Title
Understanding Daily Psychological Well-being in the Context of the Early COVID-19 Environment

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Understanding Daily Psychological Well-being in the Context of the Early COVID-19 Environment

A dissertation submitted in partial satisfaction of the requirements
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in

Psychological Sciences

by

Amanda K. Small

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Education

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Research Interest

My research examines socio-environmental determinants of stress, coping, health, and well-being. Specifically, I am interested in how features of our environments influence everyday experiences over time. I am particularly interested in how these features can impact health risk or health protection. I am also interested in how they can accumulate to predict long-term/distal health concerns and disparities, especially as they relate to variations in social status. In pursuing this research, I utilize a range of cross-sectional and within-subjects research methodologies. Frequently I use ecological momentary assessment, as well as subjective and objective assessments markers of health, including blood pressure and heart rate. The ultimate goal of this work is to increase basic knowledge as well as inform policies to reduce risk and mobilize resources appropriately to design interventions that can best target moments, spaces, and individuals at greatest risk within the environment of everyday life.

Publications

Journal Articles

Zawadzki, M. J., **Small, A. K.** & Mausbach, B. (2021). An upward cycle: Examining bidirectional relationships between everyday activities and momentary affective well-being in caregivers. *The Journal of Positive Psychology.* https://doi.org/10.1080/17439760.2021.1952646

Zawadzki, M. J., **Small, A. K.,** & Gerin, W. (2017) Ambulatory blood pressure variability: A systematic review. *Blood Pressure Monitoring*, *22*, 53-58. https://doi.org/10.1097/MBP.0000000000000230

Manuscripts Under Review

Small, A. K., & Zawadzki, M. J. (2022). Dispositional factors related to ambulatory blood pressure mean but not variability.

Small, A. K. & Zawadzki, M. J. (2022). Trait hostility moderates the relationships between work environments and ambulatory blood pressure and momentary affect

Manuscripts in Preparation

Small, A. K. & Zawadzki, M. J. (2022). Everyday stress and cardiovascular outcomes: A systematic review.

Small, A. K. & Zawadzki, M. J. (2022). Considering connections between early COVID-19 environmental features and daily psychological distress

Zawadzki, M. J., **Small, A. K.**, & Mendiola, J. (2022). Examining the effect of occurrence, type, and quality of momentary social experiences on affect and blood pressure.

Zawadzki, M. J., Kho, C., & **Small, A. K.** (2022) Applying a cultural lens to understanding the relationship between stress and psychological health in college students.

Zawadzki, M. J., Gavrilova, L., & **Small, A. K.** (2022) Is ambulatory blood pressure variability reproducible? Testing whether timing and type of assessment affects stability.

Governmental/Technical Reports

Small, A. K. (2015). *Data brief: Arizona's Controlled Substance Prescription Monitoring Program (CSMP).* Arizona Criminal Justice Commission, Phoenix, AZ

Small, A. K. (2015). *Data brief: Youth prescription drug misuse in Arizona.* Arizona Criminal Justice Commission, Phoenix, AZ

Malone, S., **Small, A. K.**, & Stevenson, P. (2014). *The Arizona Rx drug misuse and abuse initiative: A multi-systemic, multi-level approach for addressing Arizona's "silent epidemic (Efficacy Report).* Arizona Criminal Justice Commission and Arizona's Governor's Office of Children, Youth, and Families, Phoenix, AZ

Small, A. K., & Stevenson, P. (2014*). Data brief: Arizona's prescription drug misuse and abuse initiative.* Arizona Criminal Justice Commission, Phoenix, AZ.

Small, A. K., Malone, S., & Stevenson, P. (2013). *The Community Data Project Data Booklet – Casa Grande Alliance Community Coalition.* Arizona Criminal Justice Commission, Phoenix, AZ.

Small, A. K., Malone, S., & Stevenson, P. (2013). *The Community Data Project Data Booklet – MATFORCE.* Arizona Criminal Justice Commission, Phoenix, AZ.

<u>Presentations</u>

Conference Papers

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Small, A. K. & Zawadzki, M. J. (March, 2020). *The stress of the day: A systematic review of everyday stress and cardiovascular outcomes*. [Paper presentation]. American Psychosomatic Society, Long Beach, CA. https://psychosomatic.org/wp-content/uploads/2020/03/APS_ProgramBOOK_2020_REV.pdf (Conference canceled)

Small, A. K. & Zawadzki, M. J. (March, 2019). *The impact of the work environment on blood pressure and affective health varies by trait hostility.* [Paper presentation] American Psychosomatic Society, Vancouver, BC.

Zawadzki, M. J., **Small, A. K.,** & Gerin, W. (December 2016). *The importance of ambulatory blood pressure variability: Examining its psychosocial predictors and relationship with a marker of cardiovascular disease.* [Paper presentation] Congress of the International Society of Behavioral Medicine, Melbourne, Australia.

Wongsonboom, S. V., **Small, A. K.**, Zhu, M., Ross, R., Moreno, A., McCauley, B*. (May 2015). *Sexual delay and probability discounting: Devaluation of protected sex due to delay or uncertainty*. [Paper presentation]Association for Behavior Analysis International, San Antonio.

Small, A. K., McCauley, B, & Robles-Sotelo, E. (May 2014). *Modeling within- and between-trial patterns of responding on the Balloon Analogue Task (BAT).* [Paper presentation] Association for Behavior Analysis International, Chicago, IL.

Conference Posters

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Soto Rodriguez, S*., **Small, A. K.,** & Zawadzki, M. J. (April, 2021). *The relationship between COVID-19 and repetitive thoughts on anxiety and sleep in undergraduates.* [Poster presentation] National Conference of Undergraduate Research, Virtual

Small, A. K., Zawadzki, M. J., & Mausbach, B. (April, 2018). *Examining the momentary effects of social and active leisure on affective well-being in caregivers*. [Poster presentation] Society of Behavioral Medicine, New Orleans, LA.

Small, A. K., Zawadzki, M. J. & Gerin, W. (March, 2017). *Psychosocial factors and ambulatory blood pressure indexes*. [Poster presentation] Society of Behavioral Medicine, San Diego, CA.

Moreno, A. **Small, A. K.**, Gilbreath, M., & McCauley, B. (May 2015*). Children's performance on the Balloon Analogue Task.* [Poster presentation] Association for Behavior Analysis International, San Antonio, TX.

Small, A. K., Ross, R., Zhu., M., Wongsomboon, S., & Robles, E. (May 2014). *Dynamics of responding on a balloon analog task.* [Poster presentation] Society for the Quantitative Analyses of Behavior, Chicago, IL.

Ross, R., **Small, A. K.,** & Robles-Sotelo, E. (April 2014). *Dynamic adaptation to losses on the Balloon Analogue Risk Task (BART).* [Poster presentation] Western Psychological Association, Portland, OR

Invited Presentations

Small, A. K. (November, 2021). *Measuring the COVID-19 environment using Google Trend data to predict worry and coping in undergraduate students* [Paper presentation] Department of Psychological Sciences, Health Psychology Area Colloquium, University of California, Merced

Small, A. K. (February, 2021). *Effects of early COVID-19 community severity in California undergraduate distress* [Paper presentation] Department of Psychological Sciences, Health Psychology Area Colloquium, University of California, Merced

Small, A. K. (October, 2019). *The relationships between everyday stress and key cardiovascular outcomes: A systematic review.* [Paper presentation] Department of Psychological Sciences, Health Psychology Area Colloquium, University of California, Merced

Small, A. K. (February, 2019). *The impact of the work environment on blood pressure and affective health varies by trait hostility.* [Paper presentation] Department of Psychological Sciences, Health Psychology Area Colloquium, University of California, Merced

Small, A. K. (November, 2018). *Pleasant activities and affect in caregivers* [Paper presentation] Department of Psychological Sciences, Health Psychology Area Colloquium, University of California, Merced

Small, A. K. (February, 2017). *Relationships between psychosocial factors and blood pressure measures.* [Paper presentation] Department of Psychological Sciences, Health Psychology Area Colloquium, University of California, Merced

Small, A. K., & Armstrong, M. (October, 2014). *The Arizona Prescription Drug Misuse and Abuse Initiative: A multi-systemic approach for targeting Rx drug misuse and abuse*. [Data presentation] East Valley Synthetic Drug Task Force, Scottsdale, AZ.

Small, A. K. (March, 2014). *The Arizona Prescription Drug Misuse and Abuse Initiative: A multi-systemic approach for targeting Rx drug misuse and abuse*. [Paper presentation] Department of Behavioral Sciences, Arizona State University – West Campus, Phoenix, AZ.

