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Examining the Influence of Information Technology on Health Behaviors and Health Outcomes

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EXAMINING THE INFLUENCE OF INFORMATION TECHNOLOGY ON HEALTH BEHAVIORS AND HEALTH OUTCOMES

By

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DISSERTATION

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DEDICATION

This dissertation is dedicated to my mother who always energized me to dream big, and to my father who continually inspired me to strive for success. In addition, I wish to express my gratitude to my wife for teaching me to never give up hope. Last but not least, I wish to express my sincere gratitude to my brothers for their unwavering support. Without their care, love, and courage, this remarkable accomplishment would not have been possible.

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Abstract

EXAMINING THE INFLUENCE OF INFORMATION TECHNOLOGY ON HEALTH BEHAVIORS AND HEALTH OUTCOMES

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The University of Texas At Arlington, 2022

Supervising Professors: Radha Mahapatra and Sridhar Nerur

Information Technology (IT) has radically changed our daily lives and it has the potential to help us adopt healthy behaviors and improve health outcomes. This two-part study investigates the influence of IT on health behaviors in population health management.

Crises lead to severe uncertainty, high-risk perceptions, and vulnerability among people. Crisis communication through social media platforms influences people to undertake recommended behaviors that mitigate crisis consequences. Political leaders utilize Twitter to deliver crisis messages that offer mental support and empower local communities to spawn resilience and adaptability with emergent collective behaviors necessary to respond to the crisis. The primary objective of this study is to investigate the COVID-19-related tweets posted by political leaders using computational linguistics to examine the effects of crisis communication on crisis outcomes (e.g., confirmed cases). We observed that the contents of the crisis messages from political leaders have changed in consistent with the progress of the COVID-19 crisis. We also found that while tweets with analytic, authentic, and tone from the past week affected the confirmed cases in the following week, surprisingly, tweets with clout are not significantly associated with crisis outcomes. We further analyzed several significant properties of the network of political leaders on

Twitter. The findings demonstrate that the network of political leaders on Twitter is relatively dense and well-connected. A few nodes are highly dominant and have power law distribution. Our study detected *twenty-three* communities of political leaders and observed evidence of political polarization in the network. We find two large communities representing the Republican and Democratic parties at the national level. The remaining communities are reasonably well-balanced in size and center at the state level. Our findings have greater implications for leaders deploying social media during a crisis.

While chronic diseases pose tremendous challenges for patients, physicians, and care providers, lack of its management incurs exorbitant costs and can cause early death. Diabetes is a highly prevalent chronic disease that leads to health complications and comorbidity. Medically underserved populations (MUP) are relatively at higher risk of diabetes due to cultural, economic, and social barriers. Studies show that IT-enabled self-management is critical to avoid or slow the consequences of diabetes. This study investigates how to improve compliance with diabetes using IT-enabled self-management among MUPs. We designed and developed a user-centered mHealth app reflecting the needs and characteristics of the target population. To achieve this end, we used design science research methodology and articulated design principles based on the relevant theories and dominant literature to inform the design. The study contributes to reducing health disparity, a long-standing societal problem, and caters valuable insights to improve population health management.

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1.0 Study-1

Does Crisis Communication by Political Leaders on Social Media Influence Crisis Outcomes?

1.1 Introduction

Crises – Egyptian revolution, COVID-19, and the Ukraine-Russia war – challenged the norms of behavior, causing tremendous burdens for the people (Bavel et al., 2020a) (Stiglitz, 2013) (Reicher, 1984) (Turner & Killian, 1987) (Oh et al., 2013) (Schneider, 1995). For example, COVID-19 killed more than six million people[1] and is expected to impose a staggering economic cost of $12.5 trillion by 2024 worldwide[2]. The mitigating policy measures necessitate preventive efforts and call for the adoption of new behaviors to alleviate the devastating effects of such a crisis (Choma et al., 2021) (Oh et al., 2015) (González-Bailón et al., 2013) (Sæbø et al., 2020) (Riemer et al., 2020). However, the most conspicuous challenge involves communicating and persuading the public to adopt new behaviors collectively.

Recently, social media launch has radically changed how we approach crisis communication (Palen et al., 2009) (Guidry et al., 2017). Social media is regarded as the most pervasive medium for producing and disseminating information during a crisis (Watkins & Clevenger, 2021) (Shklovski et al., 2008) (Vaast et al., 2017). It is often driven by influencers, who possess unequal power and status over other users, setting the trends on the platform (Matthews et al., 2022; Park

[1] https://coronavirus.jhu.edu/map.html
[2] https://www.reuters.com/business/imf-sees-cost-covid-pandemic-rising-beyond-125-trillion-estimate-2022-01-20/

& Kaye, 2017; Chu et al., 2019; Xu et al., 2014). For instance, among other influencers, governors (London & Matthews, 2021), legislators (Engel-Rebitzer et al., 2021), government stakeholders (Wang et al., 2021), and party leaders (Niburski & Niburski, 2020) utilized Twitter in COVID-19 crisis communication to influence the public with the recommended behaviors. According to Pew Research Center, members of the U.S. Congress posted more than 27k tweets related to COVID-19 on Twitter just between Jan. 22 and Mar. 21, 2020[3]. Tweets from celebrities and politicians impacted more than the tweets from health and scientific authorities during COVID-19 (Kamiński et al., 2021). In US, 1 out of 4 people use Twitter while 7 out of 10 Twitter users consume news from it[4]. Numerous efforts are being made to examine crisis communication on social media. One promising approach is computational linguistics, which deals with the "understanding and generating of natural language" (Grishman, 1986, p. 4). The increasing evidence shows that social media posts are enriched with linguistic features (Chau et al., 2020) (Abbasi et al., 2018) that influence behaviors (Deng et al., 2021) (Depraetere et al., 2021) (X. Liu, Zhang, et al., 2020), affect sense-making in online discourse (Abbasi et al., 2018), and elicit actionable responses in crisis management (Purohit et al., 2013). Furthermore, past IS studies have recognized the potential of linguistic analysis in crisis communication (Venkatesan et al., 2021), detecting spread of infectious diseases (Xu et al., 2020), personality extraction (Adamopoulos et al., 2018), customer complaint management (Gunarathne et al., 2018), online crowdfunding (Hong et al., 2018), online reviews (Huang et al., 2017), fraudulent behavior detection (Siering et al., 2016), and organizational knowledge exchange and collaboration (Beck et al., 2014) (Ludwig et al., 2014).

While political leaders' crisis communication on Twitter has been found trustworthy and influential to the wider population (Cho et al., 2013) (Vera-Burgos & Griffin Padgett, 2020), existing studies

[3] https://www.pewresearch.org/fact-tank/2020/04/02/tweets-by-members-of-congress-tell-the-story-of-an-escalating-covid-19-crisis/

[4] https://www.pewresearch.org/journalism/2021/11/15/news-on-twitter-consumed-by-most-users-and-trusted-by-many/

have not fully gained the nuances of political leaders' Twitter-mediated crisis communication in the context of COVID-19 from the computational linguistics perspective, focusing instead on measures such as tweet frequency. There is, therefore, a need to understand the interplay between the lexical properties of tweets by people in positions of authority and collective behaviors that ensue in the aftermath of a pandemic. Thus, our study deepens our understanding of the influence of social media in general and the tweets of influential political leaders in particular in facilitating compliant behaviors during a crisis. Therefore, we seek to address the following research question-

RQ1: What is the discourse of political leaders' COVID-19-related crisis communication on Twitter?

RQ2: How do linguistic features (analytic, clout, tone, etc.) embedded in political leaders' COVID-19 tweet posts impact the COVID-19 crisis outcomes?

Drawing upon social influence theory (Kelman, 1958) and systemic functional linguistic theory (SFLT), we examine political leaders' crisis communication influence on COVID-19 infection cases. Prior studies showed that crisis communication on Twitter enables collective sensemaking and coordinated action through real-time and distributed messages overcoming spatial and temporal barriers. In addition, political leaders use Twitter to deliver official and unofficial instructions, updates, and opinions (London & Matthews, 2021) (Cuomo et al., 2021). Thus, we identified political leaders on Twitter and created a panel data set aggregating tweets and infection cases. Our research design provides rigor in detecting political leaders' networks on Twitter using state-of-the-art natural language processing (NLP) and capturing the longitudinal effects of crisis communication.

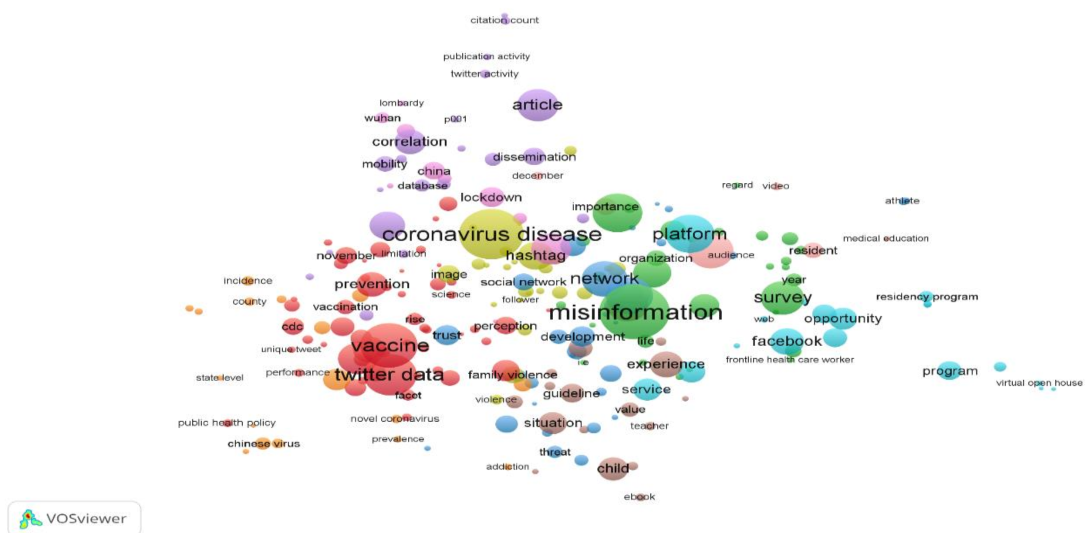
The paper makes several contributions by examining the COVID-19 crisis communication of political leaders on Twitter. First, we used advanced NLP techniques to illustrate the nature and content of tweets by political leaders during the pandemic. Second, our study employed rigorous methods to empirically validate the relationship between lexical variables derived from politicians' tweets and COVID-19 outcomes. Third, the study demonstrated how a machine learning model can be used to distinguish between COVID and non-COVID tweets. Fourth, we employed a rigorous econometric approach (i.e., PVAR) to confirm the bidirectional influence between political leaders' tweets and COVID outcomes meaning that while political leaders' crisis communication affects crisis outcomes, they also adjust the content of crisis communication with the progress of the crisis. Finally, the study clarifies how these effects differ across different stages of the crisis. These findings call upon the people with authority to meticulously conduct crisis communication during a crisis on social media platforms.

The following sections proceed as follows. The next section reviews the relevant background literature, followed by a discussión of the theories informing this study. We then formulate hypotheses for empirical testing. Subsequently, we elaborate on the machine learning techniques and data preparation procedures followed by an econometric model specification. The succeeding section discusses the findings and their implications for Research and practice. The limitations of the study and directions for future research are presented in the concluding section.

1.2 Literature Review

We searched the literature in five databases (e.g., web of science, academic search complete, CINAHL, PsycInfo, and Medline) with time (from 1st January 2020 to 8th August 2021), geography (US), and language (EN) filters. The search terms were Twitter and COVID-19. After removing all duplicates, we selected 213 scholarly published articles for analysis. First, we used VOSviewer on the titles and abstracts of the 180 articles extracted from the Web of Science to find clusters of words based on co-occurrence. Terms that occurred at least five times were included in the analysis. Figure 1.1 shows 10 clusters from VOSviewer. Second, we apply topic modeling, one of the most widely used techniques, to find potential topics from 213 articles (Kapoor et al., 2018).

Figure 1.1 Cluster Map



We ran the topic model using LDA (Latent Dirichlet Allocation) to extract important topics from the abstracts. The extracted topics are reflected in the abstracts at varying degrees (Blei, 2012). Major topics include crisis resolution, compliance, crisis management, content analysis, and fear and anxiety (Appendix A). Researchers focused on analyzing textual data from Twitter to explain and predict various behavioral and emotional aspects and pandemic outcomes. The findings of the studies reveal that tweets can be used to understand the effects of policy measures on pandemic outcomes (e.g., infection cases, death cases, detecting potential hotspots, early signals)

While crisis leads to unpredictable events that jeopardize the structural balance and engender undesirable consequences (Coombs, 2018) (Oh et al., 2013; Gruber et al., 2015; Vaast et al., 2017; Venkatesan et al., 2021; Shklovski et al., 2008; Xu et al., 2020), social media services play a pivotal role in organizing collective behaviors during a crisis (Oh et al., 2015; Shi et al., 2014). Thus researchers acknowledge that social media like Twitter facilitates information dissemination with high volume and velocity and helps circumvent spatial and temporal barriers, which are essential for collective behaviors during a crisis.

Empirical research found that Twitter messages significantly influence others to change their behaviors (Deng et al., 2018; Oh et al., 2015; L. Xu et al., 2020). Previous studies have investigated the relationship between Twitter and crisis in various contexts (Vaast et al., 2017; Zhang et al., 2016; Leonardi, 2014; Huang et al., 2015). As shown in Table 1, some studies examined the adoption of Twitter as an alternative communication channel in health crises (Guidry et al., 2017), political crises (Oh et al., 2015), and natural disasters (Ling et al., 2015; Cho et al., 2013) and social crisis (Ince et al., 2017; Blevins et al., 2019). Venkatesan et al. (2021) presented empirical evidence of using Twitter in collective behaviors in the Arab Spring movement. During the Hurricane Harvey crisis management, the mayoral office utilized Twitter to deliver guidance, optimism, and support to the affected people (Vera-Burgos & Griffin Padgett, 2020).

Table 1: Selected papers on Twitter and crisis communication

Reference	Context	Findings
Venkatesan et. al. 2021	Twitter, retweeting, social movement, social influence, the Egyptian revolution	The study finds that ‘who’ and ‘where’ activities contribute to individual social influence. Twitter's structure, such as its follower network, the number of followers, and centrality, significantly contribute to sustained influence.
Batova et. al. 2021	Trust, crisis communication of government and COVID-19, Twitter	Mistrust was present among people in response to CDC tweets on wearing masks
Xu et. al. 2020	EID, Sina Weibo, risk perception, sharing	During a crisis, social media sharing behaviors (e.g., information) are significantly associated with users'

	behavior, VAR, self-perception theory	risk perception. The perception also dynamically varies with the stages of a crisis.
Vera-Burgos et. al. 2020	Mayor, Twitter, crisis communication, Hurricane Harvey	Affirms the use of Twitter in crisis communication to the people
Vaast et. al. 2017	Connective affordance, Twitter, Gulf of Mexico oil spill	The study introduces connective affordance as collective engagement on social media during a crisis. It also confirms the relationship between technology and users.
Guidry et. al. 2017	Ebola, Twitter, Instagram, crisis communication	They found both uses of Twitter and Instagram by health organizations to be helpful in crisis communication during the Ebola crisis.
Oh et. al. 2015	Egypt revolution, Twitter, hashtags, collective sensemaking, human-machine collaborative information processing.	Hashtags changes over time indicate structural changes in the movement. Hashtags indicate information collection and situational awareness during the crisis. While symbolic hashtags funnel users' attention, word hashtags were used to share changing situational information.
Ling et. al. 2015	Thailand Flooding 2011, crisis communication, case study, ICT, Twitter, Facebook, YouTube	The study examines how social media empowers communities in three ways – structural, psychological, and resource – during crisis response.
Oh et. al. 2013	Twitter, social crisis, rumor theory, social information processing	Information with no clear source, personal involvement, and anxiety are dominating, causing factors on Twitter to draft rumors during a social crisis.
Cho et. al. 2013	Japan's 2011 earthquake, Twitter,	They examined the government's Twitter-based crisis communication and observed peer-to-peer communication and peer-generated information.

	crisis communication, government	
Starbird et. al. 2011	2010 Haiti earthquake, microblogs, collective actions	Microblogs bring us digital volunteers in the information space to contribute to collective actions.
Hughes et. al. 2009	Twitter, crisis informatics	Twitter messages during the crisis events are of information broadcasting and brokerage and lean toward information sharing.
Palen et. al. 2009	Crisis informatics, Twitter, emergency response	This seminal work widens the domain of crisis informatics and justifies the use of social media in crisis response activities.

Recently, when COVID-19 caused an unprecedented global health crisis, triggering enormous social, economic, and mental challenges (Goodell, 2020; Atkeson, 2020; Pfefferbaum & North, 2020; O'Connor et al., 2021), past studies have shown that Twitter has been widely used to persuade collective behaviors. As shown in Appendix B, some studies have investigated the influence of tweets on crisis outcomes using Twitter data, focusing mainly on how the tweet distribution, collective behaviors (e.g., social distancing), and symptoms that surfaced on tweets impacted crisis outcomes. Other studies have examined how Political leaders (e.g., lawmakers, legislators, and party leaders) adopted Twitter to deliver information and share actionable plans with the mass population, impacting the COVID-19 crisis outcomes (Engel-Rebitzer et al., 2021; Haÿry, 2021; London & Matthews, 2021; Niburski & Niburski 2020). However, even though past IS studies have shown promising benefits, to our knowledge, no studies have thus far investigated these Twitter-mediated crisis communications of political leaders using computational linguistics for the COVID-19 crisis in a longitudinal setting.

1.3 Theoretical Background

Prior literature observed that information often primarily flows from media to opinion leaders and then to the mass population (Burt, 1999; Flynn et al., 1996; Gunarathne, 2018). Opinion leaders can influence the attitudes and behaviors of others (Hellevik & Bjørklund, 1991; Rogers, 2003). They possess high social skills, rich knowledge, and appealing power to the broader audience. They also tend to have greater exposure to mass media, are more innovative and knowledgeable when changes are required, embrace intellectual challenges, and are self-efficacious in influencing others (Robertson & Myers, 1969; Rogers, 2003; Park & Kaye, 2017; Chu et al., 2019). Xu et al. (2014) reported the significant impacts of opinion leaders on political activism at the node and content level on the Twitter network. Oh, et al. (2015) demonstrated that influential opinion leaders possessed power in the Twitter space during the Arab Spring movement, and most Twitter users retweeted opinion leaders' tweets.

1.3.1 Theory of social influence (TSI)

We draw upon the *Theory of social influence (TSI)* (Kelman 1958) to better understand the influence of opinion leaders (e.g., political leaders) during the COVID-19 crisis. TSI is concerned with how individuals influence others in interpersonal and social contexts (Dholakia et al., 2004; Aral & Walker; Fulk, 1993). Prior IS research has used it in individual (Venkatesh & Davis, 2000; Lewis et al., 2003; Wang et al., 2013) and collective behaviors (*We-Intention* instead of *I-Intention*) (Bagozzi & Lee, 2002; Chen et al., 2020). Our goal in using the theory is not to test the premises but rather to inform and guide our understanding of the political leaders' influence during a crisis.

The TSI posits that an individual's beliefs, attitudes, and behaviors are influenced in accordance with referent others (Kelman 1958). The influence occurs in three ways: compliance, identification, and internalization. *Compliance* refers to the influence by referent others "not because he believes in its content but because he expects to gain specific rewards or approval and avoid specific punishments or disapproval by conforming" (Kelman, 1958, p. 53; Bagozzi & Lee, 2002; Chen et al., 2020). *Identification* denotes the acceptance of influence to "establish or maintain a satisfying and self-defining relationship to another person or a group" (Kelman, 1958, p. 53). Identification relates to referent power (Lewis et al., 2003), shared feelings, and a sense of belongingness (Bagozzi & Lee, 2002). Finally, *Internalization* occurs when an individual perceives the content of the message is "congruent with his value systems" (Kelman, 1958, p. 53) and embeds the contents into their minds as his own (Lewis et al., 2003; Chen et al., 2020). Though the effects of compliance-based influence are likely to last for a short period, the effects of identification and internalization on the influenced agents persist over an extended period due to the assimilation of referents' opinions (Fulk, 1993; Venkatesh & Davis, 2000; Wang et al., 2013). Furthermore, identification is likely to cause intentional following from referents, whereas Internalization may lead to unintentional acceptance of influence from others (Kelman, 1958).

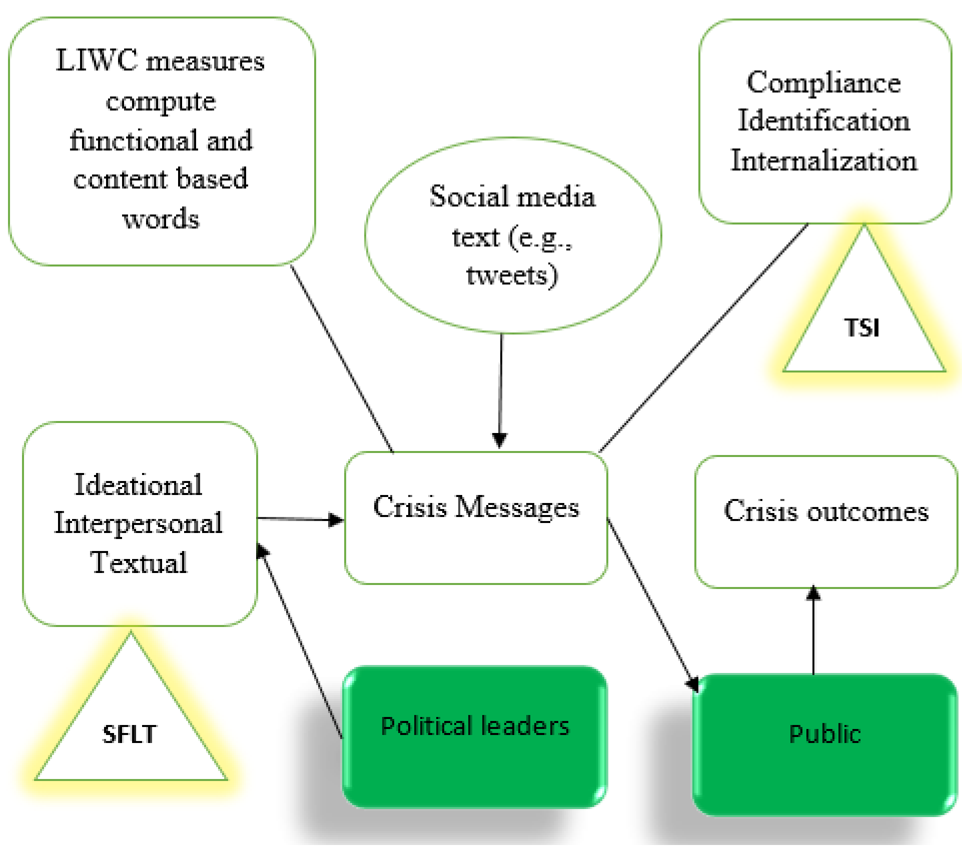
1.3.2 Systemic functional linguistic theory (SFLT)

Systemic functional linguistic theory (SFLT) is a linguistic theory that focuses on what language does in a social context instead of how language is processed in the *cerebral cortex*. The theory accentuates socio-semiotic perspectives of language because language is a system of signs to create meaning and social system influences the meaning. SFLT views that language connects semantics inseparably to pragmatics. (Halliday; & Hasan (1985) further maintain that “language is not simply a formal system, but rather a system that exists to satisfy the communicative needs of its users.”

The language of social media can be analyzed using structural features (e.g., the number of replies and retweets in a tweet) and text-based features (e.g., styles, power cues, emotions). We need to ground it in language theory to effectively analyze the subtleties of text-based features of online discourse (Abbasi 2008). SFLT has three meta-functions – ideational, interpersonal, and textual (Halliday & Matthiessen, 2004). It can be viewed that social media-facilitated language is processed in three ways – ideational (to construe the contextual experience), interpersonal (social interaction with roles and attitudes), and textual (to create messages with information). These three occur simultaneously.

Linguistic resources embedded in the text to represent contextual meaning enable us to share pandemic experiences. For instance, Zappavigna & Dreyfus (2022) studied temporal meanings in the COVID-19 tweets using the systemic functional linguistic framework to understand the context. Figure 1.2 describes that political leaders continually construed various aspects of the development of the COVID-19 crisis (ideational), realized their roles to address the crisis (interpersonal), and finally delivered messages using tweets (textual). These influence the public in terms of compliance, identification, and internalization.

Figure 1.2. Interlinks between Theoretical Framework



During the COVID-19 crisis, when people desperately needed information about the evolving situation, political leaders delivered various crisis-related updates and messages urging people to evaluate and confront the crisis. People responded to the messages with unintentional compliance or unconditional acceptance because people either conform to leaders' directives or align with leaders' political ideology. Thus, opinion leaders, social influence, and systemic functional linguistic advances our understanding of how political leaders (lawmakers, governors, or party leaders), with their power and status, are likely to influence the public on a massive Twitter network and impact crisis outcomes.

1.4 Hypotheses Development

When crisis shatters safety borders and people are desperate to gather information, social media is the primary source of information consumption (Reuter et al., 2018) (Sun & Gloor, 2021). Social media-based crisis communication overcomes temporal and spatial barriers, reflects the talks of the crowd (Ince et al., 2017) (Oh et al., 2015), and its networks are used to influence behaviors (Cheung et al., 2012) (Sussman & Siegal, 2003) Deng et al. (2021). For example, during the Egyptian revolution, social media was deployed to exert social influence to mobilize resources for social movement (Venkatesan et al., 2021). Prior studies also showed that social media posts contain rich linguistic features (Chen et al., 2020) (Xu & Zhang, 2018) and provide valuable insights into the events (Chau et al., 2020) (Ludwig et al., 2014) (Abbasi et al., 2018). Besides, linguistic analysis reveals greater sensemaking of social media posts (Abbasi et al., 2018). Appendix C shows selected linguistic studies.

We observed that tweets were utilized in COVID-19 crisis communication, and political leaders widely used them to send warnings, alerts, and persuasive messages to mitigate the crisis. For instance, members of congress posted more than 1430 tweets per day, compared to 885 Facebook posts, in 2021 (Statistica 2022)[5]. Besides, political leaders with many followers possess greater readership and credibility. While Twitter allows disseminating the vast amount of official and unofficial messages during a crisis (Oh et al., 2013; Venkatesan et al., 2021), we examine in the current study how linguistic features present in tweet messages of political leaders influence people to change opinions, beliefs, and behaviors, and thus impact crisis outcomes. We study the effects of linguistic variables such as “analytic”, “clout”, “authentic”, and “tone” on COVID-19 outcomes. These variables and hypotheses associated with them are discussed below.

1.4.1 Analytic

We define analytic as “the degree to which people use words that suggest formal, logical, and hierarchical thinking patterns” (Pennebaker 2015). Analytic texts involve logical representation increasing the persuasiveness of the message. These texts are more receptive and communicative, having a low multiplicity of themes and less ambiguity. Social media posts with analytics increase sensemaking, meaningfulness, and comprehension of the message. Meng et al., (2018) found that persuasive tweet messages increase the likelihood of diffusion through the network, indicative of message efficacy. In a similar study on Facebook, Chang et al., (2020) showed that the perceived persuasiveness of the posts enhances the post’s popularity. In e-commerce platforms, product reviews with more persuasive information influence consumer behaviors (Hong et al., 2020). Lee and You (2021) studied text-based crisis communication of the South Korean government during COVID-19. They found that those who read text messages showed higher compliance in wearing masks, maintaining social distancing, and avoiding public gatherings. While analytic tweets show

[5] https://www.statista.com/statistics/958822/total-number-posts-per-platform-per-day-congress-members-usa/

clarity and argument quality of messages, shambolic and unsophisticated tweet messages are less convincing and often fail to draw the readers' attention.

When COVID-19 challenged normal behaviors, we observed that political leaders, in their tweets, delivered informative, persuasive, and clear messages to the mass people to adopt coping behaviors (Batova, 2021). Since political leaders are public figures and people’s representatives, their messages are formal, follow concise writing styles, and show substantial credibility. We contend that the tweets of political leaders possess a higher degree of analytic and are focused, consistent, and communicative. As a result, the mass people would be persuaded to change their beliefs, opinions, and behaviors by these messages, which are conducive to inhibiting the spread of infection cases. Therefore, we posit that the analytic of political leaders’ tweets leads to a decline in infection cases. We present the following hypothesis to empirically test -

H1: Analytic of the political leaders’ COVID-19 tweets has a negative relationship with pandemic outcomes (e.g., infection cases).

1.4.2 Clout

Clout is “*the relative social status, confidence, or leadership that people display through their writing or talking*” (Pennebaker 2015). Prior studies showed that leadership and confidence conveyed through tweets influenced crisis outcomes (e.g., Egyptian political revolution (Venkatesan 2021), Thailand flooding in 2011 (Ling 2015), Hurricane Harvey (Vera-Burgos 2020), Ebola health crisis (Guidry 2017), COVID-19 pandemic (Watkins & Clevenger, 2021; Haÿry, 2021). While collective behaviors are prerequisite for resolving a crisis, tweets with high clout would herd the mass population with guidelines, motivations, and consistent paths, triggering the emergence of collective behaviors. This phenomenon can be represented by e-leadership, which is the [advanced information technology] AIT-mediated social influencing process to change behaviors (Avolio et al., 2001). Rufai & Bunce, (2020)found that the group of leaders from developed countries known as Group-7 (G7) extensively used tweets to lead people during the COVID-19 crisis. In addition, tweets with high clout would reflect the political leaders' roles in building and maintaining the leader-follower relationship. For example, Ie (2020) found that leaders play the role on Twitter as personal, party, legislative, chief executive, national, and international leaders to build leaders-followers relationships. Bulovsky (2019) studied the leadership style of 144 world political leaders on Twitter and found significant communicative styles for building pro-power and pro-people relationships.

We contend that political leaders lead and motivate the mass population to be resilient against the adversaries of the crisis. Political leaders showcase their prosocial activities, a beam of confidence, and a sense of leadership strength through their tweets to the people to recover from the crisis burdens. As a result, people responded with resilience and adapted to newly emergent coping collective behaviors, which led to the decline of infection cases during COVID-19. Thus, we hypothesize that

H2: Clout of the political leaders' COVID-19 tweets has a negative relationship with pandemic outcomes (e.g., infection cases).

1.4.3 Authentic

Authentic is "*when people …. tend to speak more spontaneously and do not self-regulate or filter what they are saying*" (Pennebaker 2015). Authentic tweets are honest and expressive texts. Prior study shows that the perceived authenticity of tweets positively affects purchase willingness, information sharing, and product brading (Zhang & Patrick, 2021) (Shirdastian et al., 2019). It increases credibility and reduces perceived deception, which is crucial when searching for reliable crisis information. Authentic tweets are characterized by straightforward, simple, and undiplomatic message content (Lee et al., 2020). In addition, authentic tweets are less ambiguous and untainted with misinformation. Oh (2013) found that ambiguity causes rumors during a crisis. In another recent study, Loomba et al., (2021) reported that misinformation negatively impacted vaccine uptake among those who stated they would get vaccinated. While propagation of misinformation increases pandemic risks and inhibits the adoption of preventive behaviors during the COVID-19 crisis (Rosenberg et al., 2020) (Tamul et al., 2020), authentic messages increase public engagement and influence behaviors. Bavel et al., (2020) suggested various approaches, such as prebunking, debunking, and nudging to assess the credibility and authenticity of social media posts.

We contend that tweets of political leaders have credibility and significantly influence the public's opinions, beliefs, and behaviors during COVID-19. Truthful and spontaneous tweets are likely to be more robust and influential. On the other hand, unauthentic and false messages are transitory and subject to avoidance, thus, failing to have a sustained influence in the broader population. So, we hypothesize that

H3: Authenticity of the political leaders' COVID-19 tweets has a negative relationship with pandemic outcomes (e.g., infection cases).

1.4.4 Tone

Sentiment has continued to be an important area of inquiry among I.S. researchers for a long time (Abbasi et al., 2019; Deng et al., 2018). Studies show that short and concise tweets carry the sentiment of the users (Srivastava et al., 2019; Zimbra et al., 2018). Moreover, unexpected events have higher sentiments than anticipated events on Twitter (Bhatia et al., 2019). Prior studies found that tweets with positive and negative sentiments are more influential than tweets with neutral sentiments. Ghiassi et al. (2016) exhibited how users use tweets to express sentiments about product brands. Similarly, Deng et al. (2018) showed the influence of tweet sentiment on stock returns at the hour level. Jiang et al. (2021) examined sentiment related to a movie's star, genre, and plot and found that sentiment is associated with higher movie sales. On Twitter, users' sentiment also helps diffuse the contents of tweets (Aletti et al., 2021).

In line with the argument, we contend that the influence of political leaders' tweets increases with the presence of sentiments in the tweets. The evidence from recent COVID-19 studies also shows that the public reacts to messages rich in sentiments (Engel-Rebitzer et al., 2021; Niburski & Niburski, 2020). Although political leaders have had different perspectives regarding adopting and practicing new behaviors relevant to COVID-19, they use positive and negative sentiments in their tweets to diffuse their stances and influence the mass population. We assume that the positive sentiments of the tweets contribute to the decline in infection cases. Our rationale is that tweets with positive sentiments tend to bolster the mental strengths that improve the morale of the mass population to conform to collective behaviors. The widespread adoption of preventive collective behaviors helps curb the spread of infection cases. Thus, we hypothesize that

H4: Positive sentiments in the political leaders' COVID-19 tweets have a negative relationship with pandemic outcomes (e.g., infection cases).

1.4.5 Crisis Stages

Given the concerns over the evolution of COVID-19 crisis episodes, people were desperate to access credible information sources. Hence, Twitter has become an effective platform for delivering real-time updates on the crisis, reaching a wider population with relatively no obstructions (Jin et al., 2011). Although most prior studies investigated the effects of Twitter on crisis outcomes from a single timeline, in a recent I.S. study, Xu et al. (2020) advocated a multistage approach to capture the dynamism of crisis evolution in the emergent infectious disease (EID). Their findings suggest that the mass population's unknown and dread risk perception of infectious disease fluctuates over the crisis stages. Thus, the evolution of crisis trails through a set of dynamic phases called the “life cycle” (Fink, 1986). From the trajectory of the COVID-19 crisis, we observed that the government initiated and adjusted over time several policy measures – shutdown and reopening of businesses, lockdown and no-lockdown period, mandatory and optional wear-a-mask – to cope with the degree of severity of the crisis (Appendix D). The effect of these policies are expected to vary across the crisis, so are the tweet messages of political leaders. We adopted a four-stage crisis framework - the Buildup stage, Breakout stage, Abatement stage, and Termination stage (Fink, 1986; Sturges, 1994) to model the dynamism of crisis. We posit that the influence of political leaders’ Twitter crisis communication changes over the different phases of the crisis.

In the *build-up stage*, everybody was uncertain about what to do since a pandemic like COVID-19 has not occured in a long time. The demand for information was high, and information gaps surfaced. The practice of lockdown was unprecedented and drove everybody into a panic. The tweet messages of political leaders were exploratory and generic. We also observed that political leaders developed a disagreement of opinions, resulting in chaos and instability. Then, symptoms or hints of the crisis sporadically and spatially begin to appear, escalating the intensity of the crisis. In the *breakout stage*, the crisis erupts, and physical, fiscal, and emotional trauma quickly spreads across society. The severity of the crisis enhances vulnerability of the people. People did not know enough and strived to accumulate more information to neutralize social and emotional instability. Tweets of political leaders were more informative, specific, and directional at this stage. However, people realized the lingering effect of the crisis. In the *abatement stage*, the situation gradually started to change when knowledge and understanding of the various facets of COVID-19 increased. Later, the instructions became more explicit and precise, and the public gathered courage and confidence to fight against COVID-19 by adopting emergent collective behaviors. Tweets instilled more hope than fear. Political leaders gathered a few success stories to share and provided a glimpse of a practical solution to the crisis at this stage. In the *termination stage*, the solution to the crisis appeared pragmatic, and people started feeling less concerned. When the vaccine was found successful, life began to normal. Gradually, the crisis paves the way to an end. Tweets of political leaders were more triumphant in the termination stage. Therefore, we posit that the influence of political leaders' crisis communication changed with the crisis progression. Putting these ideas together, we propose the following hypothesis for empirical testing -

H5: The relationship between political leaders' COVID-19 tweets and pandemic outcomes (e.g., infection cases) varies across the crisis stages.

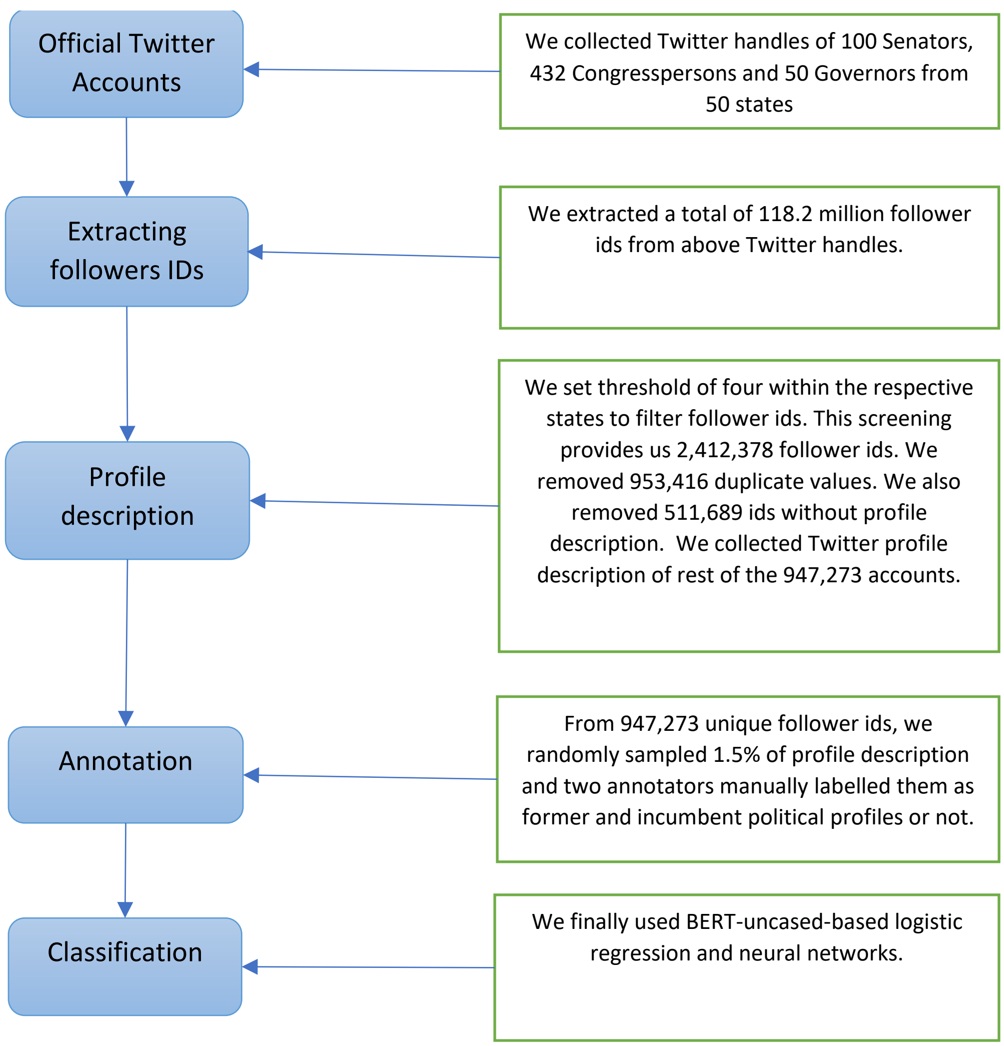
1.5 Methodology

Our analysis involves four steps: data collection, preparation, content analysis, and model estimation. *In the data collection phase*, we used the Twitter API to extract profile descriptions from the Twitter handles of legislators and governors of the U.S. *In the data preparation phase*, we constructed two classification models. First, we applied natural language processing (NLP) tools on extracted profile descriptions to classify political leaders. Second, we used a web crawler into the classified political leaders' Twitter handles to extract all the tweets from Mar. 16, 2020, through May 30, 2021. We then classified COVID-19 tweets from non-COVID-19 tweets. *In the content analysis phase*, we explored the contents of COVID-19 tweets and analyzed the hashtags, mentions, and tweets' texts. In addition, we utilized Linguistic Inquiry and Word Counts (LIWC) dictionaries to extract linguistic features of the COVID-19 tweets. *In the quantitative phase*, we specified an econometric model and applied panel vector autoregression (PVAR).

