2022

Community stress and resilience during covid-19: Assessing the emotional profile of the City of Hamilton using a social media analysis

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CHAPTER 1: USING SOCIAL MEDIA ANALYSIS TO INVESTIGATE STRESS AND RESILIENCE DURING COVID

by

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THESIS/DISSERTATION

Submitted to the Department/Faculty of Science

in partial fulfilment of the requirements for

Master of Arts in Psychology

Wilfrid Laurier University

Abstract

This study investigated stress and resilience at the neighbourhood level in Hamilton Ontario in pre- and peri-pandemic conditions using a social media analysis. Sentiment analysis of geo-located Twitter posts produced within Hamilton census tract boundaries was conducted using Stresscapes and EMOTIVE, validated software that extract and code emotional information from human language expressions about stress and hope (a proxy for stress), respectively. Baseline levels of both emotions were measured using aggregate scores at the census tract level in Hamilton from tweets produced during two pre-pandemic periods (March 2019 to July 2019; and August 2019 to February 2020), with a replication analysis corresponding to the first (March - July 2020), second (August 2020 - February 2021) and third (March 2021-July 2021) waves of the pandemic. The spatial distribution of stress and hope across the five time periods (pre- and peri-pandemic) was visualized using a geographic information system. Candidate explanatory variables (including COVID-19 cases count, visible minority status, educational attainment, household income, and household size) were examined for significant bivariate correlations with the change in stress emotions within neighbourhoods across pre- and peri-pandemic periods. Baseline hope was examined as an effect modifier of any significant relationships between explanatory variables and stress. Results suggest that variation between stress and hope emotions exist between Hamilton census tracts (n=30) over the five time periods. Among the explanatory variables, household size and household income displayed a strong bivariate correlation to stress; however, baseline hope did not modify the effect on stress of either variable.

Acknowledgements

This work could not have been done without the supervisory support of Ketan Shankardass; committee members, Michael Ungar and Todd Coleman; and the external examiner, Michelle Kondo. Their comments were helpful in improving this study. Thanks are also extended to Martin Sykora for running the Twitter data through EMOTIVE and Stresscapes and Penny Liu for obtaining the tweets from Twitter's Application Programming Interface. This research was funded in part by an Ontario Graduate Scholarship award and by the University Health Network.

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Introduction

Since its emergence in December 2019, the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that causes the COVID-19 disease has been a public health emergency warranting international concern (WHO, 2021). To date, there have been over 199 million confirmed cases globally, with over 4.2 million deaths (WHO, 2021). The burden of COVID-19 has been substantial with expenditures continuing to increase (Gebru, et al., 2021). While COVID has directly threatened and caused significant personal harm, public health interventions and government mandates such as stay at home orders and lockdowns designed to reduce the spread of the disease have also been a source of emotional distress.

Research on the associations between mental health, the pandemic, and public health measures has suggested that higher lockdown-related restrictions and increased levels of perceived life changes have been correlated with higher levels of psychological impairment (Benke, Autenrieth, Asselmann, & Pane-Farre, 2020). Overall, the direct and indirect mental health costs of the pandemic are substantial with Canadian data suggesting increased levels of stress, fear, deteriorating mental health (Dozois, 2020) and suicide (McIntyre & Lee, 2020). A recent review including international data suggests that the distribution of mental health challenges varies across the general public (Hossain et al., 2020). Variation in the burden of COVID is to be expected and additional research is needed to better understand emotional responses at the local level in Canada during COVID.

Previous research has investigated the influence of large-scale disasters and stressors on population mental health and wellbeing. Events such as mass shootings (Lowe & Galea, 2017), natural disasters (Beaglehole et al., 2018), infrastructure related calamities (Makwana, 2019) and biological disasters such as infectious disease outbreaks (Hsieh et al., 2021) contribute to several psychopathologies including PTSD, anxiety, depression, and increased substance use (North, 2016). Such disasters result in unexpected death and trauma and the associated threat of harm and danger can also induce profound personal stress (Norris, Friedman, Watson, Bryne & Kaniasty, 2002). Additionally, social processes are often disrupted during disasters with social networks, services, and access to communal resources being negatively impacted (Goldmann & Galea, 2014). This can hinder how well community members are able to adapt to disasters.

Despite the devastating effects of disasters, some communities are better able to adapt to these hardships than others (Braun-Lewensohn & Sagy, 2014). Resilience theory posits that positive contextual, social, and individual level factors can attenuate negative outcomes after adverse events (Cavaye & Ross, 2019, Rapaport et al., 2018). Community resilience focuses on the ability of a group to recover from an adversity (Berkes & Ross, 2012), and it can be understood as the process in which communities are able to galvanize supports and organize resources to thrive in a changing and uncertain environment (Norris et al., 2008). There have been urgent calls to focus on resilience during the pandemic (Vinkers et al., 2020). However, the literature on community resilience during COVID has been limited. Additional work is needed to explore how resilience plays out among community settings.

One possible reason for the dearth of literature on this topic may have to do with the methodological and logistic challenges of conducting such research. The unexpected nature of adversities makes it difficult to assess and ascertain a populations psychological profile in a timely fashion, and emotional states are highly variable, so multiple measurements are required to understand how profiles change over time. The use of cross-sectional designs is commonly used. However, the temporal ambiguity between exposure and outcome of stress and resilience of these studies limits causal inference. Establishing baseline levels of emotions retrospectively to compare to current and post disaster functioning can be unreliable and costly. Widespread displacement of people also makes it difficult to gather data on the experiences of those who are facing a disaster. Convenience sampling is often used during these times which may result in selection bias and impact the representativeness and generalizability of results (Pierce et al., 2020). Given these limitations, innovative approaches are needed to gather pre-disaster data to make comparisons to peri and/or post-disaster functioning.

One novel approach to studying community stress and resilience is by analysing the emotional content from large scale user-generated social media content. Social media allows for individuals to express their feelings towards internal or external events and circumstances, and this information can be valuable for understanding public sentiment. This method also provides dynamic insights into emotional expression and has been used to understand emotional reactions to terrorist attacks (Gruebner et al., 2016) and natural disasters (Gruebner et al., 2017). As well, it addresses many of the limitations associated with conducting research during and after disasters using more conventional methodologies.

This study will investigate the spatial distribution of community stress and resilience in Hamilton, Ontario in pre-pandemic and peri-pandemic conditions using social media analysis by:

1) Mapping differences that exist in the trajectories of pandemic related stress and resilience between Hamilton neighbourhoods (n=134).
2) Exploring how contextual neighbourhood characteristics (e.g., COVID-19 case count, health behaviours, visible minority population, education and neighborhood socioeconomic status) correlate with neighbourhood variation in stress.
3) Determining if higher neighbourhood resilience reduces the impacts on stress.

Literature Review

COVID-19 Pandemic

In December 2019, multiple patients in Wuhan, China were experiencing respiratory failure and pneumonia-like conditions with unknown etiology (Zhu et al., 2020). After intense contact tracing and deep sequence analysis, a wet animal market in the city is thought to be the origin centre of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that causes the novel coronavirus disease named COVID-19 (Mizumoto, Kagaya, & Chowell, 2020; Li et al., 2020). While the SARS-CoV-2 infection started as a localized outbreak in the city of Wuhan, the epidemic rapidly spread to a larger population of people living in several cities across China (Liu, Kuo, & Shih, 2020). The highly contagious disease has since become a global pandemic, with the World Health Organization declaring a Public Health Emergency of International Concern on March 11, 2020 (World Health Organization, 2020a). Currently, there had been over 199 million confirmed COVID-19 cases, with 4.2 million deaths around the world (WHO, 2021).

Infectious diseases have historically created significant catastrophes for communities around the world. Recent reports suggest that the emergence and resurfacing of highly transmissible and pathogenic infections are occurring at unprecedented rates (WHOb). Specifically, in the past 20 years, coronavirus-related diseases have increased in prevalence and have subsequently created a huge global burden to health care systems (De Wit, Van Doremalen, Falzarano, & Munster, 2016). In Canada, expenditures associated with infectious diseases have also been profound. For instance, a 2016 Canadian report suggested that 8.3 billion dollars is attributed to communicable diseases (including respiratory illnesses), with 44% of the total communicable disease costs representing indirect costs such as premature mortality, economic loss due to disability, and caregiving (Diener & Dugas, 2016). While these indirect costs can represent stressors associated with communicable diseases, the total estimates do not include “intangible costs" which consist of decreased personal well-being, emotional pain and suffering, and any other form of psychosocial injury that is difficult to derive economically (Diener & Dugas, 2016). The psychosocial sequalae of infectious disease are widespread and need to be considered in addition to the medical and clinical presentations of such illnesses. Further work is required to better understand how COVID-19 influences emotional distress as an intangible burden.

The development of an infectious disease requires the presence of an agent (disease-causing micro-organisms also known as pathogens), a host (an organism that carries the disease-causing agents), and an environment (external factors that affect the agent, the host, and interactions between the two). These elements and conditions known as the epidemiologic triad (Shinde et al., 2020). The epidemiological triad also provides an explanation for the spread of diseases (Tsui, Deng & Pan, 2020). For COVID, the environment would consist of contaminated areas and surfaces, respiratory droplets and any other variables that extrinsically influence the agent and allow for exposure to the host. The host would be an individual and their associated susceptibility attributes (as discussed below). Lastly, SARS-CoV-2 is the agent. To reduce the spread of COVID, disruptions need to occur in the interactions between the agent, host and environment (Tsui, Deng & Pan, 2020).

In terms of environment, various factors have been implicated in the transmission rate of COVID-19. While geographic variables such as humidity (Sajadi et al., 2020), location (Rovetta & Castaldo, 2020), and temperature (Wu, Yu et al., 2020) all appear to influence the spread of COVID-19, other social-environmental characteristics also influence the growth rate. For instance, population density (Kadi & Khelfaoui, 2020; Wong & Li, 2020), pollution (Fattorini & Regoli, 2020; Frontera, Martin, Vlachos, & Sgubin, 2020), and socioeconomic factors such as poverty (Finch & Hernández Finch, 2020) also seem to affect the spread and mortality rate of the disease.

There is also a strong body of literature demonstrating the profound effect of built environments on health outcomes (Fattorini & Regoli, 2020; Frontera et al., 2020; Pinter-Wollman, Jelić, & Wells, 2018; Reichert et al., 2020; Renalds, Smith, & Hale, 2010). Recent studies have also implicated built environments in shaping COVID-19 spread, with housing quality and living conditions being associated with death count due to the virus (Hu, Roberts, Azevedo, & Milner, 2021).

Epidemiological data from countries around the world suggests that the susceptibility to COVID-19 does not appear to be distributed equally at the individual/host level. Data from the United States Centres for Disease Control and the Chinese Centre for Disease Control and Prevention indicate that there are several sociodemographic risk factors and variables that appear to influence those who are at higher risk of contracting and succumbing to COVID-19. This includes psychological profile, comorbidities with other diseases and medical conditions, age, race, gender, immune status, occupation, nutritional intake, drinking behaviours, and substance use status (Koley & Dhole, 2020). Globally, emerging data from the onset of COVID-19 suggests that infection is more likely to occur in older males, with the median age ranging from 49- 59 years old (Chen, et al., 2020; Huang, et al., 2020; Wang, et al., 2020). As well, many COVID-19 patients have underlying comorbid health conditions including diabetes, kidney dysfunction, hypertension, or respiratory disease (Wu, Zunyou & McGoogan, 2020). Case-fatality during the onset has been highest among those over the age of 65 (National Center for Health Statistics, 2021; Yanez, Weiss, Romand, & Treggiari, 2020). It is important to note that the demographics of those who have gotten sick and those who have succumbed to the disease have changed during the pandemic, as has the spatial distribution.

While individual and environmental components of the epidemiologic triad have been discussed, it is also essential to review the pathogen component. The human-to-human route of transmission for COVID-19 consists of a person with the infection passing on the virus through respiratory droplets via sneezes, coughs, and even talking (Lotfi, Hamblin, & Rezaei, 2020; Parry, 2020; Riou & Althaus, 2020). These droplets range in size, and larger droplets tend to fall closer to their source after being generated (Borak, 2020). Smaller droplets, which can take the form of aerosols, can be suspended in the air for longer periods of time (Santarpia et al., 2020). There have been significant discussions surrounding the transmissibility of COVID-19 via aerosols and the disease being airborne (Lewis, 2020). Although there is substantial debate surrounding the transmission pathway of the airborne particles, many studies suggest it is a factor outside of aerosol generating procedures typically produced during medical interventions and in hospital settings (Morawska & Milton, 2020; Morawska et al., 2020; Zhang, Li, Zhang, Wang, & Molina, 2020). While the primary mode of transmission of COVID-19 between humans has been through direct respiratory droplet exposure via inhalation or entry through mucus membranes (such as the eyes), it is possible for self-inoculation to occur through hand-to-face transport whereby an individual touches an infected surface and then with unwashed hands touches their face (Nazlım Aktuğ Demir et al., 2021). Coronaviruses are also highly prone to mutations (Kleine-Weber et al., 2019; Yang et al., 2015). Several variants of the SARS-CoV-2 have emerged, and data suggests that these mutations are more virulent and result in increased infectivity (Haddad et al., 2021). Newer strains have also been associated with evading neutralising antibodies, making it more challenging for the body to mount an immune response (Mahase, 2021; Voloch et al., 2021).

As previously mentioned, the epidemiological triad helps in part explain the spread and variation of disease. Reducing the interactions between these variables decreases the spread of

COVID. Interrupting factors can be between any two variables such as the agent-host (protecting the host against the virus or abating the host's vulnerability), agent-environment (reducing viral burden in areas and surfaces), and environment-host interactions (reducing or eliminating the chance for the virus to infect new hosts) (Tsui, Deng & Pan, 2020). As such, several public health measures have been designed and implemented to disrupt these interactions including stay at home orders, physical distancing, and the closure of public settings including schools and businesses (Fong et al., 2020).

Although these interventions have been successful in reducing the spread of COVID (Ebrahim et al., 2020), there have been profound social and emotional consequences that merit increased attention from public health officials, policy makers and other government agencies. For instance, stay at home orders, quarantines and social distancing measures have resulted in increased levels of anxiety, depression and acute stress (Marroquin, Vine & Morgan, 2020) in addition to the concerns directly related to contracting the virus, which has resulted in a COVID specific form of anxiety called "coronaphobia" (Arora, Jha, Alat & Das, 2020). Fears and stress may continue as the pandemic evolves and individuals and communities are exposed to more COVID related content. Additionally, as more virulent strains of the virus have emerged, the risk of increased fear and deteriorating mental health may continue.

While these variants have been causing increase concern, hope has emerged with the ongoing development and distribution of vaccines (Knoll & Wonodi, 2021; Voysey et al., 2021). In order to reduce the ongoing threat of COVID-19, and to disrupt the interaction between agent and host, there has been an exigent need for the research, development and distribution of COVID-19 related therapeutic interventions and vaccines. While the COVID-19 pandemic has demonstrated the capability of an infectious disease on disrupting several aspects of human life and creating pandemic related stressors, it has also shown how concerted and multisectoral efforts can be coordinated to develop and circulate a vaccine to a large amount of people in a relatively short period of time. The ongoing collaborative efforts between academics, pharmaceutical companies, and government agencies have shown the impact of such efforts (Corey, Mascola, Fauci, & Collins, 2020). The development and distribution of the vaccine has provided a level of hope in the fight against COVID-19.

COVID-19 in Canada

The direct and indirect costs of COVID-19 have been substantial in Canada and around the world. The pandemic has resulted in a significant toll on infrastructure related to healthcare (Archer, 2020), as well as the economic (Ashraf, 2020), and social (Nicola et al., 2020) wellbeing of individuals and communities across the country. Epidemiological data from Canada provides insight into the prevalence rates of COVID-19 as well as the spatial distribution of the virus across the country (Government of Canada, 2021). The first wave of the COVID-19 pandemic started in Canada during mid-March of 2020. During this initial onset, there were approximately 1,500 daily cases. This surge in cases was followed by a summer period in which roughly 500 new cases were reported daily. Unfortunately, Canada experienced a second wave which was drastically worse than the first. From October 2020 to May 2021, case count per day was over 2000 (Government of Canada, 2021).