Small, A. K. (April, 2013). *Arizona Prescriptions Drug Misuse and Abuse Initiative*. [Data presentation] Arizona Committee on Probation, Phoenix, AZ.

Small, A. K., & Malone, S. (January, 2013). *Youth substance use trends – Yavapai County.* [Data presentation] MATFORCE Coalition, Cottonwood, AZ.

<u>Honors and Awards</u>

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Relevant Work Experience

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Institutional Service

2020 University of California Health Psychology Consortium – Programing Committee Member, (University of California, Merced)
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2019-2020 GRAD-EXCEL Graduate Student Peer Mentor (University of California, Merced)
2019-2020 Stress and Health Lab – Lab Manager (University of California, Merced)
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Abstract of the Dissertation

Understanding Daily Psychological Well-being in the Context of the Early COVID-19 Environment
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Doctor of Philosophy, Psychological Sciences
University of California, Merced 2022
Committee Chair: Matthew Zawadzki

The onset of the COVID-19 pandemic led to a pervasive environment that was both novel and unescapable for people everywhere. This prolonged and massive event operated across multiple levels of influence with impacts ranging from the most distal global environment to the most proximal immediate environment of daily life. Individuals had to deal with wide-spread challenges and uncertainties, including coping with stay-at-home orders, adapting to new safety requirements and policies, and facing fear and risk of infection as well as symptoms from the virus itself. In order to investigate the impacts of this environment on daily psychological well-being, this dissertation identified innovative environmental measures of that COVID-19 environment and connected them to individuals' ecological momentary assessment outcomes, bridging community level indicators with person level experiences. This work addressed a critical gap in the COVID-19 literature, namely that COVID-19 pandemic was not a monolithic experience but a dynamic and complex environment. Specifically, Study 1 examined the role of daily changes in COVID-19 severity at the state level by using reported cases and deaths in February and March of 2020 to predict daily distress and distress variability in emerging adults. It also considered the differential effects of accumulated cases (or deaths) and daily new cases (or deaths). Study 2 examined relationships between community level COVID-19 information seeking and individual worry and coping self-efficacy. Internet search data was used as an indicator of community information seeking based on high interest search terms related to COVID-19 and critical lockdown material resources. Findings from both studies provide support for the role of the COVID-19 environment in daily well-being at multiple levels of influence. Distress, worry, and coping all showed evidence of environmental influences. Additionally, this work supports the critical need for investigating environments and their connections over time in models that allow both the environment and the individuals to change. This work has implications for understanding the complicated well-being effects of the COVID-19 environment and findings can be expanded to other crisis and chronic stress environments. It also provides a model for more precise within-person research that better models and measures environments and the impact of those environments on key individual health and well-being outcomes.

Chapter 1: Measuring Environments: Introduction

A person's environment directly influences how they think and feel. Over time regular exposure to environments with reoccurring factors can lead to changes in health, well-being, and development. Studies that include a focus on the relationship between environmental context and the individual often results in more nuanced understandings of health and behavior. For example, research on utilization of the influenza H1N1 vaccine found that as much as 47% of the variance in vaccine seeking could be explained by aspects of a person's environment outside their own views and attitudes, such as community policies and access (Kumar et al., 2011). If an intervention sought to change vaccine uptake, failing to account for and even leverage the environmental effect would be missing a major source of influence.

Despite acknowledging the importance of environments, how best to measure and model them is not straightforward. Even defining and identifying environments poses a challenge. Douglas and Hollard (1938) defined environments as the sum of everything external to an individual which affects any aspects of life from behavior to growth and development. Bronfenbrenner (1977) further refined this definition with the ecological systems theory which defined one's environment as a nested, interrelated, and interacting set of influences, which range from the most immediate to the global. Despite being the prevailing way environments are theorized to influence individuals in health psychology research, these definitions are challenging in that they identify an environment through its relationship with the individual nested within it. In other words, these approaches effectively make an environment unidentifiable in the absence of the individual. In contrast, this dissertation will use a definition of environment more in line with Barker's behavior settings theory that posits that an environment is the system of potential external influences acting in a specific moment in time and space and providing information about the range of possible behaviors within it (Barker, 1968; Schoggen, 1989). This definition allows for the study of both the individual and the environment as independent entities, as well as the interactions between them. The implication of using this approach is that it readily allows for environments to be operationalized as entities that are as varied and complex as the people within them.

If we accept that environments are varied and complex this has direct implications for how they must be measured and modeled. A gold standard of research might seek to understand behaviors as they occur alongside the complex environments where it is occurring. Such an approach would mean that behaviors are measured within the environments as they are occurring, and also that environments and behaviors are measured in a way that allows each to vary and change over time. In order to approach that gold standard, this dissertation will first discuss and propose a direction for future environmentally grounded research that uses objective and publicly accessible indicators of environmental contexts (Chapter 1). Second, this dissertation will demonstrate how both environments and the individual's experiences can be captured in a dynamic way and modeled to account for this changing process (Chapters 2 and 3). As a whole, this dissertation will demonstrate ways to apply these improvements through two studies using the COVID-19 environment as a case study.

What Environmental Factors Matter

There are multiple ways to address the complexity of environments in research. In order to propose improvements to this type of work, a brief survey of current methods and prominent research gaps is helpful. Two major environmental approaches appear frequently in the literature. In the first approach, researchers identity a key environmental factor that acts as a driver for the influence of that environment (e.g., Lucan & Mitra, 2012; Rios et al., 2012; Weaver et al., 2013; Zhao & Chung, 2017). This may be a particularly salient or aversive aspect of the environment, such as traffic noise or level of community disorder. For example, in a study on low socioeconomic status communities, one might measure proximity to major roadways or train tracks as a predictor of sleep disturbances. A strength of this type of study is that in focusing on a single factor, researchers can devote considerable attention to the best measurement of that factor. It is critical that researchers identify the correct factor or factors, however, which can be a challenging task given the complexity of an environment.

A second set of approaches measures environments using multiple factors at a single ecological level or similar factors across multiple levels of scope (e.g., Mills et al., 2020; Schreier & Chen, 2013; Zimmer et al., 2010). For example, in a study on health care utilization, one might measure multiple factors all at the family level such as health insurance status, familial medical history, and at-home attitudes toward preventive care, or a single factors like health promotion programs at the community, state, and national levels. This approach can mean there is less focus on identifying and selecting the one key factor, but it also means a greater likelihood of including irrelevant factors that can complicate models and detract from one's ability to detect important effects. There is the additional issue of having to disentangle multiple levels of influence when working across scopes of environment to understand which level is exerting the influences. This can make it quite challenging to propose changes based on these types of approach. Innovative methods, seeking to leverage advances in environmentally grounded research, would draw from both approaches by utilizing multiple ways of indexing key factors which would provide insight into key indicators but also allow for the combined complexity of the environment as a whole. This dissertation across two studies will attempt to address environments in this way. Additionally, environments at two important levels will be consider at community and state levels.

How to Measure Environments

Environments are frequently measured using perception-based variables. There is considerable research demonstration the importance of perception of environment on behavior and health supporting the utility of such measures (e.g., Rhodes et al., 2020) . However by relying solely on indications of how an individual reports they view their environments, it is possible that subjective environmental factors are being conflated with objective environmental factors and essential information is being missed. They are separate types of influence and should be conceptualized and measured separately. For example, meta-analytic research on the environmental influences on physical activity has found that both actual crime rates and self-reported perceived safety each uniquely predict changes in levels of physical activity (Rees-Punia et al., 2017). While these two influences are intrinsically linked, environments operate independent from our perception of them and thus should also be measured independently where possible. However, often objective measures of the environment receive considerably less attention.

Perhaps part of this reduced research attention is because finding objective measures of an environment can prove challenging. Critical aspects may resist measurement or may not be immediately apparent. To illustrate the difficulty in measuring such indicators, consider how one might measure community panic. During a period of crisis, an environment of community panic could have an influence on a person's thoughts, emotions, and coping efforts. But measuring community panic is challenging as there are not objective measures of the factor. Proxy indicators can give insight into such hard to measure factors. For the example of community panic, proxies such as changes in number of panic attack treatment inquires (Adams & Boscarion, 2011), call volumes to crisis resources hotlines (Arendt et al., 2020), or even internet searches (Scheitle et al., 2018) might be used. Yet, proxies are imperfect measures of the underlying construct and still must be used with caution. In the panic example, crisis hotline call volume may indicate that more people are experiencing panic and need treatment, but it also may reflect an increased awareness and use of the resource but unchanging levels of crisis. If emergency supplies included materials with the hotline on them, it could easily be the latter. Use of proxies means that the researchers need to understand what the variable represents and how that relates to the environment they are attempting to access. This requires considerable understanding of the environments themselves and their complexities, a challenge when investigating a novel environment. The use of multiple indicators can help address this issue by relying on convergent validity. Subsequent chapters in this dissertation will present examples of use of objective indicators to measure a complex environment.