1.5.1 Data Collection and Preparation

We first collected the Twitter handles of 100 senators, 432 house of representatives in congress, and 50 governors serving the states in the U.S. Thus, we included 582 members as the initial seed. Then, we collected followers' ids and profiles description from each Twitter account. Finally, we retained unique Twitter accounts and dropped the duplicate and empty accounts (Figure 1.3).

Figure 1.3. Data Collection Procedure



1.5.2 Classification of Twitter profile

Two annotators manually labeled 14112 randomly selected profile descriptions. The agreement of the two annotators was measured by Kohen's Kappa with a score of 96%. If the profile description provides enough information, such as former and current senators, congressional representatives, governors, mayors, councilperson, political representatives, and village president, it was labeled as 1; otherwise, 0. Preprocessing of text is of paramount importance in natural language processing. We used standard python libraries – nltk and regular expression - for preprocessing the profile text. We removed 255 rows after preprocessing due to the null value.

We applied classification models. *First*, we applied logistic regression as baseline model. The data was imbalanced, with 90% of the profiles labeled non-political leaders and 10% of political leaders labeled political leaders. We used a grid search algorithm to find an appropriate class weight for minority classes. The class weight for label 1 was 0.7294, and label 0 was 0.2705. We used Glove for feature extraction and ran logistic regression. GloVe stands for Global Vector for Word Representation. It leverages the nonzero elements in a word-word co-occurrence matrix rather than on a sparse matrix or contextual window size in a large corpus. Essentially, the algorithm first creates a word-context pair so that each element in the matrix represents how often a word occurs with the context (e.g., sequence of words). Then the model takes advantage of *global matrix factorization* and *local context window methods* to provide the word embeddings for each word. There are four pre-trained word vectors. In this study, we used the Twitter pre-trained model, which has been trained with two billion tweets with 27B tokens, 1.2M vocab, uncased and 200d vectors. *Second*, we used BERT (Bidirectional Encoder Representations from Transformers) uncased-based neural networks. BERT is a context-dependent embedding model that takes words as inputs and creates subword embeddings. It uses 768 hidden layers to generate features for each sentence in the corpus. It has shown promising results in depicting the contextual sensitivity of the corpus achieving state-of-the-art outputs on numerous NLP tasks .

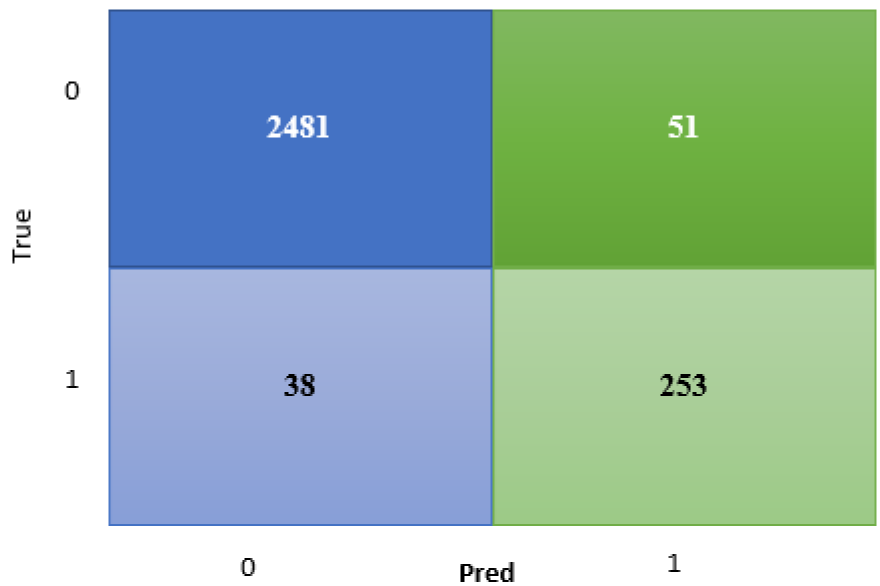
1.5.2.1 Model evaluation

The recall of the classification test computes the ratio of true positives to the true positive and false negative. It reveals the true positive against the false positive. On the other hand, the precision of the classification test calculates the ratio of true positive to true positive and false positive. Finally, the F1 score shows the balance between precision and recall. F1 is computed as (2*precision*recall)/(precision + recall). We also showed a confusion matrix to assess the performance of a classification model. Appendix E graphically demonstrates the Receiver Operating Characteristic (ROC) and Precision-Recall Curve (PRC) for the classification model of Twitter profiles. Table 2 summarizes the performance metrics for the logistic regression and neural network models. The results show that the neural network model has a 3% higher accuracy and slightly better performance in precision, recall, and F1 score. Figure 1.4 shows the confusion matrix for the BERT-based model. Hence, we deploy BERT-based neural networks to predict unlabeled Twitter profile descriptions.

Table 2: Evaluation Metrics

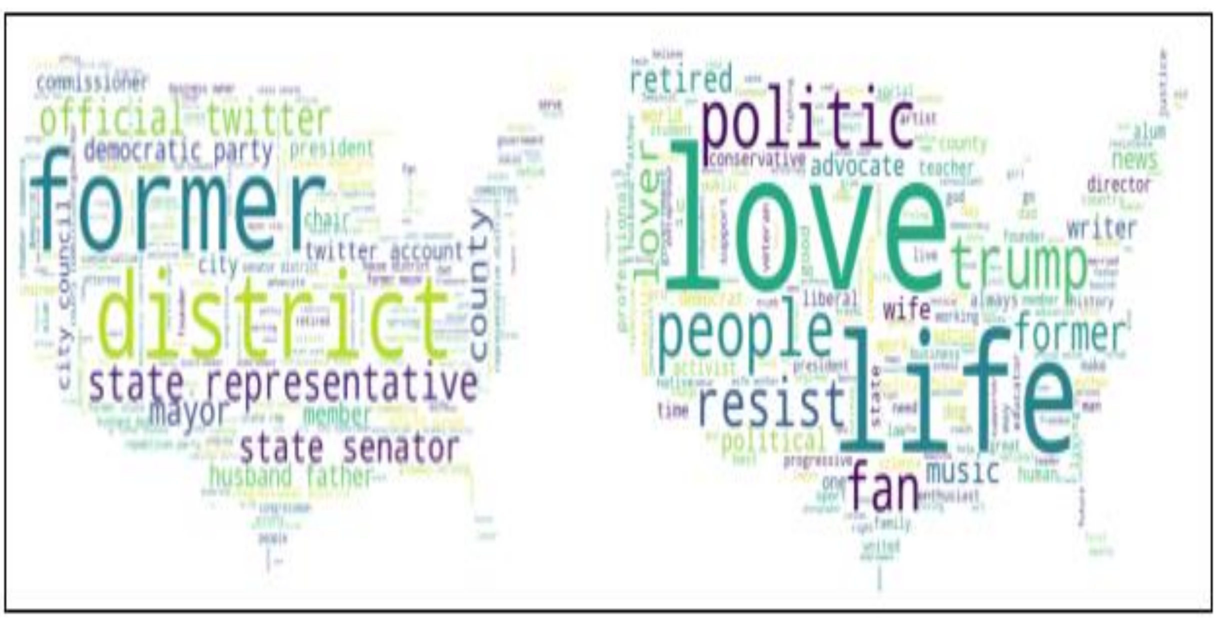
	Labels	Precision	Recall	F1 Score	Accuracy
Glove	Non-political Twitter Profile	0.98	0.95	0.97	0.94
	Political Twitter Profile	0.66	0.88	0.72	
BERT	Non-political Twitter Profile	0.98	0.98	0.98	0.97
	Political Twitter Profile	0.83	0.87	0.85	

Figure 1.4. Confusion Matrix



The model predicted 11,297 profiles as political leaders. Figure 1.5 shows the visualization of predicted political leaders' profiles in a word cloud, displaying the most frequent words relevant and consistent with our research objectives.

Figure 1.5. WordCloud: Political (left) and Non Political (right)



1.5.3 Classification of Tweets

To get COVID-19 tweets, we collected all the tweets for 11,297 profiles from Mar. 16, 2020, to May 30, 2021, using a web crawler. First, we randomly selected 12,547 tweets to label COVID or non-COVID tweets manually. There are 65% as non-COVID tweets and 35% as COVID tweets in the labeled tweets meaning that there are 1.85 times non-COVID tweets for each COVID tweet.

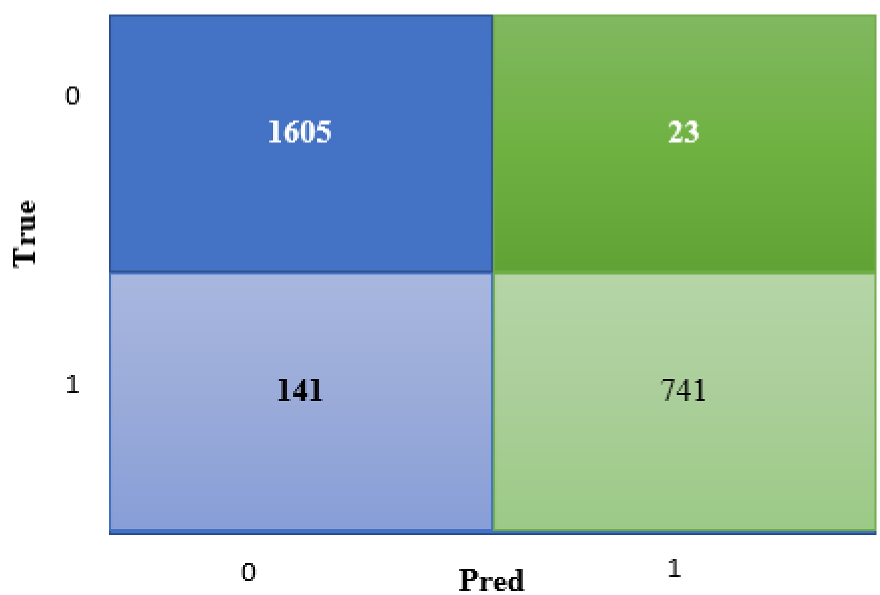
1.5.3.1 Model evaluation

We used BERT uncase-based neural networks. Finally, we deployed the classifier that predicted 611,470 COVID-19 tweets. Figure 1.6 shows the confusion matrix. Appendix F graphically shows the Receiver Operating Characteristic (ROC) and Precision-Recall Curve (PRC) for the classification model of COVID-19 tweets. Table 3 presents the evaluation metrics.

Table 3: Evaluation metrics

Label	**Precision**	**Recall**	**F1**	**Accuracy**
Non-COVID tweets	0.92	0.99	0.95	0.93
COVID tweets	0.97	0.84	0.90	

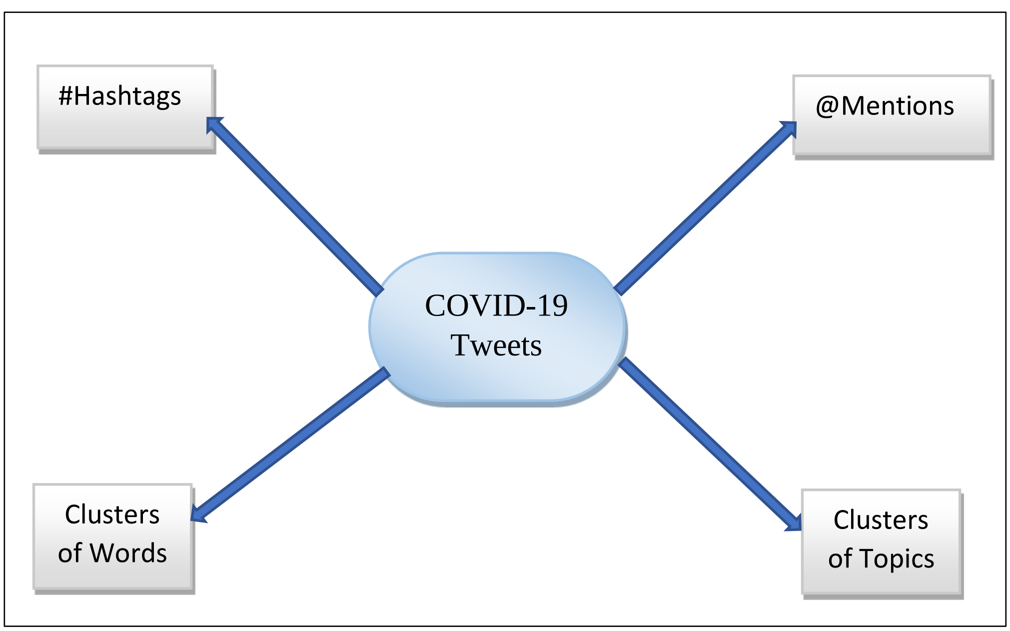
Figure 1.6. Confusion Matrix



1.6 Content Analysis

Twitter abodes valuable information (e.g., followership, retweets, hashtags, mentions) that can be useful for extracting insights about a crisis. While the information on Twitter signals the concurrent development of the crisis, previous I.S. researchers vastly utilized this opportunity to enhance understanding and responses to the situation (Gunarathne et al., 2018; Venkatesan et al., 2021). For instance, Venkatesan et al. (2021) investigated the influence of social media using retweets in the 2011 Egyptian political crisis. Stieglitz & Dang-Xuan, (2013) used retweets to indicate information-sharing behaviors of political communication on Twitter. In another study, Oh et al. (2015) examined the traces of hashtags to investigate collective sensemaking during the Egyptian Revolution. Gunarathne et al. (2018) explored retweets, hashtags, mentions, and other features of Twitter to measure influence and bystander effects in the differential customer services delivered on social media. In the current study, we examined - the frequency of the tweets across the states and the crisis stages, hashtags, and mentions – to find valuable insights into the political leaders' crisis communication on Twitter (Figure 1.7).

Figure 1.7. Content of Tweets



1.6.1 Tweet Frequency

We observe that the states with higher infection cases tend to have higher COVID-19 tweets from political leaders (Figure 1.8 and Figure 1.9). For instance, the top four states that accounted for the highest COVID-19 infection cases were California (37.88 million), Texas (29.53 million), Florida (23.20 million), and New York (21.01 million) between Mar. 16, 2020, and May 30, 2021. Our model shows that these four states - California (64.31 thousand), New York (61.25 thousand), Texas (40.26 thousand), and Florida (35.73 thousand) – also ranked top four states in terms of COVID-19 tweets from political leaders. This apparent relationship alludes to the notion that tweets from trusted and credible sources (e.g., political leaders) are consistent with the crisis outcome (e.g., infection cases of COVID-19). It indicates the responsiveness of political leaders as per the gravity of the crisis.

Figure 1.8. Number of Infection Cases

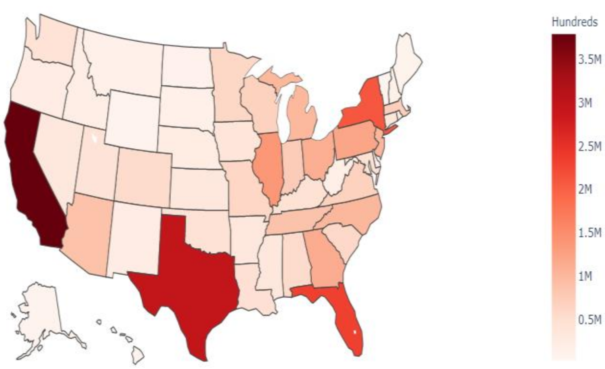
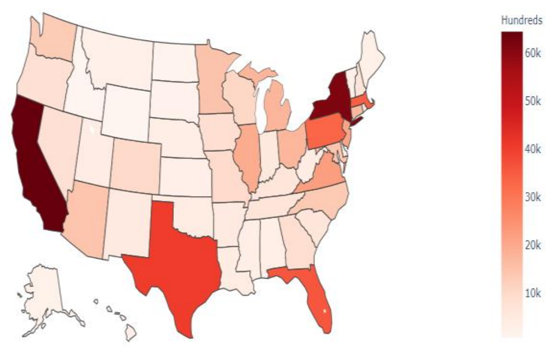


Figure 1.9. Number of COVID19 Tweets



Among these tweets, 72.30% are pure text posts, whereas 24.23% and 3.47% of tweet posts have photos and videos, respectively (Table 4). These statistics are also consistent across the various stages of the crisis. The dominance of pure text posts accentuates the focus of the study on textual analysis.

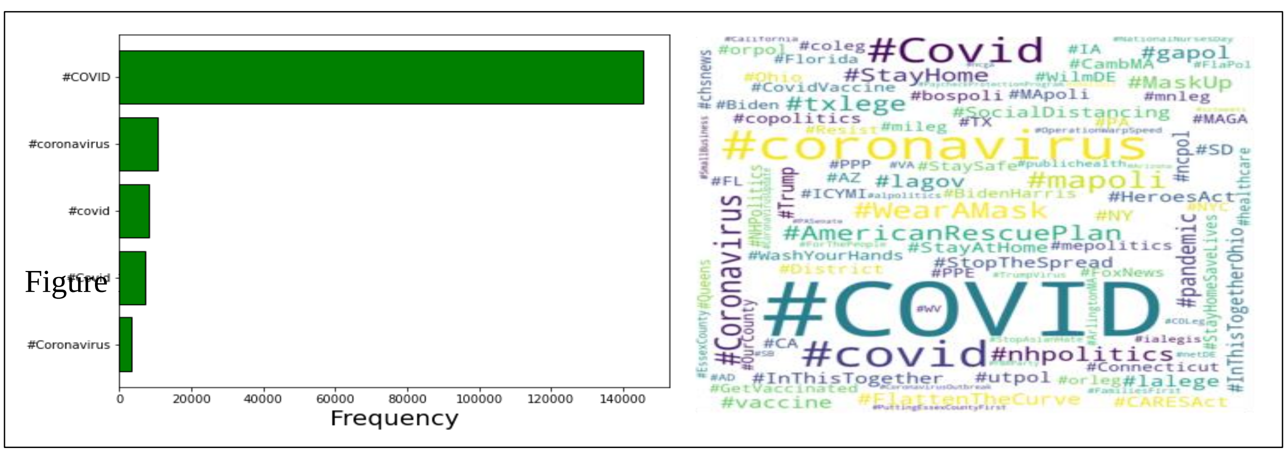
Table 4: Structure of tweets across the stages of the crisis

Tweets	Total	Buildup stage	Breakout stage	Abatement stage	Termination stage
Posts	611,470 (100%)	200,687 (100%)	116,064 (100%)	138,784 (100%)	155,935 (100%)
Only text posts	442,124 (72.30%)	143,208 (71.36%)	83,997 (72.37%)	104,160 (75.05%)	110,759 (71.03%)
Text + Photo posts	148,136 (24.23%)	50,429 (25.13%)	28,287 (24.37%)	29,819 (21.49%)	39,601 (25.4%)
Text + Video posts	21,210 (3.47%)	7,050 (3.51%)	3,780 (3.26%)	4,805 (3.46%)	5,575 (3.58%)

1.6.2 Hashtags

Next, we analyzed the hashtags from the COVID-19 tweets as they provide situational awareness (Kwon et al., 2015) and collective sensemaking (Oh et al. (2015) of the crisis. There were a total of 457,303 hashtags in the tweets. First, we found the top five hashtags related to COVID-19, 38.20% of all hashtags**.** The word cloud in Figure 1.10 shows the visualization of the top 100 hashtags, 54% of all hashtags. Then, we investigated the distribution of hashtags across the four stages of the crisis. In the first stage, the top five hashtags directly include the wording of COVID-19 (e.g., #COVID, #coronavirus). Since COVID-19 was not adequately known at this early stage of the crisis, leaders used COVID-19-related hashtags primarily to create public awareness and persuade people to stay home (e.g., #COVID, #StayHome, #FlattenTheCurve, #StayAtHome) as a precaution to slow down the spread.

Figure 1.10. Hashtag Frequency



Figure

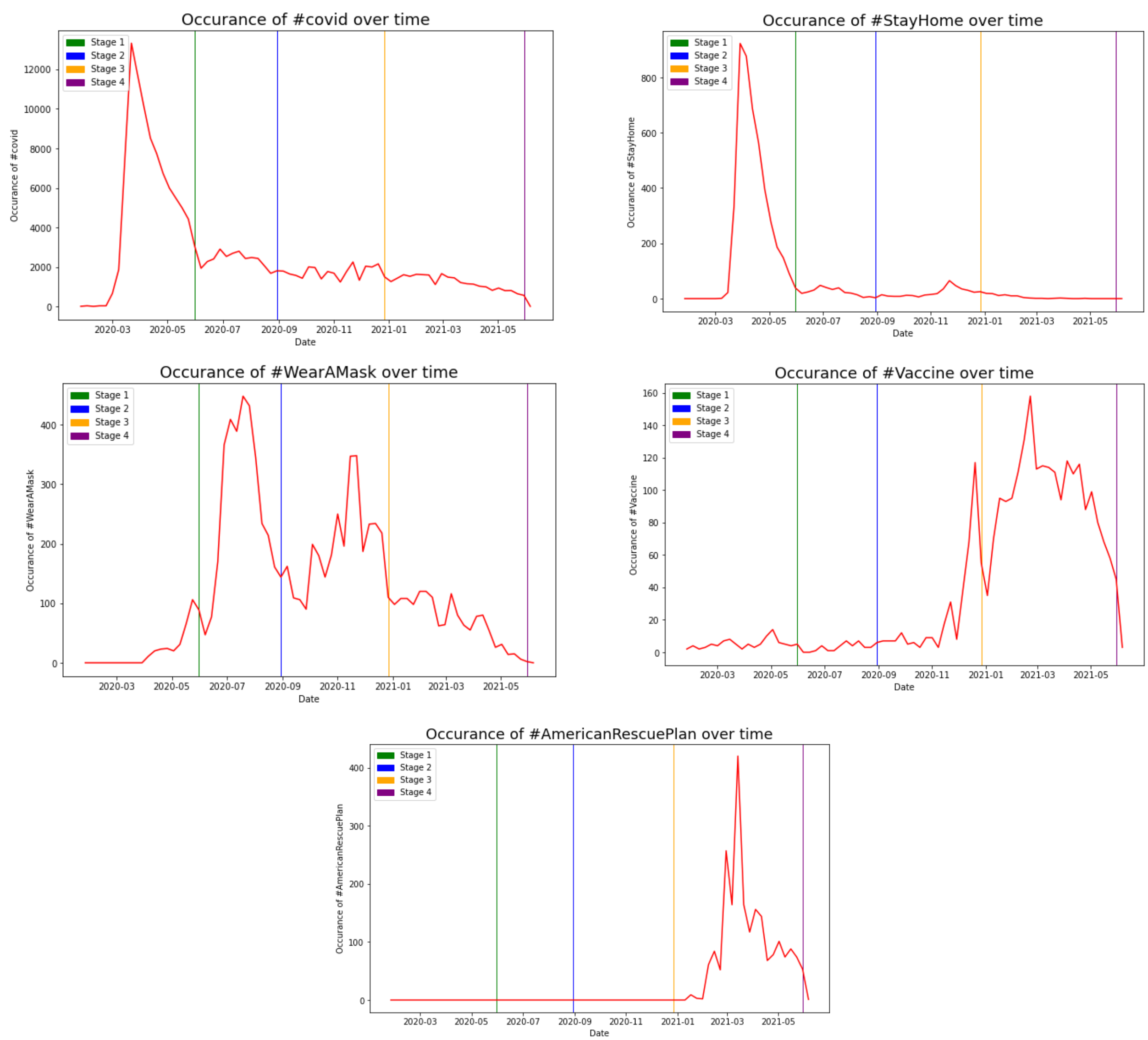
However, by the 2nd stage of the crisis, epidemiologists and scientists found it effective to wear a mask. As a result, we observed that political leaders' tweets mainly included hashtags for wearing masks (e.g., #COVID, #WearAMask, #MaskUp). While period of stage 3 was the time of the election, we find that political leaders started using their leaders' names as hashtags with covid-related hashtags (e.g., #COVID, #WearAMask, #BidenHarris, #Trump). It indicates that the leaders included their party with the covid-related hashtags to influence the election. Finally, the dominance of getting vaccinated was evident in the fourth stage of the crisis. Along with covid-related hashtags (e.g., #COVID, #WearAMask), leaders were also emphasizing economic relief funds (#AmericanRescuePlan) and vaccination (e.g., #vaccine, #GetVaccinated) (Table 5).

Table 5: Hashtags across the four crisis stages

Stages of Crisis	No. of Tweets	Tweets/ Week	No. of Hashtags	Hashtags /Week	Top Hashtags	Infection Cases	% Change
Stage 1 (11 weeks)	200,687	18,244	195,397	17,763	#COVID, *#StayHome*, *#FlattenTheCurve*, *#StayAtHome*	1,785,056	-----------
Stage 2 (13 weeks)	116,064	8,928	83,606	6,431	#COVID, *#WearAMask*, *#MaskUp*, *#HeroesAct*	4,171,423	+133.69%
Stage 3 (17 weeks)	138,784	8,164	90,889	5,346	#COVID, *#WearAMask*, *#MaskUp*, *#BidenHarris*, *#Trump*	13,185,723	+216.10%
Stage 4 (22 weeks)	155,935	7,088	87,411	3,973	#COVID, *#AmericanRescuePlan*, *#Vaccine*, *#WearAMask*, *#GetVaccinated*	13,916,886	+5.55%
Total	611,470	9,706	457,303	7,259		33,059,088	

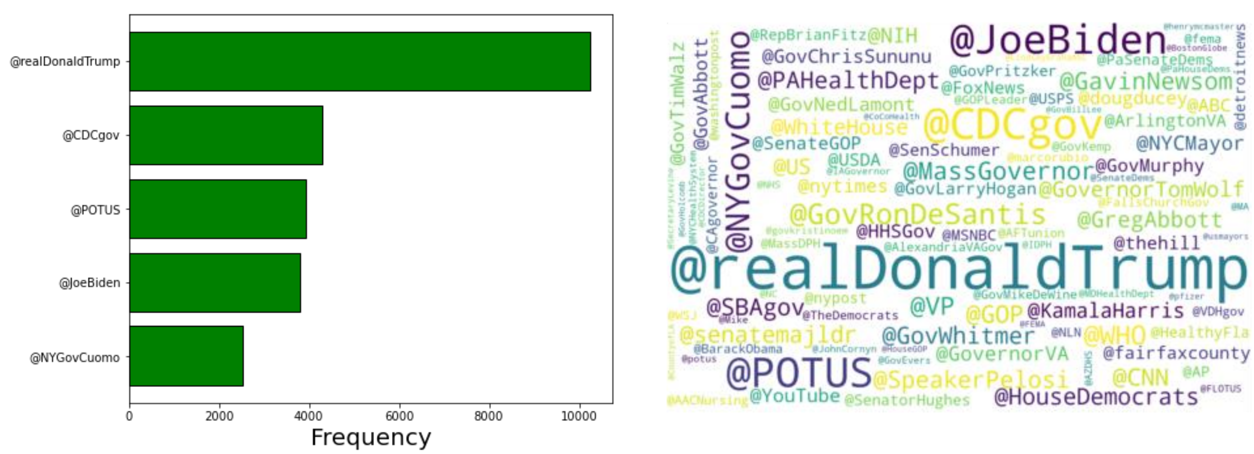
We also observed that the number of tweets and hashtags was much higher (e.g., 32.82% and 42.73%, respectively) at the beginning of the crisis than in the latter part of the crisis. A closer examination of these graphs suggests that hashtags correspond to the focus of the crisis evolution. It indicates that political leaders spread a great deal of information through their social networks to educate people about the multifaceted aspects of the crisis at the beginning. In addition, it reflects the innate drive of leaders to relay social confidence and psychological support when any unexpected crisis events surface. We also observed that #WearAMask was consistently one of the top hashtags from stage 2 through stage 4, while #StayAtHome dominated stage 1.

Figure 1.11. Trajectory of Major Hashtags



From the distribution of the top five hashtags (Figure 1.11), we understand how political leaders strive to influence people's beliefs, attitudes, and behaviors along with the evolution of the crisis. Our findings are consistent with the previous study. Oh, et al. (2015) reported that the appearance of hashtags on tweets hints at collective sensemaking through *Milling* and *Keynoting* during the unstable period of the crisis. They also manifested that such resemblance of hashtags allows the creation of information and situational awareness of the crisis. Thus, we conclude that Political leaders as power users (whose tweets are retweeted by many) played a vital role in making collective sensemaking of the COVID-19 crisis. Aligned with previous works, we suggest that political leaders craft tweets with hashtags to connect and influence the wider population, thus affecting the crisis outcomes.

Figure 1.12. Distribution of Mention



1.6.3 Mentions

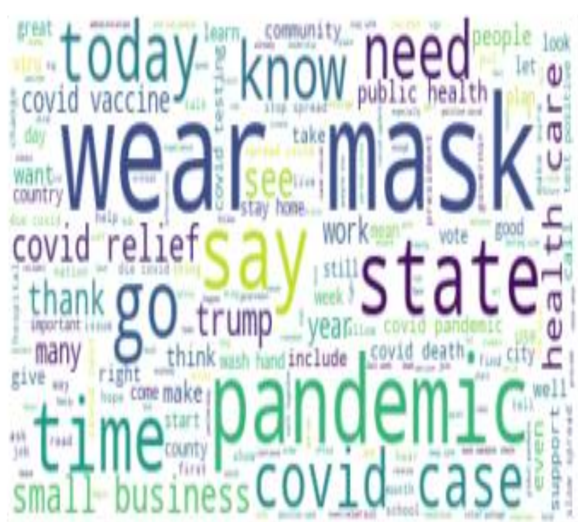
Finally, we analyzed the @mentions of the political leaders' COVID-19 tweets (Figure 1.12). Twitter allows users to tag @mention to relate the tweets with other users. Previous empirical studies show that @mention is often utilized to denote negative comments or disagreements with the user. For example, Conover et al. (2011) found that @mention entails negative connotations in the spectrum of politics. Using @mention implies that users are aware of politicians from opposite parties, consistent with the central tenet of polarization theory (Shore et al., 2018). Although the structure of Twitter space leans towards intra-channel communication within the networks, @mentions facilitate the cross-channel flow of information (Abbasi et al., 2018). We observe that the leaders from the democratic and republican parties are among the top five mentions, along with CDC. It indicates that political leaders engage in inter-party COVID-19 discourses in their tweets.

Figure 1.13. WordCloud of Tweet Texts

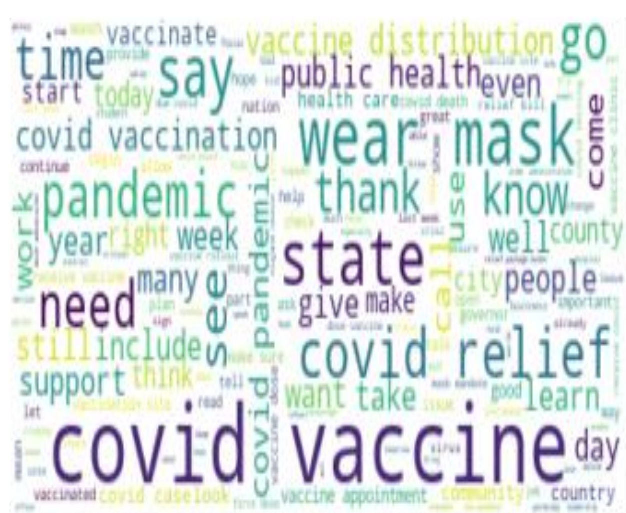
Stage 1: Buildup

Stage 2: Breakout

Stage 3: Abatement



Stage 4: Termination



1.6.4 WordCloud

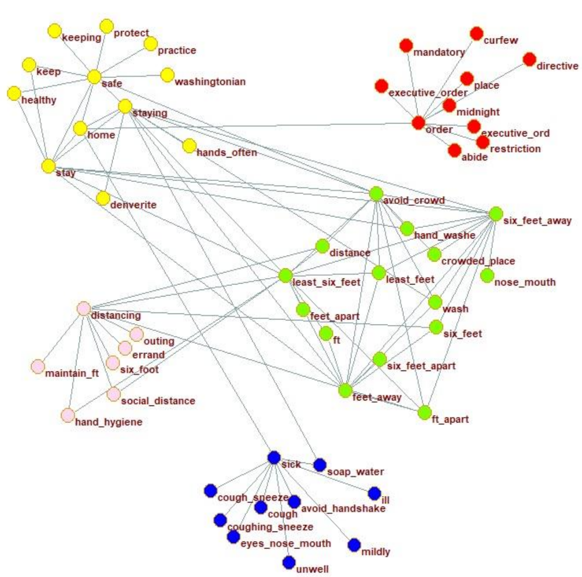
We show word clouds for each crisis stage to observe the most frequent words used in COVID-19 tweets (Figure 1.13). Stage 1 indicates that public health, stay home, and small business are more dominant and significant words. Since COVID-19 was a novel health crisis, we were unaware of its genomes. Thus, staying home was the primary guard to avoid the spread. It mainly affected small businesses. While wearing a mask was prominent in stage 2 and stage 3, the vaccine-related discussion got priority in stage 4. It is consistent with the notion that initial experiments showed that wearing a mask contains the infection. Thus, most political leaders motivated people to wear a mask. When a vaccine had proven to be effective, they delivered messages on the effectiveness of the vaccine and persuaded people to get vaccinated in stage 4.

1.6.5 Community of Words

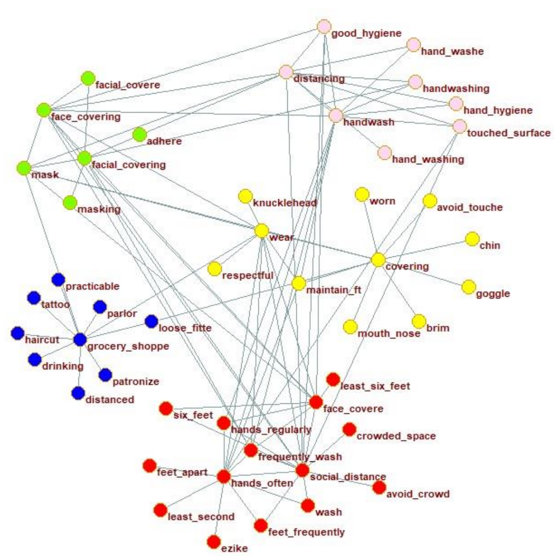
Figure 1.14 demonstrates the community of keywords for the most frequent keyword (e.g., home, mask, and vaccine) across the four crisis stages. The community shows the connected words occured together and an emerging theme.

Figure 1.14. Community of Words

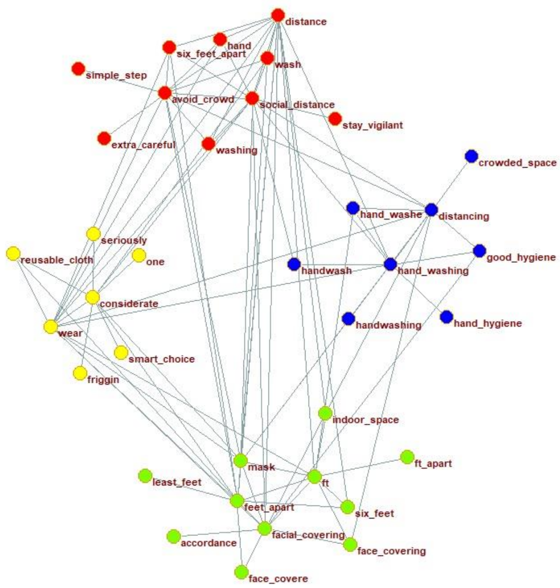
Stage 1: Community of Words based on "home" keyword



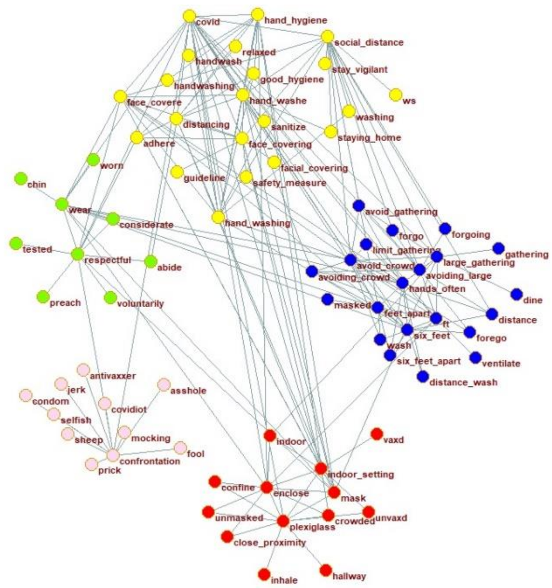
Stage 2: Community of Words based on "mask" keyword



Stage 3: Community of Words based on "mask" keyword



Stage 4: Community of Words based on "vaccine" keyword



1.6.6 Topic Modeling:

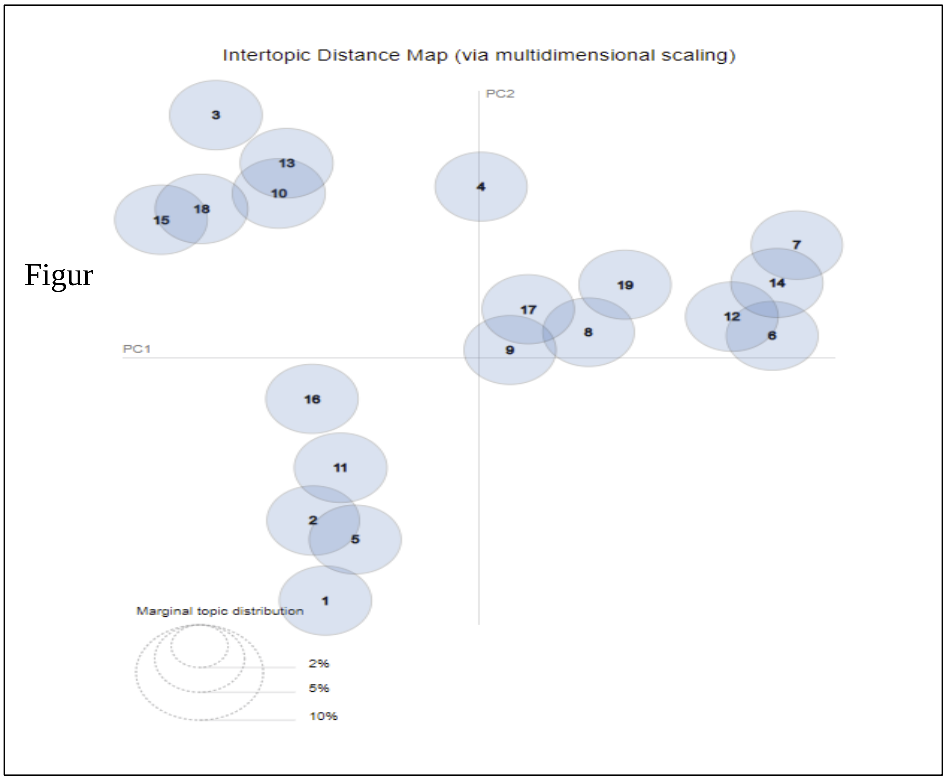
Various policy measures have caused tremendous social changes during COVID-19 (Zamani et al., 2020). Prior studies reveal the ability of social media platforms to capture the continuously evolving user-generated discourses on social changes (Thackeray et al., 2012). The role of political leaders during COVID-19 was substantially different from the general people. They were influential opinion leaders and were responsible for mandating various policy measures. This part aims to investigate the evolution of multiple actions by political leaders in the phases of crisis documented on social media platforms (e.g., Twitter).

A topic model is a useful unsupervised machine learning computational tool where either manual or dictionary-based approaches face difficulties (Shi et al., 2016). The purpose of using it in our study is to enhance the sensemaking of the tweets since it is challenging and hardly effective to sense-make from many tweets without machine learning applications. The idea behind the topic model is that the topic represents a cluster of relatively related words that frequently occur together, and each document, a group of words, belongs to multiple topics. We observe two probability distributions – word distribution and topic distribution. Due to the nature of unsupervised learning, we do not know the topics ex-ante. We have used the highest coherence score to select the number of topics.

Some standard algorithms for topic modeling are Latent Semantic Analysis (LSA), Non-negative Matrix Factorization, and Latent Dirichlet Allocation (LDA). Among these, LDA is commonly used and has been found to be consistent with human interpretation (J. Chang et al., 2009). Lee et al. (2020) preferred using LDA over other methods for three reasons: no data sparsity issue, producing human-readable keywords, and applicability in various contexts. LDA is a hierarchical Bayesian model that infers latent topics based on the distribution of words from the documents. We define a topic as "a multinomial distribution over a vocabulary of words," a document as "a collection of words drawn from one or more topics," and a corpus as "a set of all documents" (Gong et al., 2018). The output produces similar words for each topic, distributed in each document.