The total number of COVID-19 cases in Canada is estimated to be over 1.6 million with approximately 28,000 deaths (Government of Canada, 2021). Most cases during the first and second wave of the pandemic occurred in Ontario and Quebec (65% of total cases) with the two provinces also having the majority of deaths (77% of COVID-19 deaths in these two provinces). For Ontario specifically, the province has had over 551,500 confirmed cases with 540,000 people recovering and 9,360 succumbing to the disease. Data from Public Health Ontario (2021) during the second wave suggests that the case count of COVID-19 was highest among those aged 20-29 (57,356 cases), 30-39 (43,284 cases), 50-59 (40,560) and then 40-49 (39,045). Despite younger age cohorts having the highest rates of the disease, the mortality rate among this population was lower compared to other older groups. Those age 70-79, 80-89 and 90+ have the highest death rates in the province (1,1192, 2,352, and 2072 respectively). Aside from age, cumulative COVID-19 case count appears to be equal among men (approximately 136, 000) and women (approximately 140,000).

Many of the outbreaks observed in the province have occurred in long term care and retirement homes, congregate living environments, workplaces, hospitals, and school and childcare facilities. For instance, during the first wave of the pandemic, the less than 0.5% of Ontario's population that resided in long term care homes made over 70% of COVID-19 deaths (Ministry of Health, 2021). However, with the implementation of vaccines and nonpharmacological interventions (including face masks, physical distancing, self-isolation and quarantines) this number has reduced over the time (Ministry of Health, 2021).

The unequal distribution, spread, and mortality associated with COVID-19 pandemic has been well documented on other sociodemographic dimensions as well. Research has identified particular groups that are at higher risk and are to experience greater disease burden, which includes racial and ethnic minorities (Yaya, Yeboah, Charles, Otu, & Labonte, 2020) and those in lower socioeconomic brackets (Ali, Asaria, & Stranges, 2020). For instance, in the United States, the rate and burden of COVID-19 among Black populations is higher than the general population (Yancy, 2020). Outside of the direct impact of COVID, certain populations and groups have faced indirect hardships because of COVID-19. Discrimination has occurred among many Asian communities (Wu, Cary, Wilkes, Qian, & Kennedy, 2020) and migrant and newcomer populations in Canada (Tuyisenge & Goldenberg, 2021). Many news articles and statements have echoed this and described the sentiments of COVID related racism that has occurred in Canada (Bain, Dryden, & Walcott, 2020; Siddiqi, Blair, & Parnia, 2020). Rates of infection and mortality among ethnic and racial groups in Canada had previously been unclear during the onset of COVID given that race-based data was not being collected (McKenzie, 2021). While detailed demographic data on socioeconomic characteristics (in addition to racial and ethnic traits) has been limited, recent Public Health reports have included this information. Reports indicate that COVID-19 rates are over four times higher in racialized communities and that these groups have more hospital and ICU admission (Public Health Ontario, 2020). As well, the mortality rate for COVID-19 was higher in neighbourhoods that had more visible minorities (Subedi, Greenberg, & Turcotte, 2020).

COVID-19 has also negatively impacted Indigenous communities and calls have been made to ensure that social, cultural, and political determinants of health do not lead to disproportionate rates of COVID-19 related infection (Power et al., 2020). Potential causal mechanisms for these findings includes discrimination and distrust between racially diverse communities and health care systems (Jaiswal, LoSchiavo, & Perlman, 2020), lack of adequate access to health care facilities (Hajizadeh, Hu, Bombay, & Asada, 2018; Horrill, McMillan, Schultz, & Thompson, 2018), and a disparate amount of underlying health conditions (Veenstra & Patterson, 2016). Thus, it will be important to address how social inequities shape and perpetuate vulnerability to COVID-19 and how this may influence the emotional responses to the pandemic among diverse neighbourhoods and communities.

Psychological Burden of Disasters

Previous studies have investigated the influence of large-scale disasters on population mental health. Events such as mass shootings (Lowe & Galea, 2017), natural disasters (Beaglehole et al., 2018) and infrastructure-related calamities (Makwana, 2019) have been demonstrated to contribute to various psychopathologies including post-traumatic stress disorder, anxiety, and depression (North, 2016). Previous epidemics and pandemics have also resulted in poor mental health outcomes. For instance, the Ebola outbreak that affected several people in Guinea, Liberia, and Sierra Leone was associated with high rates of PTSD among those directly and indirectly impacted by the virus (Shultz, Baingana, & Neria, 2015). Other epidemics have also led to a variety of adverse psychological reactions including fear, depression, anger, health concerns, sense of powerlessness, anxiety, and emotional distress (Brooks et al., 2020; Cheng & Cheung, 2005; Huremović, 2019; Xiang et al., 2020). Previous work has suggested that symptoms related to PTSD resulting from an epidemic can last for three years post event (Sim, Chan, Chong, Chua, & Soon, 2010). These traumatic events are a source of stress for individuals and communities. This section will explore the stress, health, and the psychological impacts associated with the disaster events, as well as the vulnerabilities to these phenomena.

Individual and Community Stress

Stress has remained the subject of scientific inquiry for several decades. As such, there has been an abundance of empirical and theoretical developments aimed at better understanding the human stress process (Goodnigte, 2014; Koolhas et al., 2011; Lu, Wei & Lo, 2021; Russell & Lightman, 2019; Staufenbiel et al., 2013). A majority of this work has examined stress at the individual level. Efforts to understand community stress processes have been made in relation to disasters (Couch & Coles, 2011), although there appears to be a paucity of this work. Community stress and the associated responses when a geographic area is impacted by a shared adversity merits further investigation.

Stress is a response that is experienced at the individual level. It is a multidimensional process starting with a stimulus that leads to psychological processing, resulting in a response (Koolhaas et al., 2011; Levine, 2005). Stress has been differentiated into various forms and types. For instance, eustress is a positive stress response by which there is a beneficial outcome after one has experienced a challenging situation or stimulus (Kupriyanov & Zhdanov, 2014). In contrast, distress is a negative stress response that can have deleterious consequences (Drapeau, Marchand, Beaulieu-Prevost, 2012). As well, acute stress is often time limited, short term and can have a discreet onset and end (Thoits, 2010). Alternatively, chronic stress is longer in duration than acute stress and can be thought of as a cumulative consequence of prolonged or recurring stress exposure (Hammen, Kim, Eberhart, & Brennan, 2009). The adverse consequences of stress have been well documented. Stress has been linked to poor health outcomes including mortality (Hamer, Kivimaki, Stamatakis, & Batty, 2012) and specific medical conditions such as stroke (Bergh et al., 2014; Egido et al., 2012; Henderson et al., 2013) and heart disease (Henderson et al., 2013). Residing in a stressful settings or environment (as evidenced by exposure to violence and crime), is associated with worse psychological outcomes (Stockdale et al., 2007).

Differentiating individual and community stressors along qualitative and quantitative features can be challenging. Some have conceptualized the two as heterogenous experiences, while others have argued that they are intricate and overlapping (Hobfoll, Briggs & Wells, 1995). Applying typologies to the events that are a source of stress is one approach to distinguishing individual and community stressors. For instance, large scale adverse events such as political oppression, terrorism, biological disasters, and epidemics could be explored as community stressors. The level of disorder and turmoil these events cause at a community level would categorize these adversities as a community stressor. Events that may be classified as individual level stressor occur on a smaller scale (such as sickness or crime). However, these stressors could transition into a stressor of community concern when the number of individuals affected increases and the stressor is considered to be threatening to the larger group (Jerusalem et al., 1995).

Another difference between individual stress and community stress is the subjective experience of it. Stress is not an objective experience and at the individual's level, several idiosyncratic factors influence the experience of stress including an individual's interpretation and perception of the stressor (Reif et al., 2021). While differences in subjective appraisal may in part explain variations in stress response at the individual level, it may be of less significance for community stressors given that these adversities are more clearly defined. Despite this, there appears to be similarity in individual and community stress in terms of coping and stress outcomes given there can be differences in a community's response to a traumatic event just as difference exists at the individual level.

Overall, stress at the individual and community level share many characteristics and differentiating the two conceptually is not always clear. Jerusalem et al., (1995) proposes a three-level model that distinguishes the two. These authors suggest that the first level of stress occurs when stress is experienced by more than one person, but there is no public perception of the stress as a threat to the collective. Level two is moderate community stress in which an observable amount of awareness occurs about a stressor, but there is no action in terms of mobilizing resources to address the adversity. Lastly, level three is comprised of high community stress in which the broader community has recognized the stressor as a hazard and implements communal supports to enhancing coping. Applying this model to the COVID pandemic and exploring it in relation to different time points may shed important insights into stress responses and aid in bolstering disaster preparedness strategies.

Disasters and emotions

The rapidly changing COVID-19 landscape has drastically altered everyday life, especially with the application of strict never before used public health measures. Outbreaks related to infectious diseases create extremely stressful environments that require people to cope and respond to uncertain and unexpected conditions. Individuals and communities need to manage emotions directly related to the pandemic as well as stressors indirectly associated with the pandemic such as limitations to daily and social activities as well as economic uncertainty. As such, individuals may feel a sense of danger and fear resulting in emotional epidemics, panic, and or behavioural contagion (Huremović, 2019; Li, et al., 2020). Increased rates of psychological distress have also been documented in the general population (Xiong et al., 2020), those with pre-existing psychiatric conditions (Hao et al., 2020), and among frontline health care workers (Wang, Pan, Wan, Tan, Xu, McIntyre et al., 2020). Chronic stress, uncertainty, fear, and economic recessions have been implicated in increased rates of suicide (McIntyre & Lee, 2020; Sher, 2020) and substance use (Hobin & Smith, 2020; McKay & Asmundson, 2020). This section will discuss the emotional responses associated with the pandemic.

Emotional Response to COVID-19 Pandemic

There is a significant amount of empirical data on the epidemiology of infectious diseases. However, the epidemiology of emotions during outbreaks and other disaster merits further investigation. Emotional epidemiology emerged as a term in response to the anecdotal experiences of the 2009 H1N1 influenza pandemic where there appeared to be a concurrent emotional pandemic (Ofri, 2009). Adverse mental health outcomes that occur in tandem to epidemics and pandemics have been described as "parallel epidemics" (Yao, Chen, & Xu, 2020). An understanding of the epidemiology of emotions as well as the factors creating conditions to poor mental health outcomes during adverse events can provide insight into system level psychological interventions. Despite being highly relevant to the current pandemic, there is currently limited information on emotional epidemiology and parallel epidemics, and more research is needed into the emotional responses during the COVID pandemic that coincide with case count trends.

There have been several adverse emotional responses to the various aspects of the current pandemic. Specifically, individuals and populations report decreased life satisfaction and increased emotions of fear, social isolation and loneliness, anxiety, boredom, and stigma (Coelho, Suttiwan, Arato, & Zsido, 2020; DiGiovanni, Conley, Chiu, & Zaborski, 2004; Kodish et al., 2019). These psychological responses to the pandemic could cultivate a heightened stress response that is exacerbated by various factors. Data also suggests that mental health concerns remain high for those who recovered from COVID-19 with recent reports indicating that survivors of the virus experience higher levels of post-traumatic stress disorder (Janiri et al., 2021), as well as anxiety and psychotic disorders (Taquet, Geddes, Husain, Luciano, & Harrison, 2021).

Emerging data suggests that social isolation in conjunction with fear of contagion of COVID-19 has negatively impacted mental health (Galea, Merchant, & Lurie, 2020; Gunnell et al., 2020; Holmes et al., 2020; McGinty, Presskreischer, Han, & Barry, 2020). Fear of contagion and exposure to COVID-19 has also resulted in a reduction of emergency department visits (Hartnett et al., 2020). There has also been a decrease in psychiatric emergency department visits and inpatient psychiatric occupancy during the first wave of the pandemic in Ontario (Kim et al., 2021). These findings suggest that stress related to the pandemic is making existing morbidities worse by reducing access to services.

Several other sociodemographic factors have been associated with deteriorating mental health during the pandemic. For instance, females have been reported to be at higher risk of developing depressive symptoms when compared to male counterparts (Mazza et al., 2020; Sønderskov, Dinesen, Santini, & Østergaard, 2020; Wang, Pan, Wan, Tan, Xu, Ho et al., 2020). As well, those under the age of 40 also appear to have report greater depressive symptoms (Ahmed et al., 2020; Ozamiz-Etxebarria, Dosil-Santamaria, Picaza-Gorrochategui, & Idoiaga-Mondragon, 2020). The literature on how educational level influences depressive symptoms during the pandemic has been mixed with few studies suggesting that those with lower educational attainment report greater depressive symptoms (Mazza et al., 2020; Wang et al., 2020), and others suggesting that higher educational level is associated with more depressive symptoms when compared to those with lower educational levels (Wang, Di, Ye, & Wei, 2021). One study found that higher levels of education was positively correlated with depression and negatively correlated with satisfaction in one's life (Wanberg, Csillag, Douglass, Zhou, & Pollard, 2020). Additional work is needed to explore how educational attainment influences stress and emotional wellbeing during the pandemic.

The psychological response to infectious disease related outbreaks can have implications on the spread of the virus as well as social and emotional distress afterwards. It has been suggested that appropriate resources are generally not provided to mitigate the deleterious mental health effects pandemics and outbreaks have (Taylor, Steven, 2019). While there are competing demands for limited resources during a pandemic, it is important to consider the mental wellbeing of communities during disaster management. There have been several recommendations to attenuate the negative psychological impacts of COVID. For instance, Cullen, Gulati, & Kelly (2020) advocate for targeted mental health interventions for communities affected by COVID-19.

Continued efforts are needed to document, track, and assess population mental health during this current crisis. Researchers have noted that assessing and responding to the psychological impact of a large-scale pandemic is challenging (Pierce et al., 2020). This is because much of the psychological data available is based on convenience samples that do not have pre-pandemic information available to compare rates to, reducing the validity of the results (Pan et al., 2020). Therefore, innovative research approaches are needed for gathering and interpreting baseline data.

Neighbourhoods and Geographic Communities

Neighbourhood and geographic community have been recognized as important concepts for diverse populations and audiences. Despite the increased attention to studying these areas, delineating the terms remains a challenge. There has been considerable variation on definitions of geographic community and neighbourhood and there remains to be little conceptual agreement on the two. Many have even suggested that community and neighbourhood can be used interchangeably (Alexander, 1977; Dear & Wolch, 1989; Hallman, 1984; Huremović, 2019; Jencks & Mayer, 1990; Li et al., 2020; Suttles & Suttles, 1972). Having and using multiple or differing definitions and models of neighbourhood presents difficulties as this lack of standardization makes it challenging to compare and combine data from different studies. Identifying and utilizing appropriate geographical locations and scales to explore how things such as built environments effect health and wellbeing is important in evidence-based practice for public health and community level interventions (Koohsari, Badland, & Giles-Corti, 2013). Therefore, it is important to explore existing definitions, interpretations and terminology of community and neighbourhoods.

Conceptualizing and Operationalizing Community and Neighbourhoods

Research on health and neighbourhood has historically used an ecological based definition, wherein neighbourhoods are described physically as spatial areas with discrete borders enclosing the region (Mavoa et al., 2019). Thus, a neighbourhood's physical aspects (including built environments such as housing, buildings, roads, walkways, open spaces etc.) are often looked at in terms of influencing health and wellbeing. Boundaries for a neighbourhood in this definition typically correspond to administrative margins and rely on census tracts or postal code areas to distinguish neighbourhoods (Clapp & Wang, 2006). A challenge to using this is approach is that community members, residents and other stakeholders may not have the same bearing to the seemingly arbitrary neighbourhood points.

There are also aspatial characteristics of a neighbourhood that can contribute to its conceptualization and definition. Neighbourhoods can represent spaces of complex social interactions and this component emphasizes the social dimension of neighbourhood by examining social networks and interactions that occur in a specific space (Weiss, Ompad, Galea, & Vlahov, 2007). When looking at socially related phenomena that influence health, neighbourhood effects such as poverty (Finch & Hernández Finch, 2020), social capital, and inequality (Dahl & Malmberg-Heimonen, 2010; Veenstra, 2000) all appear to play a role in health outcomes.

Overall, neighbourhood and community remain challenging to define. However, Guo & Bhat, (2007) hypophora, "So how do we define *neighborhoods*? Or, how do we measure neighborhood characteristics and the associated effects? Our simple answer is that we should measure what matters to people over the area that really matters to people" (p.31). Overall, neighbourhoods and geographic communities can be considered as the aggregations of individuals who reside in close proximity to one another within the confines of a geographical space distinguished by social (sociodemographic and compositional characteristics), spatial (geographic boundaries) and physical (built environments) domains (Aneshensel, Harig, & Wight, Invalid date).