When to Measure Environments

Frequently missing from most research on environments is the inclusion of change over time of the environment. Although there are exceptions (e.g., Jongeneel-Grimen et al., 2014; Su et al., 2022) often even when individuals within them are allowed to vary moment to moment, day to day, etc., environments are measured statically at a single time point and with the assumption that they do not vary. For example neighborhood walkability has been related to mental health (Berke et al., 2007) and physical activity (Frank et al., 2005). Both studies consider the role of environment on individual health, however assessment of neighborhood characteristics were static. This approach accounts for constant factors like street layouts and existence of sidewalks. However, it makes no accommodation for changeable aspects of the neighborhood such as daily temperatures, frequency of traffic, presence of unleash dogs etc., all factors that influence ease of walking in environment and likely the outcomes of interest. But we are intrinsically aware that environments change. For example, as more people started remote work due to COVID-19 restrictions, the same home environment may have become a workplace during the workweek but not on a weekend (or when one has days off). By not allowing for environmental factors to vary over time, we are making assumptions about the nature of environments – that they are static. These assumptions are rarely empirically tested and, likely, are outright incorrect in many situations. This limits our ability to understand how environments, which are complex and dynamic, interact with the complex individuals who can occupy them.

COVID-19 Case Study

The COVID-19 pandemic caused by the severe acute respiratory syndrome (SARS-CoV-2) coronavirus provided an ideal environment to investigate the relationships between environments and individual's well-being. This prolonged and massive event operated across levels of influence and context (Van Damme et al., 2020). Impacts ranged from the most distal global level to the most proximal immediate environment of daily life for every person. Individuals had to deal with wide spread challenges, including coping with stay-at-home orders, learning new safety requirements, and facing infection and symptoms of the virus itself. It also created a novel environment new to most individuals. Most environments include an expected range of behaviors and stresses for the individuals within them, however with the novelty of the COVID-19 environment no such expected range existed. It was also largely an unescapable environment. With the major and minor policy changes by institutions at every level, constant media updates with opinions and vital information, and the way COVID-19 related discourses seeped into most interaction individuals were constantly immersed in the environment. People rapidly developed information fatigue about all aspects of the COVID-19 pandemic from this immersion (Guan et al., 2022). Given this environment that was pervasive, novel, and unescapable, it is not an issue of if the environment has an effect, but how might one truly measure such a wraparound environment in order to relate it to individual health.

Current Studies

In subsequent chapters I present two studies using the COVID-19 pandemic environment as a model of how to bridge dynamic objective indicators of environmental aspects with daily measures of individual psychological well-being. In both studies, objective data are used to indicate key aspects of a complex environment with models that account for evolving patterns of change and temporal dynamics. In Study 1, publicly available health prevalence data which tracks COVID-19 cases and deaths are used as an indicators of environmental severity to consider their relationship with individual daily experiences of distress. These types of environmental measures are meaningful for multiple reasons. First, these data reflect a key metric of the status of the pandemic as a whole. Measures of number of COVID-19 cases or death or hospitalizations provide key information about the state of the pandemic but also reflect the environment in which people were living. In this way they serve as an indicator for the severity and risk of the COVID-19 environment. Also these metrics were used to make policy changes across multiple levels of institutions and drove considerable media attention, further enmeshing their impact into the environment. While a direct link between number of COVID-19 cases and the distress of a person not personal impacted by a COVID-19 infection might seem to be a reach, there is a clear link between the risk environment of COVID-19 and a person's distress living within it. In this way prevalence data can serve as an indicator to measure the complex COVID-19 environment, particularly when tracked over time to allow for the variations between days.

In Study 2, community internet search data of COVID-19 terms are used as predictors of daily individual experiences of worry and copy. Internet search data are presented as an alternative means of measuring the COVID-19 environment. They access features of the environment related to community information seeking and uncertainty.

These features (and indicators of them) provide insight into aspects of the community environment that are not reflected in the prevalence data of Study 1. Internet search data can reflect the state of mind of a community, their worries and concerns and the patterns of their information seeking. This tells researchers a great deal about what the community is concerned about. Like the prevalence data from Study 1, there considerable variability and change day to day. This study provides a better understanding of how fluctuations in community level uncertainty and knowledge relate to the individual during a time of high concern and crisis such as a global pandemic.

Conclusion

In sum this dissertation provides a proof of concept of ways to study environments that account for complexity and changes over time. It also demonstrates that this type of approach is necessary to provide insight into an ongoing environment, COVID-19, and address unmeasured aspects of the pandemic in current research. These advancements can inform more precise research that better models and measures environments as well as their impact on psychological outcomes like distress and coping. This type of approach can and should be applied to research where environments have a role, which is arguable most daily life research. Until research is able to account for and measure environments in this way a significant source of influence and change may be ignored. This dissertation provides a study of several ways to advance the goal of environmentally grounded research as well recommendations for extensions of this work to the COVID-19 environment as well as other crisis environments and daily life.

Chapter 2: Daily COVID-19 Severity Environments as Predictors of Distress

The onset of the SARS-CoV-2 (COVID-19) pandemic in early 2020 had devastating global consequences. In just the first three months of the pandemic there were more than 750,000 cases worldwide, nearly 37,000 deaths, and untold economic, social, and emotional consequences (Guidotti & Ardia, 2020). What started as an acute source of stress soon grew into a stress environment that was prolonged, encompassing, and repeated – in other words, a chronic stressor environment with overwhelming aspects similar to what might be seen in circumstances such as economic disadvantage or chronic illness. The effects of this environment can be seen in mental health research, with estimates over half the general population showed symptoms of anxiety and depression in 2020 (Xiong et al., 2020).

Yet, it is reasonable to assume that the impact of COVID-19 was not a fixed influence with variation in the averseness of the environment, as well as a person's response to that environment, on a day to day basis. Using an example of chronic pain, some days pain symptoms might be more pronounced or more noticeable than on other days, with variability in these pain symptoms affecting day to day psychological distress (Okifuji et al., 2011). Extending this idea to the COVID-19 environment, some days more people were getting the virus, more people were dying, and there were less available hospital resources. On other days, the environment was less dire. Although there is evidence that living in this environment impacted a person's distress overall (e.g., Xiong et al., 2020), it is less clear what happened to a person's distress on a day-to-day basis and if changes in the severity of the COVID-19 environment predicted similar changes in distress.

COVID-19 Surveillance Data as Indicators

There are diverse ways to measure daily variability of the COVID-19 pandemic. One direction current COVID-19 pandemic research is utilizing is the use of public health surveillance prevalence data through organizations, such as the World Health Organization (WHO), U.S. Center for Disease Control, and state based public health agencies (e.g., Fu et al., 2021). These data include numbers of COVID-19 cases and deaths, as well as other metrics like utilization of hospital beds and vaccination rates. This surveillance data can be used as an indicator of the progression of the COVID-19 pandemic tracking key objective indicators that provide insight into the changing severity of that environment.

This paper will look at two of most widely available and consistently reported indicators: the number of people in a particular day who had a positive COVID-19 test and the number of mortalities due to COVID-19 in a region. These two types of indicators offer several advantages. They were amongst the most commonly collected data, sourcing from local agencies and then aggregated into county, state, national, and global data. Also, these data were very frequently shared to the general population. This included notices and updates which were disseminated daily by wellness and governmental agencies, as well as driving media news articles, policy changes, and general awareness of the state of the world during the COVID-19 pandemic. It is this second feature that is particularly valuable when considering the connection between pandemic environment severity and an individual's experience. This is supported by findings regarding the link between COVID-19 related media exposure and experiences of distress (Stainback et al., 2020). Although a person might not be able to readily recall the number of cases on a particular day, they were undoubtedly exposed to the environment that the number helped to create as it was largely unescapable. In this way, objective measures like the number of cases or deaths can serve as valuable indicators of day-to-day changes in the environment during the COVID-19 pandemic.