We have chosen LDA to identify latent themes in the COVID-19 tweets. To input the texts for performing LDA, we pre-processed them to eliminate the noises. After normalization in lowercase, we removed special characters (e.g., #, @), stopwords, and digits. Then, we lemmatized (e.g., the base form of words) texts to get more meaningfulness (Manning 2008). LDA needs to specify the number of topics. While too high or low number of topics erodes the meaningfulness of the topics, the optimal number is hard to determine. We used Pythons' Scikit-Learn module to extract 20 topics and chose 19 topics based on the highest coherence score (Appendix G). Then, we implemented LDA in Mallet (Machine Learning for Language Toolkit) to extract 19 topics and detected 4 clusters using inter-topic distance (Figure 1.15). The following discusses all the clusters in detail, and Table 6 shows the top 20 keywords. Appendix H shows the clusters of topics and keywords for four crisis stages.

Figure 1.15. Cluster of Topics



1.6.6.1 Cluster 1: Awareness and leadership

This cluster primarily discusses the behavioral side of the pandemic and political leadership to address the uncertainty and anxiety derived from the crisis. It recognizes and communicates the development of the situation (e.g., infection), various symptoms, and disease patterns. The cluster also shows that political leaders focused on recommended behaviors to avoid the infection or slow the spread. The behaviors include staying home, washing hands, and wearing a mask. They also catered hope to the public to motivate them to stay strong, fight hard and support others. Apart from the awareness, political leaders also included how they worked and planned to fight COVID-

19. We observed that COVID-19 strongly influenced the election campaign as we found the frequent mention of the leaders (e.g., *Trump*, *Biden*) in the tweets. Finally, this cluster of topics reflects how political leaders utilized social media like Twitter to create awareness about the crisis (e.g., COVID-19) and the demonstration of leadership to solve the crisis.

Table 6: Top 20 keywords for each topic

Keywords	**Topic Num**	**Topic Name**	**Cluster of Topics**
people virus thing bad real show good lot infect point disease flu problem kill science reason put young control study	1	Consequence	Awareness and leadership
spread stay home safe continue stop part hand follow order protect prevent wash virus slow healthy sick remember guideline reduce	11	Recommended Behaviors	
time make year family give good friend hope great end pandemic neighbor love feel happy celebrate veteran difficult long light	16	Optimism	
vote trump election president lie republican fail middle campaign mail american fact political administration voting party voter biden power dead	2	Political leadership	
mask wear face require mandate rule person face_covering space store cover indoor water requirement shirt remember red order buy refuse	5	Recommended Behaviors	
relief bill pass federal state support government local include act funding provide fund package legislation house colleague money aid law	10	Stimulus	
business small due program impact food assistance provide support local apply	13	Economic impact	

emergency grant unemployment pay restaurant struggle learn pandemic employee			Economy and Education
work worker pandemic life fight lose family essential save hard put healthcare protect leave woman job frontline nurse honor risk	15	Employement	
pandemic crisis economy economic country lead recovery nation back global job face leadership create national action strong world challenge future	18	Financial Challenge	
pandemic school work service continue ensure access child student support learn provide kid staff teacher expand critical education online safely	3	School reopening	
case death report positive number county covid total test today high increase rate yesterday confirm day daily datum result bring	12	Outcomes	Crisis Updates
covid testing test resident site free open county city call close center find symptom visit offer area location today drive	14	Testing	
covid day week die month news hour pinned_tweet break happen video top show understand long thousand head expect million early	6	Scale	
covid update information resource late read visit check call info office full find link include share website sign regard relate	7	Report	
health public care covid hospital patient safety medical system protect risk facility official department mental provider expert treatment issue professional	17	Healthcare support	

state covid plan make governor reopen change move place back outbreak remain decision level restriction announce policy set normal due	19	Regular living	Crisis Resolution
today join live pm response watch question discuss hold talk hear tomorrow event answer tune tonight host morning meeting update	8	Source of information	
vaccine receive vaccination start dose distribution eligible appointment week begin today supply age vaccinate effective clinic administer sign phase distribute	9	Vaccination	
community covid pandemic effort member great impact leader team issue address black story share social serve speak response partner message	4	Social support	

1.6.6.2 Cluster 2: Economy and education

This cluster of topics broadly covers various aspects of the economy and education. Political leaders at the federal and state level pondered on the struggle of the public and the need to provide support to mitigate the burden. It includes the economic challenges (e.g., jobs, small businesses) and relief funds (e.g., bills, aid, grant) to rescue the economy from recessions. Education also dominates this cluster. Since the crisis forced to shut down schools, and the reopening was a heated area of disagreement, political leaders covered a range of issues such as the safety of the students, staff, and teachers and online education.

1.6.6.3 Cluster 3: Crisis update

The topic covers various consequences of the crisis. Political leaders reported daily confirmed cases, death, and infection rates to update the public. They also motivated people to observe various symptoms and visit locations to run the test. They delivered weekly and monthly comparisons to show the magnitude of the crisis. As leaders of the people, politicians actively engaged in crisis communication to influence the behaviors and win the mandates in the election.

1.6.6.4 Cluster 4: Crisis resolution

Since the crisis shatters social safety and overwhelms the usual way of living, people desperately need the resolution to alleviate the situation. This cluster of topics broadly covers how political leaders struggled to mitigate the burdens. They appreciated and criticized healthcare and hospital systems. It also includes policies to reopen and relax restrictions to return to everyday life while checking the outbreaks. Political leaders held press conferences, attended news channels, and hosted question-answer sessions to deliver what they were doing and planning to do. When the vaccine was available, they asked people to get shot and stay safe from further aggravation. They also facilitated the distribution of vaccines in different phases. In summary, this cluster included various policy measures, social and healthcare supports, and solutions to the crisis.

1.7 Variables and Model Specification

1.7.1 Variables Measurement

The study's dependent variable is COVID-19 infection cases adapted from the John Hopkins website to measure pandemic outcomes. To prepare the model's data, we aggregated at a weekly level across 50 states to create panels. Then, we calculated the percentage of changes from a week to the following week to input into the final model. We aggregated the tweets at the weekly level instead of daily because there were not enough tweets at the daily level, and the effects of tweets take time to manifest. There was also a time lag between testing and reporting cases. In addition, we applied the percentage changes over the actual number to streamline the data across the states.

The LIWC (Linguistic Inquiry and Word Counts), a lexicon-based approach representing a text through various linguistic variables based on a set of words and word stems, has become a gold standard for measuring linguistic aspects of texts in the literature (Ashokkumar & Pennebaker, 2021; Lin et al. 2020; Moore et al. 2021). LIWC produces robust results from social media texts (Matthews et al., 2022). It looks for a dictionary match with the current target word (input words). LIWC has a dictionary size of 6,400 words, word stems, and select emoticons, and the corpus includes 231 million words from over 80,000 writers or speakers[6]. It captures more than 86% of people's words in writing and speech. IS literature adopted LIWC in their models to investigate linguistic aspects of the texts (Xu et al., 2020; Hong et al., 2018; Gunarathne et al., 2018; Yarkoni, 2010; McHaney et al., 2018; Venkatesan, 2021). We adopted LIWC's four summary variables – analytic, Clout, authentic, and Tone - to measure independent variables (Table 07). LIWC uses a scale of 100 points, denoting 0 (lowest) and 100 (highest), with 50 as midpoints. LIWC utilizes proprietary algorithms to calculate standardized scores and then convert the scores into percentiles (based on the area under a normal curve) using individual linguistic variable categories and findings from previous linguistic research (Pennebaker et al., 2015) (Pennebaker et al., 2014) (Oliver et al., 2021). Finally, we aggregated and averaged scores at the weekly level to fit into the estimation model. We split the dataset into four parts to measure its effects and feed them into the model. We included the crisis stage as moderating variable (Xu et al., 2020). We also used the time focus – past, present, and future – in the model as control variables.

[6] https://dx.doi.org/10.15781/T29G6Z

Table 7: Definition of Variables

Types of variables	Variables	Definition of variables
Dependent Variable	ConfirmedCases	percentage change of the number of COVID-19 infection cases of coronavirus within the time window *t*.
Independent Variables	Analytic	score on the level of *formal, logical, and hierarchical thinking* stored in COVID-19 tweets of political leaders within the time window *t*.
	Clout	score on the *relative social status, confidence, or leadership* conveyed through COVID-19 tweets of political leaders within the time window *t*.
	Authentic	score on the level of integrity and simplicity found in the COVID-19 tweets of political leaders within the time window *t*.
	Tone	score to indicate positive and negative sentiments found in the COVID-19 tweets of political leaders within a time window *t*.
Moderating Variable	CrisisStage	Category to denote the evolution of COVID-19 trajectory.
Control Variables	PastFocus	percentage of words in the COVID-19 tweets of political leaders that focused on the past period within the time window t.
	PresentFocus	percentage of words in the COVID-19 tweets of political leaders that focused on the present period within the time window t.
	FutureFocus	percentage of words in the COVID-19 tweets of political leaders that focused on the future period within the time window t.

1.7.2 Panel VAR Model

Panel Vector Autoregression (PVAR) considers all variables in the model endogenous and helps estimate time series in a panel data setting (Holtz-Eakin et al., 1988). Previous I.S. studies have used the PVAR to analyze dynamic relationships between variables (Deng et al., 2018; Adomavicius et al., 2012). We prefer to use PVAR over other methods for two reasons. First, it allows us to control for the endogeneity of our main variables of interest when examining the association between COVID-19 tweets and COVID-19 confirmed cases across fifty states (Love & Zicchino, 2006). Second, the PVAR methodology allows us to control for the unobserved state heterogeneity. Moreover, the PVAR method enables us to include the lagged variables in the model and thus explore the relationship between COVID-19 tweets and COVID-19 confirmed cases.

The PVAR model permits checking the interlinks between time series using Granger causality that provides valuable insights to forecast another variable. For instance, X Granger-cause Y if lagged values of X are statistically significant in the model. To achieve the effects of any lags of X, the performance of two models – a restricted model without X and an unrestricted model with X – is compared by Wald test statistic with Chi-squared distribution. The larger the test statistic, the greater the chance of concluding that X Granger-cause Y. Finally, the impulse response function (IRF) in the VAR model enables us to gauge the structural shock of an endogenous variable that has contemporaneous effects on another endogenous variable.

Figure 1.16. Econometric Model

$$\begin{bmatrix} ConfirmedCases_t \\ Analytic_t \\ Clout_t \\ Authentic_t \\ Tone_t \\ PastFocus_t \\ PresentFocus_t \\ FutureFocus_t \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \\ C_7 \\ C_8 \end{bmatrix} + \sum_{j=1}^{j} \begin{bmatrix} \alpha_{1,1} \dots \alpha_{1,8} \\ \alpha_{2,1} \dots \alpha_{2,8} \\ \alpha_{3,1} \dots \alpha_{3,8} \\ \alpha_{4,1} \dots \alpha_{4,8} \\ \alpha_{5,1} \dots \alpha_{5,8} \\ \alpha_{6,1} \dots \alpha_{6,8} \\ \alpha_{7,1} \dots \alpha_{7,8} \\ \alpha_{8,1} \dots \alpha_{8,8} \end{bmatrix} \begin{bmatrix} ConfirmedCases_{t-j} \\ Analytic_{t-j} \\ Clout_{t-j} \\ Authentic_{t-j} \\ Tone_{t-j} \\ PastFocus_{t-j} \\ PresentFocus_{t-j} \\ FutureFocus_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \\ \varepsilon_{6,t} \\ \varepsilon_{7,t} \\ \varepsilon_{8,t} \end{bmatrix}$$

The empirical model for ConfirmedCases, Analytic, Clout, Authentic, Tone, and the control variables (e.g., PastFocus, PresentFocus, and FutureFocus) are shown in Figure 1.16. Each variable is influenced by the past values of the variable itself and other variables and error terms. *C* indicates the intercept of the equation. *j* and *α* represent the coefficient matrices and optimal lags, respectively. Finally, ε is the time series white-noise error term. *ConfirmedCases* denote the change of COVID-19 infection cases at a weekly aggregated level. *Analytic, Clout, Authentic, and Tone* represent the linguistic values of each COVID-19 tweet posted by political leaders. *PastFocus, PresentFocus, and FutureFocus* indicate the count of time-related words from COVID-19 tweets extracted using LIWC. To evaluate the moderating effects, we divided the dataset into four sections corresponding to four crisis stages (buildup, breakout, abatement, and termination).

To estimate the panel VAR model, we followed the standard two-step procedures. First, we checked the stationarity of the time series. We performed the Harris-Tzavalis unit root test for panel data of all the endogenous variables. Second, after we confirmed that all the variables were stationary, we ran various criterion tests to select the optimal lag length (Deng et al., 2018; Love & Zicchino, 2006). Finally, we used the generalized method of moments (GMM) to estimate the model using lagged independent variables as instruments to control potential endogeneity. GMM is a dynamic panel data estimator that improves efficiency by using lags as instruments (Abrigo & Love, 2016). Specifically, we followed Holtz-Eakin et al. (1988) and used the first four lags of the variables of interest as instruments when estimating our model using GMM. The lags of the regressor are internal instruments widely used for the GMM model (Roodman, 2009). The GMM model expects zero co-variance between instruments and error terms.

As discussed earlier, we first classified 11,297 political leaders from 50 states and extracted all the tweets from their timelines, separating COVID-19 tweets from non-COVID-19 tweets. The length of the period is 63 weeks starting from Mar. 16, 2020, to May 30, 2021. The day of the week is from Monday to Sunday. To have meaningful patterns of influence, we considered the relationship at the weekly level. The reason is that the influence of tweets would first impact the behavioral patterns of the wider population and then require a testing procedure to report COVID-19 cases (Zeng et al., 2021).

Furthermore, we performed our analysis at the state rather than the country level. Although a few political leaders have cross-state and country-wide influence, a prior study found a positive correlation between Twitter and COVID-19 cases at the state level due to the states' differences in terms of demography, air quality, and GDP (Sun & Gloor, 2021). Finally, we used the weekly aggregated change of COVID-19 confirmed cases rather than the number of cases.

1.8 Analysis and Findings

1.8.1 Descriptive Statistics

We report summary statistics of all variables in (Appendix I). In the study, we used 611,470 COVID-19-related tweets from political leaders. We notice that the mean scores of analytic and Clout are higher than the midpoint of 50. The mean Tone score is below 50, which suggests more negative than positive tones in the tweets. On the other hand, the mean score of authentic 39.89 implies that political leaders typically posted filtered and prepared tweet content. Then, we calculate the correlation matrix and variance inflation factor (VIF) to check the presence of multicollinearity (Appendix J). The results indicate low correlation, lower VIF, and mean VIF. Thus, we conclude that multicollinearity is not a concern for the model. In the following section, we first discuss the panel vector autoregressive model (PVAR) to analyze the dynamic relationship between the contents of tweets and infection cases. Then, we present the outputs of PVAR estimated models and show the significance of the relationship between variables across the four stages of the crisis.

1.8.2 Test for Stationarity

We use STATA to estimate all the PVAR models (Abrigo & Love, 2016). To derive results for PVAR models, we first check the stationarity of the time series by performing the Harris-Tzavalis unit root test for panel data. The test result shown in Table 8 provides statistical evidence that all variables are stationary.

Table 8: Harris-Tzavalis unit root test results

	rho statistics	**z**	**p-value**
ΔConfirmedCases	0.1283	-1.2e+02	0.000
Analytic	0.3887	-80.7098	0.000
Clout	0.2166	-1.1e+02	0.000
Authentic	0.1159	-1.2e+02	0.000
Tone	0.1562	-1.1e+02	0.000
PastFocus	0.2248	-1.0e+02	0.000
PresentFocus	0.1765	-1.1e+02	0.000
FutureFocus	0.0695	-1.3e+02	0.000

1.8.3 Optimal Lag Selection

Next, we use Moment Bayesian Information Criterion (MBIC), Akaike Information Criterion (AIC), and Quinn Information Criterion (MQIC) from the moment model selection criteria to select the appropriate lag length (Andrews & Lu, 2001). Finally, we considered the optimal lag for the PVAR estimates to be one week, as both MBIC and MQIC indicate the smallest values (Table 9).

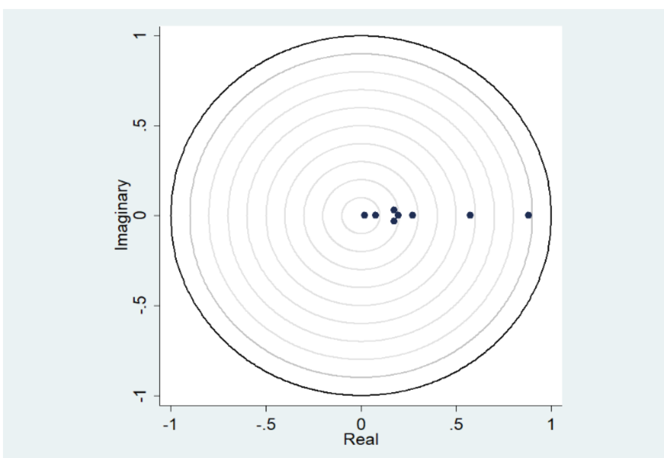
Table 9: Lag order selection criteria

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.9925	471.62	5.71e-15	***-1564.88***	-40.38	***-590.17***
2	0.9940	322.78	1.05e-08	-1204.59	***-61.22***	-473.56
3	0.9948	201.96	0.0000	-816.29	-54.04	-328.94
4	0.8450	123.54	0.0000	-385.59	-4.46	-141.91

1.8.4 Stability of the model

Next, we check the stability of the PVAR model using the eigenvalue for modulus. A PVAR model is reported as stable if the values of all moduli are less than one (Lütkepohl, 2005). The following graph (Figure 1.17) indicates that our panel VAR model is stable.

Figure 1.17. Stability of the Model



1.8.5 Coefficients Estimation

The coefficient estimates of the PVAR models are reported in Table 10. The robust standard errors are given in paranthesis. For the *ConfirmedCases* equation, the coefficient on the first lag of *ConfirmedCases* is positive and statistically significant at the 1% significance level. This is consistent with the notion that COVID-19 is a highly infectious disease, and if more people are infected, there is highly likely that more people will be in contact, and the case will rise faster. The results also demonstrate that the coefficient on *Analytic*, *Authentic*, and *Tone* are negative and statistically significant at 1%, 5%, and 1% significance levels respectively. However, the coefficient on *Clout* is not statistically significant in this equation. These show that the increase in *Analytic*, *Authentic*, and *Tone* (positive sentiment) helps decrease the *ConfirmedCases* in the following weeks. The coefficient estimates from other equations indicate that the first lag of *ConfirmedCases* is negatively associated with *Analytic*, *Authentic*, and *Tone* and is statistically significant at the 1% significance level. The first lag of *ConfirmedCases* is positively associated with *Clout* but statistically insignificant. The result suggests that COVID-19 outcomes also influence the tweets of political leaders. To further examine the dynamic relationship between the variables of the PVAR model, we now focus on Granger causality and impulse response functions (IRFs), which can capture the actions and reactions over time.

Table 10: Coefficient Estimates from PVAR Regression

	Dependent Variables							
Independent Variables	Confirmed $Cases_t$ (1)	$Analytic_t$ (2)	$Clout_t$ (3)	$Authentic_t$ (4)	$Tone_t$ (5)	Past $Focus_t$ (6)	Present $Focus_t$ (7)	Future $Focus_t$ (8)
$ConfirmedCases_{t-1}$	0.2980*** (0.0246)	-0.5981*** (0.1004)	0.0197 (0.0393)	-0.0884*** (0.0300)	-0.2596*** (0.0509)	-0.0107** (0.0049)	0.0455*** (0.0058)	0.0157*** (0.0037)

$Analytic_{t-1}$	-0.0155*** (0.0057)	-0.9621*** (0.0607)	0.2524*** (0.0414)	-0.0213 (0.0450)	0.3763*** (0.0518)	-0.0259*** (0.0045)	-0.0424*** (0.0058)	-0.0105*** (0.0036)
$Clout_{t-1}$	-0.0007 (0.0040)	0.3894*** (0.0433)	0.2794*** (0.0324)	-0.0319 (0.0358)	0.1661*** (0.0381)	-0.0147*** (0.0036)	-0.0142*** (0.0044)	-0.0064** (0.0027)
$Authentic_{t-1}$	-0.0073** (0.0029)	0.2478*** (0.0351)	0.1024*** (0.0276)	0.1490*** (0.0302)	0.1340*** (0.0373)	-0.0033 (0.0032)	-0.0180*** (0.0038)	-0.0059** (0.0024)
$Tone_{t-1}$	-0.0038*** (0.0014)	0.0270 (0.0237)	0.0013 (0.0214)	0.0385 (0.0243)	0.2409*** (0.0262)	0.0031 (0.0023)	-0.0057** (0.0027)	-0.0039** (0.0018)
$PastFocus_{t-1}$	-0.2515*** (0.0275)	1.8150*** (0.3592)	0.5090 (0.2902)	-0.1213 (0.3111)	2.3123*** (0.3682)	0.3654*** (0.0339)	-0.3614*** (0.0412)	-0.0702*** (0.0246)
$PresentFocus_{t-1}$	-0.0196 (0.0352)	3.4380*** (0.3850)	1.4905*** (0.2677)	-0.4524 (0.3051)	1.5832*** (0.3383)	-0.2074*** (0.0308)	-0.0077 (0.0371)	-0.0731*** (0.0243)
$FutureFocus_{t-1}$	-0.0274 (0.0284)	1.0194** (0.4237)	-0.5482 (0.3603)	-1.3175*** (0.3606)	-0.4922 (0.4743)	-0.1416*** (0.0464)	0.0460 (0.0460)	0.0837*** (0.0296)

****,**,* indicate statistical significance at 1%, 5% and 10% respectively*.

1.8.6 Test for Granger Causality

The analysis investigates a cyclic nexus between tweets of political leaders and infection cases. VAR model enables to capture of feedback loops among all the endogenous variables in the model. We run the Granger-causality Wald tests for multiple time series**.** The null hypothesis of Wald tests is that the coefficients on all the lags of endogenous variable x are jointly equal to zero and thus may be excluded from the PVAR model (Abrigo & Love, 2016). Although Granger causality is not actual causality, it establishes initial causality between the variables and provides evidence to conduct further analysis.

Table 11: Granger Causality Tests

	Confirmed Cases	Analytic	Clout	Authentic	Tone	Past Focus	Present Focus	Future Focus
$ConfirmedCases_{t-1}$	-	35.511***	0.252	8.672***	25.986***	4.764**	61.307***	18.331***
$Analytic_{t-1}$	7.449***	-	37.172***	0.224	52.790***	32.919***	32.919***	8.693***
$Clout_{t-1}$	0.032	80.845***	-	0.795	18.978***	17.066***	17.066***	5.680**

$Authentic_{t-1}$	6.142**	49.769***	13.825***	-	12.890***	1.053	22.744***	5.918**
$Tone_{t-1}$	7.048***	1.293	0.004	2.513	-	1.824	4.315**	4.871**
$PastFocus_{t-1}$	83.517***	25.530***	3.076*	0.152	39.437***	-	77.023***	8.152***
$PresentFocus_{t-1}$	0.311	79.871***	31.002***	2.197	21.899***	45.392***	-	9.061***
$FutureFocus_{t-1}$	0.926	5.789**	2.314	13.351***	1.077	9.327***	1.001	-
ALL	171.337***	122.399***	69.456***	35.447***	90.138***	104.981***	165.318***	31.620***

****,**,* indicate statistical significance at 1% and 5% respectively*

The panel VAR-Granger causality Wald test, reported in Table 11**,** indicates that *Analytic*, *Authentic, Tone, and PastFocus* Granger cause the changes in the confirmed cases at the 95% and 99% confidence levels. On the other hand, coefficients on the lags of the changes in the confirmed cases Granger-cause all other variables except Clout. This finding suggests that although the change in infection cases significantly influences the contents of political leaders' tweets, the infection cases do not predict the leadership and confidence prevalent in tweets during crisis management. It alludes to the notion that while tweets with analytical thinking, the authenticity of the contents, and sentiment predict pandemic outcomes, tweets with leadership and confidence do not predict pandemic outcomes.

1.8.7 Forecast Error Variance Decomposition (FEVD)

Now, we analyze forecast error variance decomposition (FEVD) and impulse response functions (IRFs). FEVD provides us with the percentage of error variance when a variable is used to explain another variable with a shock and the time a variable requires to gain equilibrium. On the other hand, IRFs show a variable's reaction to a shock in another variable. IRFs also allow us to examine whether the impact of the shock persists over time or attenuates quickly (Dewan & Ramaprasad, 2014). We used 500 Monte Carlo simulations to estimate both FEVD and IRFs. Table 12 and Figure 1.18 present the outputs from the FEVD and IRFs. From the outputs of Table 12, we observe that the forecast error variance of *ConfirmedCases* is mainly explained by the shock to itself

(94.3% in the second week, 86.97% in the tenth week) followed by *Analytic* (0.5% in the second week, 2.68% in the tenth week), *Tone* (0.1% in the second week, 0.23% in the tenth week), and *Authentic* (0.40% in the second, 1.05% in the tenth week). The explainability of *Clout* (0.02% in the second week, 0.2 in the tenth week) is the lowest for *ConfirmedCases*. On the other hand, the *Analytic* and *Tone* are mainly explained by the shocks to themselves and *ConfirmedCases*. In a nutshell, the result suggests that in the case of forecast error variance, the *ConfirmedCases* has greater explainability on the tweets than vice-versa.

Table 12: Forecast Error Variance Decomposition

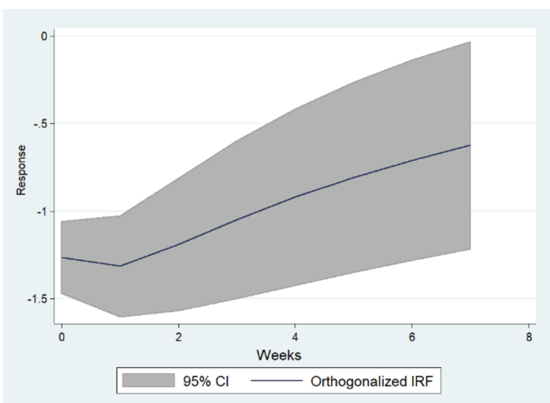
Response Variables	Forecast Horizon	**Impulse variable**				
		ConfirmedCases	Analytic	Clout	Authentic	Tone
Confirmed Cases	1	1	0	0	0	0
	2	0.9430	0.0052	0.0002	0.0040	0.0011
	5	0.8831	0.0187	0.0008	0.0092	0.0023
	10	0.8697	0.0268	0.0022	0.0105	0.0023
Analytic	1	0.0451	0.9549	0	0	0
	2	0.0493	0.8141	0.0452	0.0249	3.71e-07
	5	0.0513	0.7075	0.0839	0.0447	7.66e-07
	10	0.0515	0.6788	0.0947	0.0498	8.40e-07
Clout	1	0.0030	0.0282	0.9688	0	0
	2	0.0043	0.0704	0.8905	0.0078	0.0003
	5	0.0092	0.1407	0.7839	0.0163	0.0002
	10	0.0124	0.1770	0.7305	0.0202	0.0002
Authentic	1	0.0003	0.0101	0.0569	0.9327	0
	2	0.0008	0.0097	0.0583	0.9192	0.0014
	5	0.0013	0.0102	0.0580	0.9147	0.0019
	10	0.0014	0.0105	0.0581	0.9140	0.0019
Tone	1	0.0147	0.0380	0.0488	0.0022	0.8964
	2	0.0230	0.0950	0.0573	0.0124	0.7723
	5	0.0329	0.1845	0.0679	0.0262	0.6169
	10	0.0356	0.2267	0.0740	0.0309	0.5515

1.8.8 Impulse Response Functions (IRF):

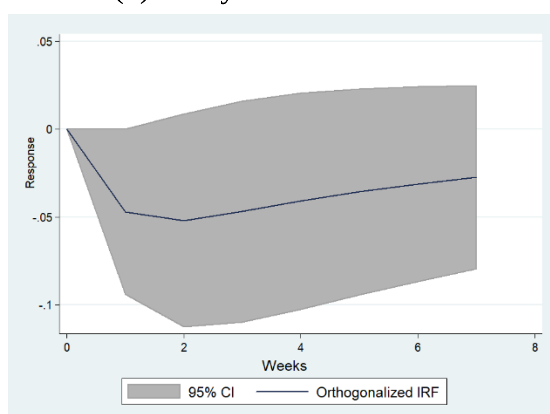
From the outputs of IRFs, it seems to surface that all variables have tendencies to converge to equilibrium after a shock, which implies their stationarity. We also see that a shock in *ConfirmedCases* causes a negative response by *Analytic*, *Authentic*, *Tone*, and vice-versa. However, a shock in *ConfirmedCases* triggers a positive response by *Clout and* vice-versa. Additionally, we also notice that shocks on *Analytic*, *Authentic*, and *Tone* have greater effects on *ConfirmedCases* (b) (f) (h) while the vice-versa has smaller effects.

Figure 1.18. Impulse Response Functions (IRF)

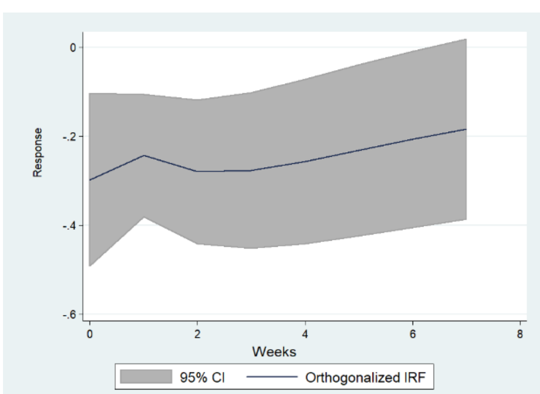
(a) ConfirmedCases : Analytic



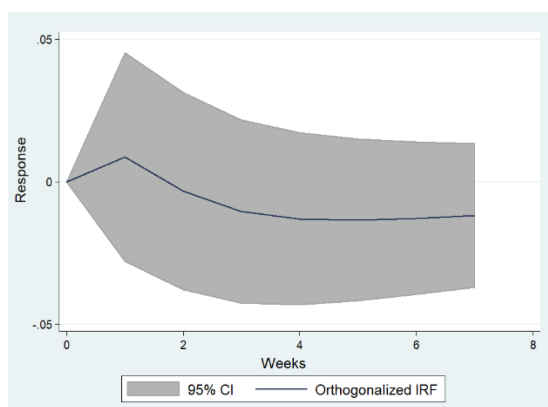
(b) Analytic : ConfirmedCases



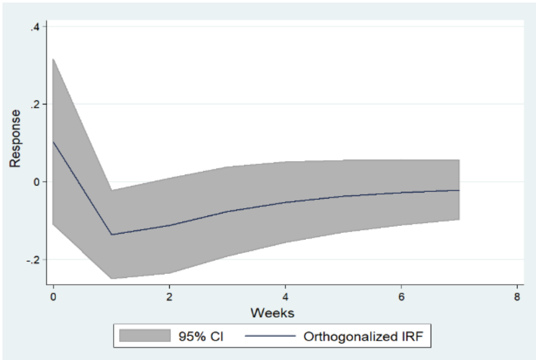
(c) ConfirmedCases : Clout



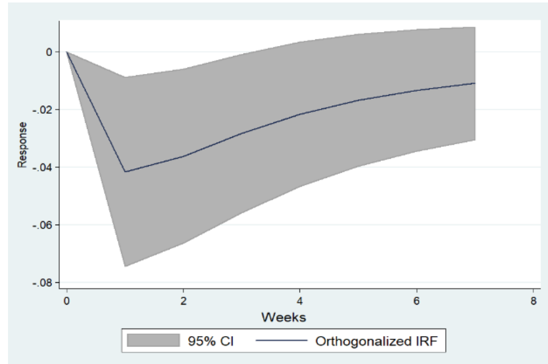
(d) Clout : ConfirmedCases



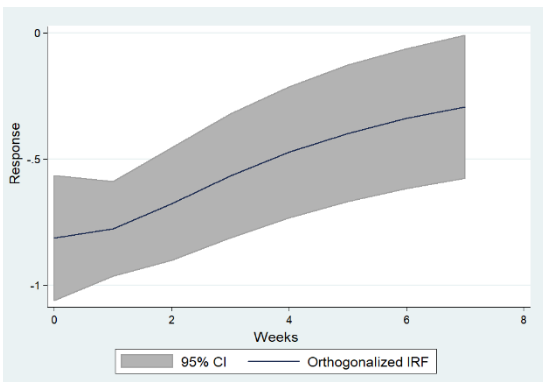
(e) ConfirmedCases: Authentic



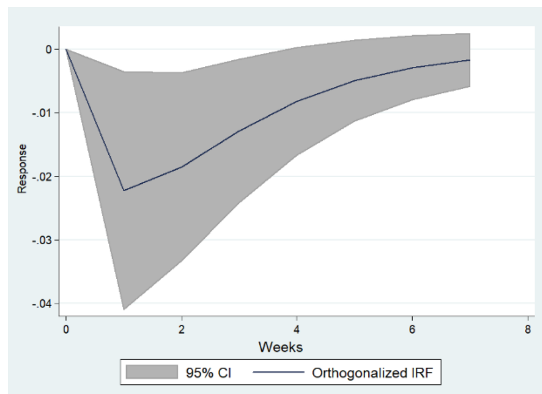
(f) Authentic: ConfirmedCases



(g) ConfirmedCases: Tone



(h) Tone : ConfirmedCases



1.8.9 Effects of Crisis Stages:

We split the data into four crisis stages to investigate the dynamic relationship between political leaders' tweets and confirmed cases. Table 13 shows the causal relationship in the build-up, breakout, abatement, and termination stages (H5). Analytic, Clout, and Authentic in the build-up stage negatively caused ConfirmedCases, whereas ConfirmedCases and Tone positively caused ConfirmedCases with one week lag. However, only *Analytic* negatively caused *ConfirmedCases* while *ConfirmedCases Clout*, *Authentic*, and *Tone* positively caused *ConfirmedCases* with a one-week time lag. In the abatement stage, *Analytic*, *Clout*, *Authentic*, and *Tone* negatively caused

ConfirmedCases. The *ConfirmedCases* of the last week positively caused *ConfirmedCases* in the following week. Finally, we observe that all the variables positively caused *ConfirmedCases* of the following week in the termination stage. Thus, the coefficients across the crisis stages indicate that the linguistic aspects of political leaders' crisis communication decreased confirmed cases the most in the abatement stage, followed by the build-up stage. The termination and breakout stages have the lowest effects on *ConfirmedCases* decrement.

Table 13: Coefficient Estimation across the Crisis Stages

		Dependent Variables				
Crisis Stages	**Independent Variables**	$ConfirmedCases_t$ (1)	$Analytic_t$ (2)	$Clout_t$ (3)	$Authentic_t$ (4)	$Tone_t$ (5)
Build-up Stage	$ConfirmedCases_{t-1}$	0.2464*** (0.0254)	-0.1595*** (0.0310)	0.0504 (0.0481)	0.2449*** (0.0584)	-0.1606*** (0.0569)
	$Analytic_{t-1}$	-0.1301*** (0.0307)	- 0.8918*** (0.1324)	0.4109*** (0.1415)	-0.7127*** (0.2104)	0.8092*** (0.2123)
	$Clout_{t-1}$	-0.0633*** (0.0207)	0.4770*** (0.0819)	0.4312*** (0.0839)	-0.7283*** (0.1378)	0.5900*** (0.1389)
	$Authentic_{t-1}$	-0.0295* (0.0171)	0.2474*** (0.0631)	0.1630** (.0692)	-0.3915*** (0.1133)	0.5429*** (0.1057)
	$Tone_{t-1}$	0.0304** (0.0014)	-0.2830*** (0.0496)	0.0956 (.0659)	0.2455** (0.1037)	-0.3209*** (0.0844)
Breakout Stage	$ConfirmedCases_{t-1}$	0.2979*** (0.0624)	-0.7324 (0.4525)	-1.0861** (0.5508)	3.3799*** (0.5813)	1.6924** (0.7112)
	$Analytic_{t-1}$	-0.0191* (0.0104)	0.4884*** (0.0680)	-0.0943 (0.0967)	0.3907*** (0.1045)	0.3530*** (0.1307)
	$Clout_{t-1}$	0.0134* (0.0074)	0.0212 (0.0521)	-0.0514 (0.0694)	0.2881*** (0.0687)	0.1998*** (0.0707)
	$Authentic_{t-1}$	0.0214*** (0.0063)	0.0892* (0.0483)	-0.1545** (0.0704)	0.4333*** (0.0687)	-0.0343 (0.0678)
	$Tone_{t-1}$	0.0098** (0.0043)	-0.0164 (0.0318)	-0.1430*** (0.0443)	0.0920* (0.0497)	-0.0072 (0.0409)
	$ConfirmedCases_{t-1}$	0.2261*** (0.0861)	2.1114** (0.9048)	-1.2161* (0.6522)	4.0976*** (0.9961)	-2.5288** (1.0161)

Abatement Stage	$Analytic_{t-1}$	-0.0529*** (0.0083)	0.4062*** (0.1169)	-0.0691 (0.0884)	-0.0053 (0.1092)	0.2401 (0.1469)
	$Clout_{t-1}$	-0.0242*** (0.0059)	0.0317 (0.0831)	0.1659*** (0.0639)	-0.0388 (0.0780)	0.2040* (0.1074)
	$Authentic_{t-1}$	-0.0176*** (0.0036)	-0.0375 (0.0625)	0.2903*** (.0448)	0.0055 (0.0517)	0.1701** (0.0716)
	$Tone_{t-1}$	-0.0090*** (0.0029)	0.1420*** (0.0452)	-0.0517 (0.0331)	0.0298 (0.0436)	0.2982 (0.0621)
Termination Stage	$ConfirmedCases_{t-1}$	0.6371*** (0.1011)	-1.3240*** (0.4594)	-0.2793 (0.5565)	-0.6030 (0.7975)	-3.3467*** (0.9413)
	$Analytic_{t-1}$	0.0545*** (0.0100)	0.3568*** (0.1026)	-0.0765 (0.1188)	-0.9124*** (0.1964)	0.7098*** (0.2240)
	$Clout_{t-1}$	0.0220*** (0.0056)	0.0944* (0.0535)	0.0408 (0.0665)	-0.3652*** (0.1016)	0.3350*** (0.1222)
	$Authentic_{t-1}$	0.0195*** (0.0046)	-0.0112 (0.0456)	-0.0807 (0.0566)	-0.2037** (0.0901)	0.1292 (0.1021)
	$Tone_{t-1}$	0.0074*** (0.0026)	-0.0210 (0.0296)	-0.0250 (0.0367)	-0.1036* (0.0532)	0.2170*** (0.0518)

****, **, * indicate statistical significance at 1%, 5%, and 10% respectively. The coefficient of PastFocus, PresentFocus, and FutureFocus are not shown due to space limitations.*

We also compared IRFs for the four crisis stages (Appendix K). The result indicates that *Analytic* strongly influenced *ConfirmedCases* in the abatement and termination stage. In contrast, it had a moderate influence in the breakout stage and a relatively mild impact in the buildup stage. On the other hand, though *Clout* remained influential on *ConfirmedCases* in the buildup, abatement, and termination stages, it had little impact on *ConfirmedCases* in the breakout stage. *Authentic* maintained a substantial effect on *ConfirmedCases* across all four stages of the crisis. Finally, *Tones* remain influential on the *ConfirmedCases* in all crisis stages except for a modest impact on the breakout stage. Thus, the result showed that *ConfirmedCases* had mixed influences across the crisis stages. To illustrate the reverse impact, we note that *ConfirmedCases* strongly influenced *Analytic* in the abatement and termination stages and had a modest influence in the buildup and breakout stages.

The IRFs demonstrated the differential influences between ConfirmedCases and tweets across the evolution of the crisis. In contrast, ConfirmedCases had relatively higher impacts on Clout in the abatement stage than all other stages. In addition, ConfirmedCases highly impacted authentic and Tones in the breakout and termination stages. Besides, ConfirmedCases was strongly influential on Tones in the abatement stage.