Given that local neighbourhoods and communities can be recognized as units of identity for various stakeholders including residents, businesses, policy makers and other partners, they remain important concepts for community planning, neighbourhood designing, and research initiatives. Planning theory and design suggests that neighbourhoods should be typified based on problems that are going to be addressed, and in terms of research, selecting a suitable neighbourhood unit can be based on practicality to augment available data (Park & Rogers, 2014), and/or also in consultation with stakeholders to better meet community needs.

Neighbourhood and Health

There is a strong body of evidence to suggest that mental health and health is the result of a combination of genetic, environmental and stress related factors (Arcaya, Arcaya & Subramanian, 2015). Focused attention should be directed towards modifiable variables that influence these outcomes especially as it relates to interventions aimed at reducing disparities in mental health at the neighbourhood level. Understanding theories that aid in explaining disparity is helpful in providing context to shape targeted interventions. For instance, emerging data suggests that the unequal impacts of COVID and growing inequities among certain populations are often related to the social determinants of health (Haynes, Cooper, Albert, & Association of Black Cardiologists, 2020; Laurencin & McClinton, 2020; Poteat, Millett, Nelson, & Beyrer, 2020; Power et al., 2020). Social determinants of health consist of a wide range of social, personal, environmental, and economic variables that influence health at the personal and population level (Lucyk & McLaren, 2017) and examining how social and economic risk factors influence stress and resilience in the context of a disaster at the neighbourhood level remains an underdeveloped area.

Neighbourhoods represent an important determinant of health. They are comprised of the social, environmental, behavioural and institutional determinants that influence the wellbeing of the people who reside in them (Oakes, Andrade, Biyoow &Cowan, 2017). Over the past few decades, empirical and theoretical developments in neighbourhood effect research have investigated specifically how neighbourhood characteristics influence resident's health (Renalds et al., 2010). As such, it is important to review how neighbourhood characteristics can influence stress, resilience, and health.

Several cross-sectional and longitudinal studies have associated neighbourhood level characteristics with health outcomes such as obesity (Ghenadenik, Kakinami, Van Hulst, Henderson, & Barnett, 2018; Maharana & Nsoesie, 2018) and cardiovascular disease (Chaix, 2009). Built environments have also been associated with stress and mental health (Evans, Wells, & Moch, 2003; Reichert et al., 2020) with neighbourhoods that have less access to resources (Hargraves & Hadley, 2003), and higher levels of traffic and noise (Song, Gee, Fan, & Takeuchi, 2007), as well as exposure to hazardous conditions (Luginaah, Isaac N., Taylor, Elliott, & Eyles, 2002) being correlated with increased levels of stress and mental illness. In addition to neighborhood characteristics influencing physical and mental health, as well as health behaviours, neighbourhoods also affect resident's ability to access appropriate and necessary resources for attaining and maintaining optimal health (Ross, Oliver, & Villeneuve, 2013).

Geographic health inequality has emerged as one of many concepts for explaining health disparity, and literature on this topic highlights how 'place' and 'space' can help in part provide an understanding of the disparities neighbor (Arcaya, Arcaya & Subramanian, 2015). In this context, space refers to the “measures of distance and proximity such that exposure to spatially distributed health risks and protective factors will change according to an individual’s precise location” (Arcaya, Arcaya & Subramanian, 2015, p.6). Spatially pattered vulnerabilities and protective factors for COVID could consist of proximity to outbreak sites and vaccine distribution centres as these are spread across space. Alternatively, ‘place’ signifies memberships related to administrative or political units such as cities, census tracts, or school districts (Arcaya, Arcaya & Subramanian, 2015). Interventions and measures that are often specific to a confined area act in a consistent manner across the region. Thus, membership to a specific place or unit influences health via programming and policies (Arcaya, Arcaya & Subramanian, 2015). Place-based stress has been explored in relation to chronic diseases (Shankardass, 2012). In terms of COVID as a stressor, research on the impacts of space and place during the pandemic has been done to explore inequalities across these domains (Buffel et al., 2020). However, potential place and spaced based emotional inequality at the neighbourhood level in a Canadian context during COVID has yet to be explored.

The burden of COVID-19 has been far reaching, but the distribution of negative impacts associated with the pandemic has not been equal across communities (Chen & Krieger, 2021). The implementation of place-based modifications to curtail the spread and growth rate of COVID-19 has been an important component to responding to the global pandemic. However, not all communities have been able to respond to the same degree given structural neighbourhood inequality. For instance, stay at home and physical distancing orders remain a challenge for individuals and families who reside in congregate settings. Additionally, certain social environments present in neighbourhoods (including social capital, social cohesion, and social interactions) act as protective factors against various health conditions including obesity, poor self-reported health, and depression (Pérez et al., 2019). Additional work is needed to better understand neighbourhood’s responses to disaster and the impacts of stress.

Community Resilience

In psychology, resilience science and research has resulted in a nuanced and more sophisticated understanding of the mechanisms that result in positive outcomes after adverse events (Cosco et al., 2017; Kentner, Cryan & Brummelte, 2018). Although resilience has historically been conceptualized as an individual’s ability to have a positive outcome after an adversity (Herrman et al., 2011), the term has been applied to broader settings. Individual resilience has led to the application of the concept at the mezzo and macro levels, and with this shift, a more synergistic and holistic relationship among individuals and their broader social context has been identified (Buikstra et al., 2010). Reviewing resilience at the community level is helpful.

Despite the devastating effects of adverse events, some communities are better able to adapt to these hardships than others (Braun-Lewensohn & Sagy, 2014). This variation in a community’s response to a hardship may in part be explained by community resilience. Community resilience has been conceptualized in several different capacities for various environments and settings (Patel, Rogers, Amlot & Rubin, 2017). Most definitions underscore resilience as being the process of galvanizing, developing and engaging with community resources in an environment that is characterized by change (Magis, 2010). It is important to emphasize that resilience is not only outcome-based but is also a process that requires a degree of adaptability wherein community members work towards a collective objective (Kulig, Edge, Townshend, Lightfoot, & Reimer, 2013; Norris et al., 2008).

Given that resilience can be applied to diverse populations, groups, and settings, it is imperative to discuss community resilience as it relates to disasters. Norris et al., 2008 provides a comprehensive theoretical framework and model of disaster related community resilience. The authors define community resilience as “a process linking a set of networked adaptive capacities to a positive trajectory of functioning and adaptation in constituent populations after a disturbance” (Norris et al, 2008 p. 130). The model component of their work begins with a stressor. A stressor is the precipitating factor that initiates the resilience process. Stressors are adverse events or circumstances that put the safety and wellbeing of a neighbourhood or community in jeopardy. There is variation in several aspects of stressors including severity, duration, and expectedness. Research investigating the severity of a stressor suggest that severity is correlated to psychosocial consequences post disaster (Norris et al., 2008). Post disaster mental health has been affected by financial loss, injury to self or others, and life-threatening events (Norris & Phifer, 1995). While stressors and disasters are often abrupt in nature, the duration in disruption to daily functioning and longer-term consequences differs. As well, the stress-diathesis theory posits that pre-existing vulnerabilities of a community may influence the responses to the stressors (Benight, McFarlane, & Norris, 2006).

While stressors may take various forms and influence communities at different levels, the optimal outcome after a stressor has occurred is for resistance to transpire (Norris et al., 2008). This means that the community can utilize resources to effectively block the stress and prevent any disruption in terms of functioning from occurring. Resistance as an outcome after an adversity rarely occurs. What generally follows is ‘adaptation’ in which distress and dysfunction are experienced during the onset of the disaster, but over the course of time and with access to appropriate resources, individuals and communities are able to return to pre-disaster functioning

(Norris et al., 2008). Thus, resilience is the process that produces adaptation as an outcome and the quicker a community can return to pre-disaster functioning, the greater resilience it is said to have (Norris et al., 2008). If a community is unable to use resilience as a process to achieve adaptation, but languishes instead, it is said to be in a state of persistent dysfunction (Norris et al., 2008). The overall goal for a community after experiencing a stressor is to achieve adaptation which can be evidenced by high levels of positive mental health, quality of life and overall functioning.

It is also important to highlight that the dynamics of disasters on community resilience differs based on stressors. Typically, disasters have been referred to as a traumatic event that are collectively experienced, negatively impacting livelihood, and resulting in changes to communities and environments (Eshghi & Larson, 2008). Disasters can be natural events, human-driven calamities, mass violence, and epidemics (Shaluf, 2007). Pandemics are uniquely positioned as a special type of disaster given the way in which they unfold. While infectious disease often has an acute onset, they are not always ephemeral in nature, meaning they do not last a short time. Just as chronic violence (such as war) can last months to years, so too can infectious diseases. Special attention is needed to study these types of disasters and more work is needed to understand the mechanisms behind chronic natural/ biological disasters and resilience.

In summary, research on resilience has progressively included social circumstances as influencing outcomes to adverse events (Panter-Brick & Eggerman, 2011). The notion that social ecological factors such as neighbourhood and community play a role in stress and resilience (Ungar, 2011) can help to better understand variation in resilience across geographic areas. Additional research is needed to make explicit considerations on how communities respond to chronic and unique stressors such as the COVID-19 pandemic. This work can help cultivate a better understanding of resilience as an outcome of emotional and chronic stress at the community level and help answer why some populations and groups are able to flourish in the face of adversity. The significance of community resilience research is far reaching, as Murray and Zautra (2011) note, “community resilience has an important role to play in helping researchers and practitioners to foster health and well-being. By intervening on a systemic level, not only can we improve the quality of our families and communities but also we can simultaneously influence individual resilience.” (p. 339).

Hope and Resilience

Hope and resilience are strongly related constructs that both consist of having a positive attitude of the future (Duggal, Sacks-Zimmerman & Liberta, 2016). Snyder (2000) describes hope as “a positive motivational state that is based on an interactively derived sense of successful (a) agency (goal-directed energy) and (b) pathways (planning to meet goals)” p.3. Previous work has implicated hope as being a buffer to negative impacts caused by adverse events and stressful conditions (Valle, Huebner & Suldo, 2006). Hope has also been conceptualized as a component of resilience and used as a proxy to better understand and establish resilience. For instance, a recent study explored hope as a resilience variable in describing COVID related stress (Braun-Lewenson, Abu-Kaf & Kalagy, 2021). Results of this work suggests that hope (in addition to sense of coherence – the ability to access and use one’s resources to cope with stressors and promote optimal wellbeing) can in part explain variation in emotional distress between different populations and groups. As well, hope appears to be a strong indicator of community resilience when analysing social media content in urban settings (Belanger, 2021).

Neighbourhood Stress Process Model

The neighbourhood stress process model provides a tool for integrating the concepts of stress, neighbourhoods, social determinants of health and resilience. By taking an ecological framework and integrating it with the stress process model (Aneshensel, Bierman, & Phelan, 2013) to document the effect of social inequality at multiple levels of the social hierarchy (Wheaton & Clarke, 2003), this model specifically provides one explanation for why some individuals can flourish in adverse environments, and others languish in these settings (Aneshensel, 2009).

The stress process component begins at the individual level with one's social location (Aneshensel, Harig, & Wight, 2016). At this stage, an individual's position along the social hierarchy is characterised by social variables including socioeconomic status and race/ethnicity. In keeping with a social determinants of health approach, lower positions along the hierarchy are associated with negative health outcomes by which an individual is exposed to greater stressors. Neighbourhood level stressors can become interconnected and influence several areas of an individual's life. Response and impacts to stressors on one's wellbeing are a function of the degree to which psychosocial resources are available and able to be galvanized to either successfully attenuate the stressor, or alternatively, lack or insufficient access to such resources results in adverse outcomes (Wheaton & Clarke, 2003). On the ecological domain, neighbourhood-related health inequity is a result of segregation. This stratification (again, often based on racial/ethnic and socioeconomic dimensions) cultivates differences in neighbourhood features which then in turn results in varying exposure to stressors and disparate access to psychosocial resources (Aneshensel et al., 2016).

Overall, the neighbourhood stress process model attempts to explain the extent to which individual as well as neighbourhood level inequality influence health and resilience in an additive fashion. Two cross-level interactions are needed for this to occur, and this consists of the compound disadvantage model and the compound advantage model (Wheaton & Clarke, 2003). In the compound disadvantage model, disadvantaged neighbourhoods are most harmful to the most disadvantaged people. Conversely, neighbourhoods with positive advantages, personally benefit those with the most advantages the most. The emphasis on the cross-level interactions suggests that neighbourhood disadvantage increases poor health related to stressor exposures via a process of compounded adversity, while stress buffering is the process of high levels of resources protecting against the impact of exposures to stressors (Aneshensel, 2009). As such, differences in the efficacy of such resources are credited for the variation in a neighbourhood's response to an adversity (Aneshensel et al., 2016). This model can be helpful when investigating variations in stress and resilience during COVID-19 in areas with historic health inequities.

Social Media Research

Several measures have been implemented to reduce the spread and infection growth rate of COVID-19. As such, public health directives have included quarantines, city wide shutdowns, limits to in person gatherings, and physical distancing policies (Ferguson et al., 2020; Karaivanov, Lu, Shigeoka, & Pamplona, 2020). This shift in reducing in person interactions has resulted in the increased use of the internet and social media (Mander, 2020). Social media has been helpful during the pandemic in multiple ways. Firstly, it provides a forum for people to interact and feel a sense of accompaniment (Chen, & Li, 2017). Secondly, in the rapidly changing backdrop of COVID-19, social media is useful in the dissemination of information from trusted and reputable officials and sources (Chan, Nickson, Rudolph, Lee, & Joynt, 2020). Thirdly, social media has also been used to aid in the detecting of outbreaks (Aramaki, Maskawa, & Morita, 2011; Li, Xu, Cuomo, Purushothaman, & Mackey, 2020), large group gatherings, and to understand attitudes and behaviours related to a crisis (Jordan et al., 2019), which is helpful in developing and implementing appropriate supports. With the proliferation of social media, analysing the data produced via online presence can be helpful in several contexts. This section explores the literature on social media research.

Social Big Data and Mental Health

Big data continues to be a rapidly developing field and refers to large sets of data that have varied and complex structures that can be processed in novel and efficient ways (Sagiroglu & Sinanc, 2013). Social media remains a highly relevant source of big data and accounts for a large percentage of available big data (Yaqoob et al., 2014). Social media specific big data has been coined ‘social big data’ and consists of the collection and analysis of the exchanges across digital platforms and networks (Bello-Orgaz, Jung, & Camacho, 2016). Given that social media continues to be pertinent, social big data can be used to investigate social and health related issues to provide meaningful patterns and trends that may not be captured using other forms of analysis.

The use of social big data (in conjunction with temporal and spatial information) has greatly benefited disaster science. Researchers investigating floods (Restrepo-Estrada et al., 2018; Wang, Mao, Wang, Rae, & Shaw, 2018), earthquakes (Addair, Dodge, Walter, & Ruppert, 2014; Crooks, Croitoru, Stefanidis, & Radzikowski, 2013; Sakaki, Okazaki, & Matsuo, 2010), hurricanes (Huang & Xiao, 2015), and droughts (Enenkel et al., 2015) have been able to describe insights into the human responses of these events. This type of methodology has also been applied to other situations such as voting behaviour (Correa & Camargo, 2017), and depicting emotions over the course of a year in urban cities (Martín, Julián, & Cos-Gayón, 2019).

From a mental health research perspective, social media content can provide unique insights into the emotional state of a person, and when done in larger numbers, the psychological wellbeing of a population. Using linguistic and behavioural cues from social media allows for the detection of emotional and psychological disorders. This method to assessing psychosocial profiles has been highly accurate in cases of eating disorders, depression, and suicidality (Sinnenberg et al., 2017). Many social media platforms provide the ideal forum for this type of research. For instance, Twitter has been used to examine mental health outcomes after disastrous events (Gruebner et al., 2017). Twitter as an online platform has been integral to fulfilling social and informational functions. Users on the social networking service can engage in conversations in a public format and send out their thoughts, opinions, and other insightful information. Twitter users can do this by sending out "tweets", messages consisting of up to 140 characters to their followers. Users are also able to follow and read other's posts and tweets can also be tagged with additional information and data including time, date, and the geographic location of where the tweet was posted from. During the COVID-19 pandemic, researchers have been using Twitter information to explore depression (Davis, McKnight, Chunara, Lizotte & Fyshe, 2020).