However, the use public health surveillance data as indicators also presents some more questions. Since these numbers changed daily, there are multiple ways to parse the data when relating it to daily psychological distress. When statistics for new COVD-19 cases and deaths were reported for the previous day (herein called daily totals), they were often accompanied by a running total of all the cases or deaths since the start of the pandemic or total cases (herein called cumulative totals). The daily totals and cumulative totals could indicate distinct aspects of the environment in terms of severity. Daily totals for cases or deaths might reflect a more acute version of severity, connecting to immediate risk posed by people currently infected. In contrast the cumulative totals could reflect a more overall severity connecting to scale and scope of the chronic stress environments. This idea builds on work in stress research showing that an accumulation of threats in a given period can compound to have additional effects on well-being (Schilling et al., 2022). It is unclear if these differences in scope are influential for daily psychological distress. However, findings linking daily national level reports of cases and deaths to daily negative mood support this approach (Zubek et al., 2021).

The indicators also exhibited different patterns of change. Cumulative totals always either increased or stayed the same on each subsequent day, whereas daily totals can range from zero to theoretically any number on any day since the current daily totals are independent from the prior days total. Additionally, COVID-19 cases and COVID-19 deaths are distinct and potentially reflect separate types of severity. While an increase in COVID-19 cases would likely also indicate a higher risk of personal infection as more individuals have the capacity to spread the virus, an increase in COVID-19 deaths, in contrast, actually show decreased risk of infection but potentially more fear as the extreme consequences of the pandemic become more apparent. This distinction is support by mood research that found unique effects of both daily total cases and deaths on negative mood (Zubek et al., 2021).

Distress During COVID-19

In connecting environmental indicators to individual experiences, it is necessary to focus on reactive outcomes. Psychological distress is a viable choice as it is highly variable from situation to situation (Scott et al., 2020). Psychological distress is the emotion turmoil that arises from the inability to cope effectively with a source of stress (Ridner, 2004). Sharing symptoms with both depression and anxiety, elevated levels of distress are both aversive in the moment and over time can lead to serious mental and physical health complications (Barry et al., 2020). As a novel and unescapable source of stress, there are many aspects of the COVID-19 pandemic likely to cause psychological distress. For example adults in the United States were eight times as likely to fit the criteria for serious mental distress in April 2020 compared to the same time in 2018 pre-pandemic (Twenge & Jainer, 2020). This is particularly true for younger people, with young adults reporting higher anxiety and depression during COVID-19 shelter in place orders compared to older adults (Glowacz & Schmits, 2020). Also, in the beginning of the pandemic, psychological distress seemed to be escalating. Holingue et al. (2020) found that over a week's time in March 2020, with each day that passed a person's likelihood of reporting psychological distress increased significantly. Other work has shown that while distress cross-sectionally increased in March and April of 2020, it had returned to starting levels by June of that year (Daly & Robinson, 2020). This would indicate that the patterns of psychological distress during COVID-19 are complex. As much of the work has been cross sectional, a within-person approach could offer key insight into the patterns of psychological distress by investigating day to day changes.

Ecological Momentary Assessment

A number of studies have applied a within-person approach to COVID-19 using ecological momentary assessment (EMA) (e.g., Fu et al, 2021; Schulz et al., 2021; Kleiman et al., 2020). In EMA, data are collected intensively over time within the daily lives of participants often assisted by technology, such as smartphones, in order to be minimally intrusive and better understand how people differ moment to moment longitudinally (Shiffman et al., 2008). As a result EMA research can detect moment to moment changes and influence. This work continues to reveal important temporally relevant patterns of the effects of COVID-19. For example, Fu et al. (2021) found that changes of the number of cases, velocity, and acceleration of rates of infection had a significant impact on an individual's anxiety even when the overall impact of COVID-19 cases were decreasing. This effect would be challenging to detect in a cross-sectional study. Thus, EMA as a within-person brief longitudinal approach can provide a dynamic understanding of how psychological distress functions over time within a changing COVID-19 environment

Additionally, by considering psychological distress over a day with multiple assessment points, different patterns of psychological distress available. Average level of psychological distress for a day provides information about how distressed a person was generally that day. This is the most commonly researched distress aspect. But, psychological distress can vary throughout the day, with highs and lows in momentary distress, thus daily distress variability could also offer insight in to relationships between environments and individual daily well-being. To better understand distress variability as a distinct concept consider the marked difference between a day with moderate amount of distress all day and a day with a distressing morning and distress-free afternoon. Although both days might result in a similar level of average distress for a person, the experience of each day would differ dramatically. Despite the difference in experience, distress variability is largely understudied. Drawing from affective research, affective variability has been found to be distinct from affective averages in EMA research (Eid & Diener, 1999) and evidence about the possible connections to health and well-being of distress variability can be found in affective variability research as well. This research has linked increased affect variability with alcohol consumption (Mohr et al., 2015) and depression (Thompson et al., 2011). But in the other direction, increased affective variability has also been connected to improved immune functioning (Jenkins et al., 2018) and could reflect an appropriate sensitivity to changing challenges and stressors. Hollenstein et al., (2013) suggested that more affective variability could reflect adaption of response to changes in contextual factors. Extending this work to distress variability, it is possible that in a potentially distressing environment, we might expect higher levels of distress variability as one is more often exposed to threats each with a distress response. However in terms of long term consequences, prolonged exposure and thus frequent and repeated activations could lead to fatigue and other issues as repeated activations wear on an individual's stress and response systems. Alternatively, prolonged exposure to a distressing environment might predict decreased variability wherein the continual presentation of sources of distress does not allow an individual to down-regulate from a highly distressed response or even emotional numbness from over exposure as has been seen in some COVID-19 research (Dyer & Kolic, 2020). By considering variability, as well as average level of distress daily, we gain insight into the patterns of the day during a crisis and further expand variability research as well as better link them to environmental features like the environmental factors of COVID-19 severity.

Present Study

This study considered the relationship between daily changes in the severity of the COVID-19 pandemic using public health surveillance data and the individual's daily psychological distress. Severity of the COVID-19 pandemic was assessed using measures of confirmed case and death in models assessing both daily totals and cumulative totals. To allow for the dynamic nature of the outcomes, both daily mean and daily variability in psychological distress were investigated using ongoing data collection at the onset of the COVID-19 pandemic. A number of preregistered hypotheses guided this study. First, regarding the relationship between COVID-19 cases and daily psychological distress, we expected that days in which more daily total COVID-19 cases are reported (hypothesis 1a) as well as days with more cumulative COVID-19 cases (hypothesis 1b) will have higher daily distress averages. Also we expected that on days in which more COVID-19 daily total cases are reported (hypothesis 2a), and more cumulative COVID-19 cases (hypothesis 2b) will predict higher daily distress variability. Second, regarding the relationship between COVID-19 deaths and daily psychological distress, we expected that days in which more daily COVID-19 deaths are reported (hypothesis 3a) and more cumulative COVID-19 deaths (hypothesis 3b) will predict higher daily distress average. Also we expected that days in which more daily COVID-19 deaths are reported (hypothesis 4a) and more cumulative COVID-19 cases (hypothesis 4b) will predict higher daily distress variability.

Also, to test the possibility that prolonged exposure to the COVID-19 pandemic might alter the impact of severity indicators, a number of exploratory analyses addressed possible interactions. Extending the models in H1-H4, we explored interactions between daily COVID-19 cases and daily COVID-19 deaths and the progression of the pandemic. These interactions were considered for both daily distress averages and variability. Lastly to consider individual difference, this study investigated personal level distress indictors as possible explanatory factors of the relationships between COVID-19 severity and distress.

Methods

Preregistration

This paper includes secondary data analysis of individual EMA data with the addition of novel collection and integration of COVID-19 data. EMA data were part of existing study that predated the on-set of the COVID-19 pandemic and creating the opportunity for a natural experiment. All hypothesis for this work were preregistered on Open Science Framework (https://osf.io/72zhw) prior to any analysis being completed.

Participants

Undergraduate participants were recruited using an online campus-based recruitment system at a public university in Central California. To be eligible, participants had to be enrolled in the university, over 18 years old, and self-identified as being Hispanic/Latinx, Asian/Asian American, or White/Caucasian American. Sixty-five students were recruited and met eligibility requirements. From the full recruitment, 53 consented to the EMA portion of the study (81.5% agreement). Subsequently only participants who provided EMA data will be referenced, analysis of baseline demographics found that EMA participants and non EMA participants only varied significantly on gender which is included as a control variable in all models. Mean age for the participants was 20.53 years old (*SD* = 2.00). The majority of the sample identified as women (81.80%). Ethnic and racial demographics were consistent with the school's distribution, with the majority of participants identifying as ethnically Hispanic/Latino (67.9%) and racially White (58.20%) or Asian (16.4%).