1.9 Further Analysis

1.9.1 Network Characteristics

Recent studies have used the network structure and extracted node attributes to yield better outcomes from the detected communities (Chunaev, 2020). We contend that topological features of the network affect the level of collaboration and cooperation among political leaders during a crisis. These result in a more significant influence on the diffusion of crisis messages on Twitter. We utilized the following-follower network and measured node and network-level metrics to analyze the network structure. Table 14 shows the basic properties of the network. The number of nodes and edges in the network is 11,297 and 842,109, respectively. All connections are asymmetrical and non-weighted. The scores for average path length, average clustering coefficient, and transitivity are 2.952, 0.373, and 0.282, respectively, which leads us to conclude that the social network of political leaders on Twitter is well-connected. However, the low negative assortativity score implies that nodes in the network may not often connect to other nodes based

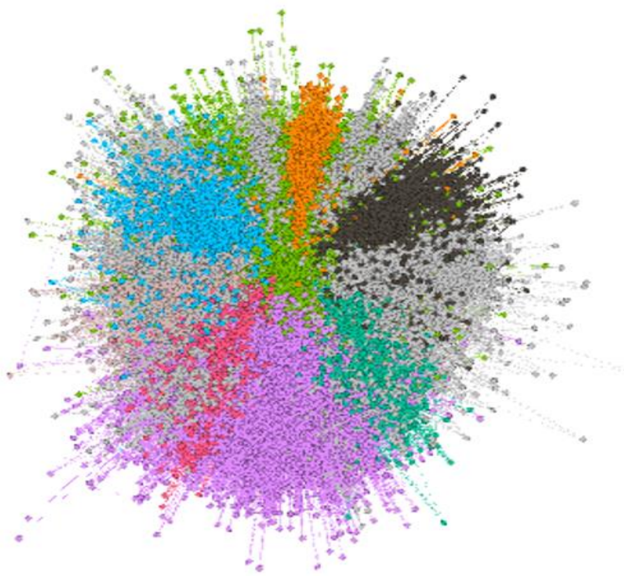
Metric	**Output**
Node counts	11297
Edge counts	842,109
Avg. In-Degree	74.543
1% of nodes	19% of in-degree
Avg. Path Length	2.952
Transitivity	0.2822
Avg. Clustering Coefficient	0.3735
Assortativity	-0.0621
Modularity	0.535
No. of Communities	23
Largest Two Community	37% of nodes
Smallest Community	1% of nodes

Table 14: Network Matrices

on similarities (e.g., degree values and political affiliation). At the node level, centrality measures indicate the structural power of a node within the graph and its role relative to others. The most straightforward yet powerful metric at the node level is its degree, which shows the number of connections a node has. The higher the degree, the more representativeness, and relevance a node have in the network (Appendix L). The result shows that 1% of nodes have 19% of in-degree.

1.9.2 Community Detection

Figure 1.19. Visualization of Political Leaders' Community on Twitter



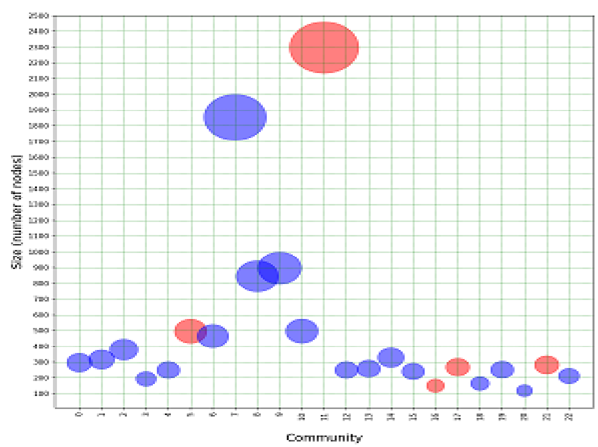
Community detection is of great importance in eliciting valuable insights from the network. The large-scale social network abodes smaller communities that can contribute to diffuse information. It is important to examine how the relative position of nodes in the community affects leadership practice. In another study, Borge-Holthoefer et al., (2015) showed the influence of network structure and community size in the context of the Egyptian revolution of 2011. Zhang & Wang, (2012) found that a node's position in the collaborative community affects the amount of contribution and allocated efforts. In a similar study, Dahlander & Frederiksen, (2012) stressed that a node's position in a community and multiple communities (Cosmopolitan) affect innovation. The community also fosters homophilous behaviors leading to political polarization, filter bubbles, and echo chambers. Thus, community detection provides nuggets of insight into the structure of the network.

A community is defined as a "group of vertices which probably shares common properties and/or play similar roles within the graph" (Fortunato, 2010). The most widely used optimization for community detection is modularity maximization. Modularity measures network segregation into partitions different from the random graph (nodes connected with independent probability). The higher the modularity, the denser the intra-module and the sparser the inter-module connections are. Using Gephi network analysis software, we detected twenty-three communities with a modularity score of 0.535, shown in Figure 1.19. A value between 0.3-0.7 indicates the relevance of communities in the graph.

1.9.3 Community Structure and Diversity

Next, we look into the structure and diversity of each community. Our data indicate that about 20% of Twitter accounts have overtly mentioned their political affiliation with either Republican or Democratic parties in their profile descriptions. Figure 1.20 shows the node distribution in communities, with the circle's diameter representing the community size. We assign red and blue colors to represent the majority of Republican and Democratic party leaders, respectively. To weigh the community's diversity, we computed the Shannon diversity index. It explains how diverse the states in a given community are. The higher the score, the more diverse the states in a community. We contend that the community formed by political leaders from diverse states enhances the likelihood of information richness and reach, which results in greater influence on the broader population. The

Figure 1.20. Node Distribution in Communities

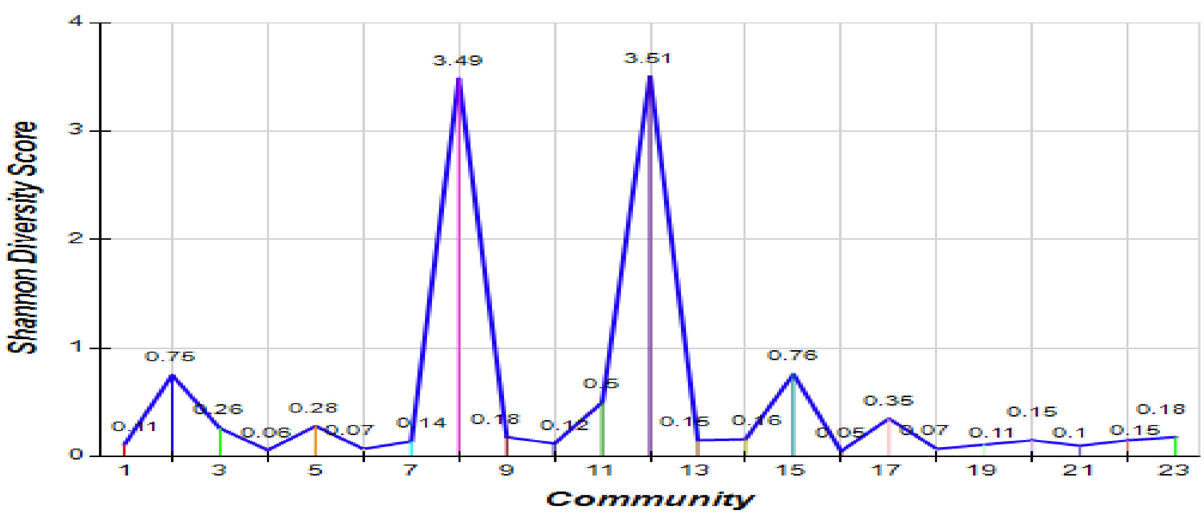


index calculates the richness and evenness of species. Richness depicts the types of species, whereas evenness describes the relative abundance of the species. The following is the formula for the Shannon diversity index calculation.

$$\textit{Shannon Diversity Index} = -\sum [(pi)\times ln(pi)]$$

The index measures the probability of species i out of k possible species. The Shannon diversity index results reveal that the minimum value can be zero when all objects in the community are of the same category or species. The maximum value is attained when all species are evenly distributed. Figure 1.21 shows that communities 8 and 11 have the highest diversity and appear more influential than others.

Figure 1.21. Community Diversity



1.10 Discussion

While crisis communication of political leaders is valuable to crisis management, our understanding of how social media-mediated crisis communication affects crisis outcomes is limited. Drawing upon the theory of social influence and the systemic functional linguistic theory, we studied linguistic features (e.g., analytic, Clout, authentic, and tone) of Twitter-mediated crisis communication of political leaders to examine the influence in the context of COVID-19. The phenomenon is worth investigating as prior studies have empirically demonstrated that political leaders widely used Twitter for political discourse that influenced the mass population. Likewise, political leaders adopted Twitter to conduct crisis communication and played significant roles in the COVID-19 crisis management. To establish the link, we deployed machine learning algorithms to identify political leaders (e.g., current and former legislators, governors, and party leaders) from the Twitter explicit network. Then we analyzed political leaders' COVID-19 tweets with a timeframe ranging from Mar. 16, 2020, to May 30, 2021, where t = 63 weeks and n = 50 states. Finally, we proposed a set of hypotheses for the empirical test.

Our analysis of tweets revealed that, as illustrated in Figure 1.8 & Figure 1.9, states with the highest number of confirmed cases have the maximum number of tweets from political leaders. Thus the apparent link between tweets and COVID-19 outcomes shows evidence that political leaders actively engaged in the Twitter platform to communicate the evolution of crisis episodes with the mass population. Moreover, the use of hashtags has also supported this notion. Previous research has shown that hashtags reflect collective sensemaking and situational awareness during a crisis (Oh et al., 2015). We observed that political leaders used hashtags consistent with the developments of the crisis. The findings also show that at the buildup stage of the COVID-19 crisis, when people did not adequately know what to do, #stayHome was predominantly used in the tweets of political leaders as a precaution. In contrast, #wearAMask dominated at the breakout stage when scientists and epidemiologists confirmed the benefits of using a mask to contain the spread.

While the abatement stage was the time of the election, hashtags - #Trump and #BidenHarris - were indispensably used with COVID-19 hashtags to indicate the political stance towards the COVID-19 crisis. When the vaccination was available, the termination stage was dominated by #vaccine and #AmericanRescuePlan, and the government initiated economic stimulus. Therefore, we conclude that political leaders deliver the concurrent development of the crisis using consistent hashtags. To further gain support for the link between tweets and COVID-19 outcomes, we counted the weekly average number of hashtags. We observed that political leaders used more hashtags at the buildup stage compared to other stages of the crisis. One possible explanation for this is that political leaders used hashtags to sensemaking of the crisis at the early stage. However, the use gradually declined as people were already aware of the crisis (Table 5). Furthermore, @mention represents the highest users from the Democratic and Republican parties. It is consistent with mild political polarization, where parties are not unaware of each other (Shore et al., 2018).

Our study further reveals key themes of the COVID-19 tweets from the political leaders that dominated the crisis communication. It is evident from the prior studies that social media in general, and Twitter in particular, can diffuse relevant information and persuade people to change their attitudes, beliefs, and behaviors during a crisis, and affect the crisis outcomes. It is important to understand the power of social media as an effective and pervasive crisis communication tool to address the major challenges during a crisis. Our preliminary analysis shows that political leaders mainly focused on awareness (e.g., stay home, flu, wash hands), leadership (e.g., control, protect, guideline, political administration), economy (e.g., small business, unemployment, Bill), education (e.g., school, online, teacher, staff), crisis updates (e.g., cases, death, test, information), and crisis resolution (e.g., hospital, vaccine, dose, distribute) in their COVID-19 tweets. Thus, our study delineates critical aspects and provides helpful directions for future research.

Our results show what linguistic features of crisis messages are pertinent and how they are related to crisis outcomes. Overall, four of five hypotheses were supported. First, our empirical tests of H1, H3, and H4 indicate that linguistic features - analytic, authentic, and tone - from the past week influenced to decrease in confirmed cases of the following week (Table 10). The Granger causality test has also supported the effects of tweets (Table 11). However, clout (H2) in tweets from the past week did not significantly influence the confirmed cases. It seems counter-intuitive that leadership and confidence conveyed through Twitter to the mass population do not affect crisis outcomes. Second, we observed a simultaneous relationship between tweets and confirmed cases. In other words, not only did tweets influence confirmed cases but also confirmed cases impacted the tweets of political leaders. For example, as reported in (Table 10), the confirmed cases of the past week are negatively associated with the analytic, authentic, and tones of the following week. The result is consistent with the self-perception theory (Bem, 1972), which posits that people adjust their perceptions dynamically with the change in information. Finally, the effects of crisis stages indicate that analytic, clout, authentic, and tone are not equally influential across the four stages – buildup, breakout, abatement, and termination – of crisis (Table 13 & Appendix K). For instance, analytic influenced confirmed cases more in the buildup and termination stage than in the breakout and abatement stage. At the same time, authentic was substantially influential on confirmed cases across all four stages. Though tones of tweets were less effective in the breakout stage, they were impactful in the buildup, abatement, and termination stages. Although clout was not significant with overall data, it is significant at the buildup, abatement, and termination stages and marginally significant at the breakout stage. Thus, the results provided empirical evidence that the influence of tweets on confirmed cases was not stagnant but varied across the crisis stages. We have also observed that the past week's confirmed cases are positively associated with confirmed cases of the following week. It indicates the nature of viral infections of contagious diseases like COVID-19.

The network of political leaders on Twitter confirms that the node distribution follows a power law, meaning a few nodes have many followers. In contrast, others have fewer followers in the network (González-Bailón et al., 2013). The finding maintains that there exist political leaders who are popular and followed across the nation, and those who are more known locally. It indicates the pervasive influence of a handful of leaders, who can primarily affect the crisis outcomes through the diffusion of pertinent messages in crisis communication.

We also found from the community detection that two dominant communities in the network comprised 37% of nodes, and the rest were relatively small and well-balanced in size. These two large communities are home to political leaders from almost all states, while other communities are centered mainly on the state level. The Shannon Diversity score also supports this characteristic of the communities. These measures provide helpful information to understand the network's behaviors. A closer observation reveals political polarization across party lines (Shore et al., 2018). The largest two communities predominantly belong to the Republican and Democratic party leaders across the states, while other communities tend to show the dominance of state-level political leaders. It implies the existence of national and state-level communities. It is crucial in crisis communication how these national and state-level communities develop crisis responses.

Finally, we observed mild political polarization on Twitter following networks among political leaders, meaning that leaders with opposite political affiliations may still follow each other. One possible explanation is that opposite political leaders do not want to be ignorant of the leaders from other parties. However, tweets and retweets are posted congruent with their political ideology. Therefore, our finding is consistent with existing literature, implying that mild political polarization is found in the following network, whereas intense political polarization could be found in the retweet network (Aragõn et al., 2013).

1.11 Implications for Research and Practice

Our study has important implications for research. First, our study provides empirical evidence that social media posts contain rich linguistic features that persuade people to change beliefs, opinions, and behaviors, thus influencing crisis outcomes. Most of the related earlier research only considered positive and negative emotions from the textual contents of posts (Deng et al., 2018) (Xu et al., 2020). Our study emphasizes the relative importance of other linguistic features, such as analytic, authentic, leadership, and tones., which significantly influence crisis outcomes. Future research should recognize various linguistic features' influence and positive and negative sentiments. Second, opinion leaders are powerful influencers. In our study, we investigated the influence of opinion leaders (e.g., political leaders) during a crisis. Our findings enriched the literature on opinion leaders and social influences. We observed from the linguistic analysis that influencers adopted social media to exert their influence during a crisis. Third, crisis communication is crucial to minimize the consequences and slow the progression of a crisis. Our study advances crisis communication literature by analyzing the relationship between crisis messages and outcomes. Understanding the linguistic aspects of crisis communication can largely improve crisis management. Finally, our novel approach to identifying political leaders from Twitter explicit data makes a valuable addition to the extant literature. While prior research studied political leaders on Twitter using fragmented approaches, our state-of-the-art machine learning-based approach incorporated millions of Twitter users to deduce the network of political leaders. The procedure could be generalizable to other influencers on Twitter as well.

This paper offers some important practical implications. First, social media is the ideal communication channel during a crisis. It provides valuable insights into the contemporary development of the crisis. The study of Twitter-mediated crisis communication in the context of COVID-19 offers evidence that the wider population considers it one of the primary sources of gathering information and updates. This is consistent with prior studies that showed how people shifted focus away from traditional media to social media for real-time crisis updates. Second, political leaders use social media services like Twitter to communicate crises. Typically, they deliver guidelines, opinions, and updates to reach the wider population, which builds the emergent collective behaviors that prevent the crisis progression. Despite prior research on political leaders' Twitter usage in crisis, comprehensive research in the context of COVID-19 was overdue. The current study showed that political leaders substantially influence crisis outcomes. Our analysis also revealed what political leaders deliver in their messages to influence the crisis. We suggest that political leaders must pay close attention while conducting crisis communication on Twitter during the crisis. Finally, our study also indicates that social media posts dynamically evolve with the development of a crisis. The panel data analysis helped capture this dynamic nature of social media posts. We observed that not only do social media posts impact the crisis outcomes but also crisis outcomes impact social media content. Future studies should recognize the simultaneity of social media posts during a crisis.

1.12 Limitations

Our study has several limitations. First, we did not directly measure behaviors and assumed that the changes in COVID-19 infection cases correspond to the compliance of collective behaviors (e.g., wearing a mask, avoiding gatherings, getting vaccinated). Studies showed that increased compliance with recommended behaviors is associated with decreased infection cases. Second, our study did not classify crisis messages (e.g., informative, situational awareness, risk exposure) and only considered linguistic aspects of the tweets. Future research may expand on measuring emergent collective behaviors directly related to the crisis outcomes.

Further studies could be taken to dig into crisis messages and examine how linguistic aspects and the particular kind of crisis messages are associated with differential crisis outcomes when confirmed cases soar rapidly and slowly. Third, we filtered profiles that follow at least four accounts of the initial seed within the state. It streamlined the data to consider active users but with the cost of restricting the scope of the dataset. Additionally, our dataset is a long panel that includes longer time series (63 weeks) than cross-sections (50 states). However, the extended time series allowed us to curate the adequate trajectory of the COVID-19 crisis. Finally, we only considered Twitter-mediated crisis communication in our study. However, there exist other social media services like Facebook and Instagram.

Future studies can include other social media platforms (e.g., Facebook, Instagram). Moreover, results could be compared with other crises, such as political or social crises, to explore any significant changes in the findings. One can also examine the affiliation of a political party as moderating effect.

1.13 Conclusion

A crisis like COVID-19 causes tremendous burdens. Researchers are interested in studying and finding ways to reduce its costs to society. Several studies recently focused on demystifying crisis communication on the Twitter platform (Sun & Gloor, 2021; Daughton et al., 2021; Cuomo et al., 2021; Engel-Rebitzer et al., 2021). The current study identified explicit networks of political leaders and examined the linguistic aspects of political leaders' crisis communication on Twitter. We applied unique and parsimonious data collection and preparation procedures. Our study showed the dynamic relationship between tweets and pandemic outcomes. Our findings indicate that tweets made by political leaders during COVID-19 had a bidirectional effect on the outcome of COVID-19. We also found that the interrelationship between tweets and confirmed cases is transitory and attenuates after one week. This study will contribute to our understanding of how social media affects crisis management. To conclude, our study fulfills a gap and provides the foundation for conducting more studies that extend the boundaries of knowledge related to the persuasiveness of tweets and how they can bring about positive change in behaviors.

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1.15 Appendix

Appendix A

Topic Modeling: Top 5 topics of papers extracted from Web of Science

Keywords	**Topics**
Vaccine cancer time concern community demonstrate treatment f ollow increase conduct relate great compare access include vacci nation professional count term history	Crisis Resolution
Social medium pandemic distancing process finding tool affect r ate interaction method effort professional order evolve timeline ongoing compare decrease mitigation	Compliance
Public health message communication agency information engag ement content official group share emergency organization analy sis effectiveness online strategy perceive action communicate	Crisis management
Public topic pandemic discussion theme identify analysis analyz e response individual discuss relate datum focus provide emotio n general text opinion world	Content analysis
User number area case infection temporal united states outbreak focus population attention city patient communication report dyn amic dataset copyright abstract risk	Fear and anxiety

Appendix B

Selected papers on Twitter and Pandemic Outcomes in the context of US

Reference	**Context**	**Findings**
(Sun & Gloor, 2021)	Twitter, google trends, and infection cases	Found lag correlation between Twitter and Google trends and number of daily cases across the US; awareness in Twitter/Google correlates with lower infection rates.

(Daughton et al., 2021)	Twitter, pandemic behaviors, and infection cases	Monitored signal of social distancing on Twitter consistent with mobility data and actual confirmed cases.
(Y. Jiang et al., 2021)	Twitter and Google Mobility Report	identified similarities between geotagged tweet data and cell phone-bound human mobility.
(Cuomo et al., 2021)	Twitter and infection cases	Observed association between the number of tweets, symptoms, concerns of COVID-19 expressed in tweets and officially reported COVID-19 infection cases
(Zeng et al., 2021)	Twitter and infection cases	Found significant relationship between twitter-based mobility data and state-level daily COVID-19 cases within seven days lag
(Kumar et al., 2021)	Twitter, infection cases, and death cases	Showed positive effects of Twitter with infected and death cases of COVID-19
(Klein et al., 2021)	Twitter, NLP, infection cases	Identified potential cases of COVID-19 from tweets with US state-level geolocations
(X. Huang et al., 2020)	Twitter and COVID-19 mitigation measures	Observed Twitter-extracted human mobility changes consistent with COVID-19 related policy measures.
(J. Kwon et al., 2020)	Twitter and social distancing	Discourse on social distancing extracted from Twitter is congruent with actual practice and may help detect potential hotspots of a pandemic.
(Cuomo et al., 2020)	Twitter and infection cases	Found statistically significant relationship between the increasing number of tweets and surge of infection cases
(Younis et al., 2020)	Twitter and social distancing	Along with datasets from Google and Instagram, the study found a significant correlation between Twitter-based data and social distancing practices.
(O'Leary & Storey, 2020)	Twitter and infection cases	found consistency between the content of tweets and infection cases during the COVID-19 pandemic

(Massaad & Cherfan, 2020)	Twitter and infection cases	Found significant associations between the geotagged distribution of tweets related to telehealth and the number of confirmed cases across the US.
(Cuomo et al., 2021)	Twitter and infection cases	Showed significant associations between the number of tweets symptoms, concerns expressed in tweets, and county-level infection cases.
(Solnick et al., 2021)	Twitter and pandemic behaviors	Results showed that the contents of tweets posted by physicians effectively enhance adherence to recommended behaviors during the COVID-19 pandemic.
(Guo et al., 2020)	Twitter and pandemic behaviors	The study found that public tweets revealed COVID-19 symptoms earlier than the CDC.
(M. Zolbanin et al., 2021)	Twitter and pandemic behaviors	The study reported that twitter-based data found a list of symptoms earlier than most states and CDC announced.
(Barnes, 2021)	Twitter and infection cases	The temporal focus of tweets can examine adherence to behaviors and infection cases of COVID-19.
(P. Xu et al., 2020)	Twitter and pandemic behaviors	Found the reflection of social distancing practices on geotagged tweets.

Appendix C

Selected Linguistic Studies

Source	**Context**	**Outcomes**
(Al-Subhi, 2022)	Metadiscourse, writer-reader interaction, persuasion	Metadiscourse an effective technique of persuasive language and enticing customers into buying products.

(M. Lee & You, 2021)	COVID-19, text messages, mobile phone, alert, survey	SMS alerts increase practicing preventive measures such as social distancing, social gatherings, visiting websites, and wearing masks.
(S. Yang et al., 2021)	ELM, linguistic style	Linguistic cues enhance review helpfulness
(Huerta et al., 2021)	COVID-19, Twitter, Massachusetts State of Emergency	After the declaration, Twitter observed heightened risk perceptions, anxiety, and decreased polarity.
(Depraetere et al., 2021)	Twitter, complaints, linguistic (in) directness, (im)politeness	Use of linguistics in lodging customer complaints and its ensuing interactions in the context of tweets
(Q. Deng et al., 2021)	Brand engagement, brand linguistics, social media, B2B marketing	Found a significant relationship between linguistic features and brand engagement. Linguistic features that facilitate central or peripheral route processing positively impact brand engagement.
(Cox et al., 2021)	Text messages, mobile phone, depression	Text messaging reduces depressive symptoms.
(L. Chen et al., 2020)	Signaling theory, linguistic style matching	Linguistic signals – sentiment, readability, post length, and style matching are positively associated with informational support in online health communities.
(S. Wang & Chen, 2020)	Upper echelon theory, CEO personality, social media, social desirability bias, Twitter, Facebook	Linguistic cues CEOs leave on social media influence both operational and financial performance.
(Jospe et al., 2020)	Empathic accuracy, mentalizing, experience sharing	"empathic accuracy" (a proxy for mentalizing emotions) is more significant when linguistic information is present.

(X. Liu, Jiang, et al., 2020)	Social support, OHC, homophily, LIWC, four levels of linguistics	Linguistic cues increase the reciprocity of information on OHC. Homophily exists. Polarized sentiment and optimistic users are highly influential.
(Abbasi et al., 2019)	Signal detection, healthcare	Twitter data has signals and noises because of salience, contextualization, and credibility. Twitter detects capabilities in health settings. The inclusion of negative reduces FP. UGC detects adverse events early.
(Zimbra et al., 2018)	NLP, Twitter, computing methodologies	Examined 28 top tweet sentiment tools.
(Abbasi et al., 2018)	Design science, NLP, LAP, coherence analysis, Twitter	Linguistic cues are associated with sense-making in online discourse
(Coesemans & De Cock, 2017)	Metapragmatic awareness, self-referencing, Twitter	Self-referencing is prominent in politicians' discourse on Twitter. Followed conciseness strategy. Twitter is both professional political communication and personal branding. Make it searchable and followable. Used for image and community building.
(Siering et al., 2016)	Convergence of communication, psychology, and computational linguistics, fraud detections	Linguistic cues (affect, emotions, sentiments etc.) are valuable for fraud detection in crowdfunding platforms.
(Rajadesingan et al., 2015)	Twitter, sarcasm detection, linguistic cues	Linguistic cues on tweets are used to identify sarcasm.

(Sah & Peng, 2015)	Anthropomorphic cues, self-awareness, health website	Linguistic cues – conversational and impersonal language – increase self-awareness, social perception, and information disclosure.
(Ludwig et al., 2014)	Linguistic style match (LSM), user communities, participation behaviors	The study found, using communication accommodation theory, that linguistic style signals community identification and affects participation quantity and quality.
(Purohit et al., 2013)	Crisis response, coordinated behaviors, Twitter	Linguistic cues – conversational properties – provide actionable emergency response in disaster communication on Twitter.
(Kaptein et al., 2012)	SMS, persuasive technology	Text messaging reduces snacking.
(Qiu et al., 2012)	Twitter, linguistic analysis, Twitter	Linguistic cues in tweets manifest personality.
(Humpherys et al., 2011)	Financial fraud, SAS 99, information manipulation theory, obfuscation hypothesis	Linguistic cues represent the financial statements' credibility and influence the disclosure range.
(Polzehl et al., 2011)	Emotional salience, NLP, anger classification, self-reference,	Linguistic cues were used for anger classification.
(Fausey & Boroditsky, 2010)	Linguistic framing, “wardrobe malfunction"	Linguistic framing can change how people construe what happened, attribute blame, and dole out punishment.
(Fuller et al., 2009)	Credibility, deception, linguistics	Linguistic-based cues assess the credibility and detect deception.
(Zhou & Zhang, 2008)	Deception detection, linguistic cues.	Automatic deception detection using linguistic cues.
(Walker et al., 2007)	Big five, personality	Using linguistic cues for recognizing personality in conversation and text

(Zhou et al., 2004)	Deception detection, linguistic cues, NLP	Used nine linguistic constructs to detect deception.
(Hyland, 2002)	Self-reference, identity, academic writing, interactions	Writers gain credibility by projecting individual authority, displaying confidence in their evaluations, and commitment to their ideas.
(Fuertes-Olivera et al., 2001)	Metadiscourse, Pragmatics, advertising	Metadiscourse is helpful for persuasive writing. They were used in advertising.

Appendix D

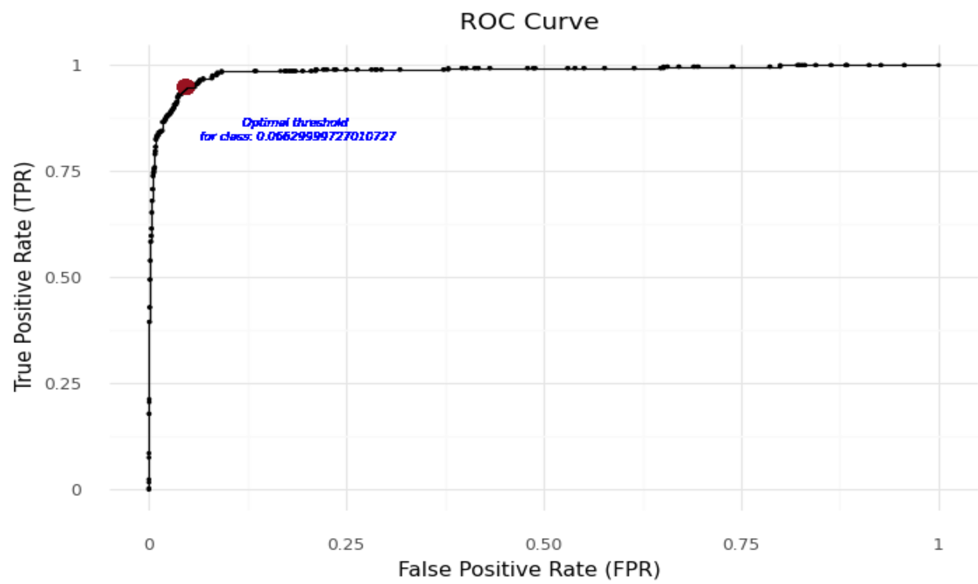
The following table demarcates the four stages of crisis in the context of COVID19 pandemic.

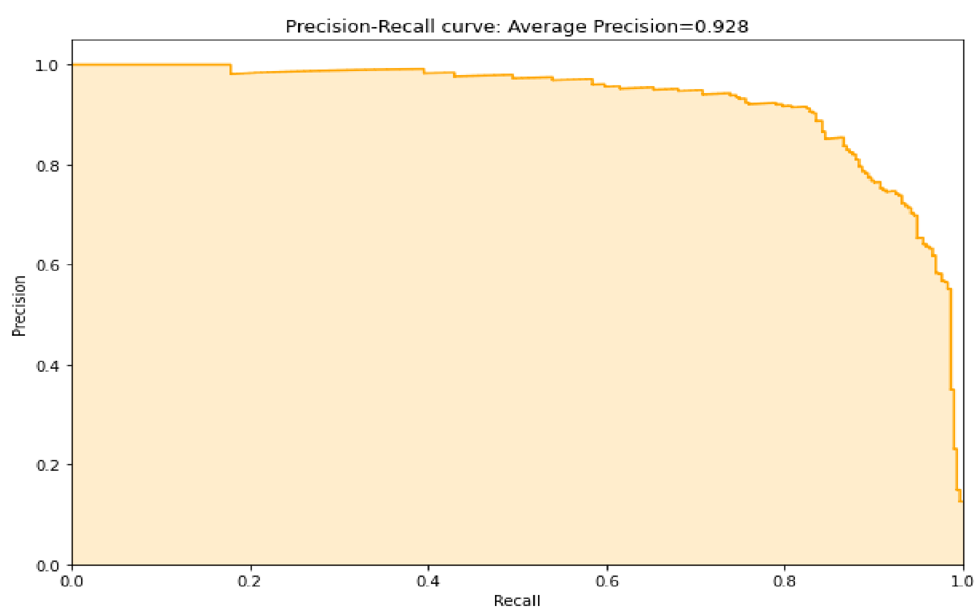
Stages of Crisis	**COVID-19 Timeline**	**Length of stages**
Build Up or Prodromal Crisis stage	• Jan 20 – CDC begin screening 3 airports. • Jan 21 – 1st confirmed case in US • Feb 3 – Public health emergency declares • Feb 25 – CDC hints COVID-19 as pandemic • Mar 13 – US Gov. declares emergency • Mar 13 – Travel bans from Europe • Mar 17 – 100 deaths in US • Mar 19 – 1st Stay-at-home order in US • Mar 25 – Mass shutdown may curb the spread • Apr 28 – People avoid seeing doctors for fever (Gallup poll). • May 12 – death tolls reach 80000 • May 28 – CDC reports “horrible toll of this unprecedented pandemic”	March – May, 2020

Breakout or Acute Crisis stage	• Jun 10 – Total COVID-19 cases rise to 2 million. • Jun 22 – STM found that undetected infections might amount to 8.7 million. • Jun 30 – CDC warns daily cases could rise as high as 100000 in US. • Jul 9 – WHO confirmed airborne transmission. • Jul 14 – US report the highest health insurance coverage losses. • Jul 20 – COVID-19 increases cancer-related deaths. • Aug 11 – Hope of vaccine increases but still needs further trials. • Aug 28 – 1st case of reinfection.	June – August, 2020
Abatement or Chronic Crisis stage	• Sept 1 – Steroids found effective for serious patients • Sept 14 – Pfizer, BioNTech went to phase 3 trials. • Sept 23 – New strain of COVID-19 confirmed in US • Oct 22 – FDA approves as first COVID-19 drugs. • Nov 17 - CDC highlights long term effects of COVID-19. • Dec 10 – FDA recommends vaccine.	August – December, 2020
Termination stage	Vaccines are being produced and distributed at large scale. People trust on the efficacy of vaccine.	January – May, 2021

Appendix E

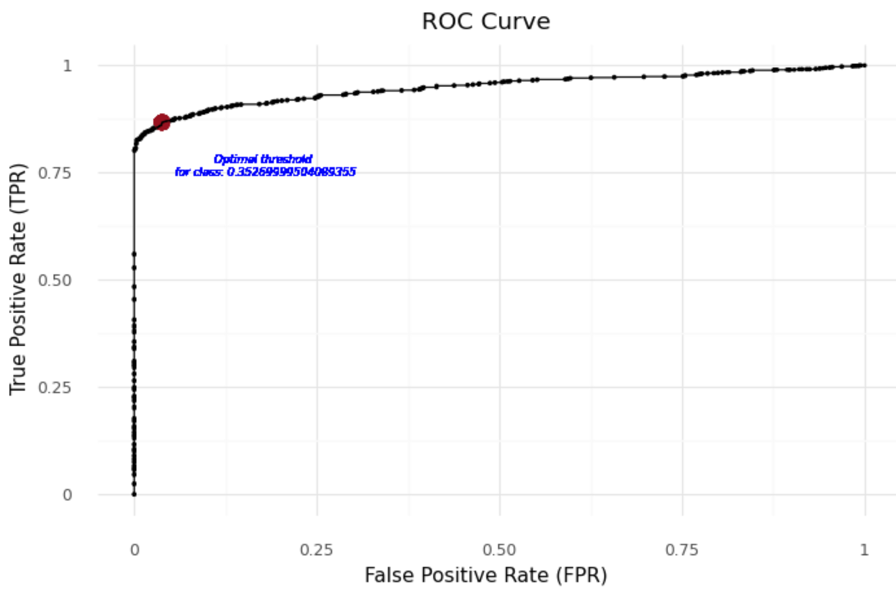
Evaluation of Twitter Profile Classification

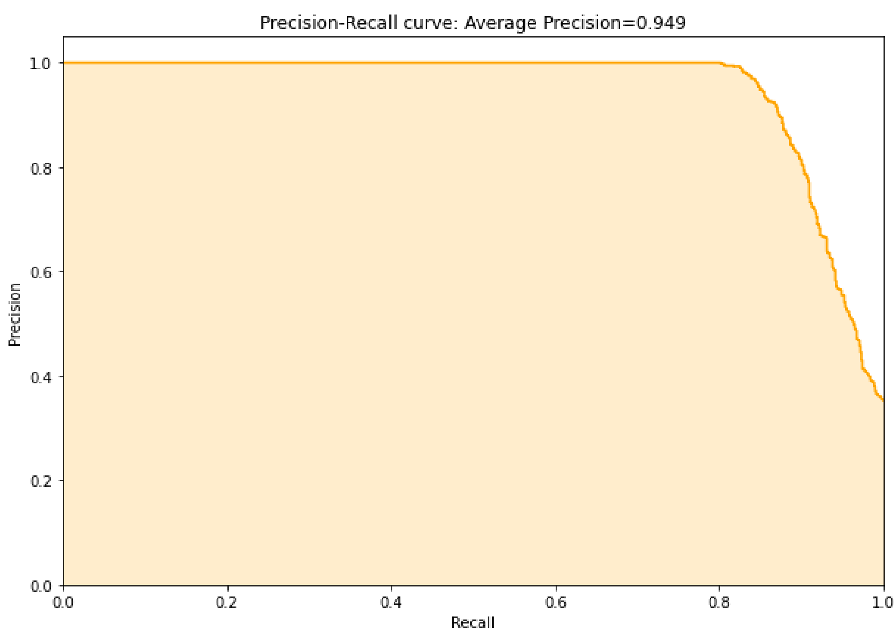




Appendix F

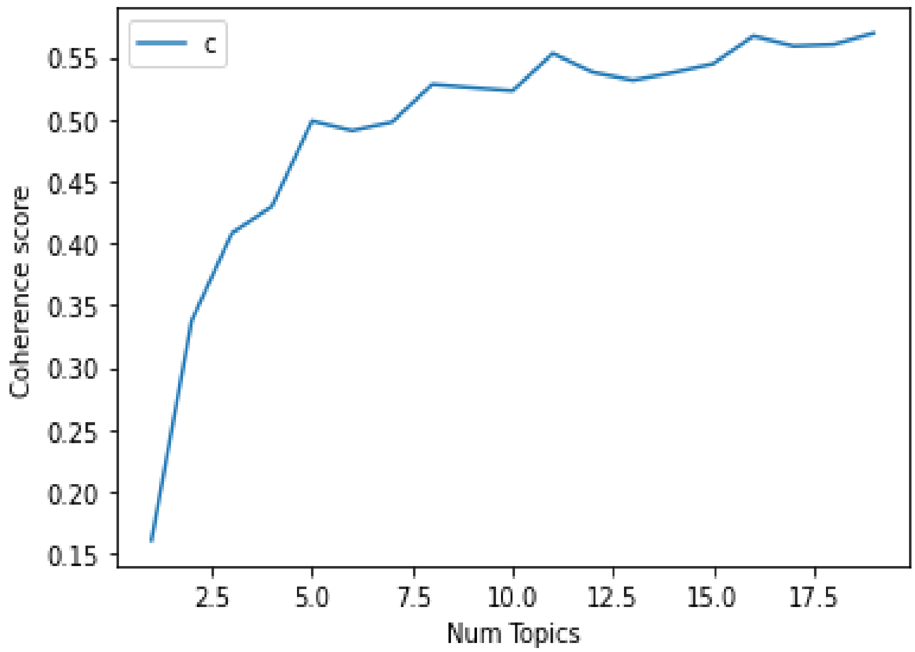
Evaluation of COVID-19 Tweet Classification