Recently, information from Twitter has been used as a form of public health surveillance. Surveillance refers to "the ongoing, systematic collection, analysis, and interpretation of health data essential to the planning, implementation, and evaluation of public health practice, closely integrated with the timely dissemination of [this information] to those who need to know" (Thacker & Berkelman, 1988, p.164). As such, surveillance systems consist of processes that collect, monitor, manage, analyze, and interpret results from data while actively disseminating findings to appropriate audiences (Groseclose & Buckeridge, 2017). Various tools can be used for public health surveillance and using Twitter as a vehicle to conduct this work has been previously done to observe epidemics (Aramaki et al., 2011) and mental health outcomes (Coppersmith, Dredze, & Harman, 2014; Jashinsky et al., 2014; McClellan, Ali, Mutter, Kroutil, & Landwehr, 2017;

Parker, Wei, Yates, Frieder, & Goharian, 2013). Twitter can also be used for diverse health surveillance as a recent systematic review examined 137 studies that used Twitter for public health research and the topics ranged from infectious disease, substance use, drinking behaviours, and cancer care (Sinnenberg et al., 2017).

Twitter offers an ideal platform for data analysis for many reasons. Firstly, information on the timing of a post as well as a user's geocoordinates can be easily accessed, which can be used to monitor a person's emotions in real time (Neuhaus, 2011). Secondly, data from Twitter users can also be combined with demographic variables to add further context into user's behaviours (Neuhaus, 2011). Lastly, social media data also provides unique opportunities to conduct investigations on human activities and emotional reactions in real time and space as well as retroactively (Yuan, 2018). These interactions can inform various community dynamics including mobility patterns (Blanford, Huang, Savelyev, & MacEachren, 2015; Lenormand et al., 2014; Longley & Adnan, 2016; Wu, Lun, Zhi, Sui, & Liu, 2014), the use and uptake of public spaces and other urban design proposals (Martí, Serrano-Estrada, & Nolasco-Cirugeda, 2017). Big data has even been used to explore factors that influence housing prices and buyer's willingness to pay (Wu, Chao et al., 2016).

To provide insight into the personal, behavioural, and social responses to an adverse event, Twitter based advanced surveillance systems can be used to analyse large quantities of real time information. This approach also addresses the concerns about lack of baseline or pre-COVID-19 data on emotional wellbeing given that tweets can be easily accessed and analyzed retrospectively. Additional studies are needed to investigate how Twitter can be used to assess the emotional profile of communities during the pandemic.

Ethical Considerations in Social Media Research

The use of using social media for research and for mental health surveillance warrants ethical consideration. There have been several positions on the ethical implications of using of social media for research purposes (Benton, Coppersmith, & Dredze, 2017; Conway, 2014; Mikal, Hurst, & Conway, 2016). The discourse surrounding this type of analysis and the ethics behind it are primarily concerned with privacy. A consideration to make includes what expectations Twitter users have when posting content. Other questions to consider include to what degree do social media users know that the content of their posts will be used for research purposes?

Some have suggested that the benefits of using Twitter for public health related research are so valuable that they outweigh the ethical dilemmas and ethical considerations that would be applied to other uses of Twitter related research (for instance for commercial profit) or other research methodologies that require ethical approval (De Choudhury, Counts, & Horvitz, 2013). Despite this perspective, it is important to note that most social media users' anonymity can be ensured by separating tweets from usernames and aggregating tweets. As well, intentional considerations can be made to reduce the risk of identifying anyone in sample tweets by limiting the use of such examples where possible, modifying language if needed given the sensitivity of the topics (emotional and mental health), and again, using aggregated data instead of individual social media posts.

When done at the neighbourhood level, social media research has the potential for reputational damage to occur which may impact the wellbeing of individuals who live in the area. Reporting on communities that are high in stress and low in resilience may cause harm in the form of stigma. To mitigate this risk, findings should be written in a way that does not potentially harm communities. This can be done by consulting with appropriate community stakeholders and incorporating input with community partners to discuss variation of research findings at the community level in a sensitive fashion.

Despite the ethical dilemmas, there are clear benefits to using social media analysis. This type of work can produce an analysis from a sizeable quantity of user-generated content and also allows for the observation of timelines over the course of a disaster to track changes in emotions. As well, perspectives and information from populations and groups who may not typically engage in mental health research may be captured in this, which has the potential to allow for the viewpoint and insights of those who belong to marginalized or underserved communities to be shared. Additionally, the raw nature of posts allows for Tweets to be unfiltered in nature which will help in accurately capturing feelings and moods.

Study Area

The City of Hamilton is midsized urban city located in southern Ontario with a population of over 536,000 people. In 2001, five suburban communities amalgamated with the central urban area to make what is now known as the City of Hamilton. Distinct geological features of the Niagara Escarpment divide Hamilton east to west bound creating a natural rift between what is colloquially referred to as the "Mountain" from and the lower part of the city. The impacts of this division on the health of residents have been an area of interests to many as several health disparities follow these divisions around the city including the upper and lower areas. Several studies over the past two decades have investigated and discussed the health disparities in the city (Luginaah, Isaac et al., 2001; Wilson, et al., 2004; Wilson, Kathi, Eyles, Elliott, & Keller-Olaman, 2009; Wilson, Kathi, Eyles, Ellaway, Macintyre, & Macdonald, 2010).

In 2010, a series of investigative newspaper articles entitled "Code Red" was published which highlighted neighbourhood level disparity and the drastic health inequities (Buist, 2010).

Major findings from the collaborative series included a 21-year age gap in mortality rates and a 16 fold difference in hospital visits and admission between certain communities (DeLuca, Patrick F., Buist, & Johnston, 2012). The Code Red series resulted in several local leaders, community agencies, politicians, and various stakeholders to galvanize in order to improve the health conditions of various neighbourhoods in the city (Buist, 2019).

Despite the increased attention, resources, and support for reducing Hamilton's health inequity, a ten year follow up to the initial Code Red series showed that there was no progress in ameliorating health disparities. In fact, health outcomes in the City of Hamilton were worse than they were during the initial Code Red report (Buist, 2019). While it is unclear how the several initiatives and interventions implemented may have shaped health outcomes (perhaps without these supports the health of the population would have been even worse), additional research is needed to investigate how social determinates of health contribute to health inequities in the city. Additional work is also needed to explore the effect of place on health. As well, given the increased interest on neighbourhoods and health, further work is needed to distinguish between environmental (contextual) and individual level (compositional) factors in an area that influence emotional health stress and resilience. Lastly, while the Code Red project examined the impacts of several social determinants of health, psychosocial measures of stress and resilience were not examined and these psychological indictors should be included to better understand the emotional aspects of health among Hamiltonians.

COVID in Hamilton

As with other cities across Ontario, COVID has taken a toll in Hamilton. To date, there have been over 21,000 confirmed cases of COVID, with 6.9% of cases resulting in hospitalization. Cumulatively, there have been 400 COVID related deaths (City of Hamilton, 2021). In terms of demographics, most cases have occurred among those age 20-29 (21.4%), with those age 30-39 having the second highest COVID infection rate at 15.4%. COVID cases based on gender appears equal with males having 49.2% and females being at 50.6%. In terms of vaccines, there have been over 671, 200 doses administered within the city (City of Hamilton, 2021).

Research Objectives

In order to respond to the pressing need for data and documentation on emotional health inequities during the COVID-19 pandemic, this study will investigate the social and spatial distribution of community stress and resilience over the course of the COVID-19 pandemic in Hamilton Ontario by: 1) Mapping differences in the experience of pandemic-related stress and resilience across Hamilton neighbourhoods (n=134); 2) Measuring how contextual and compositional neighbourhood characteristics (e.g. COVID case count, health behaviours, visibly minority and education) correlate with neighbourhood variation in stress; and 3) Determining if higher neighbourhood resilience reduces the impacts on stress. This study is well-suited to Hamilton given historic neighbourhood health inequalities (DeLuca & Kanaroglou, 2015; DeLuca et al., 2012), and multisectoral development efforts (Cahuas, Wakefield, Peng, & Agbeyaka, 2013), which may have led to variation in community resilience.

A literature review has suggested that there are several potential candidate explanatory variables that should be considered when exploring the relationship between stress and resilience during adversities: exposure (as indicated by COVID case count), health behaviours, education, socioeconomic status, visible minority status, household size, and vaccination rates.

Exposure

Research suggests that a dose-response relationship exists between exposure and psychological distress whereby increased levels of exposure produces greater levels of stress

(Neria, Nandi & Galea, 2008). COVID rates can be used as an indicator for exposure and this would consist of those who directly had COVID and/ or those who had someone close to them (such as a member of their household or a neighbour) contract the virus (Kira e al., 2020).

Health behaviours

Physical activity and healthy eating appear to have a bidirectional relationship with stress. Both healthy eating and physical activity appear to act as protective factors against stress, and, increased stress often results in decreased physical activity and the consumption of unhealthly foods (Schultchen et al., 2019). The relationship between stress, resilience and smoking status appears more complicated. Resilience appears to act as a moderator for smoking status and stress with recent data suggesting that resilience can predict never smoking status, and that those high in stress are more likely to have ever smoked (Tsourtos et al., 2019). However, a recent study on smoking and COVID related stress suggests that stress was associated with some smokers decreasing their use (14.1%), while others increased consumption (18.9%) (Bommele, et al., 2020). Relationships between disaster stress exposure and drinking behaviour have also been well documented (Cepeda, Valdez, Kaplan & Hill, 2009; Cerda, Tracy & Galea, 2011). Resilience appears to act as a mediator between stress and binge drinking (Kim & Cronley, 2020).

Visible minority population

Specific stress related to one's minority status have been explored through a minority stress framework (Dressler, Oths, & Gravlee, 2005; Meyer, 2003; Kuzawa & Sweet, 2009). A recent nationally representative study indicated that visible minority status has been associated with reduced coping during COVID in Canada as well as increased levels of fear (Jenkins et al., 2021). Other Canadian data suggests that visible minority populations are more likely to report poor psychological health than their White counterparts (27.8% vs 22.9%) (Statistics Canada, 2021).

Socioeconomic status

Socioeconomic status is an influential factor in health and wellbeing. In terms of socioeconomic characteristics at the neighbourhood level, COVID morbidity and mortality appears to be related based on international studies (Sa, 2020). Sizeable disparities have been documented related to COVID cases and area-income level (Schmitt-Grohe, Teoh, Uribe, 2020). Socioeconomic status has been linked to stress independent of other sociodemographic characteristics including age, gender and race (Cohen, Doyle, Baum, 2006).

Education

Education level has been associated with resilience after a natural disaster over the long term, with those that had higher levels of education displaying more resilience, and those with lower education attainment experiencing more struggles (Bonanno, Galea, Bucciarelli &Vlahov, 2006; Frankenberg, Sikoki, Sumantri, Suriastini & Thomas, 2013). Educational attainment may influence how one perceives and responds to stressful situations (Fiocco, Joober, Lupien, 2007). Additionally, social media use has been correlated with education attainment in some settings. A recent paper suggests that individuals in the United States with higher education level use social media more that those with less educational attainment (Hruska & Maresova, 2020).

Vaccination rate

Recent research has suggested that receipt of at least one dose a COVID-19 vaccine is associated with lower levels of mental distress (Perez-Arce, Angrisani, Bennett, Darling, Kapteyn & Thomas, 2021). These authors note that these differences in distress were beyond changes that already occurred during the peak of the pandemic.

Household Size

Crowding appears to be mixed in terms of household size and stress. A recent paper suggested that larger households were correlated with reduced psychological related challenges among children (Grinde & Tambs, 2016). As well, household crowding (more than one person per room) has been identified as a chronic stressor (Riva et al., 2014) On the other hand, the transmission of COVID among members living in a single household appears to be high (Liu, McQuarrie, Song & Colijin, 2021). Rates of incidence among members of the same household have even been reported to be higher than other respiratory syndromes (Mathur et al., 2020). Household size also appears to be a moderating factor for COVID-19 pandemic related stressors with individuals that have a low number of household members demonstrating less COVID related stressors and fears (Horesh, Milstein, Tomashin, Mayo & Gordon, 2021).

Research Paradigm

Being able to understand and communicate assumptions about reality and the nature of it is an vital component of research. Paradigms consist of the worldview and common beliefs that inform how problems can be understood. Thus, paradigms represent a shared set of beliefs that help inform the solutions to problems and consist of ontology, epistemology, methodology and methods (Brown & Dueñas, 2020). It is important to document the assumptions about the world as these conventions not only impact the interpterion of information, but also the way in which that information is collected and disseminated. The following section will explore pragmaticism as a research paradigm.

Pragmatic Paradigm

The pragmatic paradigm emerged as a resolution to the dichotomy between positivism and interpretivism. Philosophers of the pragmatic paradigm advocated that it is impossible to access truths about the world by using a single scientific method as suggested by positivism and also suggested that reality could not be determined or constructed solely using the interpretivist paradigm (Alise & Teddlie, 2010; Biesta, 2010). Instead of utilizing one rigid methodological framework, pragmatic approaches research as being pluralistic and practical that can accommodate a mixture or combination of methods to better describe the behaviour, beliefs, and consequences of participants (Biesta 2010; Creswell and Clark 2011). While pragmaticism is often associated with mixed methods approaches (Johnson and Onwuegbuzie 2004; Maxcy 2003), pragmaticism suggests that the best method for creating the intended outcomes should be used be it a single, multiple or a mixed method approach (Tashakkori & Teddlie 200).

Pragmaticism is also distinct from positivist and interpretivist paradigms in that relies on the logical process of abductive instead of an inductive or deductive approach (Campbell, 2011; Davies, 2013). Pragmatic principles emphasis the research question as being the basis for the axiology, ontology and epistemology of research as opposed to the method (Onwuegbuzie & Leech, 2005; Davies, 2013; Parvaiz, Mufti, & Wahab, 2016). Epistemologically, researchers are able to select methods that achieve their objectives. This approach allows for the research situation to be of prominence instead of the epistemological place where a scientist assumes their relationship with the participants being examined (Mertens, 2010). Pragmaticism uses a non-singular relative ontology. This refers to the combination of research methods in which any and every and any methodology that aids in the discovery of knowledge can be used (Kivunja & Kuyini, 2017). As well, a value-laden axiology perspective is taken in which research is conducted to benefit people (Kaushik & Walsh, 2019).

Overall, pragmaticism does not prioritize or commit to any singular system of reality or philosophy (Kivunja & Kuyini, 2017). Instead, the focus is on the ‘how’ and ‘what’ components of the research problem and ensuring that the use of methods match the specific research question and purpose of the study. Action research, causal comparative methodology and correlational methodology are commonly used (Kivunja & Kuyini, 2017). Given that research questions are central in this paradigm, collecting and analysis data is done in a way that is most likely to develop insights into the questions irrespective of philosophical orientation to other paradigms.

Since both the use of novel methodologies lends itself well to the pragmatic paradigm and that the perspective of research benefiting people, this study is well suited for this paradigm. Other components of this study resonate with a pragmatic approach as well. A pragmatic perspective advocates for collating different sources of knowledge with the aim of generating appropriate solutions (Johnson & Onwuegbuzie, 2004). Gaps in knowledge-to-action occur when information generated does not address practice related needs (Van De Ven, 2013). Connections should be fostered between researchers and practitioners or policy makers to develop communities of inquiry (Hannes & Lockwood, 2011). These communities of inquiry are an important component of pragmaticism and an integrated knowledge translation approach whereby collaborative processes between researchers and various stakeholders occurs can address this.

Methodology

Publicly available tweets from Twitter users will be used for this study. Twitter offers a distinct source of big data given the real-time quality of information (Sinnenberg et al., 2017). Data from Twitter's publicly available Application Programming Interface (API) will include information on the Twitter users who are generating content, the text to be analysed, geolocation, and key words. The sample will be constricted to tweets produced in Hamilton Ontario neighbourhoods. This will be done to study the temporal and spatial variation in stress and resilience.

Sentiment analysis of geolocated Twitter posts generated within Hamilton neighbourhood boundaries will be conducted using Extracting the Meaning of Terse Information (EMOTIVE), a validated software that mines and codes emotional information from human language expressions (Shaughnessy et al., 2018). EMOTIVE is an ontology-based program that was developed with the use of discourse analysis, semantics, and linguistic expertise (Sykora et al., 2013). The program uses a Natural Language Processing pipeline that enables the handling of raw text to then be sorted and categorized based on a range of fine-grained emotions. EMOTIVE is capable of comprehensive and nuanced analysis of the sociolinguistic characteristics of Tweets related to various emotions including hope, happiness, anger, fear, disgust, sadness, shame, confusion and surprise (Sykora et al., 2013). Stresscapes is a separate ontology-based program that was developed specifically to detect and assess expression of stress and the magnitude of stress-related patterns (Elayan et al., 2020). Expressions of negative emotions and text patterns related to stress, and ones that accompany stress (such as anguish and panic) are also taken into account in the Stresscapes ontology by capturing indicators of five superclasses, including terms that directly indicate stress, states caused by stress, states that may cause stress, states that may accompany stress, and finally, antonyms for stress. Stresscapes creates a total score by summing scores across the superclasses. Stresscapes has been validated as a stress detection tool (Elayan et al., 2020).