Procedure

Participants completed a baseline session on campus in which informed consent, baseline distress, and additional measures not relevant to the current paper, were collected via Qualtrics. Then participants were given the option to complete 14 days of EMA. Participants who agreed completed an EMA training conducted by a trained research assistant. During the training, participants downloaded and installed the RealLife Exp application (LifeData, Marion, IN) on their personal smartphone or lab provided iPod. Each participant created an account with the app and reviewed and practiced the EMA questions they would be responding to during the assessment period. Practice responses were not included in analysis. EMA data collection began the next morning following the baseline session. Participants responded to four prompts on their smartphone each day. These prompts were randomized to occur within each of the following blocks of time: 9:00-11:30AM, 12:00-2:30PM, 3:00-5:30PM, and 6:00-8:30PM. After the prompt, participants had up to an hour to complete assessments of distress variables, as well as other measures not included in the current paper. Following the final day of EMA, participants complete a debriefing through the LifeData application and returned any borrowed lab equipment. Participation in baseline measure was compensated with course credit. Participation in EMA was compensated with a $25 Amazon gift card.

Materials

Daily COVID-19 Environment

Based on the location of the study, daily aspects of the COVID-19 environment were measured using surveillance data for the state of California from the California Department of Public Health's (CDPH) daily press releases. Data were collected for each day of EMA in February and March of 2020. These press releases at time of publication are archived on the California Department of Public Health website (California Department of Public Health [CDPH], 2021). CDPH press releases are the information that was available in real-time and are better suited to the purposes of this study. The CDPH dataset was used instead of other data sources like COVID-19 Data Hub because the Data Hub retrospectively corrects values as updated information becomes available which is not valuable as an indicator of the real-time environment (Guidotti & Ardia, 2020). On instances where no press release was issued for a particular day, the day was computed by calculating difference scores using the preceding and following day data (in the time period for this study there were no days with two consecutive missing reports).

Four types of data were sourced from these press releases. For each study day, the daily total of new positive cases of COVID-19 in California was recorded. This reflected all cases reported to CDPH by medical facilities and public health departments in California. Additionally, for each study day the cumulative total of positive COVID-19 cases was recorded, which included the first positive case reported in January 2020 up to and including the positive cases on the day of record in California. Also for each study day, the number of new deaths resulting from COVID-19 infections in California were recorded. Additionally for each study day, the cumulative total of deaths resulted from a COVID-19 infection was recorded, which included all California COVID deaths up to and including those day of record. In order to represent the environmental influences most closely at the time of EMA, positive cases and death variables are based on the date the data were reported rather than detected. For example, if during the 24 hour period of 3/4/2020 10 new cases were detected in California hospital that information was reported on 3/5/2020 in the press releases. In interpreting results, this distinction is necessary as it reflects information participants would have had access to on the days they responding to EMA prompts, whereas there would be little awareness of COVID-19 cases and deaths being detected concurrently but not yet collectively reported.

Daily Psychological Distress.

A brief scale was used to assess psychological distress at each EMA notification. Participant responded to the following items: “How stressed do you currently feel?,” “At this moment, how sad do you feel?,” and “At this moment, how anxious do you feel?” when prompted on their smartphone. Items were sourced for other EMA research measuring affect and stress in everyday life (Scott et al., 2020; Zawadzki et al., 2019). Each response was recorded on a slider scale from 0 (*not at all*) to 6 (*extremely*). These items map on to key facets of psychological distress and are consistent with other EMA measures of momentary distress. Because predictors (COVID-19 cases and deaths) were recorded at the day level, it was necessary to aggregate the EMA data to match this data structure. For each moment, a mean score across the items was calculated. In order to assess psychological distress on a day level, two values were calculated. First, for every individual participant the mean of their four psychological distress scores each day was calculated for an average level of distress reported that day. The standard deviation of the distress values when at least three scores were reported (74.5% of days met the criteria) were also calculated for each day to determine how much variability there was in the participant’s daily distress.

Person-Level Distress

To measure person level distress using depression, anxiety, and stress at baseline, participants completed the 21-item Depression Anxiety and Stress Scale-21 (DASS21; Henry & Crawford, 2005) during the baseline session. This instrument measures negative emotional states by focusing on core symptoms. Participants responded to each item by indicating how much the symptom or state applied to them over the past week on a 4-

point Likert scale ranging from 0 (*did not apply to me at all*) to 3 (*applied to me very much, or most of the time*). The measure includes three discrete sub-scales of seven items, the depression sub-scale (sample item: "I found it difficult to work up the initiative to do things"; α = .92), the anxiety sub-scale (sample item: "I felt I was close to panic"; α = .80), and the tension/stress sub-scale (sample item: "I found it difficult to relax"; α = .83). For each subscale, a score was created by summing the relevant items with a higher score indicating more of the negative emotion state.

Analytic Plan

With up to 14 days of EMA and prevalence data per participants there is a two-level structure with days nested within people. Multilevel regression modeling was used to analyze the data by the PROC MIXED command in SAS 9.4. To test pre-registered hypothesis, four initial models were run. Separate multilevel models tested the relationships between California COVID-19 cases and daily distress average (hypothesis 1a) and daily distress variability (hypothesis 2). A second set of multilevel models tested the relationships between California COVID-19 deaths daily distress average (hypothesis 3) and daily distress variability (hypothesis 4). Each model included as predictors the daily total reported on that day and the cumulative totals of the relevant indicator. As a reminder, models used the reported day rather than the detected day. Exploratory models expanded on these initial models. In awareness of that fact that, depending on the EMA starting date participants had differing levels of pandemic exposure, person level variables of total cases and deaths on the day prior to their EMA start day were included in exploratory models. This variable is referred to as progression of the pandemic subsequently. Unlike other measures of severity, these values were unique to each participant depending on their EMA start day and a fixed value. These variables are included to control for differences in timing of data collection given the rapidly changing environments of the time. Additionally subsequent models included person-level measures of distress using the baseline scores of depression, stress, and anxiety subscales of the DASS21 (Henry & Crawford, 2005) as predictors. A number of control variables were included in all models. To account for potentially systemic difference between weekday and weekend days on distress, a variable coding days as either weekend (Saturday or Sunday) or weekday (Monday, Tuesday, Wednesday, Thursday, or Friday)was included as a control variable. Models also included gender as a control. Random intercepts were modeled to allow for different starting values on the outcomes across participants. To account for the possibility that outcomes closer in time are more strongly correlated than those further apart, an autoregressive covariance structure was specified where possible. All models included a pseudo R^2 statistic as an estimate of effect size, which calculates the correlation between the observed outcome value and the value that is predicted by the model (Singer & Willett, 2003).

Results

Descriptive Statistics

As shown in Figure 2.1a, cumulative California COVID-19 cases increased through the study period, ranging from 3 to 2,535 cases (*M* = 719.92, *SD* = 1,523.13). As shown in Figure 2.1b, daily total COVID-19 cases trended upward with consistently higher daily totals values towards the end of the study period, ranging from 0 to 1169 cases per day (*M* = 115.53, *SD* = 261.53). Likewise, as shown in Figure 2a, culminative total California COVID-19 deaths increased throughout the study period, ranging from 0 to 150 (*M* = 15.00, *SD* = 33.30). As shown in Figure 2b, daily total COVID-19 deaths also trended upward with higher values towards the end of the study period, ranging from 0 to 34 deaths (*M* = 2.50, *SD* = 6.20). Across all moments, participants reported low daily distress mean (*M* = 1.88, *SD* = 1.37) and daily distress variability (*M* = 0.70, *SD* = 0.52). Participants completed a total of 1,822 observations with 511 days of data. Participants reported low to moderate distress at baseline (Depression: *M* = 6.21, *SD* = 5.34; Anxiety: *M* = 6.96, *SD* = 4.64; Stress: *M* = 7.29, *SD* = 4.57).

COVID-19 Cases

Hypothesis 1: COVID-19 Cases and Daily Distress Average

A multilevel regression model tested the effect of reported daily total and cumulative total COVID-19 cases on daily psychological distress. Table 2.1 reports the results from this model. Contrary to hypothesis 1, there was no significant effect of either daily total COVID-19 cases (*p* = .967) nor cumulative total COVID-19 cases (*p* = .900) on average daily distress.