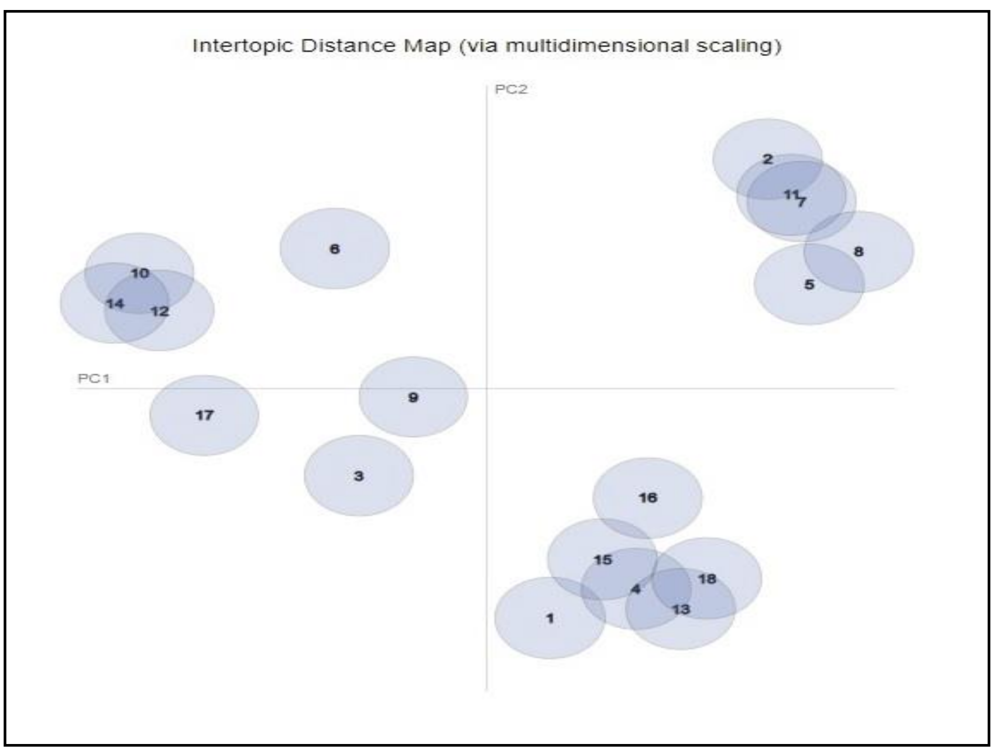
Appendix G

Coherence Score



Appendix H

Stage 1 Buildup: Intertopic Distance Map



Stage 1: Top 20 Keywords for each topic

Keywords	Topic Num	Cluster of Topics
business small relief impact provide support fund program assistance funding unemployment receive benefit economic apply affect include package employee grant	1	Hospitalization and Recommended Behaviors
due school food access bill child student close pass pay family learn service include emergency legislation extend kid provide house	4	
health public continue protect safety follow step reopen ensure work plan important service department guidance remain guideline official expert measure	13	
spread stay home safe order stop part prevent hand slow wash healthy sick virus reduce save_live limit practice avoid remember	15	
mask wear face require place make leave employee restaurant shelter park face_covering cover essential customer remember store weekend walk maintain	16	
worker care fight hospital medical patient essential health healthcare frontline supply facility critical work professional nurse provider system service donate	18	
good time thing pandemic put people lot folk line deal real mental bad long point big feel run wait hope	2	Political Leadership and Economic Challenges
community pandemic crisis country address leadership lead national vulnerable impact act policy colleague future focus economic woman opportunity demand challenge	5	
make give work pandemic back vaccine economy year great change end move month treatment decision start base develop money return	7	
work day family pandemic time life lose job hard great community friend member nation neighbor proud serve hit honor difficult	8	
pandemic trump vote global president american world election administration mail country lie million force cut republican power handle midst fail	11	

state response local covid effort emergency federal government support governor respond outbreak action provide leader prepare combat official meet team	3	
today join live question pm watch discuss hold talk tomorrow answer tune hear update tonight meeting morning host listen briefing	9	
people virus covid risk show die high person video disease infect understand infection top kill population low day flu control	6	Fear
case covid county death positive number report confirm today total resident bring yesterday datum increase announce recover statewide day additional	10	Infection and testing updates
covid testing test call open free site center resident symptom expand begin offer start week announce contact drive appointment capacity	12	
covid city week read issue outbreak today call full send office senior concern district staff reach mayor letter message member	14	

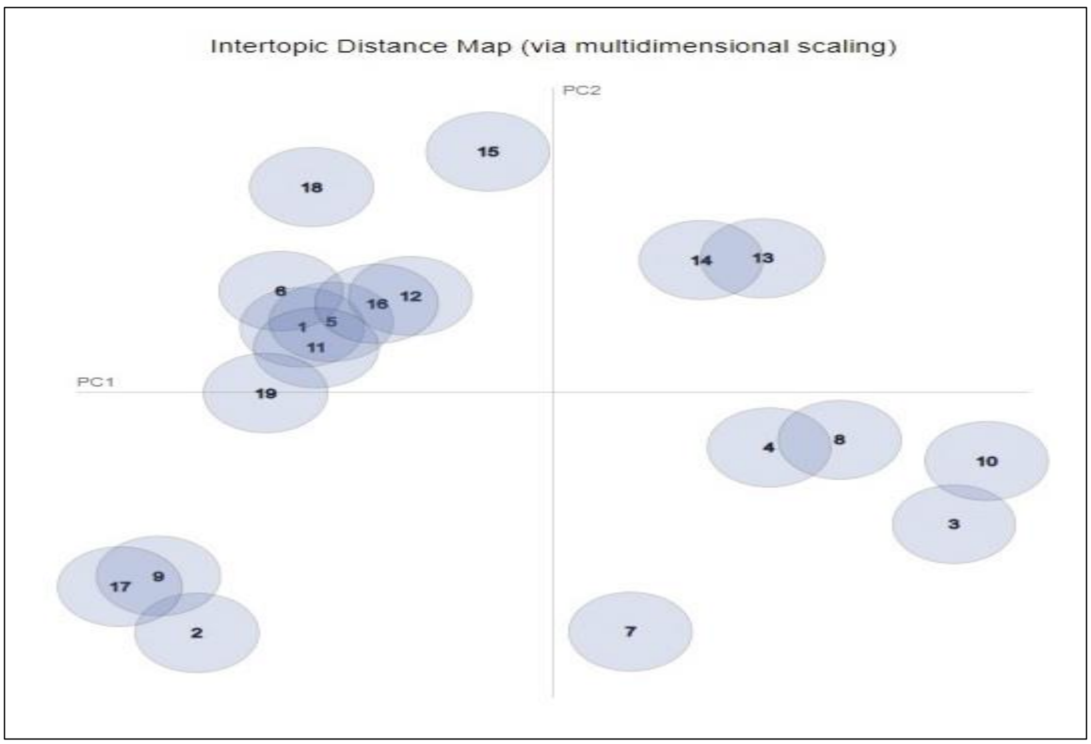
Stage 2 Breakout: Intertopic Distance Map

Stage 2: Top 20 Keywords for each topic

Keywords	Topic Num	Cluster of Topics
pandemic family due pass lose bill job pay food million struggle extend federal end act unemployment legislation rent relief house	1	Economy and public resilience
community work continue worker fight support protect hard pandemic effort service ensure essential critical proud resource serve economy leader respond	9	
health pandemic care crisis public access address global system healthcare economic expand middle administration nation act challenge facility future ensure	15	
today join update live pm response watch discuss late hear talk question hold tomorrow event covid tune morning meeting answer	2	Crisis information and Leadership
mask wear protect public face hand require wash social_distance face_covering distance cover refuse part mandate maintain space face_covere remember simple	3	
state issue order follow safety city governor public begin local government include response official policy move place sign law mandate	4	
covid people day die week month top happen death pinned_tweet open hour understand hospital kill thousand watch_video infect head close	5	
covid show datum read people full outbreak concern share release story large big week set deal population early reach add	7	
test covid testing call free visit resident find information site county result center symptom info city area week offer appointment	6	Crisis outcomes
case death report covid number positive day county total increase today bring rate patient yesterday high confirm update statewide record	10	
spread virus covid stop vaccine prevent slow action economy medical expert national science control part reduce lead effective clear treatment	8	Crisis resolution
make pandemic vote election time change office give person post mail run wait long campaign voter line republican reason party	11	

school back child plan risk reopen year student put make start kid staff safely fall return education teacher district send	12	Politics and education
trump life country people american leadership black president bad fail real world protest woman fact matter police lead dead political	14	
business provide program small impact support relief fund learn apply assistance funding grant receive recovery local open emergency employee announce	13	Relief fund
safe time stay home good great continue work friend thing family healthy hope folk feel neighbor sick love age remember	16	Caution

Stage 3 Abatement: Intertopic Distance Map

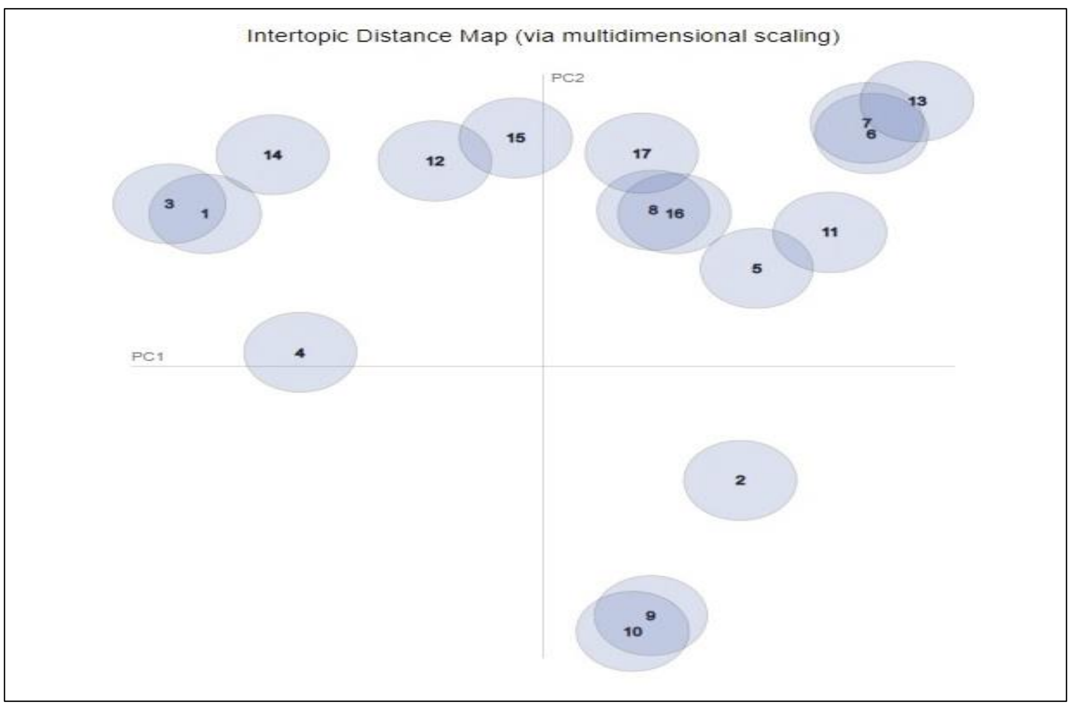


Stage 3: Top 20 Keywords for each topic

Keywords	Topic Num	Cluster of Topics
relief pass bill family include american package provide federal deal house republican struggle government aid unemployment legislation bipartisan colleague wait	1	Crisis information and Leadership
business support small local provide due impact program fund assistance restaurant apply grant food learn announce housing employee resource federal	11	
people thing good give feel party matter reason point big man folk black debate win turn refuse problem catch wrong	12	
vaccine plan end receive hope news begin distribution effective flu week distribute dose ready develop start process pfizer prepare vaccination	16	
make time year family friend good pandemic give pay leave neighbor woman decision love money spend put lot line happy	19	
trump president bad lie science country fail fact deadly leadership campaign american dead put political biden administration virus rally dangerous	5	
spread virus stop continue safe follow part protect important slow prevent holiday action safety step reduce guideline encourage travel measure	6	
covid hospital risk show day week county patient datum high state low level infection area surge nurse reach capacity treat	10	Crisis outcomes and education
covid state call read governor official hear send concern full rule release hearing restriction law break message change policy regard	3	
covid school child student close staff learn start open kid back due person team district member teacher education include reopen	4	
covid people die month life lose long death hour kill head thousand million world flu_season save understand infect top tweet	8	
case death day report positive today number update increase total covid rate high yesterday record confirm daily rise county statewide	13	Case updates and testing
test testing free visit find resident site information covid today pm symptom info week offer center result flu_shot county expose	14	

today vote join live watch election update late discuss talk early question pm hold event morning tonight voting person tomorrow	15	
work community worker pandemic fight continue hard effort essential country proud ensure protect frontline stand serve healthcare honor put support	17	
pandemic great economy job economic work crisis back recovery nation create strong experience opportunity bring impact hit future recover build	2	Healthcare and economy
health pandemic care public access important system global resource service middle crisis ensure protection critical healthcare protect act mental facility	9	
mask wear stay home hand safe wash mandate distance sick social_distance remember avoid gathering household healthy indoor protect weekend maintain	18	Recommended Behaviors
covid pandemic state face city response issue order challenge address change office national run remain effect lead leader government place	7	Authority

Stage 4 Termination: Intertopic Distance Map



Stage 4: Top 20 Keywords for each topic

Keywords	Topic Num	Cluster of Topics
covid join today live watch update question discuss late hear response hold talk read share pm answer happen meeting tonight	1	Crisis updates
covid spread virus die stop risk people show prevent science kill fact variant thousand world infection understand reduce high deadly	14	
covid case today death report day update test number total positive rate yesterday week additional datum confirm low result increase	3	
vaccine receive dose county week vaccinate administer resident vaccination shoot shot encourage adult pfizer veteran population volunteer effective announce today	10	Crisis resolution
vaccine appointment call eligible sign start information visit find age schedule register begin resident check individual group phase info link	9	
health community public access ensure expand continue important issue system leader local resource effort safety service department address black critical	11	Politics and recommended behavior
people make give time thing change long wait lot bad big put folk problem force point reason election decision real	16	
year day life lose family end month time friend hope honor remember love feel neighbor ago happy celebrate past member	17	
mask wear continue safe vaccinated stay follow home fully mandate hand protect order restriction guidance wash place guideline require good	5	
trump biden stand country lie policy action president fail leave rise speak bad law party wrong political border surge violence	8	
relief covid bill pass vote american package deliver act legislation include republican colleague house money spend fund push bipartisan support	12	Relief fund and education
school covid good back child time great student learn teacher kid person pandemic staff make reopen education return high safely	15	
work pandemic worker care fight hard woman proud essential healthcare family protect hospital serve frontline medical safe member make deserve	13	

pandemic provide business support program impact due local small_businesse family struggle funding assistance food learn small apply fund restaurant emergency	6	Hospital and economy
pandemic job economy crisis economic recovery face nation country recover lead create challenge opportunity post back work leadership strong global	7	
state vaccine distribution plan supply continue increase federal administration effort government rollout distribute governor move remain process progress quickly arm	2	Distribution channel
vaccination site covid open clinic city free testing today pm offer center run resident visit walk drive area office hour	4	Testing

Appendix I

Summary Statistics of Variables

	ConfirmedCases	Analytic	Clout	Authentic	Tone	Past Focus	Present Focus	FutureFocus
Obs.	3150	3150	3150	3150	3150	3150	3150	3150
Mean	0.30	73.00	59.91	39.89	44.56	2.32	4.65	1.39
SD	2.09	6.09	6.44	6.50	7.32	0.64	0.70	0.45
Min	-2.07	41.12	22.67	2.22	10.62	0	0	0
25%	-0.15	69.49	56.50	36.28	40.19	1.92	4.28	1.15
50%	0.01	73.45	60.24	39.68	44.13	2.26	4.65	1.35
75%	0.23	76.77	63.75	43.06	48.45	2.65	5.04	1.59
Max	53.00	99.00	85.02	91.86	99.00	6.71	9.71	7.29

Appendix J

Correlation and Variance Inflation Factor (VIF)

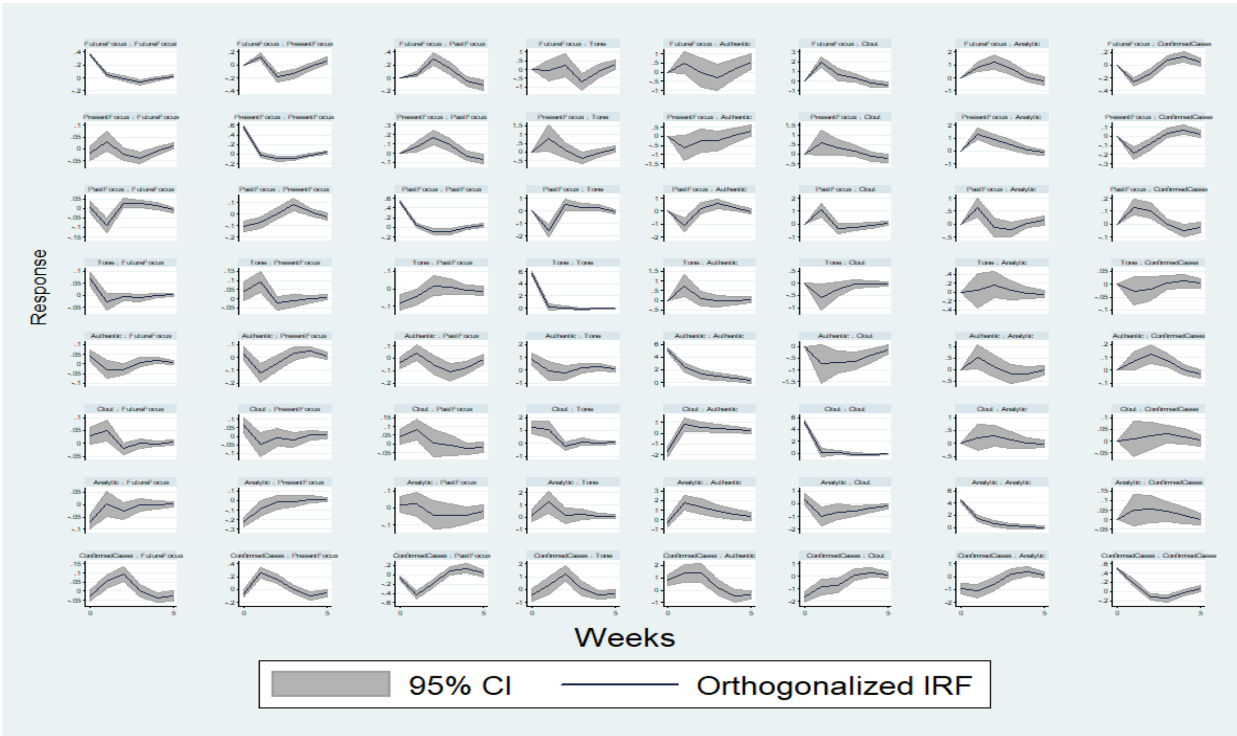
	Confirmed Cases	Analytic	Clout	Authentic	Tone	Past Focus	Present Focus	Future Focus
Analytic	0.0433							
Clout	0.0654	0.0782						
Authentic	0.0021	-0.0563	-0.2532					
Tone	0.0047	0.1614	0.2715	0.0161				
PastFocus	-0.0936	-0.2509	-0.1520	0.0149	-0.1033			
PresentFocus	0.0118	-0.3589	0.0074	0.0086	-0.0987	-0.1067		
FutureFocus	0.0259	-0.0865	0.0246	0.0494	0.0561	-0.1129	-0.0164	
VIF		1.32	1.22	1.18	1.17	1.12	1.08	1.04
Mean VIF	1.16							

Appendix K

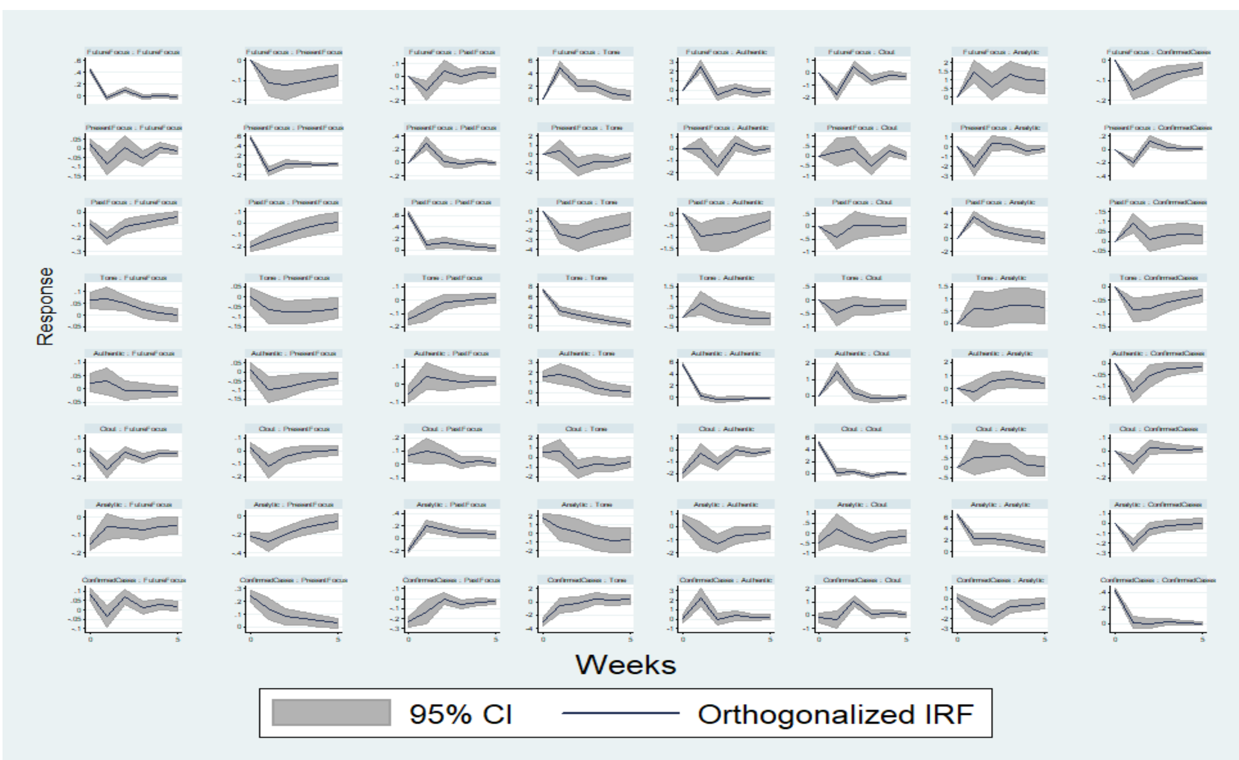
Impulse Response Functions (IRF) for Four Crisis Stages

Buildup Stage

Breakout Stage



Abatement Stage



Termination Stage

Appendix L

Top 10 well-connected political leaders in the network

User id	No. of Degrees	Degree centrality	Screen_name
15764644	7164	0.46796	SpeakerPelosi
9.7E+08	6663	0.435234	SenWarren
17494010	5783	0.377752	SenSchumer
14377605	5626	0.367496	TheDemocrats
15808765	5424	0.354301	CoryBooker
29501253	4870	0.318114	RepAdamSchiff
43963249	4770	0.311581	HouseDemocrats
72198806	4474	0.292246	SenGillibrand
2.26E+08	4375	0.28578	PeteButtigieg
15745368	3896	0.254491	marcorubio

2.0 Study-2

Improving Diabetes Self-Care Management among Medically Underserved Populations through the Use of Mobile Technology

2.1 Introduction

Chronic diseases are common health threats that incur enormous healthcare costs and lead to high mortality. According to WHO, over 41 million people globally die from chronic diseases, accounting for 71% of total deaths. In addition, people with chronic diseases tend to have higher unplanned hospital readmissions and more emergency visits (Ben-Assull & Padman, 2020) (Alluhaidan et al., 2015). Prior studies showed that self-management is the key to chronic disease management (Savoli et al., 2020). It entails a set of planned behaviors that help patients avoid unexpected consequences and slow the progression of chronic diseases. In chronic disease management, technologies (e.g., wearables, mobile apps, and under-skin sensors) enhance patients' capabilities and improve health outcomes (J. Jiang & Cameron, 2020). Liu et al. (2020) found that patients use social media services like YouTube, a popular content-sharing platform, to get vital medical information to manage their diseases. In another study, Liu et al. (2020) showed that physicians and patients collaborate in online communities to improve self-management of chronic diseases and, thus, well-being of patients. Finally, adopting electronic health records (EHR) also helps to detect risk factors and future adverse health events, thus reducing the burden of health complications (Lin et al., 2017). Information technology (IT) augments patient empowerment and self-efficacy (Brohman et al., 2020) (Thompson et al., 2020) (Son et al., 2020). Therefore, IT offers promising patient benefits in understanding and explaining the symptoms, medications, management, and results of chronic diseases. Recent studies also confirm that IT-enabled self-management (ITSM) allows patients to own the steering of chronic disease management, achieve goals, and control disease outcomes (Jiang & Cameron, 2020; Savoli et al., 2020).

Diabetes, a highly prevalent chronic disease, poses a significant health threat worldwide. Statistics show that more than 34 million individuals have diabetes in the United States alone, one in three American adults is at an increased risk of developing it[7], and the economy incurs a staggering cost of $327 billion for it annually (Yang et al., 2018). A meta-analysis of 53 randomized controlled trials found that self-management interventions help reduce hemoglobin A1c (which measures average blood sugar level over a three-month period), a much sought-after clinical outcome for diabetic patients (Chodosh et al., 2005) Extant literature also suggests that lack of diabetes self-management leads to various physical health complications such as kidney failure, limb amputation, blindness, myocardial infraction, and stroke. Furthermore, diabetes increases mental depression and leads to poor quality of life (Gonzales et. al., 2007)

The emergence of mHealth technology has promised tremendous benefits to patients with the self-management of chronic diseases (e.g., diabetes) for over two decades. mHealth is a customized and dynamic service enabling users to access medical information anytime and anywhere (Akter & Ray, 2010). mHealth, as a ubiquitous facility, influences diabetes self-management (El-Gayar et al., 2013). Further studies found that mHealth can help educate, empower, and increase patients' self-efficacy (Brohman et al., 2020; Brandell & Ford, 2013; King et al., 2010; Katz and Nordwall, 2008). Patients can access real-time data on their physical conditions (e.g., blood glucose level,

[7] https://bit.ly/3VPsGMW

blood pressure, or heart rate) using innovative mHealth technologies and make various behavioral and medical decisions based on the data. In a recent study, Ghose et al. (2022) reported empirical evidence of how mHealth contributed to changing the modalities of diabetes self-management.

Knowing the proper way to manage diabetes is vital, and mHealth technology as a platform can enrich patients with diabetes management (Brandell & Ford, 2013). The use of mHealth apps and the dyad communications between patients and healthcare professionals through mobile technology can lead to positive diabetes self-care outcomes and reduce the need for healthcare personnel, which in turn can lessen healthcare costs (Baron et al., 2012). Several studies found that utilizing mHealth records results in improved glycosylated hemoglobin levels and higher self-efficacy in diabetes management, which is strongly associated with self-care behaviors. Thus, the enormous benefits of mHealth in diabetes management are the critical motivation of our study. Secondly, despite having numerous mobile apps, only 13% of them could be helpful in diabetes self-management (Brzan et al., 2016). More importantly, mobile apps for diabetes are prone to fail due to not being designed for either Type 1 or Type 2 with specifications (Preuveneers & Berbers, 2008; Holtz et al., 2017). Besides, El-Gayar et al. (2013) emphasized user-centered design to reflect the needs and characteristics of the patients in designing an effective mHealth app.

Thirdly, Access to healthcare services for medically underserved populations (MUPs), often from marginalized and minority populations, has been a long-standing challenge in the U.S. MUPs are specific sub-groups of people living in a defined geographic area with limited access to primary care providers, infant mortality more than usual, people living under the poverty line and more elderly populations. (Health Resources and Services Administration, 2020)[8] and face economic, cultural, and linguistic barriers to healthcare. MUPs are more vulnerable to diabetes consequences than others (Reyes et al., 2017; Spencer et al., 2011) (Heitkemper et al., 2017). According to American Diabetes Association (ADA), near-poor and poor populations have increased by 74%-100% between 2011 and 2014 in diabetes prevalence compared to high-income people[9]. In addition, the risk of diabetes is 60% higher among African Americans and 59% higher among Hispanic Americans than non-Hispanic white Americans (U.S. Department of Health & Human Services, 2020)[10]. Given the limited health and digital literacy, MUPs struggle to comprehend and interpret various health indicators of diabetes self-management. ADCES (American Diabetes Care & Education Specialists) and ADA (American Diabetes Association) formed a task force to address language issues in diabetes care (Dickinson et al., 2017).

Prior studies on the design and development of mHealth apps catering to the needs and characteristics of MUPs are scanty. This critical yet relatively unexplored phenomenon motivated us to examine the use of mHealth in diabetes self-management among MUPs and to ascertain whether mHealth delivers similar benefits and challenges to them, given their socio-economic status, education, and lifestyles. To achieve this end, we build and evaluate an appropriately designed mHealth app with monitoring and feedback systems to improve diabetes self-management among MUPs. Our design is based on design principles supported by dominant literature and relevant theories. Thus, we frame the following research question -

[8] https://bit.ly/3YeoNTn
[9] https://bit.ly/3iKqfMS
[10] https://bit.ly/3BpITQA

RQ: How can we design an effective mHealth app for diabetes self-management of medically underserved populations (MUPs)?

To answer our research question, we developed a prototype of the mHealth app through an iterative process following the design science approach. Our study makes significant contributions to theory and practice. First**,** using available technologies (e.g., mHealth) to improve diabetes self-management would lessen the burden on healthcare systems and thus lower healthcare costs. Second, our design articulates design principles guided by theory and domain knowledge. These principles would provide directions in designing prototypes to influence health behaviors for MUPs. Third, our mHealth app has incorporated ADCES-7 diabetes self-care behaviors. It would validate the efficacy of those behaviors with mobile technology for MUPs. ***Finally,*** our study will contribute to reducing health disparities by allowing MUPs to self-manage type-2 diabetes and maintain healthy lifestyles.

The structure of the remaining paper is as follows: we briefly discuss the background of the study. Then we draw on relevant literature to position our study. The following section presents the design science research methodology. Then we introduce design principles and demonstrate samples of the prototype. We then describe an outline for the field experiment, statistical analysis, and expected findings. Finally, we conclude with future directions.

2.2 Research Background

A disease that lasts more than three months and is not curable by medication is considered a chronic disease (Rijken & Dekker, 1998). While chronic disease is a biomedical condition that “implies an expected long duration and lack of cure”, chronic illness is “the personal experience of living with the affliction that often accompanies chronic disease” (Martin, 2007). The disease is “malfunctioning or maladaptation of biologic and psychophysiological process in the individuals; whereas illness “represents personal, interpersonal and cultural reactions to disease or discomfort” (Kleinman et al., 1978). Termed an “invisible epidemic” by WHO, chronic diseases limit individual daily walks of life and impact families and communities[11]. It causes at least seven out of ten deaths, accounts for 86% of healthcare costs in the US (Kvedar et al., 2016), and creates long-lasting health disturbances. The alignment between the disease-oriented view by physicians and the illness-oriented view by patients – nature and cause of the problem – is of great importance in developing a shared treatment model and therapeutic outcomes (Kleinman et al., 1978).

Chronic disease management is an umbrella term that includes various preventive efforts from clinical and home-based interventions materialized individually and collectively to control risk factors. The major chronic disease risk factors include being overweight, lack of exercise, drinking, smoking, and binge eating. Prior studies extensively highlighted the home-based intervention - self-management – to manage chronic disease (Coleman et al., 2009) (K. R. Lorig et al., 1999).

To minimize complications and control exorbitant healthcare costs, chronic diseases like diabetes need comprehensive and continuous management programs different from acute conditions. Among numerous approaches, patient-centric self-management is considered the most effective approach (Brohman et al., 2020) (Ghose et al., 2022). Patient-centric self-management benefits from a proactive instead of a reactive approach. It allows patients to control the disease and supports healthcare providers in delivering efficient chronic care. In a recent study, Thompson,

[11] https://bit.ly/3PmS0HB

Whitaker, Kohli, et al. (2020) studied chronic care deliveryand argued that patients' treatment could be planned early instead of later, termed 'Temporal Displacement of Care' to avoid complications. In chronic care delivery, if healthcare providers undertake preventive steps (e.g., early check-ups), they can treat chronically ill patients early and avoid serious complications . This arrangement will result in positive healthcare values measured by improved health outcomes and lowered costs.

2.3 Literature Review

2.3.1 Behavior and Health Behavior:

It is difficult to find any unanimous definition of behavior as it interests multiple disciplines. There are mainly two schools of thought – behaviorism and cognitivism (see Calhoun & El Hady, 2021 for details). Though exhaustively searching and defining behavior is not the scope of the study, we will provide some widely used definitions of behavior from both schools. Behavior is the response of an individual or group to stimulus except for any incremental changes (Levitis et al., 2009). Behavior is the movement of muscles. Physically, it depends on the motor cortex and neurons of the brain. Stimulating the neurons to initiate the behavior or behavior change is vital. Merriam-Webster Dictionary defines behavior as "the response of an individual, group, or species to its environment." Behavior is a response to controlled stimuli that can be objectively observed or measured (American Psychological Association). Behavioral psychologists regard behavior as the only objective phenomenon, while cognitive psychologists believe that internal aspects connect and interact with behavior. Some behaviors are easy to change and thus need little effort, whereas some behaviors are hard to change and require well-thought behavioral interventions. Each intervention points out certain target behaviors, which may have sub-behaviors. For example, exercise is a target behavior, which is a general type. The sub-behaviors related to exercise may include admission to the gym, timing of exercise, types of exercise, etc. Therefore, we must cautiously map out target behaviors and sub-behaviors while optimizing effective behavioral interventions.

Health behaviors are the key to quality of life. The term health behaviors refers to a person's personal attributes, including beliefs, expectations, motives, values, perceptions, and other cognitive elements; their personality traits, including emotional and affective states; and their behavior patterns, actions, and habits that contribute to maintaining, restoring, and improving their health (Gochman, 1997). Parkerson et al. (1993) included social changes, policy development, actions of individuals, groups, and organizations, coping skills, and improved quality of life in health behavior definition. It is also important to discuss illness behavior to comprehend health behaviors.

Illness behavior encompasses how people monitor their bodies, define and interpret symptoms, take corrective action, and utilize a variety of sources of help, including the formal healthcare system (Mechanic, 1986). In other words, it is how people respond to the condition under which they feel abnormal. It is broadly categorized into self-care behavior and healthcare utilization behavior. Kasl & Cobb, (1966) delineated three health-related behaviors - illness behavior (behaviors aimed at identifying the cause and treatment for perceived symptoms), health behavior (behaviors aimed at preventing disease or designed to detect it at an asymptomatic stage), and sick-role behavior (behaviors associated with the treatment of defined diseases to restore health). Illness Behavioral Model (IBM) posits that somatic or visceral signals (symptoms), cognitive appraisals, phenomenologic experience, and ethnocultural influences define coping responses (i.e., self-care and help-seeking) (McHugh & Vallis, 1986). Cultural dimensions, socio-economic status, emotional arousal, and environmental stress substantially influence the perception of illness behaviors (Mechanic, 1986).

What constitutes adopting and maintaining healthy behaviors is a growing area of interest. The fundamental challenge is to answer why people behave the way they do and how to motivate people to change their behavior. A widely used model - Heath Behavior Model (HBM) - posits that an individual tends to adopt targeted health behavior if the individual believes to be severely vulnerable and the outcome from the behavior outweighs perceived barriers. Social Cognitive Theory tells us that behavior change happens when individuals believe in self-efficacy (the ability to perform a behavior) and outcome expectancies (the incentive to do a behavior). The Theory of Reasoned Action postulates that an individual's attitude and social pressure result in intention, and intention, in turn, leads to behavior. Five factors influence the magnitude of intention - attitude, social pressure, self-image, emotion, and perceived self-efficacy. Finally, we can view that intention, skill, and lack of constraints are necessary to perform a behavior.

Fogg, (2002) introduced a persuasive design approach to surmount the challenges of behavior change. In designing persuasive technology (e.g., mobile app), *Fogg's Behavioral Model* (FBM) provides a framework that suggests that the convergence of three things – motivation, ability, and trigger – can alter focal behavior (Fogg, 2009). The following describes the use of design to influence diabetes self-care behaviors.

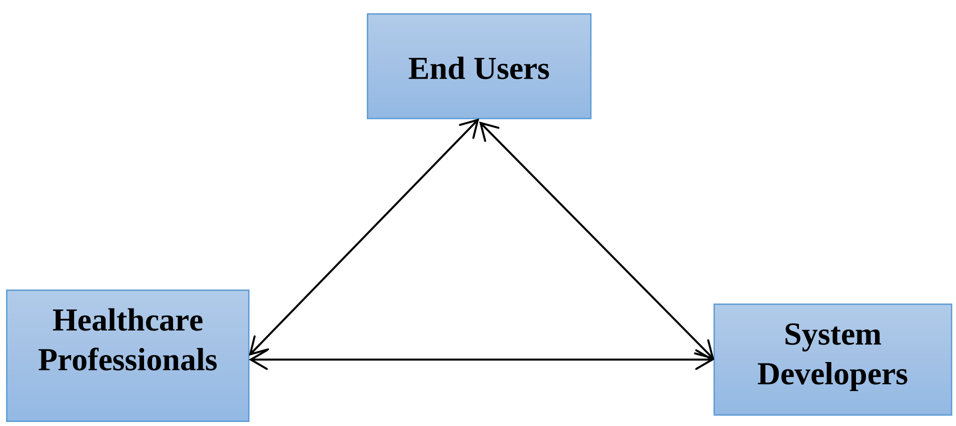
2.3.2 Design for Behavior change

Design for behavior change can play a critical role in the self-management of chronic diseases. An appropriate design provides a successful framework to help people change their behavior and maintain a physically active lifestyle (Consolvo et al., 2009). For example, the persuasive design incorporating gaming elements was found to stimulate patients with dementia and change their behavioral pattern (Visch et al., 2011). Proper design of robots persuaded people in the workplace to choose healthy meals. Mindful design influenced behavior change through patient empowerment (Niedderer et al., 2014). A good design delivers patient safety and care, whereas poor design erodes safety and causes detriment to patient care (Ulrich et al., 2008). Ludden et al., (2017) found a positive impact of design on minimizing the daily intake of sugar-based beverages. Design thinking has recently found increased interest in education, leadership, entrepreneurship, and healthcare (Knight et al., 2020) (Pande & Bharathi, 2020) (Beckman, 2020). It generates a stronger case in healthcare to innovate novel technologies and solve critical problems. The other important design aspect is the alignment between tasks and system features necessary for IT design success (e.g., task technology fit theory (Goodhue & Thompson, 1995). In the context of chronic care delivery, Aron & Pathak (2021) described a fully and partially connected system of interdependence. Though appropriate design can cause behavior change, Buchanan (1992) regarded the design problem as wicked, as it constantly evolves.

User-centered design (UCD) dominates over other approaches, such as technology-centered design (TCD). While UCD integrates information to match the users' goals, tasks, needs, and abilities, providing the lever of control to users, TCD promotes design-induced error by human adaptation to the design (Endsley, Mica & Jones, 2004). The salient objective of UCD is to deliver value to the users instead of sophisticated technology with exquisite programming (Norman & Draper, 1986). A systematic review of the use of design for older adults supported the positive outcomes from the adoption of UCD that considers the limitations and specific characteristics of the users for a product design (Duque et al., 2019).

In healthcare interventions, UCD is an iterative cycle among patients with diabetes, healthcare professionals, and system developers shown in Figure 2.1. A co-designed system, reflecting users' decisions and choices and those of healthcare providers, significantly improves diabetes self-management behavior (Fico et al., 2020). A study to design an efficient learning tool for children shows that graphic designers face more difficulties when users do not participate in the design process, suggesting the adoption of UCD methods (dos Santos & Tiradentes Souto, 2019). The use of UCD in designing mHealth systems has been helpful for heart failure self-management among older adults (Cornet et al., 2017) and in evidence-based treatments for psychosocial intervention (Lyon & Koerner, 2016). UCD-supported mHealth would have positive effects on diabetes self-management. Baron et al. (2012) found that using mHealth apps and the dyad communication between patients and healthcare professionals through mobile technology can lead to positive diabetes self-care outcomes and reduce the need for healthcare personnel resulting in lower healthcare costs. Therefore, it is imperative to assess the needs of end-users and their willingness to engage in activity targets to develop an informed user-centered design (Weinheimer et al., 2020).

Figure 2.1. User-Centered Design



While UCD design has been found to be effective in influencing behavior change, researchers are keen on using UCD design to persuade and motivate users to adopt desired behavior patterns .

Persuasive Technology (PT) advocates using design to reinforce individual behavior through motivation, ability, and triggers (Fogg, 2002). PT enhances the user's engagement and performance without manipulation or coerción. The idea behind persuasive technology design involves influencing the psychological attributes of the users to change their behavior. To be persuasive, one intentionally designs the features of the technology in a way so that users strive to adopt targeted behaviors. Fogg's Behavioral Model (FBM) examines what makes a design persuasive. FBM posits that user and technology must align to achieve the desired results. The user needs adequate motivation and ability to perform the task, and technology will trigger the user to do it. Persuasive design is likely to render expected outcomes when users have high motivation and ability to perform the targeted behaviors, and the triggers align with the appropriate context.