Measures

Outcome Variables

The classification of stress and hope emotions from the final tweets will be done using Stresscapes and EMOTIVE. Stress in tweets will be dichotomized into stressful (case=1) or non-stressful (no case=0). Hope will be coded similarly.

After tweets are coded and emotions identified, temporal classification will occur. Tweets included in the analysis will consist of ones from distinct phases of the pandemic. This will be done for Hamilton based tweets posted during the first, second and third wave of the pandemic (March - July 2020, August 2020 - February 2021 and March 2021-July 2021 respectively) and from March 2017 to February 2018 to establish baseline levels of stress and hope. The geo-coordinates of tweets will be plotted over a neighbourhood level map of Hamilton using ArcGIS, a system used to interpret and analyse spatial data.

Candidate Explanatory Variables

Data provided for candidate explanatory variables were taken from Open Hamilton (City of Hamilton, 2020). Open Hamilton provides data and information on the City of Hamilton, some of which is derived from custom tabulations from Statistics Canada's 2016 Census. The City of Hamilton's Public Health Services prepares COVID related data from the Ministry Case and Contact Management System.

COVID rates

COVID-19 case counts by neighbourhood is provided by the City of Hamilton. This data is provided by the Public Health Case and Contact Management Solution, which is responsible for obtaining information from Public Health Units and working to prevent the spread of the virus (Ministry of Health, 2021; Ministry of Health System Emergency Management Branch, 2021). COVID rates of confirmed will be analysed for all three waves of the pandemic in Hamilton based on a resident's permanent address. COVID rate per 100,000 population will be used.

Health behaviours

Health behaviours consisted of percentage of people who currently smoke, have low fruit and vegetable consumption, consume alcohol exceeding cancer prevention recommendations, and are physically active during leisure time (City of Hamilton, 2020).

Visible minority population

Visible minority population will be operationalized as whether a person belongs to a visibility minority group and will be represented by the percentage of individuals in a household who identify as a visible minority (person of colour).

Neighbourhood socioeconomic status

Socioeconomic status was based on a neighbourhood's average household income (sum total incomes of households divided by total number of households), which will be represented based on based on 7 categories: under $25,000, $25,00- $49,999, $50,000-$79,999, $80,000-$99,999, $100,000-$124,999, $125,000-$149,999, and over $150,000.

Household Size

Household size was based on the average number of people residing in a private household based on 5 categories: 1 person, 2 persons, 3 persons, 4 persons, and 5 or more persons.

Education

Information provided from respondents living in private dwelling was used to establish highest educational attainment. The hierarchy used to derive education consisted of no certificate, diploma or degree, high school graduation, trades, college, or university.

COVID Vaccination Rates

Vaccination data was provided by ICES (Institute for Clinical Evaluative Sciences) COVID-19 Dashboard (ICES, 2021).

Statistical Analysis

Statistical analysis will be undertaken using IBM SPSS version 27. To examine the temporal evolution of stress and hope, an analysis will be done with a mixed effect model. Mixed effect models can be used to analyze non-independent, multilevel, or correlated data (Harrison et al., 2018) and will allow for the modelling of neighbourhood level explanatory variables of stress and resilience. This technique accounts for random and fixed effects and are similar to linear regression models and can be used when working with non-independence in data (such as such as social media users within neighbourhoods). Mixed effects model requires the outcome variable to be continuous, and in this analysis, change in the proportion of tweets indicating stress or hope from baseline to each wave (wave 1, 2 and 3) will be done. Trends in stress and hope will also be analysed by completing multiple models. The first, second and third model will be for levels of stress and hope during each respective wave of the pandemic. A fourth and final model will be completed to examine the slope of the trend in resilience and stress from baseline levels across all subsequent waves.

Spatial regression models will be used to compare rates of stress and resilience between the three waves of the pandemic as well as the corresponding time pre-pandemic conditions. Spatial regressions are appropriate given that this method is able to address complexities that emerge when applying regression methods to geographic or spatial data. ArcGIS will be able to build the spatial regression models and help explore the relationship between stress, resilience and the selected candidate variables.

To determine if there are significant clusters of stress and resilience in Hamilton and to better understand regional variations of stress and resilience as it relates to variables such as COVID case count in an area, an analysis will be conducted using SaTScan. SaTScan (Kulldorff, 2021) will be able to perform space-time scan statics for stress and resilience and allow for cluster detection and evaluation. Scan statistics consists of using a scanning window to move across space and time while documenting stress and resilience inside the window at each neighbourhood. The number of observed cases of stress and resilience will be counted for each neighbourhood. The space-time scan statistic will note any excesses cases in an area which will be further analysed to determine statistical significance (Kulldorff, Heffernan, Hartman, Assuncao & Mostashari, 2005).

Explanatory variables will be selected for a multiple regression model using chosen candidate variables by completing a series of steps. Each automated step will evaluate the candidate variables using *t* statistics for the variable coefficients. As such, candidate contextual risk factors for this study will be identified where there are significant bivariate correlations with the change in stress and hope emotions in neighbourhoods. Bivariate correlations will be calculated among the appropriate variables using Pearson’s coefficient of correlation (Pearson’s R).

A backward stepwise regression procedure will be conducted. This will include all variables that correlate significantly with stress and hope emotions in neighbourhoods. Stepwise regressions use statistical significance to determine which explanatory variables should be included in a multiple-regression model. Using a backward-elimination rule will involve examining all possible explanatory variables for significance and discarding the least explanatory variables one a time. This removal of variables stops only when the remaining variables are all statistically significant ($p< 0.05$). Backward-elimination is an approach for this study given the appropriate number of candidate variables. Statistically significance will be set at $p<0.05$. Multicollinearity will be a salient issue for regression analysis, and collinearity diagnostics will be conducted for all variables in the fully adjusted model.

Finally, to examine if change in resilience moderates the level of stress at the neighbourhood level, effect modification will be examined. Tests for effect modification by resilience will compare model fit statistics for the final model of neighbourhood stress from the backwards stepwise regression to a model that includes neighbourhood resilience as well as cross product terms for neighbourhood resilience and explanatory variables. For each explanatory variable in the final model, a separate cross product term will be included. Effect modification will be identified a significant improvement in the model fit statistic from the final model of neighbourhood stress to the expanded model of interest.

Limitations

This methodology should be interpreted with the following limitations in mind. Firstly, EMOTIVE is only able to analyze tweets in English. This may exclude populations that tweet in languages other than English and may not capture resilience, stress, and the mental health profile of all communities. Secondly, this study relies on those who access to internet and express themselves on social media. The intricacy of social media accessibility and adoption of internet use for all communities needs further investigation in the COVID-19 context. Thirdly, only tweets that were geolocated will be included, and tweets that do not have this geotagged information will not be captured in the analysis. Overall, the study will not be representative of the entire city of Hamilton population, rather Twitter users in the city who have publicly available accounts that are geotagged and may similarly not represent all areas of the city equally, rather those that have users that tweet in specific locations with geotagging on. Thus, it remains unknown if publicly available geotagged tweets are correlated with stress and resilience. Fourthly, different forms of stress may not be distinguished in the analysis. For instance, it may not be possible to distinguish tweets that reflect feelings of eustress (a positive response to a stressor) compared to distress (a negative response to a stressor). Along these lines, less obvious expressions of stress may not be detected by EMOTIVE. Fifthly, the analysis included data from the 2016 Census and baseline tweets were from 2017-2018. Future research would benefit from using more recent data from the 2021 Census and baseline tweets from 2019. Lastly, vaccine status as an explanatory variable may be influenced by demographic characteristics. The province of Ontario developed a three-phase plan for vaccine rollout that prioritized high risk populations and groups including health care workers, seniors living in congregate settings and facilities, and those over the age of 80 (Ontario, 2021). As such, some individuals and communities were not able to access vaccines at the same time. Thus, there may be an important limitation to consider if some communities were not able to access vaccines as readily as others, and if that pattern is associated with stress and resilience.

Relevance

Understanding what builds resilience at the community level is important to investigate so that appropriate interventions can be implemented to support those in need during the widespread psychological distress the COVID-19 pandemic is having. This timely study will develop a method for examining and tracking neighbourhood mental health inequalities during pandemics and will contribute to the scant literature on assessing emotional wellbeing using social media during COVID-19. Knowledge produced from this thesis will also be used to plan targeted interventions to foster community resilience during future waves of COVID-19 and subsequent pandemics in urban settings. It will also be of great interest to see the temporal changes associated with pandemic related changes including the onset of COVID-19, implementation of never before used public health measures (such as lockdowns, universal masking, and physical distancing), and the delivery of vaccines.

Knowledge Translation and Exchange

This proposed thesis will contribute to the identification of places in Hamilton where post-pandemic recovery efforts may need to be targeted and benefit more generally to the growing literature about the mental health impacts of the COVID-19 pandemic in urban cities across Canada. An integrated knowledge translation approach will build on existing work with decision-makers in the City of Hamilton's Neighbourhood Development office, which has already identified community resilience as an important issue to better understand in order to improve health equity. As such, staff from The City of Hamilton Neighbourhood Development Office will help interpret relationships observed and identify implications for intervention, as well as identify gaps in the analysis. Dissemination engagements will include presenting results at neighbourhood planning groups and committees, to Hamilton city staff and policy makers, and the use of media releases for the general public in and around Hamilton. Additionally, information generated from this thesis will be presented for academic audiences in the form of peer reviewed publications and conference presentations.

Ethics

Information collected and analysed for this study will be from publicly available data. As such, ethical approval is not needed.

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Chapter 2: Community stress and resilience during covid-19: Assessing the emotional profile of the City of Hamilton using a social media analysis

Introduction

Since its emergence in December 2019, the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that causes the COVID-19 disease has been a public health emergency warranting international concern (WHO, 2021). To date, there have been over 572 million confirmed cases globally, with over 12 million deaths (WHO, 2022). The burden of COVID-19 has been substantial with expenditures continuing to increase (Gebru, et al., 2021). While COVID has directly threatened and caused significant personal harm, public health interventions and government mandates such as stay at home orders and lockdowns designed to reduce the spread of the disease have also been a source of emotional distress (Eichenberg, Grossfurthner, Kietaibl, Riboli, Borlimi & Holocher-Benetka, 2021).

Research on the impact of the pandemic (including public health measures and the economic consequences of COVID-19) on mental health suggests that higher lockdown-related restrictions and increased levels of perceived life changes have been correlated with higher levels of psychological impairment (Benke, Autenrieth, Asselmann, & Pane-Farre, 2020). The cross-sectional study conducted by Benke and colleagues (2020) examined feelings of depression, anxiety, loneliness, psychological distress and life satisfaction among residents across all federal states in Germany. In Canada, the direct and indirect mental health costs of the pandemic are substantial with data suggesting deteriorating mental health and increased levels of stress, fear and suicide (Dozois, 2020; McIntyre & Lee, 2020). A recent review containing international data at the continent level (including North America) suggests that the distribution of mental health challenges stemming from COVID-19, public health interventions (quarantines and lockdowns), fear of getting infected, and psychological sequelae from contracting COVID varies within large-sized populations (Hossain et al., 2020). Additional research is needed to better understand emotional responses during the pandemic at the local level in Canada during COVID.

Previous research has investigated the influence of large-scale disasters and stressors on population mental health and wellbeing. Events such as mass shootings (Lowe & Galea, 2017), natural disasters (Beaglehole et al., 2018), infrastructure related calamities (Makwana, 2019) and biological disasters such as infectious disease outbreaks (Hsieh et al., 2021) contribute to several psychopathologies including PTSD, anxiety, depression, and increased substance use (North, 2016). Such disasters result in unexpected death and trauma and the associated threat of harm and danger can also induce profound personal stress (Norris, Friedman, Watson, Bryne & Kaniasty, 2002). Additionally, social processes are often disrupted during disasters with social networks, services, and access to communal resources being negatively impacted (Goldmann & Galea, 2014). This can hinder how well community members are able to adapt to disasters.

Despite the devastating effects of disasters, some communities are better able to adapt to these hardships than others (Braun-Lewensohn & Sagy, 2014). Resilience theory posits that positive contextual, social, and individual level factors can attenuate negative outcomes after adverse events (Cavaye & Ross, 2019, Rapaport et al., 2018). Community resilience focuses on the ability of a group to recover from an adversity (Berkes & Ross, 2012), and it can be understood as the process in which communities are able to galvanize supports and organize resources to thrive in a changing and uncertain environment (Norris et al., 2008). There have been urgent calls for governments, decision makers, clinicians, and researchers to focus on resilience during the pandemic (Vinkers et al., 2020). However, the literature on community resilience during COVID has been limited. Additional work is needed to explore resilience in community settings following disasters.

Hope and resilience are strongly related constructs that both consist of having a positive attitude of the future (Duggal, Sacks-Zimmerman & Liberta, 2016). Snyder (2000) describes hope as “a positive motivational state that is based on an interactively derived sense of successful (a) agency (goal-directed energy) and (b) pathways (planning to meet goals)” p.3. Previous work has implicated hope as being a buffer to negative impacts caused by adverse events and stressful conditions (Valle, Huebner & Suldo, 2006). Hope has also been conceptualized as a component of resilience and used as a proxy to better understand and establish resilience. For instance, a recent study explored hope as a resilience variable in describing COVID related stress (Braun-Lewenson, Abu-Kaf & Kalagy, 2021). Results of this work suggests that hope (in addition to sense of coherence – the ability to access and use one’s resources to cope with stressors and promote optimal wellbeing) can in part explain variation in emotional distress between different populations and groups. As well, hope appears to be a strong indicator of community resilience when analysing social media content in urban settings (Belanger, 2021).

There are significant methodological and logistic challenges of conducting research about disaster-related community stress and resilience, which may be contributing to the dearth of literature on this topic. The unexpected nature of adversities makes it difficult to assess and ascertain a population’s psychological profile in a timely fashion. Further, emotional states are highly variable, so multiple measurements are required to understand how profiles change over time (Kessler & Wittchen, 2008). The use of cross-sectional designs is commonly used. However, the temporal ambiguity between exposure and outcome of stress and resilience of these studies limits causal inference (Benight & McFarlane, 2007). Establishing baseline levels of emotions retrospectively to compare to current and post disaster functioning can be unreliable and costly. Widespread displacement of people also makes it difficult to gather data on the experiences of those who are facing a disaster. Convenience sampling is often used during these times, which may result in selection bias and impact the representativeness and generalizability of results (Pierce et al., 2020). Given these limitations, innovative approaches are needed to gather pre-disaster data to make comparisons to peri and/or post-disaster functioning.

The challenges of collecting data in traditional methods have resulted in clinicians and researchers engaging in a range of methods to better capture individual's emotional responses to adversity. Ecological Momentary Assessment (EMA) is one example of methods that involves collecting information using real time data on participants emotions and behaviours (Shiffman, Stone, Hufford, 2008). This also involves studying these emotions and behaviours in one's natural environment to better understand people's responses and behaviours in their natural setting. The application of EMA to disaster research has the potential to provide more nuanced data collection and analysis especially when examining emotional responses to adversities and unique approaches are needed to better understand how to measure emotional responses in real time and in natural environments.

One novel approach to studying community stress and resilience is by analysing the emotional content from large scale user-generated social media content. Social media allows for individuals to express their feelings towards internal or external events and circumstances, and this information can be valuable for understanding public sentiment. This method also provides dynamic insights into emotional expression and has been used to understand emotional reactions to terrorist attacks (Gruebner et al., 2016) and natural disasters (Gruebner et al., 2017). As well, it addresses many of the limitations associated with conducting research during and after disasters using more conventional methodologies.

A review of the literature review suggests several potential explanatory variables when exploring the relationship between stress and resilience during the COVID-19 pandemic: COVID case counts, education, visible minority status, and household size.

COVID-Case Count

Research suggests that a dose-response relationship exists between exposure and psychological distress whereby increased levels of exposure produces greater levels of stress (Neria, Nandi & Galea, 2008). COVID rates can be used as an indicator for both direct experience of the virus as well as indirect experience via being close to someone close who contracted the virus (e.g., a member of their household or a neighbour) (Kira e al., 2020).