Hypothesis 2: COVID-19 Cases and Daily Distress Variability

A multilevel regression model tested the effect of daily total and cumulative total COVID-19 cases on daily psychological distress variability. Due to convergence issue, an autoregressive structure was not possible for this model. Table 2.1 reports the results from this model. Contrary to hypothesis 2, there was no significant effect of either daily total COVID-19 cases (*p* = .129) nor cumulative total COVID-19 cases (*p* = .716) on daily distress variability

Progression of the COVID-19 Pandemic - Cases

A multilevel regression model tested the effect of the progression of the COVID-19 pandemic and the interaction between daily total COVID-19 cases and progression of the pandemic on daily average psychological distress. Table 2.2 reports the results from this model. Similar to the models for hypothesis 1, there was no significant effect of either daily total COVID-19 cases (*p* = .892) nor cumulative total COVID-19 cases (*p* = .839) on average daily distress. Additionally, there was not a significant effect of the progression of the pandemic (p = .839) nor the interaction between daily total cases and progression of the pandemic (*p* = .858).

A multilevel regression model tested the effect of the progression of the COVID-19 pandemic and the interaction between daily total COVID-19 cases and progression of the COVID-19 pandemic, on daily psychological distress variability. Due to convergence issue, an autoregressive structure was not possible for this model. Table 2.2 reports the full results. As in the model testing hypothesis 2, there was no significant effect of cumulative total COVID-19 cases (*p* = .732) on daily distress variability. However, there was a significant effect found of daily total COVID-19 cases on daily distress variability (*p* = .037) in this model. Contrary to hypothesis 2, days with higher daily total COVID-19 cases compared to days with lower daily total cases predicted a decrease in distress variability. Additionally, although the interaction of daily total COVID-19 cases and progression of the pandemic did not significant predict daily distress variability (*p* = .147), there was a significant effect of the progression of the pandemic on daily distress variability (*p* = .016) in the direction predicted by hypothesis 2 such that the more the pandemic had progressed at start of EMA the more distress variability was found.

COVID-19 Deaths

Hypothesis 3: COVID-19 Deaths and Daily Distress Average

A multilevel regression model tested the effect of daily total and cumulative total COVID-19 deaths on daily psychological distress. Table 2.3 reports the results from this model. Contrary to hypothesis 3, there was no significant effect of either daily total COVID-19 deaths (p = .859) nor cumulative total COVID-19 deaths (p = .584) on average daily distress.

Hypothesis 4: COVID-19 Deaths and Daily Distress Variability

A multilevel regression model tested the effect of daily total and cumulative total COVID-19 deaths on daily psychological distress variability. Due to convergence issue, an autoregressive structure was not possible for this model. Table 2.3 reports the results. While there was no significant effect of daily total COVID-19 deaths (p = .937) on daily distress variability, there was a trend for cumulative total COVID-19 deaths on daily distress variability (p = .057). The effect was in the direction opposite from expected with days that had higher cumulative total COVID-19 deaths predicting a decrease in distress variability.

Progression of the COVID-19 Pandemic - Deaths

A multilevel regression model tested the effect of the progression of the pandemic in terms of deaths and the interaction between daily total COVID-19 deaths and progression of the COVID-19 pandemic on daily psychological distress. Table 2.4 reports the results from this model. Contrary to the findings testing hypothesis 3, there was no significant effect of either daily total COVID-19 deaths (p = .602) nor cumulative total COVID-19 deaths (p = .571) on average daily distress. Additionally there was not a significant effect of the progression of the pandemic (p = .975) nor interaction between daily total deaths and progression of the pandemic (p = .453).

A multilevel regression model tested the effect progression of the pandemic and the interaction between daily total COVID-19 daily and progression of the COVID-19 pandemic on daily psychological distress variability. Due to convergence issue, an autoregressive structure was not possible for this model. Table 2.4 reports the results. Again there was no significant effect of daily total COVID-19 deaths (p = .298) on daily distress variability. However, a significant effect was found of cumulative total COVID-19 deaths on daily distress variability (p = .004). As was the case in the COVID-19 cases model, the effect was in the direction opposite from expected with days that had higher cumulative total COVID-19 deaths predicting a decrease in distress variability. Additionally, while the interaction of daily total COVID-19 deaths and progression of the pandemic did not significant predict daily distress variability (p = .110), the progression of the pandemic in terms of deaths did predict daily distress variability (p = .008). As with COVID-19 cases model, as the pandemic progressed more daily distress variability was found.

Explanatory Analysis

Person-level Distress

Based on the results from models predicting daily distress variability, we theorized that a person level effect might impact the inverse relationships between COVID-19 environmental severity and distress variability. We proposed that people who had higher depression, anxiety, or stress at baseline might show a sensitivity to the distressing environment that was unique. In order to test potential personal level moderators of the found relationships between COVID-19 indicators and distress variability, depression, stress, and anxiety subscales of the DASS21 were included in multilevel regression models testing the effect of daily total COVID-19 cases and cumulative total COVID-19 deaths on daily distress variability. Please see Table 2.5 for full model results. All model effects remained consistent, with significant effects of daily total COVID-19 cases (p = .036), cumulative total COVID-19 deaths (p = .005), and progression of the pandemic in terms of cases (p = .035) and deaths (p = .022) as significant predictors of distress variability. Additionally person-level anxiety (ps = .024) predicted daily distress variability in similar inverse relationships in both models, while person-level stress (p = .035) showed a direct relationship with daily distress variability in only the COVID-19 case model and a trending relationship in the COVID-19 deaths model (p = .060).

Additional Exploratory Analysis

To better understand the prior models results, additional exploratory models were run. When considering the patterns of data of COVID-19 deaths, it was noted that the first COVID-19 death was not reported until approximately halfway through the data collection period (March 5, 2020). We investigated if the extended period of initial zero value days were masking significant effects. Multilevel regression models reexamined the relationship between COVID-19 deaths and daily distress limited to days in which the cumulative COVID-19 deaths were greater than zero. Model results can be found in Table 2.6. All model effects remained consistent in this constrained time period, with significant effects of cumulative COVID-19 deaths (p = .005) and progression of the pandemic (p = .005) as significant predictors of less distress variability. Of further note, with the additional focus, there was an increase in adjusted pseudo R^2, which increased from .04 to .10, accounting for more of the variance in distress variability.

Discussion

The purpose of this paper was to consider the relationship between daily changes in the severity of the COVID-19 pandemic and an individual's daily psychological distress. While the many of the initial hypothesis of this work were not supported, findings from exploratory analysis and effects in the opposite direction of those predicted reveal key relationships between COVID-19 environmental severity and daily distress.

First, none of the COVID-19 severity measures – daily total cases, cumulative total cases, daily total deaths, nor cumulative total deaths – were significant predictors of daily psychological distress on average. This would suggest that amongst emerging adults, generally how distressed a person was during the onset of the COVID-19 pandemic was not informed by the day-to-day changes in the pandemic severity. In contrast, there were several relationships found with distress variability. We found that an increase in the number of daily total COVID-19 cases predicted less distress variability that day, an opposite pattern than we had expected. It is unclear if this is a resilient response which could be protective or may represent a decrease in the individual's capacity to respond to potentially distressing information, perhaps from a numbing effect. These two interpretations could have drastic different long term effects. A resilience response might represent a form of coping, while numbness in the context of an inescapable stressor like COVID-19 could be related to depression and other health concerns. It is notable that depression rates world-wide during 2020 were seven times higher than previous years (Bueno-Notivol et al., 2021). Potentially, distress variability change is a mechanism of this increase. Little is known about the day-to-day implications of distress variability. While Breaux et al. (2020) found a connection between distress variability in adolescents and social function, it remains an under-researched construct. As a result, the health and well-being implications are unclear. From related affective variability research, there is some indication that higher variability could reflect great flexibility to adapt to situational factors (Hollenstein et al., 2013) and improve immune system functioning (Jenkins et al., 2018) but decreasing negative affective variability has been related to worsening sleep outcomes (Leger et al., 2019). Future research is needed to determine if this effect applies to distress variability as well.

We also found that an increase in the cumulative total of COVID-19 deaths predicted the same pattern of less distress variability. This is particularly noteworthy as cumulative totals never decreased between days which makes this finding troubling. It indicates that distress variability in relationship to COVID-19 deaths would consistently decrease, with potentially increased lack of responding to daily life experience.

It is also notable that no similar effect was found for daily total COVID-19 deaths nor cumulative total COVID-19 cases. This pattern is evidence to support that these two types of surveillance are indicators of difference aspects of the environments. It suggests that for the environmental aspect that COVID-19 cases indicators, perhaps risk of exposure, individuals are sensitive in terms of distress to the immediate changes day to day. But for the environmental aspect that COVID-19 deaths indicators, perhaps fear of more dire consequence, it is the larger compounded scope of this consequence that has a relationship with distress.