Often technologies are found to be usable but difficult to be engaging. Developing a design that influences people to change their behaviors is vital. Fogg offered captology (Computers As Persuasive Technology) to incorporate persuasive design into the technology. The model posits that B = MAP (Behavior = Motivation, Ability, and Prompt). Here, motivation and ability are continuous variables, whereas prompt is binary. According to Fogg (2019), one needs to first look at the prompts followed by abilities and motivation to change behavior. It occurs that self-drive is more critical than infusing motivation to change behaviors. Fogg developed behavior grids, which indicate 15 ways of behavior change. The grid has two dimensions –behavior types , and duration. In the case of encouraging a behavior, MAP has to be present at the same moment, whereas one of these three elements in MAP is weakened in the case of discouragement. In our study, we want a permanent change of known behaviors, which fall in either Path-Blue or Path-Purple category in the Fogg behavior grid. Fogg summarized behavior change using two maxims – i) help people do what they want to do, ii) help people feel successful.

The ultimate challenge of design for behavior change is to ensure user engagement with design. Often, users lose interest in technologies and discontinue engaging with them due to the absence of receptiveness. Gamification has turned out to be an effective way to enhance user engagement. It involves providing gameful experiences to elicit behavioral outcomes (Hamari et al., 2014). Gamified design is usually linked with gameful design that uses design elements of games in non-game contexts to motivate users' behaviors (Deterding et al., 2011). It can inspire behavior change (Zichermann & Cunningham, 2011) and enhance user engagement (Kuo & Chuang, 2016). A literature review of scholarly papers found that gamification yields positive behavioral and psychological results. Park et al. (2019) designed, developed, and evaluated theory-grounded gamified design for training and learning and found significant effects on learning outcomes and user engagement behaviors. Similarly, evidence from the use of gamification incentives in the design of an mHealth app for the self-management of Type 1 diabetes among adolescents showed an improvement in adherence behaviors (Cafazzo et al., 2012). Thus, Gamification has become an effective way to produce positive behavior change in healthcare (Faiola et al., 2019). Although the gamified design has often been found to influence users' behaviors positively, many have resulted in failure because of poor design (Hamari et al., 2014; Domínguez et al., 2013). Hamari et al. (2014) cautioned designers about two significant points – a) the role of the context being gamified and b) the quality of the users.

To summarize, the m-Health app design has improved physician-patient interaction, self-management of chronic diseases, and the relationship between patients and primary care providers. Besides, m-Health itself is considered a motivational factor for patients. Diabetes patients have also experienced positive outcomes from using m-Health applications. However, there is a dearth of appropriately designed mHealth app to promote work for diabetes self-management among medically underserved populations (MUP).

2.3.3 IT-enabled Self-Management:

Self-management is the key to chronic disease management. Prior studies suggest that chronically ill patients need to adopt self-care behaviors proactively. The patient-centric model bolsters effective self-management. Unlike the paternalistic model of healthcare, which does not promote the engagement of patients in the health decisión making process, the patient-centric model allows patients to participate in managing diseases actively and promotes various mechanisms conducive to self-management.

Self-management is an iterative all-encompassing dynamic process. It can be defined as “the individual's ability to manage the symptoms, treatment, physical and psychosocial consequences and lifestyle changes inherent in living with a chronic condition” (Barlow et al., 2002a). Others define self-management as the interactions with family, healthcare provider, and community to understand and manage various aspects – symptoms, treatments, health conditions, and so on (Richard et al., 2011). Cognitive, behavioral, and emotional responses are vital to successful self-management. Schulman-Green et al. (2012) identified three self-management categories. The first category involves focusing on illness needs, tasks, and skills necessary to own one’s health. Examples are learning, goal setting, and problem-solving. The second category is activating, coordinating, and utilizing healthcare, social, and spiritual resources. The third and final category is living with a chronic illness, coping with emotions, and integrating them with daily life. Dadgar & Joshi (2018) identified seven self-management activities – communication with healthcare providers, drug management, information usage, lifestyle management, management of psychological consequences, social support systems, and symptoms management. Association of Diabetes Care and Education Specialists (ADCES) presented seven self-care behaviors for diabetes self-management – healthy coping, healthy eating, being active, taking medication, monitoring, reducing risk, and problem-solving (Kolb, 2021). While self-management is an effective way to avoid complications from chronic diseases, it demands continuous and comprehensive efforts from the patient to monitor health conditions and coordinate with family members, physicians, and care providers (Bodenheimer et al., 2002). To be effective in self-management, patients coordinate with physicians, decide on the temporality of care, and change health behaviors. *Self-efficacy* is critical in short-term and long-term health behavior change and maintenance (Strecher et al., 1986). Self-efficacy means that an individual has the confidence to perform activities to reach the goals, such as eating healthy foods, sleeping adequately on time, and continuing exercise (Savoli et al., 2020) (Bodenheimer et al., 2002). Besides, behavior change is the result of efficacy expectations (one's expectation about the ability to perform a behavior) and outcome expectations (one's expectation about the consequences of committing a behavior) (Bandura, 1977).

‘Self-management interventions’ are the endeavors to successfully implement self-management initiatives (Savoli et al., 2020). For example, Ghose et al. (2022) examined the effects of using mHealth for diabetes self-management and found that mHealth intervention leads to positive health, behavioral, and economic outcomes. In another recent study, Son et al. (2020) showed that the intervention using Bluetooth-enabled inhalers increases the efficacy of asthma self-management.

To avoid complications and slow the progression, patients with chronic disease are strongly recommended to execute strategies daily through clinical interventions and home-based self-management. Self-monitoring (SM) is one such strategy essential for self-management. SM involves recording and interpreting the disease pattern, adjusting health behaviors, and coordinating with healthcare providers (McBain et al., 2015). It significantly reduces hospitalization and healthcare cost. Since self-monitoring involves data curation, paper-based médium often fails due to memory intensity and physical efforts. IT-enabled self-monitoring has the potential to alleviate these difficulties and help patients efficiently manage self-monitoring, thus improving self-management (Jiang & Cameron, 2020).

IT-enabled self-management (ITSM) interventions have shown promising benefits in chronic disease self-management. ITSM interventions enable patients to communicate with healthcare providers, access and manage real-time data, receive personalized feedback and alerts and monitor health and behavioral outcomes (Brohman et al., 2020; Thompson et al., 2020; Jiang & Cameron, 2020; Ahmed et al., 2016). In addition, ITSM creates opportunities for patients to learn more about diseases.

ITSM offers various affordances (action possibilities) to manage the disease. Jiang & Cameron (2020) applied affordance to demonstrate the interlinks between chronic care actions and outcomes. By reviewing 159 scholarly articles, they identified four themes related to ITSM - functionalities, user experience, goal achievements, and intermediate results. Technology-mediated learning offers valuable opportunities to enhance patients' understanding and to change self-care behaviors for chronic diseases to achieve improved health outcomes (Kelley et al., 2011). Table 1 shows selected ITSM studies.

Table 1: Selected Papers on IT-Enabled Self-Management

Reference		**Context**	**Findings**
(Ghose et al., 2022)	MISQ	mHealth app, diabetes self-management, personalized feedback,	mHealth app improves diabetes self-management. The mobile app is more effective than a personal computer (PC)-enabled app. However, personalized reminders in mobile apps increase privacy concerns leading to lower health improvement. Telehealth also substitutes offline visits.
(Vaithilingam et al., 2022)	IJIM	Unified Theory of Acceptance and Use of Technology (UTAUT), Urban poor, use of mobile technology	Using the Unified Theory of Acceptance and Use of Technology (UTAUT), the authors suggested five key facilitating conditions – infrastructure, technical, legal, financial, and self-efficacy - to predict the use of mobile technology among poor urban.
(Sharma et al., 2022)	JMIR	mHealth app, diabetes self-management, low-income population, health disparity	The study examined the access to the mHealth app by the low-income population. It developed a framework to increase the coordination and effective usage of mHealth in smoking cessation, diabetes self-management, and medication adherence.
(Aron & Pathak, 2021)	JAIS	Theory of task technology fit (TTF), physician chronic care delivery	the study found, drawing on task-technology fit, that digitization of medical information is instrumental to physicians for efficient and quality chronic care delivery.
(Savoli et al., 2020)	MISQ	Attribution theory, learned helplessness theory, Self-management	The study identifies three self-management styles – autonomous, engaged, and reliant and three patient views of information systems – imposer, facilitator, and protector.

(Liu et al., 2020)	MISQ	YouTube, medical information, and technology-enabled interventions.	This research focused on the effect of medical information delivered on social media platforms like YouTube on chronic care. The study found three dimensions of collective engagement – nonengagement, selective attention-driven engagement, and sustained attention-driven engagement.
(Son et al., 2020)	MISQ	Smart asthma management,	Based on Bluetooth-enabled Asthma inhaler usage, the study showed a better and more satisfactory analysis of inhaler data to improve Asthma management.
(J. Jiang & Cameron, 2020)	MISQ	Affordance actualization theory (AAT), design science, literature review, self-monitoring	The authors studied IT-based self-monitoring (ITSM) for chronic diseases in this review paper. They identified four major themes – key ITSM functionalities, ITSM system use, achievement of chronic care goals, and intermediary outcomes.
(Thompson, Whitaker, & Jones, 2020)	MISQ	IT, analytics, chronic care, and healthcare costs.	The study focuses on the interaction between IT and analytics to increase healthcare value and chronic care by displacing time. They found that this interaction lowers HbA1c, reduces emergency visits, and decreases healthcare costs.
(Zhang & Ram, 2020)	MISQ	Design science, chronic disease, asthma self-management, Machine learning.	The study ponders on the triggers and risk factors of asthma exacerbations. These are interconnected and environment-focused factors. Behavior change – drinking, smoking, exercise, and medication - are important preventive efforts. Hispanic populations are genetically at higher risk of asthma.

(Ben-Assull & Padman, 2020)	MISQ	Multiple chronic diseases, readmission, analytics	The study discusses how risk stratification, profiling, multi-morbid, and heterogeneity of patient characteristics predict emergency visits of chronically ill patients.
(Liu et al., 2020)	MISQ	Diabetes self-management, DID, instrumental variable, patient-physician partnership, Online health communities (OHC)	The research deals with the effects of physician-driven online health communities on patient well-being. They reported that while physicians' participation significantly improves patient well-being for diabetes and depression, patients' participation Works Good only for depression.
(Brohman et al., 2020)	MISQ	Feedback Intervention Theory (FIT), GLM models, chronic care, self-management, patient adaptation	The study discusses the effects of the feedback system on patient behavior changes in chronic care. Two technology feedback (medical alert, and compliance alert) and three provider feedback (outcome, corrective, and personal) were studied.
(Chen et al., 2019)	JAIS	Online health communities(OHC), social capital, health literacy, social network, machine learning	The study investigates the antecedents to consumer-to-consumer online health communities and found that structural social capital is the significant antecedent for informational and emotional support exchange in OHC.
(Dadgar & Joshi, 2018)	JAIS	ICT-enabled diabetes self-management, design science, twelve values, value sensitive design (VCD)	The study examines the role of ICT in diabetes self-management. Using value-sensitive design (VSD), the authors identified 12 values of chronically ill patients related to ICT adoption. It used a design science approach.
(Lin et al., 2017)	MISQ	Clinical intelligence, patient risk profiling,	The research examined electronic health records (EHR) to address risk profiling and

		design science, Bayesian multitask learning (BMTL)	predict personalized and predictive care. Using the design science paradigm, their Bayesian multitask learning (BMTL) outperforms the existing mechanism for patient risk profiling.
(Bardhan et al., 2015)	ISR	Readmission, heart failure, predictive healthcare analytics.	This study investigates the associated factors for readmission of chronically ill patients. It answers three questions (Will readmit? How often? And When?). It found health IT usage of hospitals, patient demographics, visit characteristics, and payer type is significantly associated with patient readmission risk.
(Kallinikos & Tempini, 2014)	ISR	Social media, patient self-reporting, networking, medical knowledge creation	The study examines the network of patients and self-reporting data to understand the health status of patients. It provides avenues for medical knowledge creation using social media platforms.
(Yan & Tan, 2014)	ISR	Online health communities(OHC), self-management, latent health outcomes	The study analyzes the effects of online health communities on self-management and patients' health outcomes. It found three factors – informational, emotional, and social support – drive OHC participation.
(Menon & Kohli, 2013)	ISR	The business value of healthcare IT investment, panel data, chronic care delivery	The study focused on the impact of Healthcare IT (HIT) on insurance and patient care. They found that past HIT is negatively associated with malpractice of insurance premiums but positively associated with chronic care and moderates to mitigate risk factors.

(Rajan et al., 2013)	JAIS	Telemedicine, chronic care, healthcare IT, community hospitals	The study discusses the use of telemedicine for patient care delivery. Contrary to intuition, they found telemedicine does not always increase value relative to in-person visits.
(Angst et al., 2012)	JMIS	The business value of IT, Structure-process-outcome, physician-patient relationship,	This research investigates the role of IT investment in interpersonal communication in hospitals and patient care satisfaction. It suggests that IT improves the physician-patient relationship and hospital performance.
(Heart et al., 2011)	JAIS	Organizational Justice Theory (OJT), physician compliance, EMR, drug prescription notifications	The study discusses the physicians' compliance with the recommendation for drug substitutes using electronic medical records. This computerized notification reduces costs by 4%.
(Kelley et al., 2011)	JAIS	Precede-Proceed model (PPM), IT adoption, type-2 diabetes self-management, health outcomes	The research examines the effects of adopting eHealth systems on type-2 diabetic patients' self-management.

Now, we look into a few instances of IT-enabled self-management. Electronic Health (eHealth) has shown promising benefits in managing chronic diseases and addressing challenges. Prior studies found that eHealth adoption helps type-2 diabetic patients adhere to self-care behaviors (Kelley et al., 2011). Telemonitoring has also shown positive outcomes in the self-management of chronic diseases. Customized and instantaneous feedback from providers and systems using telemonitoring technologies enables patients to identify the risk factors early and seek support

(Brohman et al., 2020). Among others (e.g., video consultation, interactive voice, web-based telemonitoring), automated and mobile telemonitoring effectively manage risk factors and reduce hospitalization (Kitsiou et al., 2015). However, concerns are raised about the effectiveness of telemonitoring feedback if patients' characteristics and contextual factors are ignored. For example, Mercer et al. (2016) found that older adults, who are most affected by chronic diseases, often are overwhelmed with the system requirements and data interpretation. Another instance of ITSM is Health IT (HIT), which helps to increase physicians' efficiency, patient care and lower healthcare costs (Aron & Pathak, 2021) (Bardhan & Thouin, 2013). IT-based benefits are well-established in many fields – retail, manufacturing, customer care, and supply chain management. It also substantially benefits health care delivery that involves multidisciplinary teamwork, which is information intensive and largely depends on collaborative efforts among care providers. The use of HIT can streamline the process of delivering accurate, timely, and seamless information (Wagner et al., 2001; Bates et al., 2001; Aron & Pathak, 2021). It helps specialist physicians improve care by preprocessing unstructured information into semistructured information using annotations, hyperlinks, and searchable keywords (Aron & Pathak, 2021). While chronic disease and mental health conditions incur 90% of healthcare costs[12], HIT can substantially push healthcare costs down by effectively managing clinical processes at the individual patient level. Prior studies investigated the effect of healthcare IT on self-management, behavioral and health outcomes, engagement, and healthcare costs. With slightly mixed results, researchers often found a positive association between healthcare IT and self-management (Lancaster et al., 2018) (Ghose et al., 2022) (Bardhan & Thouin, 2013).

[12] https://www.cdc.gov/chronicdisease/about/costs/index.htm

However, patients' health literacy, privacy concerns, and frustration may impede IT-enabled self-management success (MacKey et al., 2016; Ghose et al., 2022; Hess, et al., 2007). Savoli et al. (2020) examined causal attributions of the effective use of ITSM for asthma patients using a web-based SM portal. They identified three SM attributional styles - autonomous who perceived portal as imposer), engaged who perceived the portal as facilitator), and reliant who perceived the portal as a protector). The study also suggests that patients with the *imposer* style found using the ITSM disturbing, forcing them to behave in specific ways, asking for medication, and offending when negatively evaluated by the system. They also showed frustration, anger, and a sense of intrusión. Patients with the *facilitator* style viewed ITSM as a helping assistant, coach, and source of additional resources. They felt joy, motivation, and optimism with the use of ITSM. Finally, patient with the *protector* style considered ITSM life-saver that cared like a mother. They also showed positive emotions with the use of ITSM. Besides, this study also revealed that the attitude of patients toward illness and how they manage it affects the effectiveness of ITSM. Engaged patients benefited the most while autonomous patients benefited the least from the ITSM whereasreliant pateints moderately Benefited from ITSM.

Another major challenge for ITSM is that patients tend to avoid adopting it due to a lack of focus on patient-centric design (Dadgar & Joshi, 2018) (Jacelon et al., 2016). Dadgar & Joshi, (2018) suggested adopting a patient-centric design to mitigate the negative impacts of techno-centric design and identified twelve value sensitivities to improve the efficacy of self-management of chronic diseases like diabetes. The design of patient-centric artifacts includes both techno-centric functionalities of the design and the beliefs and values of the patients. This results are higher self-efficacy and empowerment and better self-management.

Further research is warranted to understand the effect of ITSM on marginalized populations who have limited exposure to IT. . Moreover, it is vital to recognize the fit of system features with the needs of the task. Besides, the slow adaptation of healthcare sectors to emerging technologies also poses a concern. The current study aims to focus on mHealth-based self-management.

2.4 Contextualization of ITSM

Context enables us to establish the interactions among variables. Johns (2017) defined context as situational or environmental constraints and opportunities that affect behaviors. Contextualization can be in three phases – research design, measurement and analysis, and reporting. Vaithilingam et al. (2022) studied the use of mobile technology in the urban poor's context to understand their mobile usage challenges. In the current study, we examine mHealth for diabetes self-management in the context of medically underserved populations (MUPs) to advance the knowledge of ITSM for chronic disease management. The following depicts the context of the study.

2.4.1 Mobile Health (mHealth)

The emergence of mHealth technology has promised tremendous benefits to patients with chronic diseases (e.g., diabetes) for over a decade. By 2025, the cost of treating chronic disease could rise to $15.5 trillion, and 10-20% of the costs of chronic disease management can be reduced using remote health monitoring (Manyika et al., 2013). The use of smartphones has constantly been increasing for more than a decade. While only 35% of Americans owned a smartphone in 2011, the share increased to 85% in 2021[13]. The share is 83% for households with an annual income lower than $50k. According to Statista, Apple App Store[14] and Google Play Store[15] have

[13] Demographics of Mobile Device Ownership and Adoption in the United States | Pew Research Center
[14] Healthcare apps available Apple App Store 2022 | Statista
[15] https://www.statista.com/statistics/779919/health-apps-available-google-play-worldwide/

approximately 120k mHealth apps. Pew Research Center reports that the mHealth app tops the number of users (62%), followed by banking (57%), job search (43%), and educational content (30%)[16] users.

mHealth interventions (mobile phone text messaging, wearable or portable monitoring devices, and smartphone applications) have been effective for behavior modifications and self-management (Wang et al., 2017). In a recent study, Ghose et al., (2022) provided empirical evidence of how mHealth contributed to changing the modalities of diabetes self-management. Patients can access real-time data on their physical conditions (e.g., blood glucose level, blood pressure, or heart rate) and make various behavioral and medical decisions based on the data. Such an approach to self-management empowers patients by enhancing self-efficacy and self-autonomy.

Although smartphone and mHealth usage has promising benefits, extant research is inadequate to explain factors affecting the effective use of mHealth for low-income populations (Sharma et al., 2022). Moreover, critics complain about mHealth usage for privacy concerns as being too intrusive and due to lack of data credibility (Ghose 2022). The technology adoption framework provides a parsimonious theoretical framework that predicts the use of technology in various settings (Vaithilingam et al., 2022). The Unified Theory of Acceptance and Use of Technology (UTAUT) posits that four factors - performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating factors (FC) - affect the use of technology. Prior studies revealed that hedonic (non-instrumental use) and utilitarian (instrumental use) use of mobile technology are interlinked. Vaithilingam et al. (2022) conducted a study among the urban poor in developing countries. They found that facilitating factors (FC) – infrastructure, technical and support services, legal and

[16] https://www.pewresearch.org/internet/2015/04/01/chapter-two-usage-and-attitudes-toward-smartphones/

regulatory framework, financial factors and affordability, and self-efficacy- influence the use of mobile technology. FC refers to the extent a user believes that the environment enables a user to use the system. IT-enabled interventions are contingent upon context-specific facilitating factors. Hence, knowing and implementing the right approach for mHealth interventions would be helpful to self-management. Medically underserved populations have distinct characteristics – low health literacy and low digital literacy – that demand careful attention before implementing IT-enabled mHealth intervention for self-management.

2.4.2 Diabetes Self-Management

Diabetes is a cardio-metabolic chronic disease that causes debilitating effects on quality of life and leads to high mortality. According to the Centers for Disease Control and Prevention (CDC), it is one of the most prevalent chronic diseases and the seventh leading cause of death[17]. It is a highly prevalent, costliest chronic disease, disproportionately affecting non-Hispanic blacks and Hispanics in the US (Gucciardi et al., 2013). The effects of diabetes are far-reaching and cumulative. It complicates other health problems and leads to irreversible damage. To slow its progression, patients with diabetes must practice certain self-care behaviors – monitoring blood glucose, exercising, dieting, etc. The lack of proactive preventive efforts could cause life-altering effects. An effective move is to predict and proactively displace the timing of treatments in the preventive state, make care resources available to fit the patient's expectations, and avoid unexpected visits to the emergency room (Thompson, Whitaker, Kohli, et al., 2020). They developed a novel system to displace the timing of treatment using healthcare IT and analytics.

[17] https://www.cdc.gov/diabetes/basics/quick-facts.html

While diabetes affects all segments of the population, the dangers of complications for the marginalized, low-income populations are likely very high.

Self-management programs significantly improve health behaviors (e.g., regular exercise, symptom management, visiting the doctor's office) and health status (e.g., pain management, depression, fatigue), and self-efficacy (Lorig et al., 2001). Prior studies found that effective self-management of chronic disease allows patients to avoid the burden of disease and leads to satisfactory lifestyles (Savoli et al. 2020; Eva et al. 2018; Lorig et al. 2001). Self-management is "the individual's ability to manage the symptoms, treatment, physical and psychosocial consequences, and lifestyle changes inherent in living with a chronic condition" (Barlow et al., 2002b). Diabetes self-management involves behavioral changes. To effectively manage diabetes, the Association of Diabetes Care and Education Specialists (ADCES) recommends seven critical areas for diabetes self-management: healthy coping, healthy eating, being active, monitoring, taking medication, problem-solving, and reducing risks. *Healthy Coping* means developing a positive attitude towards managing physical conditions and maintaining emotional well-being. It helps develop healthy ways to cope with stress and create a supportive environment. *Healthy Eating* comprises setting realistic eating goals, knowing the right balance of food nutrients, and tracking the impact of various food intakes. *Being Active* involves engaging in physical movements to enhance metabolic functions. Diabetic patients are encouraged to build a strong motivation to develop active habits. *Monitoring* means checking and tracking glucose levels, blood pressure, sleep pattern, mood, medications, and eye and foot care. The use of mobile app trackers and continuous glucose monitoring (CGM) tools help diabetes patients perform monitoring activities effectively. *Taking Medication* involves filling the prescription, keeping a list of medications, taking them at the right time, and managing medication beliefs and concerns. Being a progressive disease, individuals with diabetes often require taking medications at some point in time. *Problem Solving* is a three-step process – identifying the trigger of the problem, finding an appropriate solution, and taking the right action at the right time. Finally, *Reducing Risk* refers to the behaviors that help avoid or slow the progress of health and mental complications. Examples of such behaviors include regular doctor checkups, eye exams, foot care, and symptoms management.

Although IT-enabled self-management has shown hopes for improving diabetes self-management, there has not been enough research on designing appropriate IT-enabled (e.g., mobile app) self-management to enhance patients' engagement with the systems and adherence to diabetes self-care behaviors for medically underserved populations. The current study attempts to fill this gap and advance the knowledge of diabetes management using mobile technology.

2.4.3 Medically Underserved Populations (MUPs)

Health disparity has been a long-standing challenge in the US. It persists among the medically underserved population (MUP), where primary care providers are in shortage. Baishya & Samalia, (2020) termed low-income people as the 'bottom of the pyramid' (BOP). Health disparity represents the differences in the incidence, prevalence, mortality, burden of diseases, and other imbalances in health conditions among specific population groups in the US. For example, people of color, including Hispanics, received worse care than Whites for about 40% of quality measures from 2000 to 2017[18]. Studies reported that health literacy is lower among Black and Hispanic adults than among White adults (Kutner et al., 2006). These health disparities compound health problems and create barriers to adequate healthcare services. Moreover, the low economic status

[18] https://bit.ly/3BsrXsL

may pose a challenge, especially to MUPs, by limiting their access to technology and traditional health resources, thus leading to poor management of diabetes.

Though several prior studies show that diverse and low-income populations demonstrate equal, even sometimes higher interest in the adoption of mHealth for chronic disease management (Ramirez et al., 2016; Purnell et al., 2014), health and digital literacy may impede users' readiness and potential effectiveness of mHealth design interventions. Inadequate adoption and limited access to technologies for seeking health information among the medically underserved population (MUPs) raises the digital divide. MUPs are identified with low e-health literacy and limited use of technology for health (Connolly & Crosby, 2014). An assessment of internet access for health information services revealed that the digital divide exists at the level of information use (Zach et al., 2012).

Diabetes patients with low literacy often have low adherence to self-care and higher exposure to risk factors (Bailey et al., 2014). (Seo et al., 2015) showed that inadequate health literacy thwarts patient-involved decision-making among MUPs. A study of medical records of type-2 diabetes patients found that limited health literacy results in unintentional medication nonadherence among MUPs (Fan et al., 2016). Another study among MUPs revealed that the lesser the health literacy, the lower the propensity of MUPs to change the number of health habits (Kaphingst et al., 2015). However, a six-month-long quasi-experimental study on the use of mammography in breast cancer among MUPs has shown that enhanced care, health education program, and nurse support increase the effectiveness of the intervention. (Davis et al., 2014). Therefore, we argue that a well-designed intervention of the mHealth app for diabetes self-management among MUPs would significantly improve health outcomes in chronic disease management.

Though mHealth offers significant benefits to patients with chronic diseases, empirical evidence still lacks whether it is helpful for medically underserved populations characterized by limited health literacy and digital literacy. This phenomenon motivated us to explore the use of mHealth among MUPs and to examine whether mHealth delivers similar benefits and challenges to them, given their socio-economic status, education, and lifestyles. In the current study, we draw on theories and articulate design principles to appropriately design a diabetes self-management mHealth app for medically underserved populations. Our study has expanded design principles that can be generalizable to another patient-centric mHealth app. In addition, our mHealth app integrated ADCES7 diabetes self-care behaviors and provided an opportunity to corroborate the effectiveness of those behaviors with mobile technology. We measure the efficacy of the mHealth app in diabetes self-management. The effectiveness of the mHealth app is measured by the use of app-enabled facilities that helps users to achieve the goals of diabetes self-management (Burton-Jones & Grange, 2013). The ineffectiveness of the mHealth app does not help the user to achieve goals or adhere to self-management activities (Savoli et al., 2020).

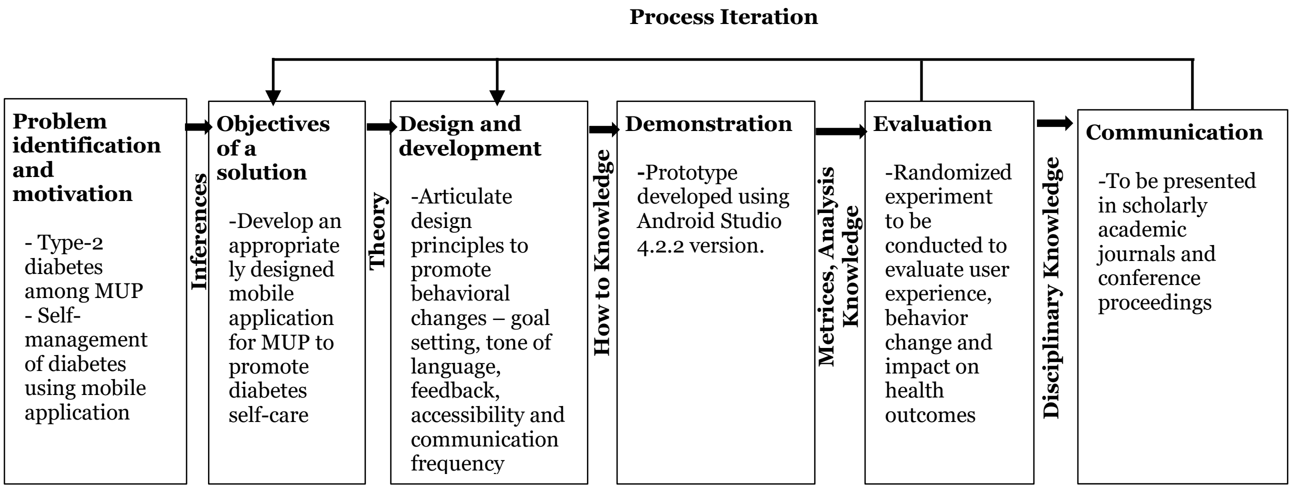
2.5 Research Methodology

2.5.1 Design Science Research

Design science as a research methodology is gaining acceptance among IS researchers. . It offers a rigorous methodology to create an IT artifact to address an unsolved yet significant problem through development and evaluation (Hevner et al., 2004). Artifacts are constructs, models, methods, and instantiation. Peffers et al. (2007) defined an artifact as "any designed object with an embedded solution to an understood problem." Due to the novelty of our design, it is a search process into the relevant theories and dominant literature to derive a solution to the problem.

Peffers (2007) outlined a six-step process to conduct design science research in IS discipline. Figure 2.2 presents the research methodology in this research.

Figure 2.2. Design Science Process



2.5.1.1 Problem Identification and motivation

Medically underserved populations have limited access to primary care providers and face economic, social, and language barriers in diabetes self-management. Health Professional Shortage Area (HPSA) creates an “Index of Medical Underservice” from 0 to 100 using four criteria – poverty, older population, infant mortality, and primary care physicians. A score of 62 or less is designated MUP. Though the US healthcare sector incurs the highest cost globally, there are more than 3,769 designated medically underserved populations/areas in the primary care category in the US[19], where numerous challenges hinder access to healthcare services. In this phase, we identified problems of diabetes self-management among MUPs: (1) limited health literacy creates a significant barrier to understanding the significance of the necessary self-care

[19] https://data.hrsa.gov/topics/health-workforce/shortage-areas

behaviors and complying with those behaviors for diabetes management (2) limited digital literacy that hinders the effective utilization of available technology (e.g., diabetes mobile app) (3) lack of motivation to initiate and maintain diabetes self-care behaviors and (4) language barrier impedes the readability of various graphs, charts, and texts. We argue that addressing these issues is critical to the success of diabetes self-management among MUPs. IT-Enabled self-management has the potential to improve chronic care management (Jiang & Cameron, 2020; Savoli et al., 2020). In particular, the emergence of the mHealth app has shown promising benefits in diabetes self-management (Ghose et al., 2022). An appropriately designed mHealth app that addresses the unique problems faced by MUPs would help improve diabetes self-management among these patients.

2.5.1.2 Define the objectives for a solution

Though there are numerous mobile applications for diabetes self-care management, none is designed to focus on MUP's unique characteristics and type-2 diabetes self-management. The primary objective of this study is to design an effective diabetes self-management mHealth app for MUPs. The problems identified in phase 1 do not necessarily result in specific objectives of the artifact (Peffers 2007). It is important to set concrete goals to solve the above problems. The significant challenges to serving MUPs include specifying goals for diabetes self-care behaviors, monitoring progresses towards the goal, communicating with patients understandably, and using an alert and reminder system that is motivating and engaging. Thus our first objective is to increase compliance with diabetes self-care behaviors. The pattern of type-2 diabetes makes it necessary to adhere to these self-care behaviors. The second objective is to improve much-coveted health outcomes such as lowering and improving BMI. Both objectives would cater to patient empowerment and self-efficacy to self-manage diabetes. In addition, achieving and maintaining the first objective leads to positive results in the second objective. For example, exercise is an essential aspect of diabetes self-care behavior. Using technologies could help patients remind and monitor the amount of exercise, which will have a spillover effect on improving HbA1c and other aspects of self-management. The third objective is to evaluate the mental distress of living with diabetes, as inner mental strength plays a vital role in maintaining self-care behaviors. Finally, we aim to measure user experience to observe how the interface has been able to reflect the patients' expectations.

2.5.1.3 Design and Development

In the design phase, we searched the literature for the requirements of the artifact. We articulated design principles drawing on dominant literature in chronic illness management, motivation, and gamification. We integrated the functionalities of the mHealth app from ADCES-recommended self-care behaviors for diabetes self-management. We included gamified elements to enhance user engagement with the interface and presented the interlinks of system components in the system architecture.

2.5.1.4 Demonstration

We plan to conduct a field experiment with type-2 diabetes patients from medically underserved populations. The demonstration phase requires to use of the artifact in solving the problem. We first run a pilot study with seven patients for ten days to assess the performance of the artifacts. Finally, we outline field experiments with the intervention and control groups to evaluate the artifact's effectiveness in solving the problem. The feedback from the pilot will be incorporated into the final design.

2.5.1.5 Evaluation

The evaluation phase includes measuring the performance of the artifact toward the solution of the problem and comparing the results against the objectives defined in step 2. The evaluation phase provides empirical evidence for the solution to the problem. We will use two data sets – in-app user data and survey data. The in-app data include user-set goals, self-reported performance data against those goals, and app usage data (e.g., log-in time, used notification to open the app, etc.). The survey data include questionnaires for diabetes self-care activities, emotional well-being, and user experience. We will use both data sources to run difference-in-differences (DID) analysis to assess the app's effectiveness in type-2 diabetes self-management among MUPs.

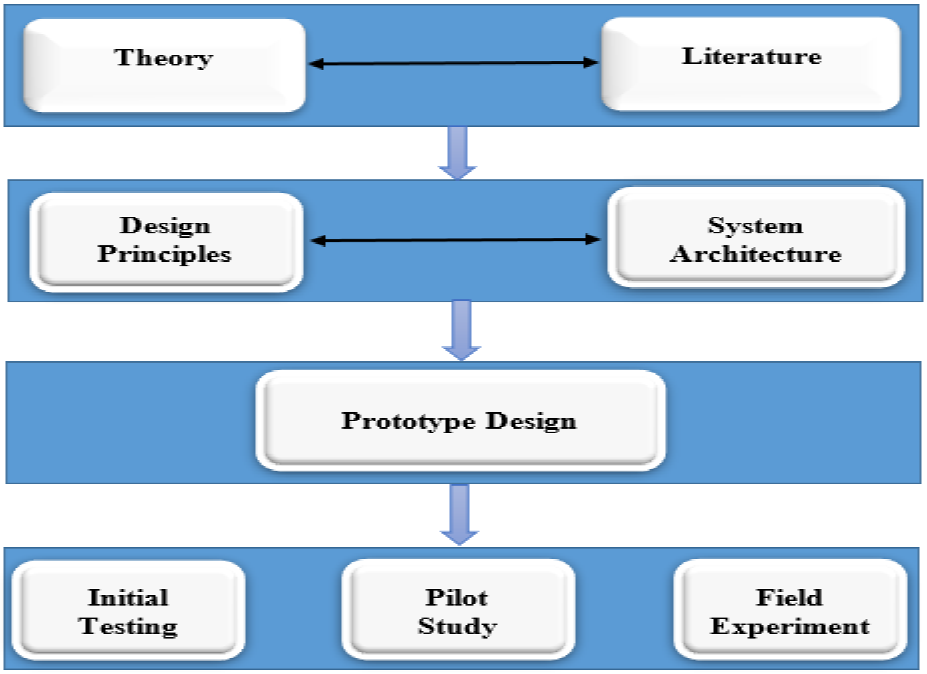
2.5.1.6 Communication

In the communication phase, we will communicate the significance of the problem, the effectiveness of artifacts to resolve the problem, and the rigor of the design process to the research community. This communication aims to gain validity from the relevant and appropriate audiences. We have already presented interim progress (e.g., design principles, prototype) at an IS conference (Murad et al., 2020).

2.6 Design Principles

This section will elucidate how our objectives to design and develop an effective mHealth app informed the articulation of six design principles that support IT-enabled diabetes self-management for MUPs. Design principles were based on the dominant literature and relevant theories. We then drew relationships among different components of the system in the system architecture, which were aligned with design principles. Design principles include patient-centered design, goal-setting, feedback system, decision-making, patient engagement, and communicative interface. Finally, we demonstrate the mHealth app prototype, which is an artifact instantiation (Hevner et al., 2004). Figure 2.3 shows the derivation of design principles in a diagram.

Figure 2.3. Framework of Design Principles



2.6.1 Design Principle 1: Patient-Centered Design

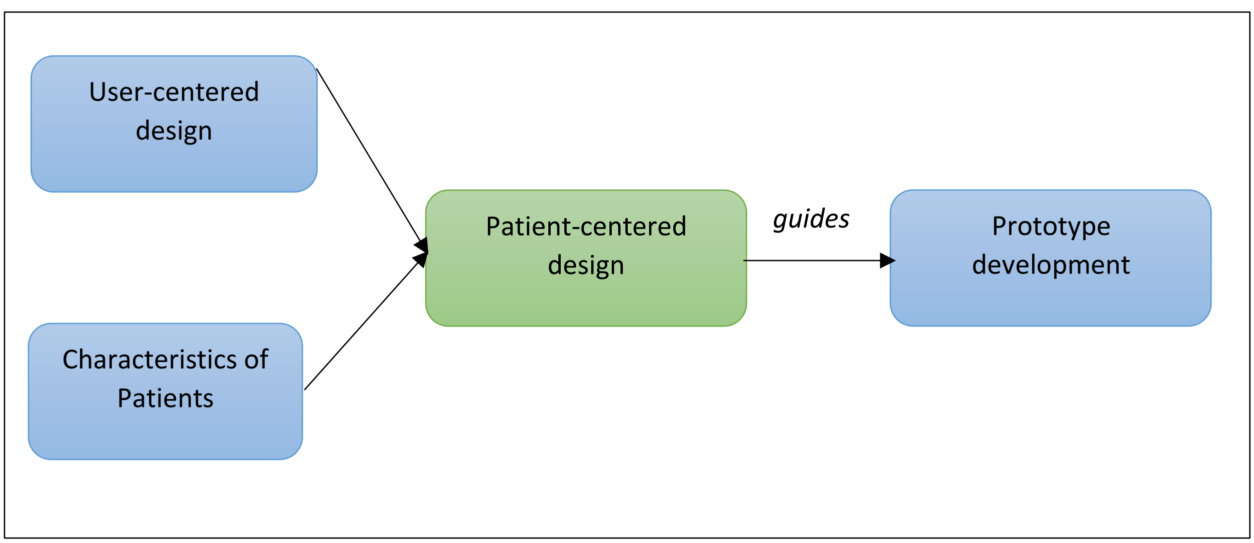
Patient-centered design (PCD) refers to an iterative process of contemplating the design aspects aiming at the needs and characteristics of the patient. We focused on extracting various recommendations from user-centered design (UCD) and examined the uniqueness of medically underserved populations (MUP) to articulate the PCD principle. PCD is an effective way to design and develop an mHealth app. PCD requires the designer to empathize with users and appreciate their uniqueness, focusing on their needs, characteristics, and capacities. The design of an mHealth app must incorporate appropriate terminology, consistent workflow functionality, and user interfaces (e.g., visibility, navigation, scrolling) (Couture et al., 2018). Patient participation in designing and developing diabetes self-management mHealth applications is positively associated with higher behavioral compliance and positive health outcomes (Fico et al., 2020).

Self-management of chronic illness involves complying with a set of recommended behaviors. The heterogeneity of patients often creates barriers to developing a comprehensively helpful design. The salient challenge of IT-based self-management often derives from the design aspects influencing the users' continued intention to use the design. Often mHealth app fails to reap optimal outcomes due to shortcomings in the design process (Griffin et al., 2019; Ghose et al., 2022). Cornet et al. (2019) discussed two types of design errors - user-reality error (Type 1 design error) and clinical-reality error (Type 2 design error) – in the context of patient-centered design. In addition, the patient's knowledge about the disease, efforts for self-care behaviors, and relevant technologies affect the use and effectiveness of the design. The appropriate design reflects the context and needs of the users.