Visible minority population

Specific stress related to one's minority status has been explored through a minority stress framework (Meyer, 2003). Minority stress was originally conceptualized as stressors that affect sexual minorities (Meyer, 1995), but has been applied to visible minority populations more recently (Dressler, Oths, & Gravlee, 2005; Kuzawa & Sweet, 2009). A recent nationally representative study indicated that visible minority status has been associated with reduced coping during COVID in Canada as well as increased levels of fear (Jenkins et al., 2021). Other Canadian data suggests that visible minority populations are more likely to report poor psychological health than their White counterparts (27.8% vs 22.9%) (Subedi, Greenberg & Turcotte, 2020).

Education

Education level has been associated with resilience after a natural disaster over the long term, with those that had higher levels of education displaying more resilience, and those with lower education attainment experiencing more struggles (Bonanno, Galea, Bucciarelli &Vlahov, 2006; Frankenberg, Sikoki, Sumantri, Suriastini & Thomas, 2013). Educational attainment may influence how one perceives and responds to stressful situations (Fiocco, Joober, Lupien, 2007). Additionally, social media use has been correlated with education attainment in some settings. A recent paper suggests that individuals in the United States with higher education level use social media more that those with less educational attainment (Hruska & Maresova, 2020).

Household Income

Socioeconomic status is an influential factor in health and wellbeing. In terms of socioeconomic characteristics at the neighbourhood level, COVID morbidity and mortality appears to be related based on international studies (Sa, 2020). Sizeable disparities have been documented related to COVID cases and area-income level (Schmitt-Grohe, Teoh, Uribe, 2020). Socioeconomic status has been linked to stress independent of other sociodemographic characteristics including age, gender, and race (Cohen, Doyle, Baum, 2006).

Household Size

Family size and the number of individuals within a household can have an influence on a person's mental health and wellbeing. For instance, household crowding a condition in which the amount of people living in a residence surpasses the size/ space of the available dwelling area (WHOb, 2018). Household crowding can lead to stress in the home and cause adversities among residents and has been associated with increased risk of infectious diseases and stress (WHOb). Family size has also been associated with mental health with recent studies suggesting it can be a predictor for mental health disorders such as anxiety (Ahmad, Rahman & Agarwal, 2022; Hosen, Mamun & Mamun, 2021)

Research Questions

This study will investigate the social and spatial distribution of community stress and resilience in Hamilton, Ontario, in pre-pandemic and peri-pandemic conditions using analysis of geotagged social media content by answering the following questions:

1) What differences exist in the trajectories of pandemic related stress and resilience between Hamilton neighbourhoods pre- and peri-pandemic?;
2) Which contextual neighbourhood characteristics are correlated with neighbourhood variation in stress?; and,
3) Does higher neighbourhood resilience reduce the impact of contextual neighbourhood characteristics on neighbourhood variation in stress?

Methodology

Study Area

The City of Hamilton is midsized urban city located in southern Ontario with a population of over 536,000 people. In 2001, five suburban communities amalgamated with the central urban area to expand the size of the City of Hamilton. Distinct geological features of the Niagara Escarpment divide Hamilton east to west bound creating a natural rift between what is colloquially referred to as the “Mountain” from and the lower part of the city. The impacts of this division on the health of residents have been an area of interests to many as several health disparities follow these divisions around the city including the upper and lower areas. Several studies over the past two decades have investigated and discussed the health disparities in the city (Luginaah et al., 2001; Wilson, et al., 2004; Wilson, Kathi, Eyles, Elliott, & Keller-Olaman, 2009; Wilson, Kathi, Eyles, Ellaway, Macintyre, & Macdonald, 2010).

In 2010, a series of investigative newspaper articles entitled "Code Red" was published which highlighted neighbourhood level disparity and the drastic health inequities (Buist, 2010). Major findings from the collaborative series included a 21-year age gap in mortality rates and a 16-fold difference in hospital visits and admission between certain communities (DeLuca, Buist, & Johnston, 2012). The Code Red series resulted in several local leaders, community agencies, politicians, and various stakeholders to galvanize to improve the health conditions of various neighbourhoods in the city (Buist, 2019).

Despite the increased attention, resources, and support for reducing Hamilton's health inequity, a ten year follow up to the initial Code Red series showed that there was no progress in ameliorating health disparities. In fact, health outcomes in the City of Hamilton were worse than they were during the initial Code Red report (Buist, 2019). While it is unclear how the several initiatives and interventions implemented may have shaped health outcomes (perhaps without these supports the health of the population would have been even worse), additional research is needed to investigate how social determinates of health contribute to health inequities in the city. Additional work is also needed to explore the effect of place on health. As well, given the increased interest on neighbourhoods and health, further work is needed to distinguish between environmental (contextual) and individual level (compositional) factors in an area that influence emotional health stress and resilience. Lastly, while the Code Red project examined the impacts of several social determinants of health, psychosocial measures of stress and resilience were not explored and these psychological indictors should be included to better understand the emotional aspects of health among Hamiltonians.

In April 2021, there had been over 21,000 confirmed cases of COVID, with 6.9% of cases resulting in hospitalization. Cumulatively, there have been 400 COVID related deaths (City of Hamilton, 2021).

Twitter Data

All publicly available tweets containing information about geo-location (i.e., geo-coordinates) from users located in the City of Hamilton between dates March 1st, 2019 to July 31st, 2021 were included in this study. Twitter offers a distinct source of big data given the real-time quality of information (Sinnenberg et al., 2017). Data was obtained from Twitter's Application Programming Interface (API) and included information on the Twitter users who were generating content, the textual expression (i.e., the tweets), and the geolocation of the tweets. Estimates of tweets that are geotagged has been calculated to be 1-3% (Leetaru et al., 2013). However a recent 2019 policy change in the way geolocated features are set on Twitter has potentially reduced the number of geotagged tweets by 50% (Cao, Hochmair, & Basheeh, 2022; TwitterSupport, 2019) ArcGIS software was used to include all tweets from census tracts that had at least 21 tweets in each of five analytic time periods (i.e., pre-pandemic waves 0 (March 2019 to July 2019) and 1 (August 2019 to February 2020), and peri-pandemic wave 2 (March - July 2020), 3 (August 2020 - February 2021), and 4 (March 2021-July 2021). Census tracts with 20 or fewer tweets in any one analytic period were excluded to ensure a minimum sample size within geographic units. After the tweets were coded and emotions identified, temporal classification occurred. Social media analysis can be an EMA as it allows users to produce content in the own environment in real time.

Outcome Variables

Sentiment analysis of geolocated Twitter posts generated within Hamilton neighbourhood boundaries was conducted using Extracting the Meaning of Terse Information (EMOTIVE) and

Stresscapes, validated software that mine and code emotional information from human language expressions (Shaughnessy et al., 2018). EMOTIVE is an ontology-based program that was developed with the use of discourse analysis, semantics, and linguistic expertise (Sykora et al., 2013). The program uses a Natural Language Processing pipeline that enables the handling of raw text to then be sorted and categorized based on a range of fine-grained emotions. EMOTIVE is capable of comprehensive and nuanced analysis of the sociolinguistic characteristics of Tweets related to various emotions including hope, happiness, anger, fear, disgust, sadness, shame, confusion and surprise (Sykora et al., 2013). The use of EMOTIVE was restricted to hope tweets as a proxy for resilience. Stresscapes is a separate ontology-based program that was developed specifically to detect and assess expressions of emotional stress and the magnitude of stress-related patterns (Elayan et al., 2020). Expressions and text patterns related to stress (such as anguish and panic) are also considered in the Stresscapes ontology, as are states that may induce stress, states that may accompany stress, and antonyms for stress. For instance, terms such as "upset" "can't sleep" and "I'm jealous" are marked as stressful (Elayan et al., 2020, page 80). Stresscapes creates a total score by summing scores across the superclasses. Stress in tweets were dichotomized into stressful (case=1) or non-stressful (no case=0). EMOTIVE uses a more simple one-dimensional ontology system to analyse and code feelings of hope from text. Hope was dichotomized in the analysis in the same way as stress.

Explanatory Variables

Open Hamilton (City of Hamilton, 2020) had publicly available data for candidate explanatory variables. Open Hamilton provided data and information on the City of Hamilton, some of which was derived from custom tabulations from Statistics Canada's 2016 Census. The

City of Hamilton's Public Health Services prepared COVID related data from the Ministry Case and Contact Management System.

COVID rates

COVID-19 case counts by neighbourhood were provided by the City of Hamilton. This data was provided by the Public Health Case and Contact Management Solution, which is responsible for obtaining information from Public Health Units and working to prevent the spread of the virus (Ministry of Health, 2021; Ministry of Health System Emergency Management Branch, 2021). Data included in this analysis was COVID case counts on May 28 2020. The census tract layer for this spatial joint was taken from Open Hamilton's COVID-19 Case Counts by Census Tract (Open Hamilton, 2020).

Visible minority population

Visible minority population was operationalized from the 2016 Canadian Census data as whether a person belongs to a visibility minority group and was represented by the percentage of individuals in a household who identify as a visible minority (person of colour).

Household Size

Household size was based on the average number of people residing in a private household based on 5 categories: 1 person, 2 persons, 3 persons, 4 persons, and 5 or more persons. The analysis included the proportion of those in households with 3 or more people and was dichotomized in the analysis as such.

Education

Information provided from respondents living in private dwelling was used to establish highest educational attainment. The hierarchy used to derive education consisted of no certificate, diploma or degree; high school graduation; postsecondary certificate, diploma or degree. The analysis included the proportion of those with no degree.

Household Income

Total incomes of households was represented in the census data based on 7 categories: under $25,000, $25,00- $49,999, $50,000-$79,999, $80,000-$99,999, $100,000-$124,999, $125,000-$149,999, and over $150,000. Household income was dichotomized for the analysis by indicating the proportion of households with income under $50,000.

Statistical Analysis

Statistical analysis was undertaken using IBM SPSS version 27, while maps of the census tracts were created using ArcMap 10.1. Univariate and bivariate analysis was done for candidate explanatory variables. A correlation structure was conducted to determine if the covariates in the analysis were independent among themselves and to address potential collinearity/multicollinearity with +/-0.7 being used as a cut off for a strong bivariate correlation among the explanatory variables (Yoo, Mayberry, Bae, Singh, He & Lillard, 2014). A Pearson correlation analysis was also done to examine how candidate explanatory variables correlate with the trajectory of stress. The alpha level for this correlation analysis was set to 0.10; a more generous alpha level than typical was used to include borderline significant correlates that could become statistically significant in a multivariate model.

Logistic regression models were used to calculate stress and hope trajectories among census tracts during pre- and peri-pandemic periods. Logistic regression models were separately fit for stress and hope ~ census tract x wave. The trajectory (slope) of stress and hope over time for census tracts was represented as odds ratios (OR): no slope=1, decreasing slope= 0 to 1, and increasing slope= 1 or above. This slope represented the change in average hope and stress scores across the selected periods. Trajectories of stress and hope were used by calculating the probability at wave 0. The OR (the slope reported below) is represented by the following formula:

Odds at t= probability at time t/ (1+probability at time t)

As such, the OR for any wave in comparison to the one proceeding it would be 't+1'. This would represent the next plot on the trajectory.

Data for the choropleth maps were based on the proportion of stressful and hopeful tweets in each census tract as the average dichotomous variables in each wave.

To examine if change in resilience moderates the level of stress at the neighbourhood level, effect modification was examined. A cross-product term was created for baseline hope with each of the explanatory variables that had a significant correlation with the stress trajectory, and separate models were run that included one of the cross-product terms along with the relevant base terms (i.e., hope and one of the explanatory variables). Statistically significant effect modification was identified where the cross-product term below the alpha level of 0.05.

Results

Of Hamilton's 190 census tracts, 30 (15.8%) had complete data on COVID case count, census related information, and 21 or more tweets over all 5 waves. Table 1 provides the descriptive statistics for the proportion values of the explanatory variables. Among these variables, household income and family size appear to have the highest mean score and SD, and COVID case counts with the lowest mean and SD.

Table 1. Summary of explanatory variables across census tracts (n=30)

Characteristics of population living in census tracts	**Mean**	**SD**	**Range**

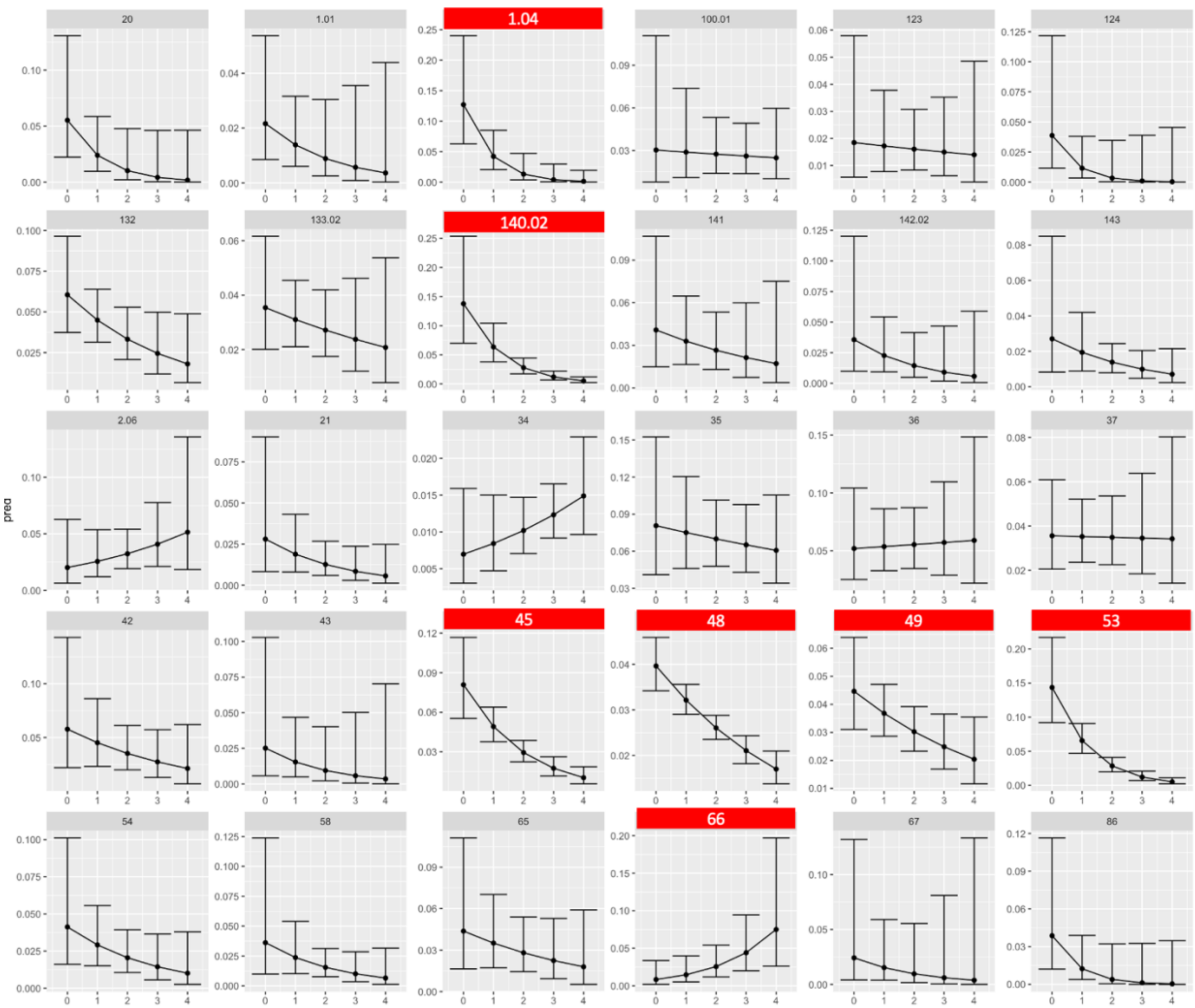
% of resident who have COVID	4.00	2.38	1.1-13.9
% of residents who are visible minorities	21.33	14.76	1.4-57.2
% of residents with no educational degree	19.66	8.44	7.3-38.6
% of households with 3 or more members	35.51	14.39	4.8-64.1
% of households with an income of 50k or less	40.75	19.68	13.8-75.1

Table 2. Summary of proportion of stress and hope emotions across census tracts and by time-period

	Pre-Pandemic				**Peri-Pandemic**						**Total**	
	Baseline Pre-COVID Wave 0 (n=30)		Baseline Pre-COVID Wave 1 (n=30)		COVID Wave 2 (n=30)		COVID Wave 3 (n=30)		COVID Wave 4 (n=30)		Total (n=150)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total Tweets	191.90	503.45	250.47	612.41	255.53	643.25	300.40	646.52	198.63	375.77	239.39	559.74
Proportion of Stressful Tweets	3.55	3.57	3.34	2.11	4.14	2.93	1.28	1.55	1.26	2.24	2.71	2.82
Proportion of Hopeful Tweets	9.99	5.59	10.31	6.59	14.10	6.52	6.28	5.17	4.05	5.82	8.95	6.84

Figure 1 provides a visual representation of differences in the trajectory of the proportion of stressful tweets within each census tract across pre- and peri-pandemic time periods. Table 3 describes the odds ratio for change in stress across time periods within each census tract. P-values indicate that the trajectory of stress across time was significantly different from flat in seven census tracts. Among all census tracts, 26 had a decreasing stress trajectory with four trajectories increasing over time (census tracts 2.06, 34, 36 and 66).