From the explanatory investigations, we found that these effects were not explained by personal level distress as they remained consistent even when anxiety, stress, and depression measures were included in the models. Additionally, greater anxiety and greater stress in these models both predicted decreased daily distress variability, further suggesting that a decrease in variability may reflect a negative impact on well-being. This is consistent with work showing a flattened recovery from acute stress in instances of anxiety and anxiety symptoms, reflecting a decreased ability to return to normal following a distressing event (Fiksdal et al., 2019). In the context of this paper, as the severity of the pandemic increased, individuals may show less ability to recover following encountering the first distress of the day resulting in sustained distress.

Interestingly, we also found a consistent effect of the progression of the pandemic on distress variability. While this variable was originally conceived as a control variable to account for difference in data collection timing, the pattern of results on distress variability is worth noting. When other COVID-19 severity indicators are included in the models, we see consistent positive relationship between progression of the pandemic and distress variability, such that as the pandemic progresses distress variability increases. This may indicate an adaption to the pandemic over time outside of severity concerns. However this is an area for further research. As our sample were undergraduates, it is important to note that other work has found that young adults samples show higher level of instability of distress over time, suggesting that it is a developmental period of significant fluctuation even in time periods that are not a global pandemic (Flett et al., 1995; Pepper & Coyne 1996).

Implications

The COVID-19 environment has many factors that can challenge well-being. This work suggests that the severity of that environment in terms of numbers of cases and deaths is one of those challenges. It also suggests that this challenge was not a static ever-present factor but one that varied day to day. This has important implication for how we conceptualize and measure chronic stress environments. It also suggests that one-time measurements are potentially missing critical fluctuations. These fluctuations are particularly meaningful when considered through the lens of intervention. By tracking changes in the environment it is possible to pinpoint moments or days when buffering resources are particularly needed or influential. For example, if, as we found here, distress variability is likely to be low on days when the COVID-19 case count (or other indicators for other environments) are high, then those are days in which efforts need to focus on promoting well-being, assisting with resilience building, and providing escapes from persistent distress. In contrast, if daily new COVID-19 death counts seem not to influence distress, then invention efforts targeting distress should adopt a model of graduated resources to correspond with the compound effect of the cumulative death counts. In response to COVID-19 circumstances a number of such intentions have been developed (e.g., Bäuerle et al., 2020; Brog et al., 2021; Riva et al., 2021) as well as other brief distress interventions that predated COVID-19 (e.g., Yardley et al., 2019), using the findings from this study could better inform when and where their use would be most needed. In this way, metrics of the environment can inform well-targeted interventions.

Beyond the COVID-19 environment, this work highlights unique aspects of the onset of a chronic stressor or traumatic event and the environment that surrounds and interacts with it. These events can range for the personal level such as a layoff or to much larger ecological level such as the California wildfires which have widespread ecological and economic impacts. These circumstances are often fast evolving and critically important, making research both challenging and needed. This is also often little preparation time and researchers must rely on ongoing studies to understand the event, most of which begun with different research aims. An environmental approach can make research more achievable by providing an opportunity to combine existing datasets with outside indicators of the environments in which the event is happening. Including these types of measure to psychological and health research during this types of events allows for both a better understanding of critical places and times and the people experiencing them.

Limitations and Future Directions

This work is promising in that it reveals different impacts of the severity of the COVID-19 environment however caution should be used when attempting to generalize these findings to other populations and circumstances. This work relied on a natural experiment opportunity. It used EMA data that was not originally designed to test the main research questions of this study but was ongoing at the onset of the COVID-19 pandemic. As a result, while the data was leveraged to offer important insight into the connections between environmental severity and individual distress, future work is needed to expand these results to other time periods and populations that may be more apt or a strong complement for the present hypotheses. For example, research conducted during the subsequent surges in cases during variants of the COVID-19 virus could provide important insight into the prolonged and varied experiences of the COVID-19 pandemic as could periods of decreased severity.

While participant characteristics are consistent with the region, the impacts of the environment might differ in a less rural setting with a more condensed populations and thus more frequent exposure to others and their reactions to environmental changes. Further California, where the study was conducted, was amongst the first U.S. locations effected by COVID-19 with many of the early cases occurring there. This means that participants in the study were likely exposed to COVID-19 information earlier than other places in the U.S. and information was more immediate relevant to their daily lives. This early exposure may have altered awareness and sensitivities to COVID-19 and may not be representative of other places with different timelines of relevance. Future work should attempt similar analysis in other locations where data is available.

In addition to other geographical regions, scale of environment should also be considered. This study used state level numbers, but it is possible that more localized numbers, such as county or city might show stronger or different relationships with distress based on immediacy to the individual. In contrast, national and global numbers were considerable larger and more universally reported with potentially differing impacts on distress. Future work should attempt to consider this question to determine optimal scale of environment for understanding the distress of individuals.

Another limitation of this work is that environmental exposure has been inferred for participants with the assumption that living within an environment is sufficient for exposure effects. In other research focuses, these is evidence that living in a given environment is sufficient exposure to see impacts of that environment (e.g., Ludwig et al., 2012). However our work focused on a considerable larger environment than such past work. Thus, future work should expand this study’s finding by including a measure of exposure or awareness of the environment to supplement objective measures of the COVID-19 environment.

A related limitation is that models for this work were run with each major type of indicator (cases or deaths) in isolation. While this approach allows for the focused consideration of that indicator, it is unlikely the effects of the environment were experienced in isolation. A natural evolution of the work would be to consider multiple indicators and their impact on distress and other aspects of psychological well-being simultaneously. Using both types of indicators would allow for the identification of shared variance between indicators as well as unique effects as was found in Zubek et al. (2020). Added complexity in these types of investigation would provide further insight into the environmental effects of COVID-19. Lastly, we were not able to utilize an autoregressive structure in any of the models predicting distress variability. This is likely due to less data available in these operationalizations which resulted in decreased power in the models and thus decreased ability to model parameters. Data from a longer time period or a different time period could assist with these issues and should be an area of future research.

Conclusions

Distress during COVID-19 continues to be a source of concern, both while the pandemic is ongoing and in terms of prolonged effects of life during the COVID-19 pandemic. These results provide insight into the patterns of that distress experience. They reveal critical information about the relationships between fluctuating stressful environments and psychological experiences within them. Moreover they reveal exciting avenues for future research in considering distress in terms of variability particularly as it relates to well-being over time.

Chapter 3: COVID-19 Information Seeking Environments as Predictors of Coping

The internet is a primary information source for most people in the United States including during the COVID-19 pandemic (McClain et al., 2021). What and how people are searching for on the internet as a group can reveal valuable information about the thoughts and needs of a community. An increase in internet searches for a particular term, such as coronavirus, indicates a new awareness of that term and/or a change in the relevance of that topic in the lives of community members. During a crisis period, researchers can use internet search patterns to gain a view of a community's environment. This information that could be difficult to obtain otherwise (e.g., the crisis might prevent direct observation). Such information can further be used to understand the lives of individuals within that environment, including their worries and concerns and how they are coping with the crisis. This paper will seek to leverage community internet search data as an indicator of the environment to relate it to daily experiences of stress and coping during the onset of COVID-19 pandemic.

COVID-19 Environment

The onset of the COVID-19 pandemic in early 2020 was marked by considerable upheaval, uncertainty, and panic (Koffman et al., 2020). In the space of a few months, people first learned of the SARS-CoV-2 coronavirus, positive cases and death counts locally and worldwide escalated, the WHO declared COVID-19 a global pandemic, and community lockdowns and shutdowns started to take effect. This was a period of considerable upheaval and uncertainty, with the environment and its potential effects changing on a day-to-day basis.

The COVID-19 pandemic environment was also complex with many environmental aspects interacting to affect the lives of individuals. Environment aspects included general uncertainty about the virus and its impact on communities, as well as concerns about access to important resources with supply issues and restrictions likely. There continues to be considerable research about the COVID-19 pandemic, but less has focused on specific aspects of the COVID-19 environment and the relationships between those aspects and the individuals within it. The aspects are not static and underwent frequent changes and posed new challenges, fluctuating at different paces and at separate times.