Previous studies examined the effectiveness of the PCD mHealth app in the context of underserved populations. Tang et al. (2016) found evidence that patient-centered mHealth could improve patient care for the underserved population. In another systematic study, Tarver & Haggstrom (2019) reported that patient-centered mHealth could reduce health disparity and the digital divide and serve medically underserved populations. Alluhaidan et al. (2015) built patient-centered mHealth technology and found it effective in reducing hospital readmission for heart failure patients.

Patient-centered design is based on user-centered design (UCD). Since Don Norman coined the term in 1986, UCD has become a practical approach to designing impactful technology (Weinheimer et al., 2020). UCD is an iterative design process that involves investigating user needs, developing prototypes reflecting those needs, and evaluating the effectiveness of user performance (Griffin et al., 2019). It is founded on the frequent feedback from users to refine the design's critical elements to enhance the intervention's use and effectiveness. Studies demonstrated that by placing users at the center of the design process, UCD makes it easier to understand users and relate them to the technology (Graham et al., 2019). It also emphasizes the context of use and users' goals, tasks, needs, and abilities. Gulliksen et al. (2003) described the advantages of using UCD over mere focus on technology focus. Prior studies found UCD effective in designing mHealth for colorectal cancer screening (Griffin et al., 2019), chronic heart failure (Cornet et al., 2019), and opioid use disorder (Ray et al., 2019). The benefits of UCD include greater usability, increased patient commitment, and reduced design errors. Besides, the UCD approach can abate concerns raised between research and practice in evidence-based treatment (Kazdin, 2008). (Weinheimer et al. (2020) found the use of UCD to improve adherence, enhance user engagement, and show positive results for behavioral interventions in the context of binge eating and obesity. Figure 2.4. graphically depicts that patient-centered design is based on the user-center design approach and understanding user characteristics, which set criteria for prototype development.

Figure 2.4. Patient-Centered Design Principle



Our design focused on simplicity to facilitate what users want to do rather than to impose what they need to do. Patients are not forced to set and achieve all goals. Instead, they can choose from a recommended set of goals, and our design features help them accomplish those self-set goals. It allows users to keep track of their accomplishments. It includes reminders and feedback systems from time to time to reflect patients' performance. Thus, the tone of feedback messages is written in a congratulatory way when goals are met ("Great Job! You have met your exercise goal for today!") or neutral/encouraging way if goals are not fully met ("Great start towards your goals for the day. Keep it up!"). Studies show that judgmental language that demeans or shames the patient leads to diabetes distress, negatively impacting health outcomes (Dickinson et al., 2017). The messages need to use language that is a) non-judgmental and based on facts, b) does not shame the patient, and c) respectful, inclusive, and gives hope. An extensive literature review reveals that medically underserved populations have low socio-economic status, limited health and digital literacy, face cultural and language barriers, and do not have access to primary care providers (Table 2).

Table 2: Characteristics of medically underserved populations.

Characteristics of MUP	**Source**
Lower socioeconomic status (SES)	(Tarver & Haggstrom, 2019) (Heitkemper et al., 2017) (Reyes et al., 2017); (Zach et al., 2012) (Shea et al., 2009)
Limited health literacy	(K. A. Kaphingst et al., 2016) (Chesser et al., 2016) (Fan et al., 2016) (Seo et al., 2015) (Bains & Egede, 2011)
Limited digital literacy	(Connolly & Crosby, 2014) (Zach et al., 2012) (Moore et al., 2009)
Shortage of primary care providers	(Wong, 2015); (Zach et al., 2012)

Cultural and linguistic barriers	(Ricci-Cabello et al., 2014); Health Resources and Services Administration (HRSA), 2022

Simple and short messages enhance comprehension and communication for patients with low literacy skills (Doak et al., 1996). Since MUPs are characterized by low literacy rates and limited language skills (Ricci-Cabello et al., 2014), our mHealth app does not use graphs, charts, or complex language, commonly found in many mHealth applications. All messages and instructions are developed at a middle-school reading level. Messages are committed conversationally using active voice, simple words, and short sentences (Doak et al., 1996). Speech bubbles attached to a stylized stick figure are used to simulate a person providing feedback (e.g., a buddy).

2.6.2 Design Principle 2: Goal Setting

According to goal-setting theory, goals serve as strong motivators of human behaviors, and goals with rationale and a high level of commitment are highly likely to be achieved (Latham & Locke, 1991). Goal commitment represents the firm conviction to accomplish a goal." Prior study shows that goal setting influences employee behaviors, impacts attitudes, and improves their performance in the organizational context (Pervaiz et al., 2021). Goal setting has also been extensively studied in consumer behavior literature. Consumers always set goals, and it's essential to understand the dynamics of consumer goals to influence their behaviors. The process of goal setting enhances the chances of achieving the goal. It involves prethinking, ability, motivation, and commitment. While specific goals are more achievable, vague goals create confusion and demotivate to exert efforts. Goal setting and action plans are critical to the effective self-management of chronic illnesses (Lenzen et al., 2017). Our goal-setting design principle involves patients setting proximal and distal goals for self-care behaviors. It includes the user in planning and enhances psychological engagement to induce behavior change.

Goal setting has effectively delivered primary care for chronically ill patients and encouraged them to engage in self-care activities. (Lenzen et al., 2017). A systematic review of 27 studies on patient-centered stroke rehabilitation found that patient-centered goal setting improves self-efficacy, increases motivation, lessens anxiety, and empowers patients (Rosewilliam et al., 2011). A high goal tends to fall apart if the user is not committed to the goal. The findings of a study revealed that diabetes patients with higher goal commitment perceive the goal as less complex and achieving positive behavior change (Miller et al., 2012). User participation and feedback are critically important to set appropriate goals. Specific and challenging goals with appropriate feedback lead to higher performance (Locke & Latham, 2002). Goals also motivate individuals to measure progress (Consolvo et al., 2009). It is also important to examine the types of goals – learning goals (to self-improve) and outcome goals (to show competence) since study shows that users react differently to learning and outcome goals (Welsh et al., 2019).

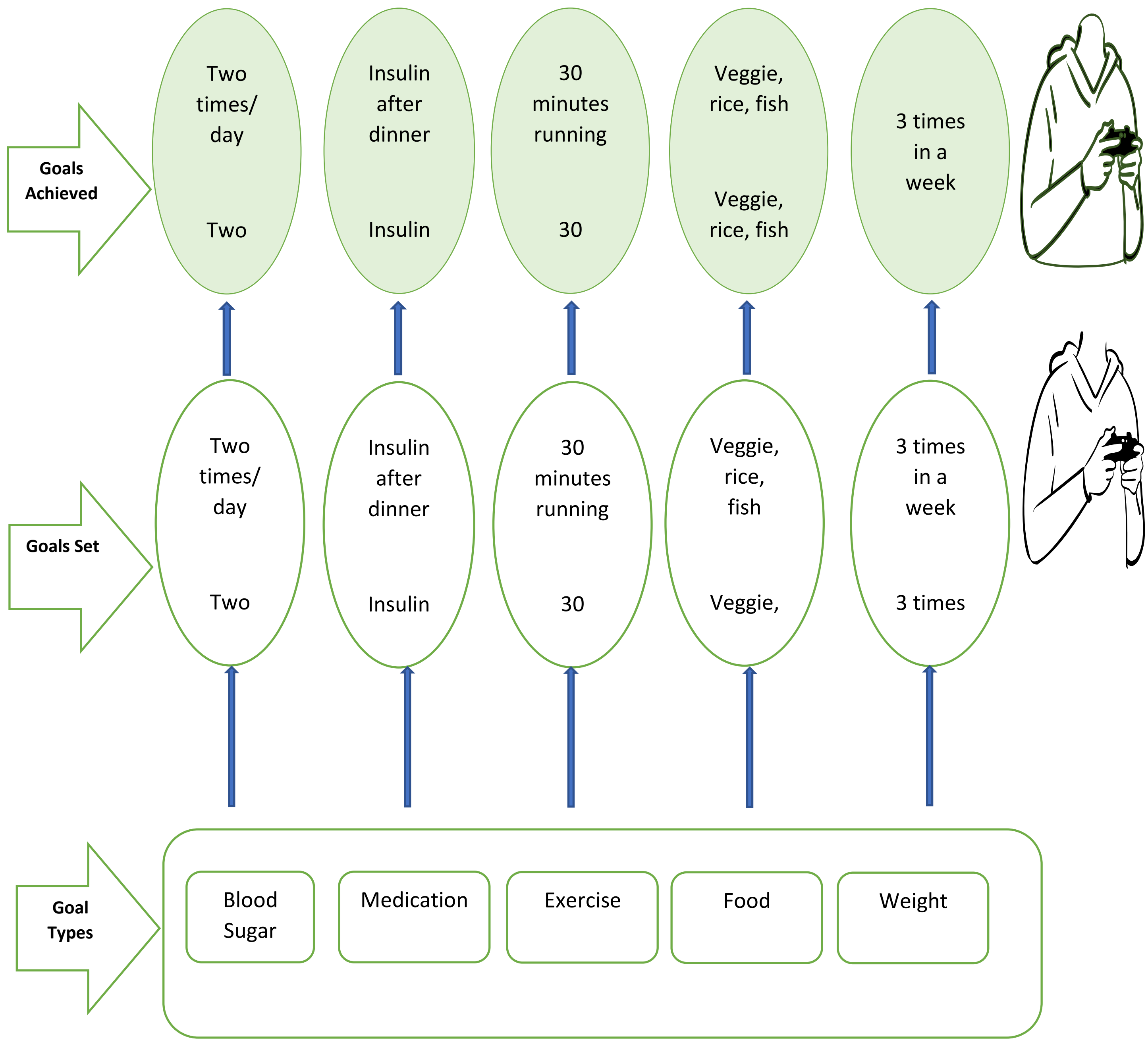
Lenzen et al. (2017) identified four phases for effective goal setting in self-management interventions. In the *preparation phase*, patients learn about behaviors necessary for disease management through patient education, patient reflection, and identification of topics. In the *formulation of goals and action plan phase*, patients develop explicit and written goals and action plans. In the *coping planning phase*, patients analyze possible barriers and facilitators to the action plans, weigh their confidence, and formulate strategies to overcome the obstacles. In the *follow-up phase*, patients monitor and evaluate the progress of the goals.

The difference between goals and performance determines the level of effort a patient needs. Barriers deriving from a lack of supportive components impede optimal outcomes and goal achievements. For example, user-centered goal-setting interventions in rehabilitating adults with health conditions fail to accrue optimal results due to the absence of supporting components (Kang et al., 2022). Giessner et al. (2020) also showed that minimal and maximal goal setting could cause satisfaction or dissatisfaction to the user.

We argue that self-management of chronic illness largely depends on the patient's commitment to self-care behaviors (e.g., routine check-ups, doctor visits, eating healthy foods, and physical exercise). Patient-induced goal-setting becomes an effective way to engage patients in self-care activities. In primary care, collaborative goal setting allows caregivers and patients to set goals, which were found effective in many cases. However, lack of autonomy, miscommunication, and transparency of goal setting impedes optimal outcomes.

Mobile technology can immensely help patients to keep track of their progress. We integrated the idea of goal setting by the patients based on their ability and motivation. Users can set daily and weekly goals per their needs and abilities, increasing the likelihood of achieving goals. Since goals are great motivators and enhance the user's commitment, our designed prototype encourages the user to set attainable goals and increases goal commitment with game elements such as points, mission accomplishment, and club membership. While goal setting plays a pivotal role in the self-management of chronic illness, patients can benefit from being able to monitor the progress toward goal achievement, which can lead to satisfaction, self-esteem, and self-efficacy. Our design allows patients to set goals for self-care activities based on the abilities and motivations of the patients. It ensures autonomy and reduces the chances of mental anxiety from low performance. Goal setting helps to improve performance because it leads to higher motivation, goal relevance, and reference points (van Lent & Souverijn, 2020). Clarity and difficulty of goals also play essential roles in achieving the goals. Specific and measurable goals are likely to be attained more than vague and indeterminate goals (Locke & Latham, 2002). Figure 2.5 demonstrates that the patient in the prototype set goals for ADCES-recommended diabetes self-care behaviors and self-report the performance towards the goals. Patients can visually view the progress of the goals in the progress bar.

Figure 2.5. Goal-setting Design Principle Implementation



Uplifting the goals' difficulties can gear users to exert increased efforts (van Lent & Souverijn, 2020). In our design, we specifically defined and incorporated ADCES-recommended self-care behaviors and allowed the user to input measurable goals. We used gamified elements in the design to perceive the goals' difficulties. Our design not only allows users to set goals but also helps manage the goals. Table 3 provides summary of the design principles

Table 3: Summary of Design Principles

Design principles	Implementation	Source
DP1: Patient-Centered Design Patient-centered design (PCD) refers to an iterative process of contemplating and implementing the design aspects aiming at the needs and characteristics of the patients.	• No graphs or charts used. • Messages and instructions at a middle school reading level. • Feedback in a conversational style, active voice, simple words, and short sentences. • Text-to-speech conversion • Messages a) are non-judgmental and based on facts, b) do not shame the patient, and c) are respectful, inclusive, and give hope • Tone in an encouraging manner	• Importance of design - Cornet et al., (2019); (Couture et al., 2018) • User-centered design (UCD) - (Gulliksen et al., 2003); (Griffin et al., 2019); (Graham et al., 2019); (Fico et al., 2020) • Application of UCD in colorectal cancer screening (Griffin et al., 2019), chronic heart failure (Cornet et al., 2019), Alluhaidan et al., (2015) and opioid use disorder (Ray et al., 2019). • Use of patient-centered design (PCD) for MUPs - Tang et al., (2016); Tarver & Haggstrom (2019)
DP2: Goal-Setting The goal-setting design principle involves patients setting daily goals for self-care behaviors.	• Incorporate ADCES-recommended diabetes self-care behaviors • Allow patients to input measurable and specific goals • Clarity of goals • Reminding patients of the goals	• Goal setting theory - (Locke & Latham, 1990); (Consolvo et al., 2009); (Welsh et al., 2019); (Locke & Latham, 2002); (van Lent & Souverijn, 2020) • Goal setting for behavior change - Lenzen et al., (2017); (Pervaiz et al., 2021); (Tuk et

		al., 2021); (Giessner et al., 2020) • Goal setting for patients - (Rosewilliam et al., 2011); (Miller et al., 2012); (Kang et al., 2022)
DP3: Feedback System The feedback principle entails sending reminders and alerts to the patients based on their goals and performance for self-care behaviors.	• Providing feedback on the deviation between goals and performance. • Alerts and reminders have been included to provide feedback. • Two types of alerts – compliance alerts and medical alert • Two times reminders - morning and evening reminders	• Fogg's Behavioral Model (FBM) - (Fogg, 2009) (Fogg & Euchner, 2019) • Feedback intervention theory - (Kluger & DeNisi, 1996); Brohman et al., (2020); (Shute, 2008) • Feedback in self-management - (Baron et al., 2012); (Choi et al., 2016) (Abrashkin et al., 2016); (Sahakyan et al., 2018)
DP4: Decision-Making The decision-making design principle emphasizes the active participation of the patients in deciding what, when, and how to perform self-care activities.	• Patients aware of the required activities such as daily exercise, monitoring blood glucose, and regular medications. • Prompts used to persuade patients to make decisions regarding the behaviors • visual cues in the app nudge patients • Helpful links to diabetes management to make rational and educated decisions.	• Social cognitive theory - (Bandura, 1998) (Bandura, 1977) • Transtheoretical model of behavior - (Prochaska & Velicer, 1997) (Prochaska, 2008a) Janis et al., (1976) • Patients' decision making in self-management - (Williams et al., 1998); (Wu et al., 2017)
DP5: Patient-Engagement The patient engagement design principle refers to the direct and persistent interactions between	• Earning points, • Recognized by badges • Mission accomplishment, • Level upgrades,	• Self-Determination Theory (SDT) - (Ryan & Deci, 2000); (Bovermann & Bastiaens, 2020); Liu, Santhanam, & Webster, 2017)

patients and technology for self-care management.	• Challenges to achieving honorary club membership,	• Gamified design - (J. Park et al., 2019); (Garett & Young, 2019); (Hamari et al., 2014) • Gamification in self-management - (Cafazzo et al., 2012); (Pernencar et al., 2018); (Pramana et al., 2018)
DP6: Communicative Interface Design The communicative interface design principle includes easy accessibility, consistency of functionalities, ease of use, and avoiding clutter for better usability.	• Large icons and easy-to-read text, • low information density, • comfortable visual cues, and an easy-to-navigate interface. • Consistent and representative features to easily recognize tasks. • vocalization feature • Simplistic patients data entry with minimum efforts	• Hick's law - (Chapman et al., 2016) (Lowdermilk, 2013). • Chunking principle - (Chapman et al., 2016) • Perceived ease of use (Venkatesan 2000)

2.6.3 Design Principle 3: Feedback System

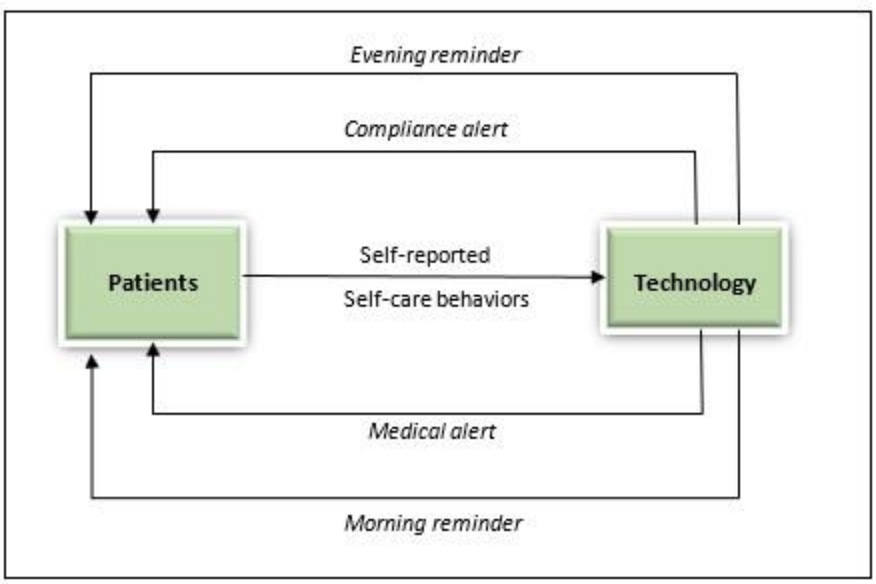
The feedback principle entails sending reminders and alerts to the user based on their goals and performance for self-care behaviors. A systematic review reveals that the mHealth feedback system based on patient-transmitted diabetes-related information positively affects diabetes self-management (Baron et al., 2012). The feedback system helps patients identify deviations between goals and performance and makes patients aware of appropriate behaviors to minimize the differences (Brohman et al., 2020; Kluger & DeNisi, 1996). Frequent and regular feedback promote self-care behaviors by encouraging the user to interact with the app regularly. Therefore, feedback is expected to impact both behavioral and health outcomes.

Community paramedics (CP) directly provide medical support to chronically ill patients. Prior studies show that feedback delivered through CP telemonitoring helps patients self-manage chronic diseases (Brohman et al., 2020; Choi et al., 2016; Abrashkin et al., 2016). They showcased the implications of formative feedback to alter behaviors to improve learning. The feedback literature shows a positive result on the behaviors and performance if they are “nonevaluative, supportive, timely, and specific” (Shute, 2008). However, the success of a feedback system largely depends on the characteristics of the user and tasks.

According to feedback intervention theory (Kluger & DeNisi, 1996), feedback makes individuals aware of the gap between goal and accomplishment and promotes behavior that reduces such gaps. Using feedback intervention theory, Brohman et al. (2020) have studied the technology-provider-patient feedback ecosystem concerning chronic disease management. In their feedback ecosystem, the system sends alerts to providers in the first stage, and providers deliver feedback to patients in the second stage. Their findings have several significant aspects. First, feedbacks are multifaceted. For example, technology feedback (medical and compliance alerts) and provider feedback (outcome, corrective, and personal) have differential outcomes and engagement of the patients. Since the current study only involves the effect of technology on patients’ self-management, our mHealth app delivers compliance alerts in the morning and evening and medical alerts when patients' self-reported entries exceed the safety line (Figure 2.6). Besides, our app also provides in-app feedback. Second, feedback must align with the capabilities of the patients so that they can meaningfully interpret the messages. In the current study, given the characteristics of the medically underserved population, we construct the messages at the fifth-grade level and avoid graphs and charts to minimize cognitive efforts.

The feedback is incorporated into the design as a “trigger” following the persuasive design paradigm. According to Fogg’s Behavioral Model (FBM), an individual tends to perform target behavior when a trigger occurs, given that the motivation and ability remain above the threshold. FBM asserts that a shift in target behavior will only happen if three factors (sufficient motivation, ability to perform, and an effective trigger) synchronously converge. Individuals with higher ability and motivation are highly prone to reach the target behavior with the proper timing of the trigger (Fogg, 2009). If mHealth could integrate core motivators, simplicity factors, and behavior triggers into the mobile application, individuals will likely perform target behavior. Persuasive technology is intended to design artifacts to automate behavior change. However, individuals are inevitably not at the same stage of readiness to make behavior change. Persuasion through design artifacts would produce expected results if the appropriate stage were known and converged with interventions received.

Figure 2.6. Reminders and Alerts



We deduce that the design of an artifact to change behavior has to be backed by the motivation to act and the ability to perform a target behavior. Furthermore, the intention to behave, which is a function of a causal chain linking attitudes, subjective norms, and perceived behavioral control of an individual, influences a target behavior to happen. Consequently, individuals can be better persuaded by culturally adaptive user-centered design, which reflects the differences.

Our mHealth app incorporated two sets of alerts – a compliance alert and a medical alert from technology to patients to deliver feedback (Brohman et al., 2020; Sahakyan et al., 2018) (Figure 2.6). Since the core aspect of patient-centric self-management is to enhance the self-efficacy and empowerment of the patients, both alerts reflecting patients' self-reported vital signs allow them to manage the disease. The compliance alert denotes the discrepancies between patient pre-set goals and daily achievement. If the patients fall short of the goals, the system sends alerts about the discrepancy. These serve two purposes. First, it reminds patients how active they were throughout the day in the self-care behaviors regiment. Second, the non-judgmental and encouraging language of the alerts motivates patients to adhere to self-care behaviors the next day. This indicates cascading effects of feedback, which shows the adjustments of behaviors on the subsequent performance (Kluger & DeNisi, 1996). Medical alerts are triggered when the patients' self-reported vital signs go outside the safety border. For example, if blood sugar entry is below 80 or rise above 180, the system immediately alerts the patient about contacting their healthcare provider. Since the prototype allows self-reported data, user's discretion is necessary to avoid incorrect entry.

2.6.4 Design Principle 4: Decision making

The decision-making design principle emphasizes the active involvement of the patients in deciding what, when, and how to perform self-care activities. According to the Middle-Range

Theory of Self-care of Chronic Illness, self-care of chronic illness requires an individual to be involved in the decision-making process with three overarching behaviors – self-care maintenance, monitoring, and management – to maintain health (Riegel et al., 2012). One widely used cognitive model is the social cognitive theory (SCT), which explains influencing factors for individual behaviors. SCT outlines the interactive and dynamic interplay between individuals, environments, and behaviors. According to SCT, perceived self-efficacy, outcome expectancies, perceived impediments and facilitators, and goals are crucial factors in determining behavior. Decision-making has become necessary in patient-centered care. Individuals are involved in cognitive processes to make decisions on health behaviors. Behavior change is a process that goes through several stages. The transtheoretical model of behavior change is more appropriate for underserved patients who are characterized as "non-compliant, unmotivated, resistant, and not ready" (Prochaska, 2008b). The Transtheoretical Model (TTM) assumes that people do not change behaviors quickly but go through a cyclical process.

According to TTM, behavior change is "a process that unfolds over time and involves progress through a series of stages: pre-contemplation, contemplation, preparation, action, maintenance, and termination" (Prochaska, 2008b) shown in Figure 2.7. In the pre-contemplation stage, patients do not intend to change or adopt new behaviors in the near future. For example, a diabetic patient does not plan to quit smoking. In the contemplation stage, unlike patients in the pre-contemplation stage, they decide to adjust their behaviors and search for relevant information and feedback to change problem behaviors. In the preparation stage, patients develop a sense of commitment to bring changes very soon and get ready with little initial effort. In the action stage, patients have been involved with a stringent course of action and have shown adherence to the changes. Yet, the risk of returning to previous behavior is high, and relapse could occur. Therefore, patients need to be cautious to avoid deviations. The next stage of behavior change is maintenance. The new behavior has become a habit, and the risk of returning to previous problem behaviors is very low. The final stage is termination, where individuals continue to practice new behaviors effortlessly instead of old ones, feel accomplished, and confidently overcome barriers. Patients are now in control of their behaviors.

The pros and cons of changing behaviors often dominate the individual's mindset (Prochaska, 2008). Emerging technologies like the mHealth app support patients in the stage of change. While pre-contemplation, contemplation, maintenance, and termination stages are more stable, preparation and action stages are prone to be more changeable. Earlier research on behavior change assumed that a person would not begin to change behaviors unless his gains from the change exceeded the losses. Janis et al. (1976) conceptualized the gains and losses with eight constructs: utilitarian gains and losses to self, utilitarian gains and losses to others, approval or disapproval to self, and approval and disapproval to others.

Figure 2.7. Stage of Behavior Change

Stages of Changes	Descriptions	Implementation
Precontemplation	Individuals not intended to change	Do not use mHealth app
Contemplation	Individuals made up mind to change behavior	motivate patients to self-manage diabetes to enhance compliance and derive better health outcomes
Preparation	Individuals prepared for taking actions	Incorporate ADCES recommended behaviors and allow setting goals, reminders, and alerts, and using helpful links on diabetes
Action	Individuals initiating action sufficient to reduce the risk	Organize self-care activities, represent them with easy-to-use features, and set alerts and reminders for timely action
Maintenance	Individuals avoiding relapses, behaving consistently, and showing higher self-efficacy	keep tracks of the progress of actions, engage and motivate to recur using points, badges, and club memberships
Termination	New behaviors became habits and no temptation to undo	New healthy behaivors attained, and yet mHealth app could continue to assist

Autonomy plays a vital role in decision-making. A design that embeds user autonomy leads to positive diabetes management (Williams et al., 1998). A well-thought design allows users autonomy to set goals, achieve them, and encourage consistent decision-making over time. The design provides a skeleton of diabetes self-care behaviors. It should not dictate users to initiate specific directions. For example, appropriate design should allow users to set goals and record achievements for physical exercise but should not specify when, how, and how long to exercise. However, it is also important to be careful when design allows users to make a clinical decision (Wu et al., 2017). The adoption of the mHealth app provides knowledge about the disease and how to use the technology for disease management. It enhances the health and digital literacy of diabetic patients. An mHealth app contributes to higher emotional bonding, increasing patients' attachment to the app. Prior studies show that low self-esteem for chronically ill individuals significantly hinders self-management and coping behaviors (Bedrov & Bulaj, 2018). Low self-esteem also creates a sense of self-stigma and reflects poor self-reflection (Corrigan et al., 2006).

Our mHealth app facilitates patients in various stages of decision-making. While using the app, patients are continuously aware of the required activities such as daily exercise, blood glucose monitoring, and regular medications. The reminder and alert system elevates awareness and persuades patients to make decisions regarding the behavior. Besides, helpful links to useful websites for diabetes management enhance the knowledge level of users and help them make rational and educated decisions. Finally, the visual cues in the app always nudge patients to active by practice self-care behavior. According to Fogg, imposing behavior change hardly gets successful; instead, one should help patients change where patients want to bring changes. In our design, we include non-judgemental and motivating messages and show a sense of accomplishment to enhance users' self-esteem.

2.6.5 Design Principle 5: Patient Engagement

Patient engagement design principle refers to direct and persistent interactions between patients and technology for self-care management. Patient engagement is a prerequisite to improving patient-centered care. It positively affects health outcomes. While patients have access to various technologies, engaging them with a particular technology (e.g., mHealth) is critical to the effectiveness of the intervention. Patient engagement is “the process of building the capacity of patients, families, carers, as well as health care providers, to ease and support the active participation of patients in their care, to enhance safety, quality and people-centeredness of health care service delivery” (WHO, 2016). Examples of patient engagement may include the number of times they log in, check notifications, the amount of time spent, and various functionalities using features. (Li et al., 2022) found that such engagements with the mHealth app are positively associated with low depressive symptoms. Cheikh-Moussa et al. (2020) also found that higher patient engagement with mHealth interventions results in better outcomes with chronic cardiometabolic diseases. They also found that smartphones with reminders improve patient engagement.

Gamification has been widely used to enhance user engagement with technology. It is "the use of game elements and the process of game-thinking and game mechanics to engage users and solve problems" (Lee & Jin, 2019). It has been found helpful in various sectors such as education, health, task management, user-generated content, etc. (Deterding, 2012). The Gamification framework is a combination of mechanics (rules and rewards), dynamics (intrinsic motivators), and aesthetics (end-user response outcomes) (Kuo & Chuang, 2016). Several factors contribute to the rise of gamification, such as cheaper technology, tracking personal data, availability of gaming mediums, etc. (Deterding, 2012). Gamification can influence human motivation and behavior change (Zichermann & Cunningham, 2011) and enhance user engagement (Kuo & Chuang, 2016). It provides a better user experience for interactive systems (Seaborn & Fels, 2015). Evidence from the implementation of a gamifying environment in a website demonstrates that gamification promotes user attraction, motivation, engagement, and retention with the activities (Kuo & Chuang, 2016). In marketing, gamification is considered a next-generation customer engagement method (Zichermann and Cunningham, 2011). Organizations will increasingly focus on gamifying different aspects of the business to manage innovation processes (Gartner, 2015)[20].

While players/users of the system use extrinsic factors of motivation, such as rewards, to change short-term behavior, intrinsic factors of motivation, such as autonomy, are used for long-term behavioral change, known as meaningful gamification (Nicholson, 2015). Meaningful gamification leads to behavior changes that can be both short-term and long-term. Nicholson (2012)advocates using user-centered meaningful gamification to affect long-term changes. Nicholson (2015) provided six concepts to guide meaningful gamification - Reflection, Exposition, Choice, Information, Play, and Engagement (RECIPE). Kim (2015) supported the design of gamified applications with a clear goal, user types, and user variables such as gender, age, and culture. Often gamified applications fail to fetch desired user engagement due to copycat applications without appropriately adapting to the specific context (Kankanhalli et al., 2012). The learning style of users to process information affects gamification outcomes. Aligning between player types and learning styles in gamification provides an adaptive framework to augment

[20] https://bit.ly/3uIT5js

players' performance (Abdollahzade & Jafari, 2018). Park et al. (2019) designed, developed, and evaluated theory-grounded gamified design for training and learning and found significant improvements in learning outcomes and user engagement.

Gamification has recently become a popular way to produce positive behavior change in healthcare (Faiola et al., 2019). Evidence from the use of gamified mHealth app indicates that it contributes to the improvement of compliance behaviors for the self-management of Type 1 diabetes among adolescents (Cafazzo et al., 2012). The study shows that gamification of the mHealth app leads to positive outcomes in improving self-management of chronic illness (Miller et al., 2016). Table 4 summarizes selected research publications on gamification in health and healthcare.

Table 4: Selected papers on gamification in health and healthcare

Source	**Findings**
(Floryan et al., 2019)	Articulated theory-driven gamification principles for internet-based interventions.
(Garett & Young, 2019)	pointed out the efficacy of smartphone-based applications in delivering medical education online
(Cechetti et al., 2019)	Investigates mHealth-based monitoring for people with hypertension by two designs – one with the game elements and one without game elements. The result showed that the intervention group with gamified elements spent more time with the app and maintained greater control of their health.
(Fang et al., 2019)	In this randomized controlled trial, the authors develop a novel exercise intervention with gamification to help reduce overweight and obesity in children. The intervention improved metabolism, health behaviors, and anthropometric measures.
Floryan et al., 2019	Articulated five independent yet interrelated gamification principles – meaningful purpose, meaningful choice, supporting player

	archetypes, feedback, and visibility – for digital health interventions. The study found support for the validity of the principles.
(Harris, 2019)	The study explores the effect of a community-wide gamified intervention named "Beat the Street" for physical activity. A pretest and posttest analysis found that gamification technique decreases physical inactivity and increases behavior change. The study was conducted for two years.
(D. Liu et al., 2017)	In this seminal paper, the authors explicate the notion of gamified information system and develop design framework to create meaningful engagement for users in the system. Then the authors articulate a set of design principles for such gamified information systems.
(Acquadro & Arnould, 2017)	In this conceptual paper, the authors reaffirm the usefulness of gamification with various digital platforms (e.g., smartphone, tablets, and computers). However, gamification was found to be effective for short-term user engagement.
(Pernencar et al., 2018)	The authors design a mobile application involving gamification techniques to prevent obesity among adolescents. In this preliminary study, the authors explore design guidelines and evaluate user experience with the interface.
(Pramana et al., 2018)	The results show that patients using gamified design have higher usage patterns and spend more time in-app than non-gamified mHealth systems.

Malone (1981) argues that people engage in an intrinsically motivated activity if they do it for their own sake, not for external rewards (e.g., money or status). This theory has links to the use of game elements and mechanics as 'motivational drivers' and has three core elements that drive an individual's motivation: challenge, fantasy, and curiosity. Challenge permits users to develop a sense of efficacy and competence. Challenging goals, uncertain outcomes, and performance feedback systems test the user’s capability and enhance self-esteem. Fantasy creates a mental image of things unavailable within the user's real experience. Factors such as metaphors, in-game characters, and avatars present emotional appeal to the user. Curiosity occurs when the user feels a sense of insufficient knowledge gap (cognitive curiosity) or feels a sense of sensory stimulations (sensory curiosity). Sound, visual effects, randomness, complexity, and incomplete knowledge increase users' curiosity.

Self-Determination Theory (SDT) depicts the intrinsic motivation of human beings as an inherent tendency to embrace novelty and challenges for using one’s capacity, which influences mental health, behaviors, and well-being (Ryan & Deci, 2000). In gamification, SDT is a practical framework for users’ motivation and learning outcomes (Bovermann & Bastiaens, 2020; Liu, Santhanam, & Webster, 2017). This theory is also applied to the motivational pull of video games and predicts changes in users' well-being, enjoyment, and preference (Ryan et al., 2006). SDT argues that three intrinsic psychological needs promote motivation: 1) autonomy – the need for freedom and meaningful choice to choose users’ goals and activities; 2) competence – the need to gain mastery through overcoming difficulty levels of tasks that enhances one’s abilities; 3) relatedness – the need to connect to others and compare one’s performance with peers.

With the practical lens considering the health and digital literacy of medically underserved populations and the theoretical framework of Malone’s motivational driver and Self-determination theory, we integrated the gamified features to design and develop our mHealth app for diabetes self-management. We argue that the gamified design of the mHealth app engages users in diabetes self-care behaviors and contributes to behavior change. We implemented points, badges, progress, and club membership in the design as aspect of gamification. For example, the user earns 10 points for the successful accomplishment of each activity. A progress bar shows what activities have been achieved and what have not. A daily badge is awarded if all the activities are completed for the day. The accumulated badges qualify users to get membership in clubs. There are five clubs – warrior, captaincy, governor, presidency, and elite. The number of badges earned helps the user ladder up club membership.

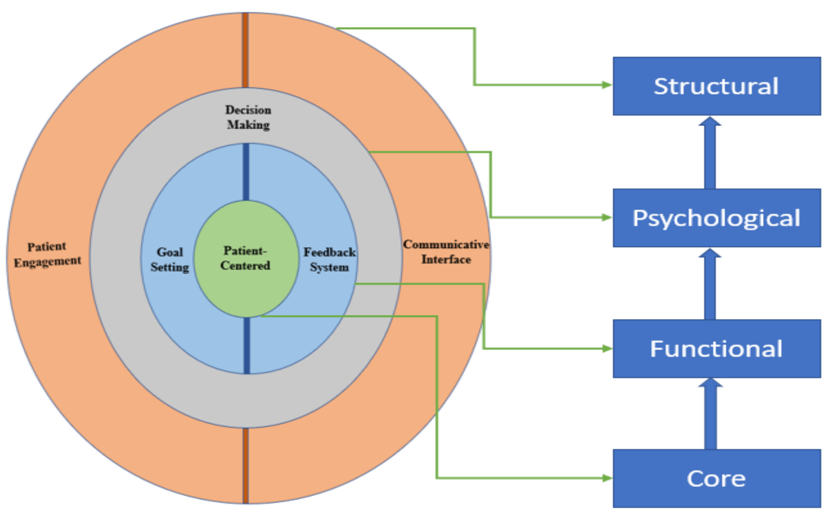
2.6.6 Design Principle 6: Communicative Interface

An effective design enables users to interact with design components (e.g., looks, styles, terminology) intuitively and effortlessly. A study on pregnant working women who used the mHealth *Pregnancy and Work* app has identified 82 problems with usability and revealed that the significant challenge for usability is associated with the interpretation of the terminology (van Beukering et al., 2019). Technology Acceptance Model (TAM) posits that ease of use affects the user's intention to use and perceived usefulness (Venkatesh, 2000). Perceived ease of use is "the extent to which a person believes that using a technology will be free of effort." According to Hick's law, the number of choices available to users and the time spent deciding to use them occur in a logarithmic fashion (Chapman et al., 2016). In other words, the more the number of items to choose from, the longer the response time is for the users (Lowdermilk, 2013). According to the chunking principle, objects adjacent to each other are perceived as more related than objects far apart (Chapman et al., 2016). An appropriate design should place all self-care activity objects as a chunk to make them easily accessible. It also minimizes cognitive load on the user.

The communicative interface design principle relates to the consistency of functionalities, easy accessibility, and ease of use. To ensure a comfortable user experience and enhance the design's usability, it is crucial to communicate various design features seamlessly with the patient. The design should emphasize better usability by avoiding clutter and confusion in the workflow.

Keeping in mind the language and literacy skills of MUP, our mHealth app interface features large and easy-to-read text, low information density, visual cues, and easy-to-navigate screens. Following Rao and Ramey (2011), both verbal and written communication are provided to enhance accessibility. A vocalization feature enables users with limited reading skills to use the app without challenge. Users can complete the tasks in the application as expected. The consistency of functionalities emphasizes that users do not need to face unknown workflows to complete tasks. The interface creates mental models and metaphors rooted in users' knowledge. Finally, the design requires users to use minimal time and effort to enter, view, and change the data points.

Figure 2.8. Interlinks Among Design Principles



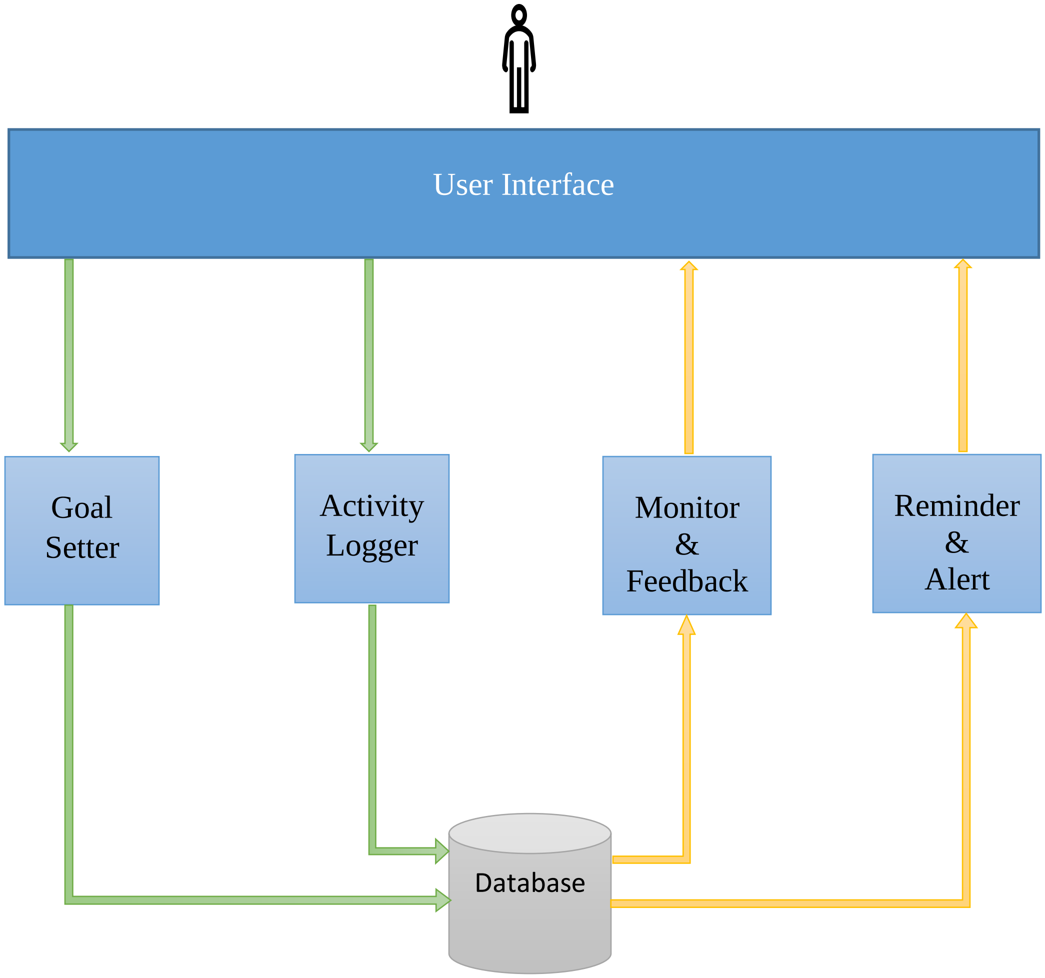
In summary, Figure 2.8 shows the interlinks among the design principles. The core of the diagram is the patient's need, while goal setting and feedback systems comprise the functional aspect of diabetes self-management. Decision-making is an all-encompassing design principle that involves the patient to decide what to do and what not to do. Finally, the mHealth app includes structural features- patient engagement and communicative interface - to motivate patients to interact with the app.