Figure 1. Proportion of tweets with stress emotions within census tracts across study periods



*Red highlighted census tract denotes significant trajectory

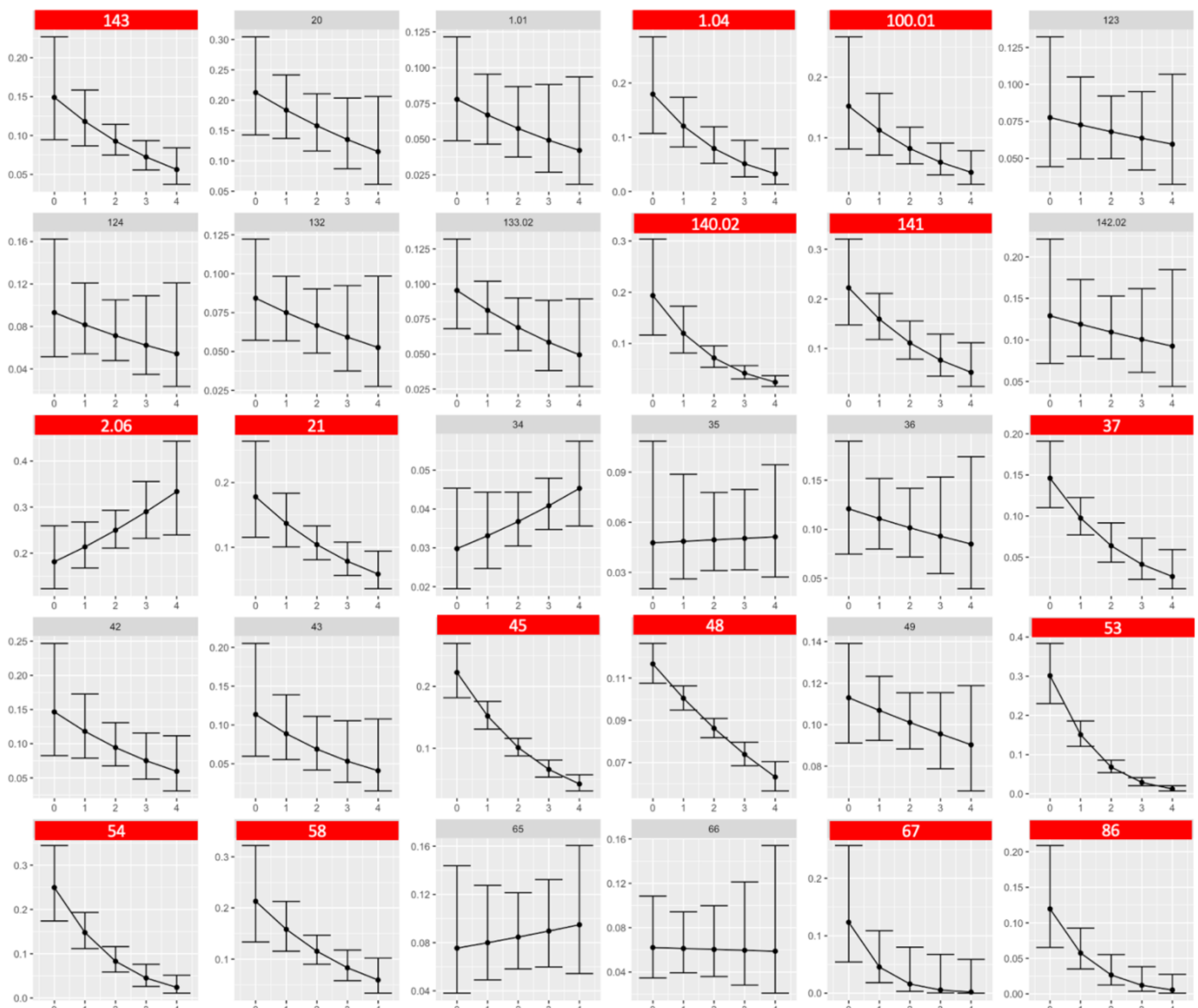
Table 3. Odds ratios for change in stress emotions within census tracts across study periods

Census Tract ID	Log Odds	P Value	Odds Ratio
20	-0.868	0.063	0.420
1.01	-0.452	0.221	0.636
1.04	**-1.195**	**0.003***	**0.303**
100.01	-0.051	0.831	0.950
123	-0.071	0.789	0.932
124	-1.241	0.092	0.289
132	-0.314	0.059	0.730
133.02	-0.137	0.424	0.872
140.02	**-0.859**	**0.000***	**0.424**
141	-0.223	0.423	0.800
142.02	-0.464	0.251	0.629
143	-0.341	0.189	0.711
2.06	0.242	0.336	1.274
21	-0.405	0.164	0.667
34	0.192	0.175	1.212
35	-0.077	0.567	0.926
36	0.034	0.861	1.034
37	-0.010	0.948	0.990
42	-0.260	0.251	0.771
43	-0.498	0.305	0.608

45	**-0.533**	**0.000***	**0.587**
48	**-0.217**	**0.000***	**0.805**
49	**-0.202**	**0.049***	**0.817**
53	**-0.871**	**0.000***	**0.418**
54	-0.360	0.143	0.698
58	-0.434	0.184	0.648
65	-0.230	0.316	0.795
66	**0.565**	**0.027***	**1.759**
67	-0.469	0.423	0.626
86	-1.168	0.073	0.311

Figure 2 provides a graphical representation of differences in the trajectory of the proportion of hopeful tweets within each census tract across the 5 time periods. Table 4 describes the odds ratio for change in hope across pre- and peri-pandemic periods within each census tract. P-values indicate that the trajectory of hope across time was significantly different from flat in fifteen census tracts. Among all census tracts, 26 census tracts had a decreasing hope trajectory, with four (2.06, 34, 35, and 65) having an increasing hope trajectory over time.

Figure 2. Proportion of tweets with hope emotions within census tracts across study periods



*Red highlighted census tract denotes significant trajectory

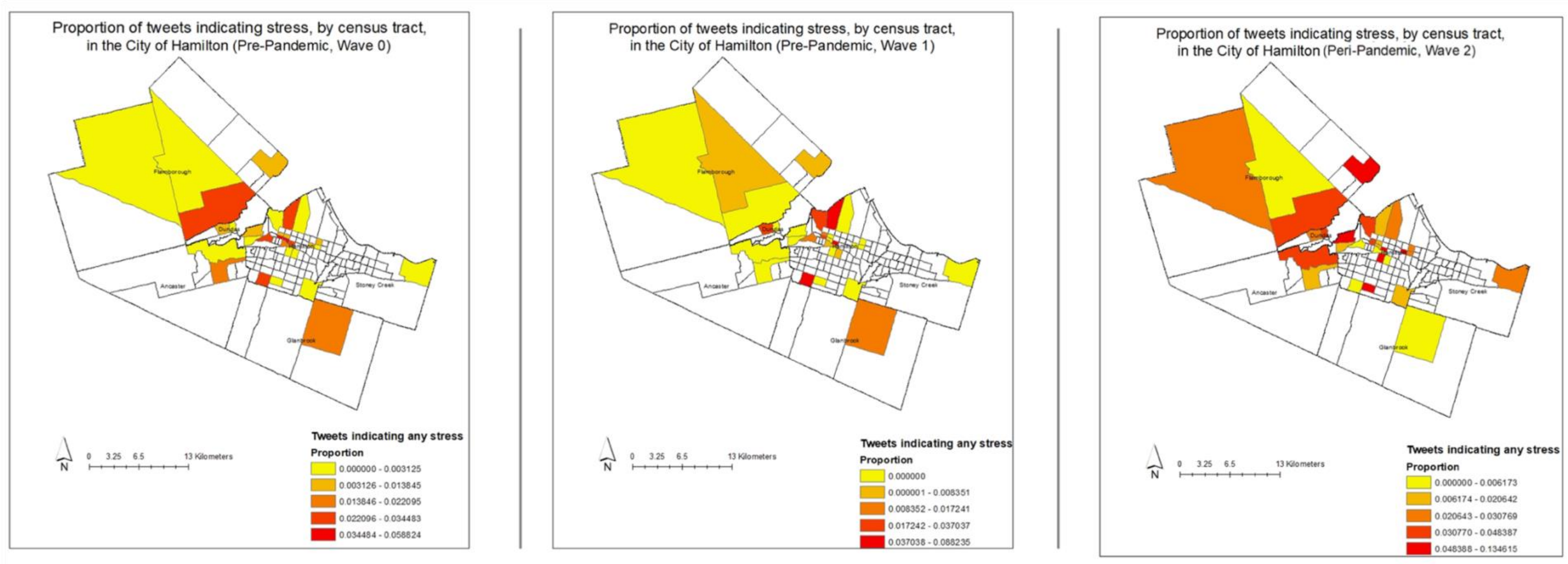
Table 4. Odds ratio for hope associated with each progressive wave

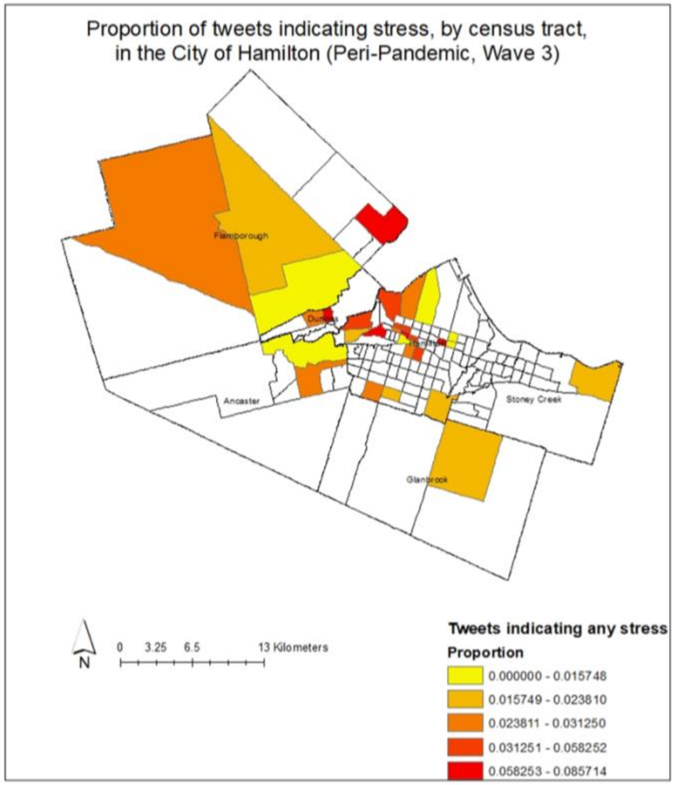
Census Tract	Log Odds	P Value	Odds Ratio
143	**-0.269**	**0.011***	**0.764**
20	-0.182	0.137	0.834
1.01	-0.163	0.235	0.850
1.04	**-0.466**	**0.004***	**0.627**
100.01	**-0.348**	**0.013***	**0.706**
123	-0.071	0.593	0.932
124	-0.145	0.371	0.865
132	-0.126	0.277	0.881
133.02	-0.177	0.108	0.838
140.02	**-0.568**	**0.000***	**0.567**
141	**-0.413**	**0.004***	**0.662**
142.02	-0.093	0.554	0.911
2.06	**0.204**	**0.049***	**1.226**
21	**-0.310**	**0.004***	**0.733**
34	0.109	0.152	1.115
35	0.019	0.904	1.019
36	-0.098	0.505	0.906
37	**-0.460**	**0.000***	**0.631**
42	-0.249	0.079	0.779
43	-0.274	0.132	0.760

45	**-0.466**	**0.000***	**0.627**
48	**-0.168**	**0.000***	**0.845**
49	-0.062	0.290	0.940
53	**-0.889**	**0.000***	**0.411**
54	**-0.651**	**0.000***	**0.522**
58	**-0.365**	**0.005***	**0.695**
65	0.063	0.643	1.065
66	-0.014	0.934	0.986
67	**-1.081**	**0.029***	**0.339**
86	**-0.803**	**0.002***	**0.448**

A series of choropleth maps (i.e., statistical maps that use color gradients to correspond with data intensity within a geographic; Adams, Li & Zhang, 2020) were created for each wave to provide a visualization of changes in the proportion of stress (Figure 3) and hope (Figure 4) tweets across the census tracts over study periods and based on the trajectory within each census tract.

Figure 3: Series of choropleth maps displaying the proportion of stressful tweets per census tract during study time periods




Proportion of tweets indicating stress, by census tract,
in the City of Hamilton (Peri-Pandemic, Wave 3)
Flamborough
Dundas
Ancaster
Stoney Creek
Glanbrook
N
0 3.25 6.5 13 Kilometers
Tweets indicating any stress
Proportion
0.000000 - 0.015748
0.015749 - 0.023810
0.023811 - 0.031250
0.031251 - 0.058252
0.058253 - 0.085714

