larger following, than the general public (Mirbabaie et al. 2020). Thus, we can compare what types of actors may be driving this change in the community's retweeting behaviour during the initial phase of the pandemic, which, in turn, allows us to examine affordance activation dynamics during crises.

Further, this categorisation allows us to examine how different groups engage with a specific topic and how others interact with the content generated by these groups. In this way, we can explore the dynamics of online discourse and gain deeper insights into the behaviour and motivations of different actors within our dataset (Miranda, Wang, et al. 2022, pp. 1425–1427). As actors often belong to multiple categories (Kotlarsky et al. 2022), we utilise a cascading categorisation approach to fit user accounts into the most meaningful categories (Kishore et al. 2023). Each actor is assigned a category without evaluating the year the tweet was published to maintain comparability. In the future, we also plan to manually code each tweet to gain further insight.

3.3   Lexical Framing (Phase 3)

Lexical framing involves situating concepts and patterns within an existing body of knowledge to extend a specific discourse (Berente et al. 2019). A "lexicon" represents a particular language used by a community to represent their specific knowledge (Habermas 1984; Miranda, Berente, et al. 2022). It provides researchers with a language to generate and formulate relevant findings. Computationally intensive researchers synthesise three different types of lexicons: practice, method and theoretical (Miranda, Wang, et al. 2022). Practice lexicons represent distinct components of the phenomenon under study that carry significance within a particular community. In this study, we focus on technologically-mediated mental health discourse, where certain terms, for example, are used to represent a variety of mental health issues. Method lexicons represent the assumptions associated with different methodological choices. In this study, we manually identify and examine prominent actor groups. Lastly, theoretical lexicons represent the theoretical discourses researchers utilise when constructing a theoretical contribution. This work's potential theoretical contribution is lexically framed in the context of collective affordances (Leonardi 2013; Nan and Lu 2014; Sæbø et al. 2020; Vaast et al. 2017). Specifically, examining the dynamics of collective affordance activation.

3.4   Diachronic Analysis (Phase 4)

Originating from linguistics, diachronic analysis involves the evolution of language over time (Saussure 1916). In organisational research, it refers to changes in action patterns over time (Barley 1990). In IS research, it focuses on analysing a singular technological phenomenon over time in order to generate theory (Berente et al. 2019). In our study, diachronic analysis involves analysing the dynamics of multiple actor groups over multiple crisis stages to contribute an initial understanding of collective affordance dynamics.

4   Empirical Findings

4.1   Synchronic Analysis

As shown in Table 1, categorisation resulted in 14 distinct actor groups – five of which represent organisations and nine of which represent different types of individuals. From a synchronic perspective, health organisations produced the most highly retweeted updates (148) across the time period. Individuals were categorised separately from influencers based on recent research differentiating influencer categories (Boerman 2020; Kay et al. 2020). Influencers were further divided into three distinct categories (i.e., micro, meso and macro) based on this research.

		Definition	Count
Organisations	**Health Organisations**	Health-focused organisations; mental health foundations; mental health charities.	148
	Government Organisations	Associated with or funded by government.	30
	Not-for-profit Organisations	Charities; voluntary organisations; unrelated to mental health.	67
	Media Organisations	Media companies; news outlets.	45
	Organisations	For-profit; companies; brands.	85
Individuals	**Professionals**	Counsellors; psychologists; psychiatrists; doctors; clinicians.	40
	Advocates	Mental health advocates; activists.	40
	Government Individuals	Unrelated to politics; government workers; police officers.	14
	Politicians	Individuals involved with politics.	40
	Media Individuals	Media individuals; reporters; news writers; associated with one or more media organisations.	25
	Micro Influencers	Individuals with > 1,000 and < 10,000 followers.	45
	Meso Influencers	Individuals with > 10,000 and < 100,000 followers.	61
	Macro Influencers	Individuals with > 100,000 followers.	102
	Individuals	Individuals with < 1,000 followers.	15

Table 1: Cascading actor groups and definitions.

4.2   Diachronic Analysis

From a diachronic perspective, different clusters dynamically emerged over time (Table 2). Cluster 1 shows that government organisations, not-for-profit organisations, for-profit organisations, media organisations and health organisations were retweeted the most, on average, in the early phase of the pandemic. Cluster 2 shows that advocates, government individuals, media individuals and politicians were retweeted the most, on average, in the later phase of the pandemic. Cluster 3 shows that advocates, professionals, individuals, macro influencers and meso influencers were retweeted the least, on average, in the early phase of the pandemic. This observation highlights the varying influences of different actors in mobilising collective affordance activation on social media during the course of the pandemic.

Specifically, during the early-crisis phase of the pandemic, organisations played a pivotal role in driving heightened retweeting behaviour. Conversely, updates generated by individual users received relatively less attention during this phase. As the pandemic progressed, a shift occurred, and trusted individuals emerged as significant drivers of collective affordance action in the late-crisis phase of the pandemic. This transition likely reflects changes in user preferences, information needs, and evolving trust dynamics during the prolonged crisis.

		2018	2019	2020	2021
Organisations	**Health Organisations**	419	423	590	622
	Government Organisations	356	300	803	540
	Not-for-profit Organisations	498	284	557	376
	Media Organisations	344	314	946	677
	Organisations	425	366	906	450
Individuals	**Professionals**	350	600	235	467
	Advocates	487	578	314	1,107
	Government Individuals	493	336	484	539
	Politicians	292	623	543	695
	Media Individuals	178	297	440	823
	Micro Influencers	359	791	604	696
	Meso Influencers	751	520	508	577
	Macro Influencers	1,466	853	552	1,428
	Individuals	563	600	216	218

Table 2: Actor groups by average retweets (red represents the lowest value for the actor group and green represents the highest).