2.7 System Architecture

2.7.1 System Architecture

System architecture represents a conceptual model of system components, behaviors, and interrelationships among the components. It describes the system structure and the requirements for the system to function. The system architecture of our mHealth app is comprised of three layers (Figure 2.9). In the top layer, the user interacts with the system using the user interface. In other words, it establishes connections with the users through the views. In the middle layer, a user sets goals based on the ADCES7 self-care behavior framework, keys in daily performances against those goals, sets reminders, adds medicines, and monitors the goals' progress. A user also views the tracker to read individual and aggregate results. The app system sends two notifications – one in the morning and the other in the evening – about goals and daily performances. The user can also set custom goals and schedule reminders to enable them to keep track of events helpful in managing diabetes. The system uses the user's health data (e.g., blood glucose level) to create necessary alerts. It empowers the user to manage their health condition actively. In the bottom and final layer, the database stores, monitor, and send feedback for the user inputs. The database mainly does two functions. First, it stores user credentials, goals, and daily user inputs. Second, it delivers data to the prototype to compare daily inputs against the goals and provide alerts and reminders to the users.

Figure 2.9. System Architecure



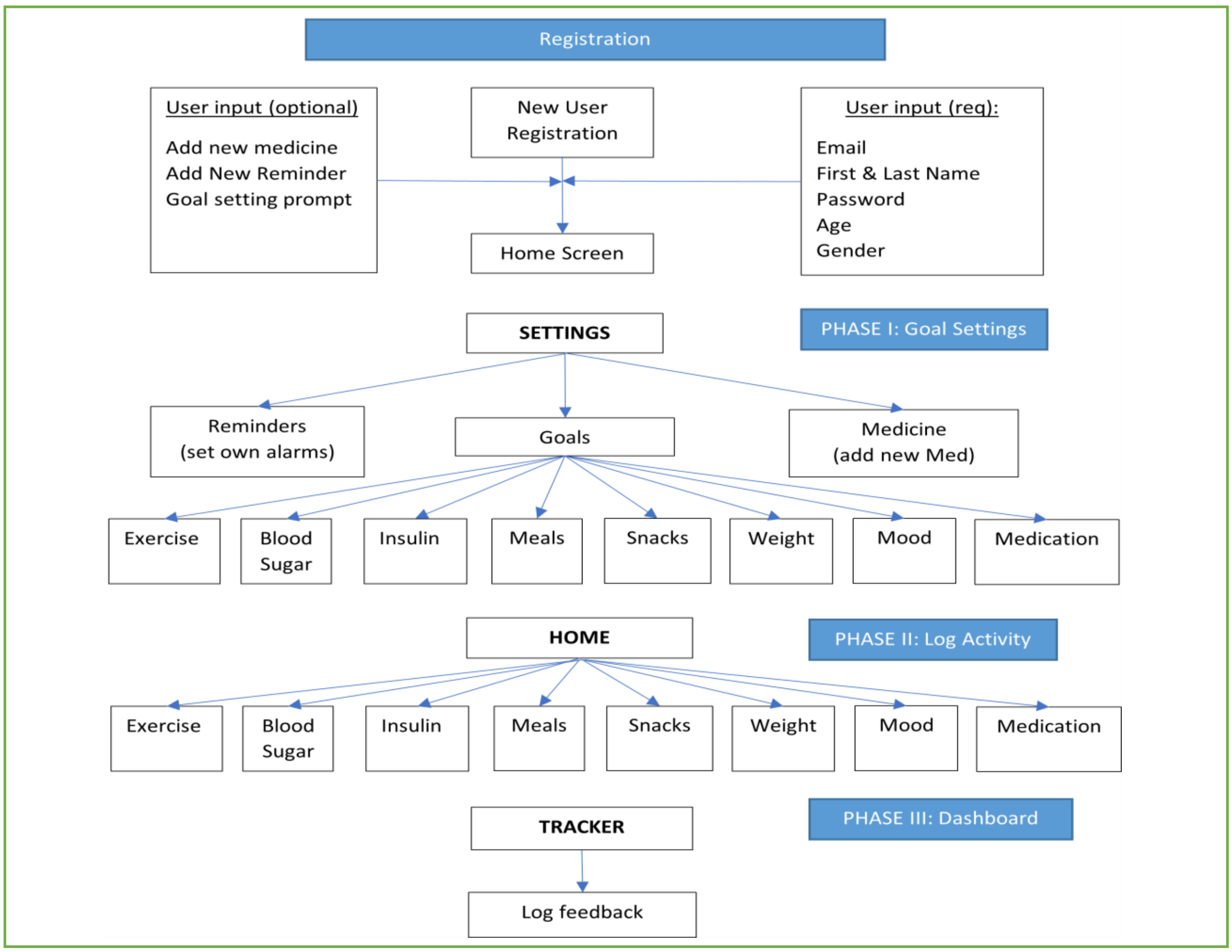
The app was developed using Android Studio 3.5 (updated to 4.2.2 during development) and supports most smartphone devices. It is compatible with Android 4.1 through Android 10 and can be updated to Android 11 if necessary. Google Firebase 16.0.9 (core firebase functionality) and Firestore 17.1.2 (cloud storage) store data. The database is HIPAA compliant and uses encryption to protect patient data.

2.7.2 User Journey

Figure 2.10. documents the user journey . After the registration process, the user lands on the home screen with three navigation options – setting, home, and tracker. The setting screen allows users to change goals and set customized reminders. It also shows daily earned badge for the whole

week. Users can also check their club membership from setting screen. The tracker screen is similar to a dashboard where users can read about performances. It shows the most recent data entry and average value wherever applicable. Finally, the home screen hosts icons with label to log input for various self-care activities. It also shows the progress bar and earned points and badges.

Figure 2.10. System Architecure



2.7.3 Prototype

Figures 2.11 and 2.12 show sample screenshots of the prototype. Using the above design principles, theoretical framework, and ADCES7 guidance, we designed the prototype for diabetes self-management for the MUPs (Murad et al., 2020).

Figure 2.11. Prototype

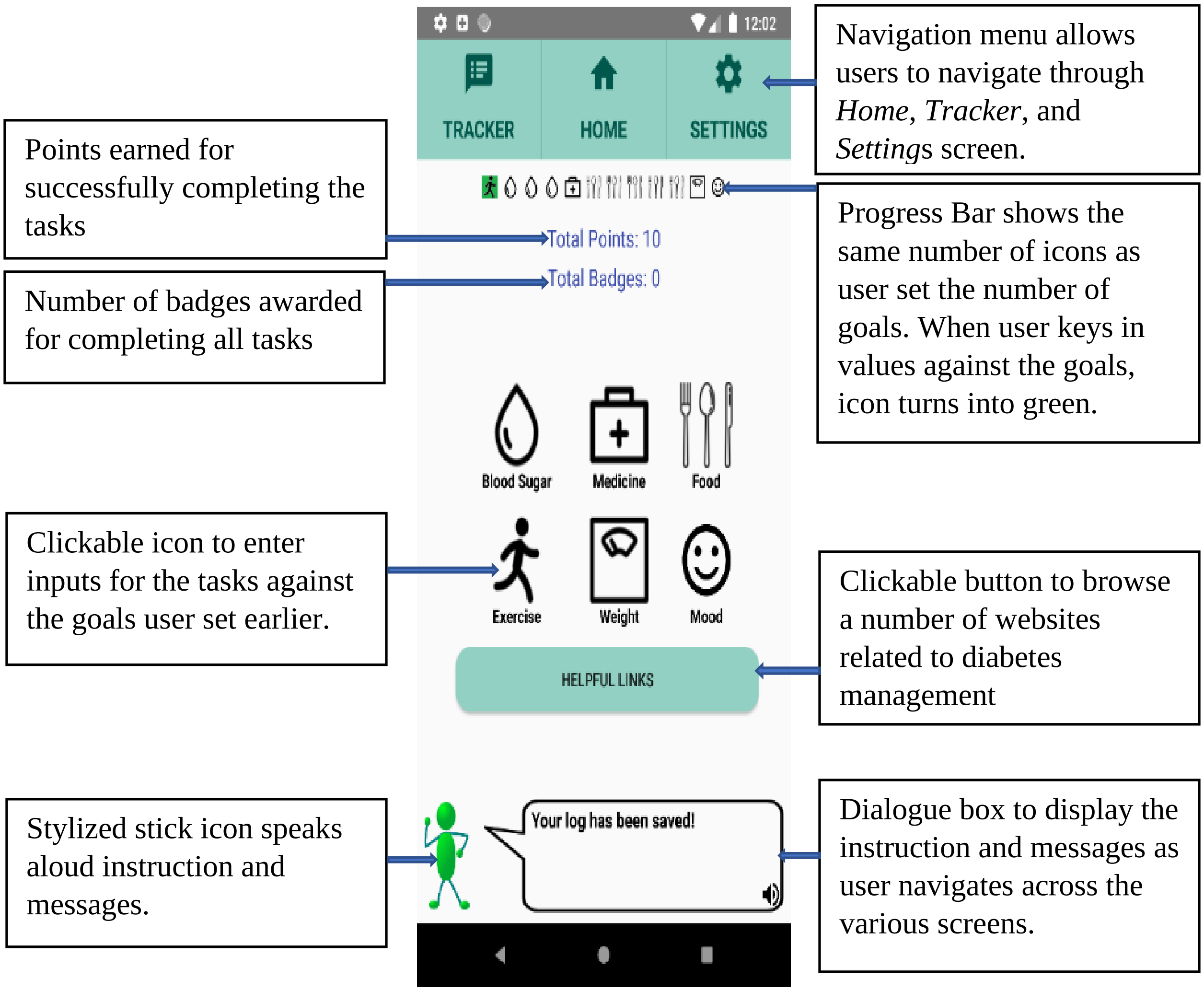
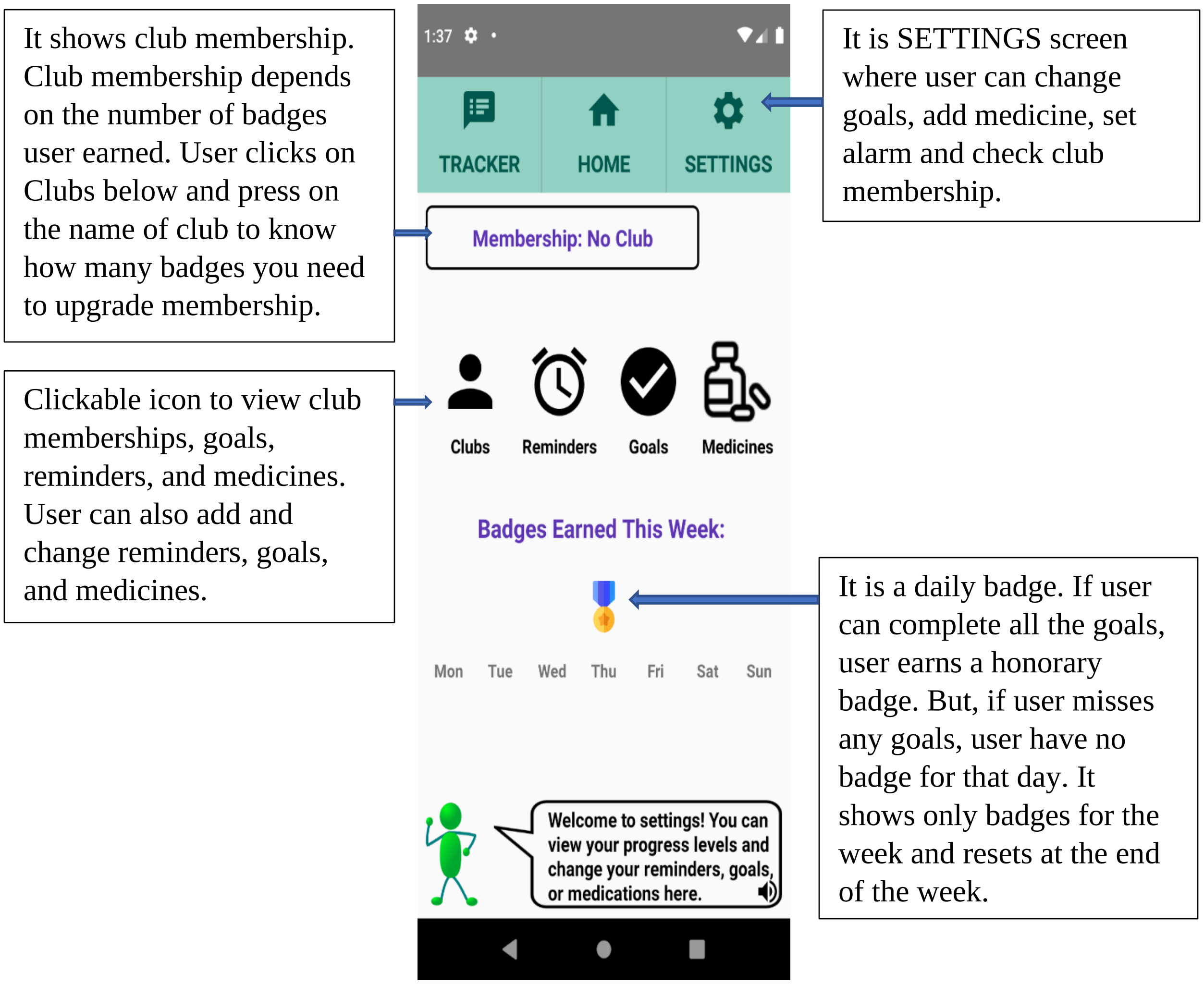


Figure 2.12. Prototype



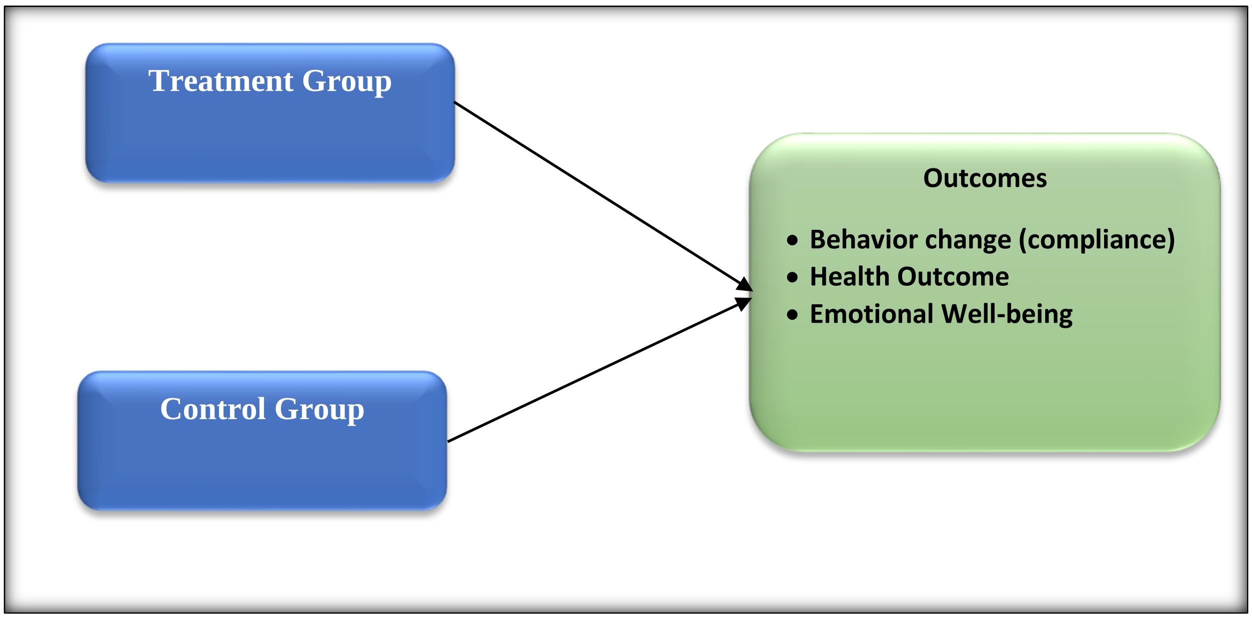
2.8 System Evaluation

The functionalities and effectiveness of the prototype are evaluated in three phases – initial testing, pilot study, and field experiment. The first phase included the views of experts and their knowledgeable insights. This phase aimed to fix the bugs, validate the user inputs, upgrade versions, and finally identify areas to improve the initial prototype. The second phase involves conducting a pilot study with actual patients on a small scale. We plan to recruit ten patients from MUPs and ask them to use our mHealth app for seven days. The main objectives of this phase are to understand how actual patients react to the design and collect feedback to improve further in the final version. We design a set of open-ended questions to ask the users after the pilot study. The third and final phase involves conducting a field experiment. Appendix A presents relevant questionnaires used for this study. We detail the procedure as follows:

2.8.1 Experimental Design

To evaluate the effects of the mHealth app on compliance with ADCES-recommended diabetes self-care behavior, emotional well-being, weight, and HbA1c, we will conduct a field experiment. The experiment will be based on type 2 diabetes patients from medically underserved populations, with 100 subjects randomized into a treatment group and a control group. In the treatment group, subjects will use an mHealth app designed specifically for this study. The subjects in the control group will continue to manage their diabetes as usual without receiving any mHealth-based support directly from the study. Specifically, the treatment group will use the app and receive reminders and alerts through it, while the control group will not use it nor receive any direct information on managing diabetes. The use of the mHealth app in the treatment group is expected to positively correlate with self-care behaviors and emotional well-being and negatively correlate with HbA1c and BMI (Body Mass Index). Thus, it will be crucial to assess whether the HbA1c level has decreased and diabetes self-management has improved among the treatment group. Figure 2.13 shows the conceptual framework of the system evaluation.

Figure 2.13. Conceptual Model for Evaluation



2.8.2 Procedure

Subjects of the experiment will be recruited through a local hospital. A recruitment flyer will be sent to prospective participants who are enlisted in the hospital database. We will randomize the subjects into the treatment group and control group. We then briefly explain the study's objectives and to-dos, including the main functionalities of the mHealth app for the experiment group. We create a written script to avoid variations in the explanation and maintain consistency during the briefing. For the duration of the experiment (3 months), users in the treatment group will receive reminders and/or prompts twice a day (8 am and 8 pm Central Time) through the mobile app about their daily goals (five goals for five functions every day). The users themselves will set these goals.

For example, participants set a goal to do physical exercise for 20 minutes daily, which amounts to 140 minutes per week. On a daily basis, they will key in the amount of time they spend on physical exercise. The mobile application will provide feedback to patients based on self-reported data entry. The subject will require approximately 10 minutes every day to accomplish the tasks in the app. The control group will not use any mobile app for diabetes management. The procedure of the experiment was approved by the Institutional Review Board (IRB). Based on the previous related studies, we expect that the difference in HbA1c will be a size of 0.4 or more between treatment groups and control groups (Peimani et al., 2016).

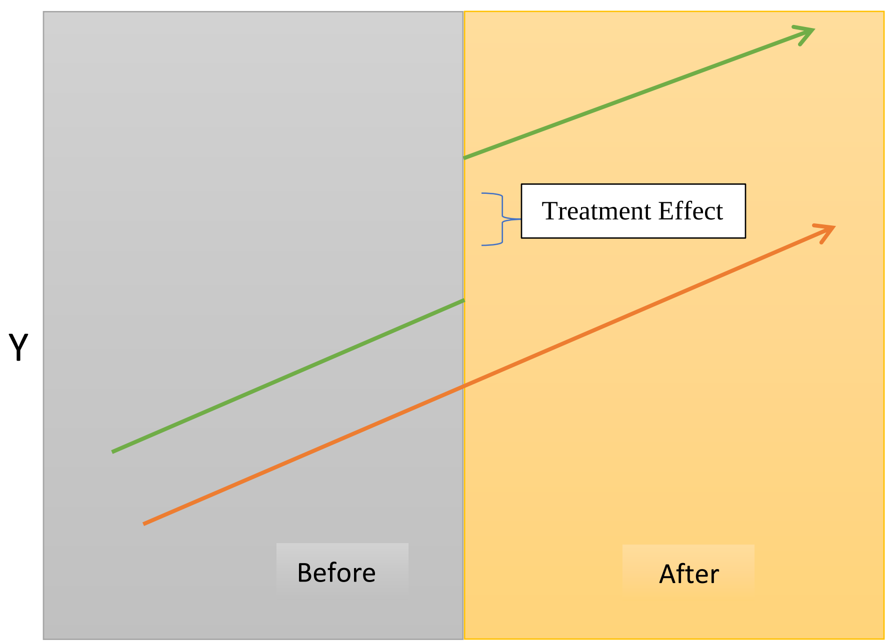
2.8.3 Variables and Measurement

The evaluation phase is based on a set of diabetes-related measures for both the treatment and control groups. First, compliance with diabetes self-care behaviors will be measured by the Summary of Diabetes Self-Care Activities (SDSCA) questionnaire on a scale from 0 to 7. Second, we will assess the subjects' emotional well-being with two emotion questionnaires – Problem Areas In Diabetes (PAID) and Diabetes Distress Scale (DDS). Finally, the average blood sugar (HbA1c) value will be collected from the hospital patient record. To compare the treatment's effects, we will conduct all the surveys at the beginning and the end of the experiment. After conducting the reliability and validity check of the questionnaires, we will use the difference-in-differences (DID) technique to ascertain the effects of the treatment by comparing the changes in the dependent variable over time between the treatment group and the control group. For the comparison between the treatment group and control group in terms of HbA1c, we will estimate the following model:

$$y_{it} = \beta_0 + \delta_0 after_{it} + \beta_1 treated_{it} + \delta_1 after_{it} * treated_{it} + u_{it}$$

where *y* is HbA1c; *after* is the post-intervention period; *treated* is the patient who received the intervention, and *u* is the disturbance term. The coefficient of interest is δ_1, which represents the DID effect or the effect of treatment on the outcome. It is the difference in outcomes between after and before for the treated units and after and before for the control units. Given our hypothesis, we expect coefficient δ_1 to be significantly positive. The following figure graphically shows the treatment effects (Figure 2.14).

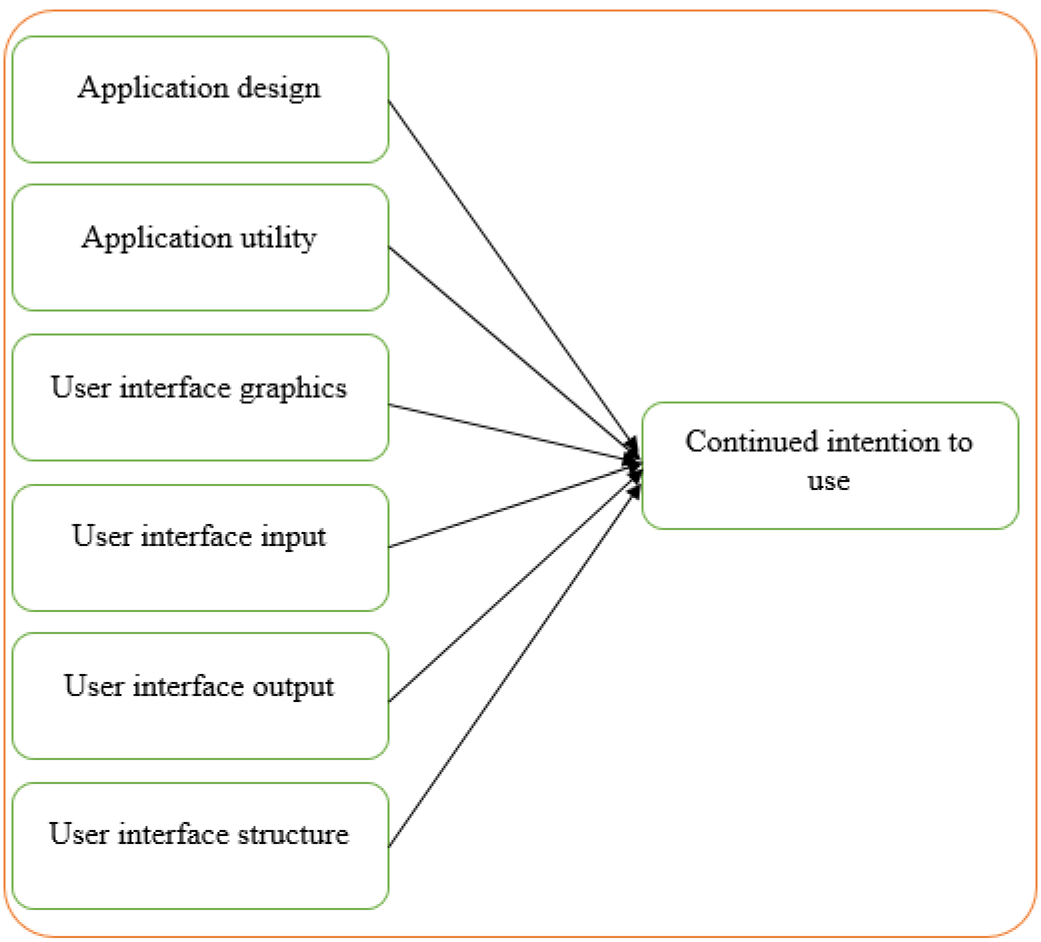
Figure 2.14. Treatment Effect



We will check the robustness of the above model in three phases. *First*, the baseline data will be compared between the two groups using t-tests and the Chi-Square test. *Second*, the pre-and post-intervention will be tested by paired t-test. *Third*, an analysis of covariance (ANCOVA) will be conducted to evaluate the differences between groups using the pre-intervention measures as covariates. The DID technique relies on the parallel trend assumption, which requires that the difference in outcome between the treatment and control group remains the same in the absence of the treatment. We will test this assumption by including the lags and leads of the treatment variable in our model.

To assess the usability of the mHealth app for the treatment group, we will utilize a validated questionnaire (Agarwal & Venkatesh, 2002). After checking the reliability and validity of the measurement scale, we will run a statistical model. Figure 2.15 shows the independent and outcome variables.

Figure 2.15. Usability Model



2.9 Discussion

Diabetes is the seventh leading cause of death in the U.S. Diabetes-related death increased by 14% in 2019-2020 due to delays in care delivery during the pandemic (CDC, 2021). While the cost of diabetes care accounts for 1 in 4 dollars of healthcare expenses (Riddle & Herman, 2018), the terrible consequences of diabetes limit the course of life and create dreadful marks on the emotional state of the patient. Disparities in diagnosed diabetes constitute a significant challenge. CDC reported that non-Hispanic black (black), Hispanic, and poorly educated adults are more vulnerable to diabetes than other segments of the population (Beckles & Chou, 2016). Diabetic patients with low socioeconomic status struggle to adhere to recommended self-care behaviors due to their lifestyle and limited health and digital literacy. Patient-centered self-management activities that focus on recommended self-care behaviors rather than only medication can substantially help improve patients' health outcomes and delay or help avoid the debilitating effects of diabetes (Savoli et al., 2020).

mHealth technology promises new opportunities to improve patient-centered care delivery and helps to enhance compliance with diabetes self-care behaviors (Shaw et al., 2020). Through telemedicine, app-based monitoring, reminders and alert systems, patient portals, and access to online health communities, mHealth technology facilitates the adoption of pro-diabetes self-care behaviors (Brohman et al. 2020; Shaw et al. 2020; Jiang and Cameron 2020). While mobile technology can help marginalized populations with diabetes self-management, our understanding of what factors influence their intention to adopt mobile technology is limited. Furthermore, past research on IT-enabled self-management for chronic care lacks a robust theory (Jiang & Cameron, 2020).

We designed a prototype of the mHealth application for diabetes self-management targeting MUPs. While our target population widely uses mobile technology in daily communication, using mHealth for diabetes self-management is limited. Design without the reflection of end-users characteristics tends to fail to derive the expected behavioral and health outcomes. To inform the design of the appropriate prototype, we articulated six design principles – patient-centered design principle, goal-setting design principle, feedback system design principle, decision-making design principle, patient engagement design principle, and communicative interface design principle. These design principles are rooted broadly in chronic illness management, motivation, system development, and the tenets of motivational and behavioral theories (e.g., goal-setting theory, feedback intervention theory, Fogg's behavioral model, transtheoretical model of behavior, and self-determination theory). The interrelationship of the principles implies that the core of the design is the patient, where goal setting and feedback systems represent functional aspects. Decision making principle demands psychological effort from the patient and encompasses the functional area. Finally, patient engagement and communicative interface involve structural dimensions that facilitate the interaction between the mHealth and the patient. We incorporated them in the iterative process of the design. We argue that designing and developing a mHealth app with these design principles would enhance compliance with diabetes self-care behaviors and improve health outcomes for medically underserved populations.

2.10 Expected Contributions

We expect our study to make several contributions. We articulate six design principles based on motivational and behavioral theories to investigate diabetes self-management in medically underserved populations. We hope to validate the effectiveness of these principles. We expect that these design principles expand self-management literature, explicating the role of mHealth in chronic illness management. The study's practical contribution includes designing and developing the mHealth app targeting the characteristics and needs of MUPs. These people face difficulty accessing primary healthcare in the absence of a universal healthcare system. We expect that the use of the mHealth app will improve compliance and health outcomes. Finally, we hope our study improves health disparities by utilizing available technology. It is essential to have adequate health and digital literacy to maximize the effectiveness of IT-enabled self-management for patients with type 2 diabetes. We expect that our mHealth app, designed specifically for MUPs, will contribute to improving health and digital literacy. By using mobile technology for diabetes self-management, MUPs will be able to understand recommended self-care behaviors better.

2.11 Conclusion

Managing diabetes on one's own is a challenging task. Nevertheless, the advent of mobile technology can facilitate diabetes self-care behaviors and mitigate the problems associated with diabetes. While numerous studies have examined mobile technology for diabetes self-management in the literature, there are fewer studies that target marginalized populations, including MUPs. Due to their low socio-economic status, limited health literacy, and limited access to digital technology, they are at an increased risk. In order to fill this research gap, we investigated how to design and develop an appropriate mobile application that can meet the needs and characteristics of MUPs.

An objective of this study is to develop mobile technology-based interventions for improving diabetes self-management. We expect our design principles to guide practitioners in designing an appropriate mobile app to address chronic disease management. This research contributes to improving chronic illness management, thus reducing health disparities, a primary goal of population health management in the U.S.

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2.13 Appendix

Questionnaire

Pilot study

We are interested to know about your experience of using the mHealth app.

Functionality

1. Can you please tell us what you were generally doing on the app?
2. How comfortable do you feel using this mobile app?
3. How would you evaluate the quality of the app?
   [ease of use?]
   [usefulness?]
   [features?]
   [design?]

Challenges

4. Can you please tell us about your difficulties during the usage?
5. Are there any functionalities of the system that you did not like? Why?
6. Can you think of any unexpected experience that you had during your usage? If yes, can you describe what happened?

Expectations

7. Is there any other functionality you would like to add to the app (which presently does not exist)?
8. If you could continue using the app, would you do it? Why?
9. Is there anything else you would like to add regarding your experience with the app?

Outcomes

10. How did you manage your diabetes before using the app?
    [Exercising?]
    [Taking medications?]
    [Communicating with your nurse and doctor?]

[Looking for information?]

[Coping with emotional problems?]

11. Since you started using the app, what changes do you see in how you manage your diabetes as a result of using the app?

[Exercising?]

[Taking medications?]

[Communicating with your nurse and doctor?]

[Looking for information?]

[Coping with emotional problems?]

Summary of Diabetes Self-Care Activities (SDSCA) Questionnaire

The questions below ask about your diabetes self-care activities for the **past seven days**. If you were sick during the past seven days, please think back to the last seven days you were not.

Diet

1. How many of the last SEVEN DAYS have you followed a healthful eating plan?
0 1 2 3 4 5 6 7

2. On average, over the past month, how many DAYS PER WEEK have you followed your eating plan?
0 1 2 3 4 5 6 7

3. On how many of the last SEVEN DAYS did you eat five or more servings of fruits and vegetables?
0 1 2 3 4 5 6 7

4. On how many of the last SEVEN DAYS did you eat high fat foods such as red meat or full-fat dairy products
0 1 2 3 4 5 6 7

Exercise

5. On how many of the last SEVEN DAYS did you participate in at least 30 minutes of physical activity? (Total minutes of continuous activity, including walking).
0 1 2 3 4 5 6 7

6. On how many of the last SEVEN DAYS did you participate in a specific exercise session (such as swimming, walking, biking) other than what you do around the house or as part of your work?

0 1 2 3 4 5 6 7

Blood Sugar Testing

7. On how many of the last SEVEN DAYS did you test your blood sugar?

0 1 2 3 4 5 6 7

8. On how many of the last SEVEN DAYS did you test your blood sugar the number of times recommended by your health care provider?

0 1 2 3 4 5 6 7

Foot Care

9. On how many of the last SEVEN DAYS did you check your feet?

0 1 2 3 4 5 6 7

10. On how many of the last SEVEN DAYS did you inspect the inside of your shoes?

0 1 2 3 4 5 6 7

Smoking

11. Have you smoked a cigarette – even one puff – during the past SEVEN DAYS?

0. No 1. Yes

12. If yes, how many cigarettes did you smoke on average? Number of cigarettes:---------

Overall

13. How many of the last SEVEN DAYS have you effectively followed your overall diabetes self-care activities?

0 1 2 3 4 5 6 7

Problem Areas In Diabetes (PAID) Questionnaire

Which of the following diabetes issues are currently a problem for you?

Items	Not a problem	Minor Problem	Moderate Problem	Somewhat serious problem	Serious problem
1. Not having clear and concrete goals for my diabetes care?					
2. Feeling discouraged with my diabetes treatment plan?					
3. Feeling scared when I think about living with diabetes?					
4. Uncomfortable social situations related to my diabetes care (e.g., people telling you what to eat)?					
5. Feelings of deprivation regarding food and meals?					
6. Feeling depressed when you think about living with diabetes?					
7. Not knowing if my mood or feelings are related to my diabetes?					
8. Feeling overwhelmed by my diabetes?					
9. Worrying about low blood sugar reactions?					
10. Feeling angry when you think about living with diabetes?					
11. Feeling constantly concerned about food and eating?					
12. Worrying about the future and the possibility of serious complications?					
13. Feelings of guilt or anxiety when you get off track with my diabetes management?					
14. Not “accepting” my diabetes?					
15. Feeling unsatisfied with my diabetes physician?					
16. Feeling that diabetes is taking up too much of my mental and physical energy every day?					
17. Feeling alone with my diabetes?					
18. Feeling that my friends and family are not supportive of my diabetes management efforts?					
19. Coping with complications of diabetes?					

20. Feeling “burned out” by the constant effort needed to manage diabetes?					
21. Overall, having diabetes is					

Diabetes Distreses Scale

Items	**Emotional Burden (5 items)**	**Physician Related Distress (4 items)**	**Régimen Related Distress (5 items)**	**Diabetes Related Interpersonal Distress (3 items)**
1. Feeling that diabetes is taking up too much of my mental and physical energy every day				
3. Feeling angry, scared, and/or depressed when I think about living with diabetes.				
8. Feeling that diabetes controls my life.				
11. Feeling that I will end up with serious long-term complications, no matter what I do				
14. Feeling overwhelmed by the demands of living with diabetes.				
2. Feeling that my doctor doesn’t know enough about diabetes and diabetes care				
4. Feeling that my doctor doesn’t give me clear enough directions on how to manage my diabetes				
9. Feeling that my doctor doesn’t take my concerns seriously enough.				
15. Feeling that I don’t have a doctor who I can see regularly about my diabetes				
5. Feeling that I am not testing my blood sugars frequently enough.				
6. Feeling that I am often failing with my diabetes regimen.				
10. Not feeling confident in my day-to-day ability to manage diabetes.				
12. Feeling that I am not sticking closely enough to a good meal plan.				
16. Not feeling motivated to keep up my diabetes self-management.				

7. Feeling that friends or family are not supportive enough of my self-care efforts (e.g., planning activities that conflict with my schedule, encouraging me to eat the "wrong" foods).				
13. Feeling that friends or family don't appreciate how difficult living with diabetes can be				
17. Feeling that friends or family don't give me the emotional support that I would like				
18. Overall feeling that diabetes distresses me.				

Mobile Application Usability Questionnaire

The following statements measure mobile application usability. Please express your agreement to what extent you disagree or agree for each statement by ticking a bubble as

- **1 = Strongly disagree**
- **7 = Strongly agree.**

Application Design:

Statements	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Overall, I think this mobile application is designed well.	○	○	○	○	○	○	○
In general, I believe that this mobile application has a great design.	○	○	○	○	○	○	○
Generally speaking, this mobile application is well designed.	○	○	○	○	○	○	○
I am very satisfied with the overall design of this mobile application.	○	○	○	○	○	○	○

Application Utility:

Statements	**1**	**2**	**3**	**4**	**5**	**6**	**7**
To me, this mobile application is very functional.	○	○	○	○	○	○	○
Overall, I think that this mobile application is useful.	○	○	○	○	○	○	○
Generally speaking, this mobile application serves its purpose well.	○	○	○	○	○	○	○
In general, I believe that this mobile application is of value to me.	○	○	○	○	○	○	○

User interface graphics:

Statements	1	2	3	4	5	6	7
Overall, I think that the graphics displayed on this mobile application are designed effectively.	○	○	○	○	○	○	○
In general, the interface graphics of this mobile application are designed well.	○	○	○	○	○	○	○
Generally speaking, I like the graphics displayed on the interface of this mobile application.	○	○	○	○	○	○	○
Overall, this mobile application has very good user interface graphics.	○	○	○	○	○	○	○

User Interface Input:

Statements	1	2	3	4	5	6	7
In general, this mobile application allows me to input data easily.	○	○	○	○	○	○	○
Overall, the user input mechanisms are designed effectively on this mobile application.	○	○	○	○	○	○	○
I am very satisfied with the input mechanisms of this mobile application.	○	○	○	○	○	○	○
Generally speaking, it is easy to type in data into this mobile application.	○	○	○	○	○	○	○

User interface output:

Statements	1	2	3	4	5	6	7
In general, the content of this mobile application is presented effectively.	○	○	○	○	○	○	○
Overall, I believe that this mobile application presents contents very well.	○	○	○	○	○	○	○
Overall, I think that this mobile application presents content effectively.	○	○	○	○	○	○	○
I am very satisfied with the way that this mobile application presents content.	○	○	○	○	○	○	○

User interface structure:

Statements	1	2	3	4	5	6	7
Overall, I think this mobile application structures information effectively.	○	○	○	○	○	○	○
In general, this mobile application is structured very well.	○	○	○	○	○	○	○

I am very satisfied with the way this mobile application is structured.	○	○	○	○	○	○	○
Generally speaking, this mobile application is structured nicely.	○	○	○	○	○	○	○

Continued intention to use:

Statements	1	2	3	4	5	6	7
I intend to continue using this mobile application.	○	○	○	○	○	○	○
I want to continue using the mobile application rather than discontinue.	○	○	○	○	○	○	○
I predict I will continue using this mobile application.	○	○	○	○	○	○	○
I plan to continue using this mobile application.	○	○	○	○	○	○	○
I don’t intend to continue using this mobile application in future.	○	○	○	○	○	○	○
Chances are high that I will continue using this mobile application in future.	○	○	○	○	○	○	○