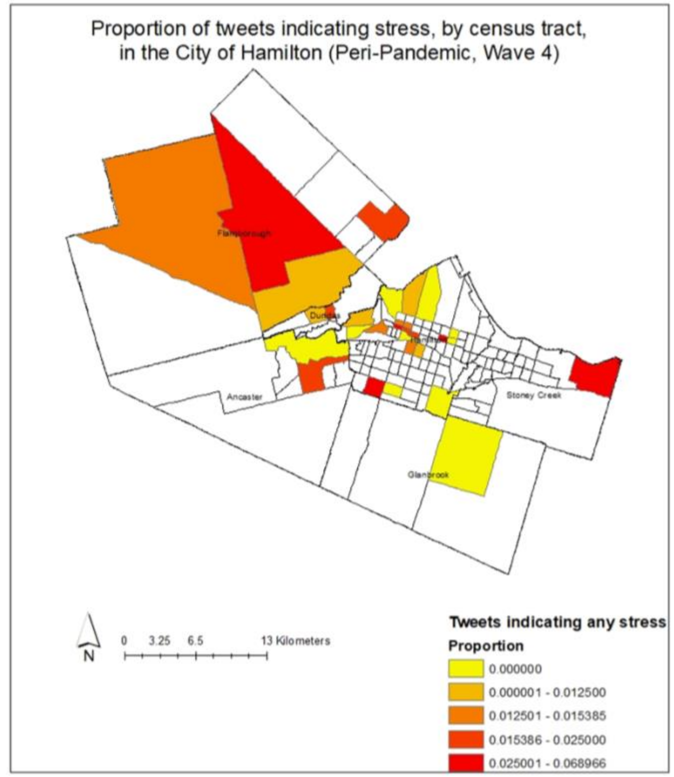
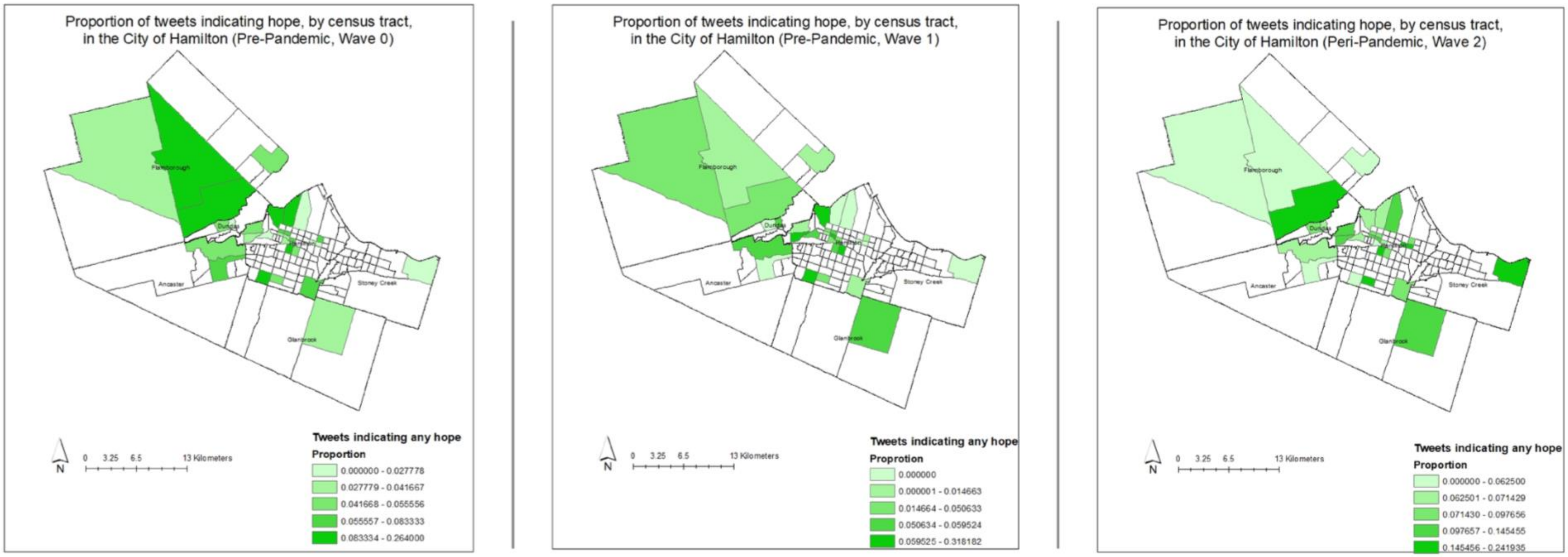
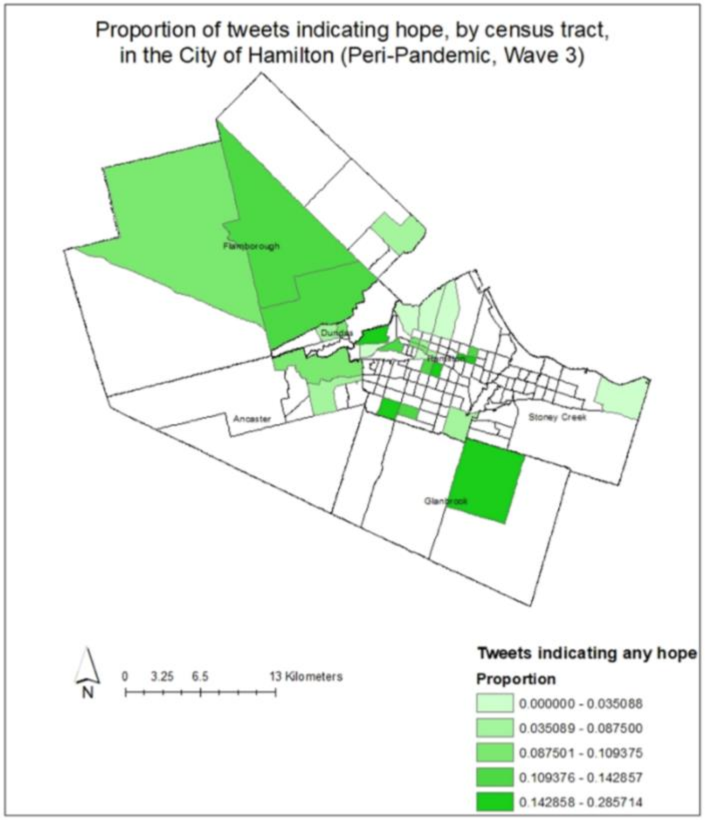

Proportion of tweets indicating stress, by census tract,
in the City of Hamilton (Peri-Pandemic, Wave 4)
Flamborough
Dundas
Ancaster
Stoney Creek
Glanbrook
N
0 3.25 6.5 13 Kilometers
Tweets indicating any stress
Proportion
0.000000
0.000001 - 0.012500
0.012501 - 0.015385
0.015386 - 0.025000
0.025001 - 0.068966

Figure 4: Series of choropleth maps displaying the proportion of hopeful tweets per census tract during study time periods




Proportion of tweets indicating hope, by census tract,
in the City of Hamilton (Peri-Pandemic, Wave 3)
Flamborough
Ancaster
Stoney Creek
N
0 3.25 6.5 13 Kilometers
Tweets indicating any hope
Proportion
0.000000 - 0.035088
0.035089 - 0.087500
0.087501 - 0.109375
0.109376 - 0.142857
0.142858 - 0.285714

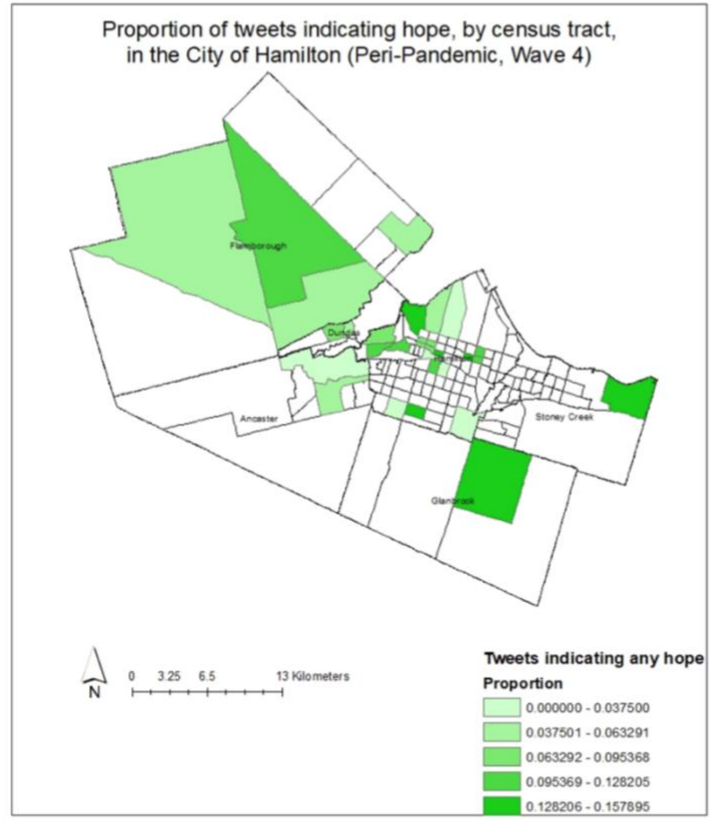

Proportion of tweets indicating hope, by census tract,
in the City of Hamilton (Peri-Pandemic, Wave 4)
Flamborough
Ancaster
Stoney Creek
N
0 3.25 6.5 13 Kilometers
Tweets indicating any hope
Proportion
0.000000 - 0.037500
0.037501 - 0.063291
0.063292 - 0.095368
0.095369 - 0.128205
0.128206 - 0.157895

Table 5 provides the bivariate analysis for all variables. Many of the explanatory variables displayed a significant correlation to each other. For instance, household income was highly correlated with COVID case count ($r(29)=.462$, $p=.010$, visible minority status ($r(29)=.585$, $p<.001$), no degree ($r(29)=.486$, $p=.006$) and household size ($r(29)=-.823$, $p<.001$). Two variables displayed a strong bivariate relationship with stress; household income ($r(29)=.444$, $p=.014$ and household size $r(29)=-.503$, $p=.005$. The cross-product of hope with household income ($p=.929$) and household size ($p=.388$) were not statistically significant in multivariate models, suggesting that the effect of these explanatory variable on stress was not modified by baseline levels of hope.

Table 5: Pearson correlations matrix for candidate explanatory variables and trajectory of stress

		Covid cases	Visible minority	No degree	Household income under 50k	Household size of 3 or more	Log odds stress
Correlation	**Covid cases**	1	.658*	.230	.462*	-.181	.155
	Visible minority	-	1	.177	.585*	-.277	.181
	No degree	-	-	1	.486*	-.139	.184
	Household income under 50k	-	-	-	1	-.823*	.444*
	Household size of 3 or more	-	-	-	-	1	-0.503*
	Log odds stress	-	-	-	-	-	1

***Correlation is significant at the 0.10 level (two-tailed test)**

Discussion

Results from this exploratory study provide insights into stress and resilience in Hamilton Ontario. The findings of this study suggest that neighbourhood variation in stress and hope does exist at the census tract level throughout pre- and peri-COVID-19 pandemic time periods. Overall, seven of the 30 census tracts were significantly different in the stress trajectory analysis and half (15) in the hope trajectory analysis. Trends of stress and hope appeared to decrease over the five time periods in many of the census tracts. However, four census tracts did have increases in the trajectories of stress and hope, with census tracts 2.06 and 34 showing the same trend in trajectories in both stress and hope. Among all areas, census tract 124 had the greatest increasing stress trajectory and census tract 66 had the smallest decreasing stress trajectory with a difference of 6-fold between the two. For hope, there was an almost a four times difference between the trajectories in the census tract with the greatest increasing hope trajectory (census tract 2.06) and the one with the smallest decreasing hope trajectory (census tract 67). When examining candidate explanatory variables that were hypothesized to in part explain differences in stress related emotions, household income and household family size appeared to be correlated with pre-pandemic stress as well as the overall trend of stress. Counter to our expectations, hope emotions within census tracts did not appear to modify the effects of household income and household family size on stress.

Differences in stress trajectories throughout the pandemic may in part be explained by sociodemographic variables not included in this analysis. While this study examined seven unique variables that were hypothesised to influence stress and resilience, only two ended up showing a significant correlation with stress. Other work has examined other factors that may in part explain variation in stress. For instance, Kondo et al.'s recent study investigated stress and neighbourhood characteristics, and results suggest that walkable streets, offsite alcohol outlets, and assault rates appear to increase stress in a neighbourhood, while attributes such as collective efficacy, access to parks, and rates of homicide appeared to decrease feelings of stress during the pandemic (Kondo et al., 2022). Future studies that analyze social media to assess the spatial distribution of stress should investigate potential relationships with similar variables including ones that social connectedness, social capital and social cohesion.

The case for social media to examine community resilience has been made. Recent work has encouraged the use of Twitter as a tool to measure and assess community resilience given the several strengths it provides including being able to assess temporal and spatial trends of emotions and responses to adversities (Rachunok, Bennett, Flage & Nateghi, 2021). However, the authors of this study did not mention using hope as a proxy for resilience. Although expressions of hope on social media was not found to moderate the effects of income and family size on stress in this study, the use of hope as a factor of resilience in a matrix of many merits further exploration especially on online platforms.

The two variables that were highly correlated with stress was household size and household income. These findings are in keeping with existing literature. For instance, longitudinal studies have suggested that socioeconomic status, income, neighbourhood disadvantage and poverty are related to higher levels of stress as well as poor mental health outcomes (Ennis, Hobfoll & Schroder, 2000; Santigo, Wadsworth & Stump, 2011). During COVID, many quarantine interventions required individuals to remain in their homes. Research investigating the relationship between pandemic stress and life satisfaction has found while stress has a significant negative relationship with life satisfaction, the correlation between stress and life satisfaction is strongest amongst people that are living in a single person household or residing with many other people

(Oh & Neal, 2021). There are several possible explanations that may explain this association. For instance, living with others during a contagious pandemic could be a source of stress for habitants. Alternatively, the nature of the relationship between household members is also important as the number of residents may not have as much of an influence on stress as opposed to the nature of the relationship between household members (Okabe-Miyamoto et al., 2021).

Additionally, throughout the pandemic, cities in the province of Ontario had different COVID related restrictions. At one point, Hamilton COVID case counts resulted in the reimplementation of lockdown measures that had previously been lifted in the city but were still active in neighbouring regions including Peel Region, Toronto, and Windsor-Essex County (Crawley, Thibedeau & Powers, 2020). To more clearly contextualize trends that we observed in Hamilton, future research could examine variations of stress at a larger level and/or include multiple cities.

The interaction between one's neighbourhood and health as communities represent an important determinant of health (Oakes, Andrade, Biyoow &Cowan, 2017). There is a strong body of evidence to suggest that mental health and health is the result of a combination of genetic, environmental and stress related factors (Arcaya, Arcaya & Subramanian, 2015). Focused attention should be directed towards modifiable variables that influence these outcomes especially as it relates to interventions aimed at reducing disparities in mental health at the neighbourhood level.

All levels of government should review and implement enhanced mental health policy to address covid related stressors and fund public health and community based mental health initiatives to improve the negative psychological impacts of COVID-19. For instance, concerns about provincial cuts to public health units has been identified (Glauser, 2019). These changes to services and programming can negatively affect the delivery of mental health related assistance can have lasting impacts. In addition to establishing better mental health policies and appropriately funding mental health agencies, other strategies can be implemented to better promote resilience in the face of adversity including promoting positive mental health and reducing barriers to engage in mental health services.

The notion that social ecological factors such as neighbourhood and community play a role in stress and resilience (Ungar, 2011) can help to better understand variation in resilience across geographic areas. Additional research is needed to make explicit considerations on how communities respond to chronic and unique stressors such as the COVID-19 pandemic. This work can help cultivate a better understanding of resilience as an outcome of emotional and chronic stress at the community level and help answer why some populations and groups are able to flourish in the face of adversity.

Limitations

This study should be interpreted with the following limitations in mind. Firstly, EMOTIVE and Stresscapes are only able to analyze tweets in English. This may exclude populations that tweet in languages other than English and may not capture resilience, stress, and the mental health profile of all communities. Along these lines, nuances in the English language may similarity not be recognized by these programs. For instance, cultural idioms, sarcasm, and false reassurances in response to distressing emotions (toxic positivity) may not be accurately distinguished by language processing systems. Secondly, this study relies on those who have access to the Internet and express themselves on social media. The intricacy of social media accessibility and adoption of Internet use for all communities needs further investigation in the COVID-19 context. Thirdly, only tweets that were geolocated were included in the analysis. A recent study investigated differences among social media users with and without geotagged content (Karami, Kadari, Panati, Nooli, Bheemreddy & Bozorgi, 2021). Results indicated that geotagged users were not representative of the broader Twitter user population and that geotagged users tend to share more information about themselves and tweet more positive words. This may have implications into the levels of hope scores given that there may be a bias. Conversely, exposure to COVID-19 social media content has been associated with poor mental health outcomes (Ni et al., 2020). While the use of social media for dissemination of up-to-date information and to engage in public health surveillance has benefits, caution should be exercised as prolonged social media use during COVID can have adverse mental health effects and that could in turn produce more negative content among social media users and their online networks. Thirdly, the present study was not representative of the entire city of Hamilton population with only 15.7% of total census tracts being represented and consisting only of Twitter users in the city who have publicly available accounts that are geotagged. Future research should investigate if census tracts with 21 tweets or more differ based on sociodemographic variables between tracts that do not have greater than 21 tweets over specific time spans.

Fourthly, different forms of stress may not be distinguished in the analysis. For instance, it may not be possible to characterise tweets that reflect feelings of eustress (a positive response to a stressor) compared to distress (a negative response to a stressor). Along these lines, less obvious expressions of stress may not be detected by EMOTIVE. Lastly, the analysis included data to characterize candidate explanatory variables from the 2016 Census, which may have changed by the time of the COVID-19 pandemic m. Future research would benefit from using the more recent data from the 2021 Census as the updated data would provide a more accurate information of social, economic and demographic conditions on the ground during the COVID-19 pandemic. As such, caution should be used when using results for planning purposes. Overall, confirmatory research would be of benefit to corroborate or validate findings from this current study. Utilizing mixed methods and triangulation with other relevant indicators could provide further insight into local variation in emotional wellbeing during stressful events. As such, social media analysis may be used as one method as part of a larger research strategy.

Conclusion

Despite these limitations, this exploratory study appears to be the first of its kind to use a social media analysis to longitudinally investigate trends and correlations of hope and stress across Hamilton, Ontario, a city with historic social and health disparities. The psychological response to infectious disease related outbreaks can have implications on the spread of the virus as well as social and emotional distress afterwards. While there are competing demands for limited resources during a pandemic, it is important to consider the mental wellbeing of communities during disaster management. As such, continued efforts are needed to document, track, and assess population mental health during this current crisis. Results of this study do provide novel insights into the impact of resilience as a buffer to stressors occurring during COVID using a unique methodological approach. Results can also be used proactively to better plan for future disasters and can help inform interventions for communities experiencing stress. This type of analysis may be of benefit to other cities comprised of residents with a strong social media presence to assess and track emotional wellbeing.

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