5 Theoretical Contributions

The goal of this work is to contribute an initial understanding of collective social media affordance activation dynamics during crisis scenarios. Through analysing social media trade data generated by the most retweeted actor groups over time, we identify changes in collective affordance activation across three crisis phases (Table 3). Retweeting as a social media feature activates two affordances: (1) content sharing and (2) meta-voicing (Karahanna et al. 2018). Content sharing involves distributing content to others whereas meta-voicing goes further as it "is not simply voicing [an] opinion, but adding metaknowledge to the content that is already online." (Majchrzak et al. 2013, p. 41). While we plan to clarify the difference between these two types of affordances in future research, our current findings indicate three unique collective utilisations of these two affordances.

	Pre-crisis Phase	Early-crisis Phase	Late-crisis Phase
Collective Affordance Activation	Decentralised Actor Content Sharing and Meta-voicing	Centralised Organisational Content Sharing and Meta-voicing	Centralised Actor Content Sharing and Meta-voicing
Exemplars	Micro Influencers; Meso Influencers; Individuals	Government Organisations; Media Organisations	Politicians; Government Individuals; Media Individuals
Illustration			
Instance			

Table 3: Collective affordance activation dynamics.

In the pre-crisis phase, mental health discourse participants engage in decentralised actor content sharing and meta-voicing, wherein they retweet content from unverified sources like micro influencers and individuals. Outside of crisis situations, mental health awareness discourse tends to be driven by individuals and influencers discussing the importance of mental health (Makita et al. 2021). Transitioning to the early-crisis phase, collective engagement with mental health discourse undergoes a significant shift towards the activation of centralised organisational content sharing and meta-voicing. The community directs its attention to official sources of information produced by diverse types of organisations, including media outlets, and companies. In the late-crisis phase, there is a slight decentralisation of collective engagement, with a focus on the activation of centralised actor content sharing and meta-voicing. The collective attention shifts towards individuals explicitly associated with formal organisations (e.g., politicians), prominent figures with substantial followings (e.g., macro-influencers), and those explicitly affiliated with mental health causes (e.g., advocates). These findings contribute to a more nuanced understanding of the interactions between actors and collective affordances during crises, opening avenues for future research in the dynamics of technologically-mediated crisis communication.

6   Practical Contributions

While practical implications are still under development, we believe that the findings of this study have several potential practical implications for understanding and managing the dynamics of discourse on social media platforms during crisis scenarios. These implications can guide policymakers, advocates, and organisations in formulating effective communication strategies and interventions to promote collective well-being and support during challenging times. Affordance activation also reflects individual needs (Karahanna et al. 2018) which provides insight into why technology use behaviours may be changing over time. Understanding the needs motivating a collective entity's use of technology during crises provides insights into the primary purpose individuals engage with technology during crises.

7   Conclusion

This study explores the dynamics of engagement with collective social media affordances during crises. Social media can serve as a platform for collective engagement with a diverse set of affordances during crises. We examine shifts in collective affordance dynamics within the online mental health community using Twitter. A comprehensive social media trace dataset was collected and analysed using Data-Driven Computationally Intensive Theory Development as a guiding methodology. Analysis uncovers that collective engagement transitioned from decentralised actor utilisation in the pre-crisis phase to centralised organisational utilisation in the early-crisis phase, culminating in centralised actor utilisation in the late-crisis phase. The study's theoretical contribution lies in its integration of dynamics within an online setting, advancing collective affordance knowledge, while practically identifying key actors in shaping online discourse across distinct phases of a crisis.

While this paper outlines both theoretical and practical contributions, both types of contributions will be further refined in future work. Specifically, as retweets have the potential to activate two unique affordances, content sharing and meta-voicing, future work will focus on clarifying if and how these affordances are activated differently across crisis phases. Further, while content sharing is egocentric in nature (e.g., solitary, does not require other users to be actualised), meta-voicing is inherently allocentric in nature (e.g., social, requires the involvement of other users to be actualised) (Karahanna et al. 2018). This also indicates that the same behaviour could be driven by different purposes by different users. Lastly, lexical framing will be considered in greater detail in future research. Overall, this work suggests that the motivations underpinning retweeting behaviours are heterogenous across users and tied to users' distinctive needs, which aligns with the domain's understanding of collective affordances.

This study should be viewed in light of its intrinsic limitations. Results from a specific social media platform, such as Twitter, may be difficult to generalise to other platforms, especially as Twitter use is dominated by specific countries and regions and the data collected is restricted to English. Thus, future research should consider integrating a more comprehensive range of platforms and languages. The process of manually categorising and analysing actor groups is highly subjective, thereby expanding the sample size as well as carrying out different types of analyses, including computational analyses, will be done in future research. Further, while using a cascading approach provides valuable insights, it introduces limitations as some user accounts fit into multiple categories. We will consider the best approach to addressing and refining and redefining related actor groups (i.e., politicians and government individuals) in the future. Lastly, retweets only represent one indicator of engagement, thus future research will consider integrating other indicators to identify an appropriate sub-sample.

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