Prior to March of 2020 coronavirus was a novel word to most people and few had encountered SARS-CoV-2 as a concept. As COVID-19 began to become a subject of worry and news coverage, there was considerable confusion and uncertainty. In a very brief period, COVID-19 as concept became the subject of constant conversation with major impacts on daily life. It became something to fear and worry about and fight and be angry about. Even as community agencies sought to educate the public, social media platforms were filled with a wide spectrum of accurate and inaccurate information, including conspiracy theories about the source of the virus (Choli & Kuss, 2021) and blatant xenophobia (Chou & Gaysynsky, 2021). Even asking "What is coronavirus" became a loaded question, leading to considerable confusion and uncertainty that was difficult to address (Koffman, et al., 2020). Information seeking about COVID-19 became necessary for daily life as policies changed and risks increased. While there are similarities to past pandemic conditions, COVID-19 involved significantly more uncertainty (Romiti & Talerico, 2021). As an aspect of the COVID-19 environment, COVID-19 specific information and uncertainty had considerable potential to impact well-being both as a source of worry and a threat to coping.

Another aspect of the COVID-19 environment was concerns specifically related to material resources, such as bread, water, and toilet paper. With lockdowns and stay-at-home orders anticipated, people perceived a scarcity of key resources as demonstrated by widely reported panic buying (Islam et al., 2021). This type of community behavior has been suggested to be linked to feelings of anxiety and loss of control of daily life. Faced with this loss of control, individuals sometimes use resource acquisition in excess as an attempt to coping with something uncontrollable. (Sim et al., 2020). While clearly connected to general concerns about COVID-19, specific community level concern around material resources is a distinct and potentially influential aspect of the environment. This aspect has the potential to relate to individual well-being, particularly around stress and coping, differently than uncertainty about COVID-19. However, research as not yet looked at such differences.

Internet Search Data

Internet search data (ISD) has been helpful in public health surveillance efforts during the COVID-19 pandemic. Internet inquiries reflect what topics are on a community's collective mind. Models using internet searches for "coronavirus" (Lee et al., 2021; Mavragani & Gkillas, 2020; Walker & Sulyok, 2020), as well as COVID-19 symptoms, such as "loss of smell" (Walker et al., 2020) predicted COVID-19 cases and deaths at multiple levels of geography. ISD also had provided insight into mental health concerns that are unique to the COVID-19 time period (Brodeur et al., 2021), as well as tracking prevention awareness through terms such as "wash hands" and "face mask" (Lin et al., 2020). Bento et al. (2020) found that on the days immediately following the announcement of the first positive local COVID-19 case, "coronavirus" related queries increased significantly with a rapid return in searches to pre-announcement levels within two weeks. This set of studies indicates several things: first that there is a connection between events in the community and ISD, and second that these effects are not sustained and fluctuate as community needs change.

Frequently, health research using ISD focuses on population level outcomes rather than individual level outcomes (Nuti et al., 2014). A strength of ISD is that it can provide insight into the community environment, the next step is to connect it to person-level effect, like individual worry or coping. Other work has found that ISD for mental health terms can be predictive individual self-reports of mental health concerns. Searches for depression, suicidal ideation, and loneliness all predicted self-reports of the same concern (Knipes et al., 2021). Interestingly while increased loneliness searches predicted higher self-reports of loneliness, both depression and suicidal ideation showed inverse relationships with self-reports of the concern. Further making the case linking ISD to individual outcomes, Fang et al. (2021) found that even behavior, specifically likelihood to respond to survey questions, can be predicted by ISD of relevant community factors such as terrorism and disease risk terms. Decreased community level concern was related to increased survey participation. Taken together this past work demonstrates both the link between ISD and individual well-being and behavior, as well as highlights the need for well identified search terms in addressing these relationships.

Psychological Response to COVID Environment

Psychological responses to the COVID-19 environment are complex, especially during the onset of the pandemic in early 2020. Using a network analysis based on surveys from U.S. and Canadian adults, Taylor et al. (2020) identified three major hubs of individuals' psychological responses to COVID-19. These hubs were worries about the dangerousness and risk of COVID-19, COVID-19 coping through reassurance-seeking and self-protective behaviors, and avoidance through beliefs that the risk of COVID-19 was exaggerated. Notably, two of these areas – worry about the dangers of COVID-19, and COVID-19 specific coping efforts, including panic buying and use of personal protective equipment – were linked. These two linked psychological responses include an aspect of direct response to the perceived risks posed by COVID-19 either through a future focused emotion response or a proactive problem focuses response. There is considerable potential for environmental changes to influence these response. Linking ISD to these responses could provide insight into how they fluctuate and react to day to day changes in the COVID-19 environment.

Worry

Worry is intrusive repetitive negative thoughts about future risks and threats. It is typically an unpleasant emotional experience but can also include buffering or coping benefits. In the COVID-19 environment, worry was a particular concern with the WHO recommending information restriction efforts to minimize worry in the general public, should the constant media coverage prove distressing (World Health Organization [WHO], 2020). More worry was related to a greater perception of the severity of the pandemic (Sobkow et al., 2020). Elevated levels of worry are problematic as they relate to insomnia and depressive symptoms (Bajaj et al., 2020) and are associated with higher levels of distress and lower life satisfaction (Blix et al., 2021). Research has found that not only did individuals differ in their general levels of worry during COVID-19, but there was also significant within-person variability (Lodder et al., 2021). Also worry was found to fluctuate considerably during 2020 with these fluctuations predicting insomnia severity from one time point to the next (Brown et al., 2022).

Despite a growing body of research about worry during COVID-19, missing from this work is consideration of connections between worry and the COVID-19 environment and how the daily changes in that environment could relate to worry. In addition to the usual sources of stress and worry of daily life, the COVID-19 environment brought with it a new set of pandemic related stress. Additionally, the COVID-19 environment was one in which most people were facing stress, worry, and uncertainty with COVID-19 as a shared stressor. In research looking at patterns of Twitter activity during this period, top themes surrounded concerns about the impact of COVID-19, the economy, and ways to mitigate risks of infection (Abd-Alrazaq et al., 2020). While interactions with other people in the community might provide outlets to process and cope with worry but it also could easily provide more information to generate worry. Worry during COVID-19 did not show buffering effects from social support (Moore et al, 2021). This suggests that the impact of one's community may have complicated effects on worry. Investigation into the relationship between community level responses to COVID-19 worries and the worry of an individual nested in that community could improve our understanding of the connections between environment and individual experience. A goal of this paper is to address this relationship, linking real time day to day changes in the COVID-19 environment to experiences of worry.

Coping Self-Efficacy

Coping efforts are a second major area of response to the COVID-19 pandemic. Coping self-efficacy, a person's confidence in their ability to cope effectively, is a key aspect of these efforts. In the transactional model of stress (Lazarus & Folkman, 1984), a critical step in appraising and dealing with stress is answering the question, "Can I deal with this threat?". Additionally, coping self-efficacy is a protective factor for acute stress disorder in at risk groups during COVID-19 (Shahrour & Dardas, 2020). It mediates the relationships between exposure to COVID-19 and mental health problems (Zhang et al., 2020) and has been found to be a critical mediator of psychological distress during past crises (Benight et al., 1999; Benight et al., 2000). It also relates to health behaviors such as problem eating behavior under stress (MacNeil et al., 2012) and physical activity (Gyurcsik et al., 2002). But as resources and risk change, one's confidence in a given moment may also change as the available coping resources and therefore one's ability to cope effectively must be re-evaluated in the face of a new or changing threat. Research suggests that variability in coping self-efficacy may be related to less strain when faced with a threat as a person is better able to match the current needs of their environment (Peng et al., 2015).

In the context of COVID-19, one's environment influenced both the threat posed by COVID-19 and the resources availability to address it. Drawing from threat perception research, aspects of familiarity, controllability, immediacy of danger, and level of knowledge are all key in determining how much of a threat something is to you (Cori et al., 2020). In the COVID-19 environment, these were all changing, particularly during the onset of the pandemic. Indeed, research has found a day-to-day escalation in threat perceptions by people during the first week of the pandemic in March 2020 (Wise et al., 2020). Meanwhile, resources both material and personal were consistently constrained under evolving challenges and policies. By relating measures of community environment to individual coping, we can investigate how community level information seeking patterns relates to individual coping and how that interaction varies over time as the environment changed.

Ecological Momentary Assessment

Use of ecological momentary assessment (EMA) is particularly promising in understanding the changing COVID-19 environment. In EMA, a micro-longitudinal design is used wherein individual participants respond to repeated assessments over multiple days within the environment of their daily life. These designs allow for a within-person approach that investigates how individuals change over time and in varying contexts (Shiffman et al., 2008). EMA investigations of worry during COVID-19 have revealed a number of important relationships including a reciprocal relationship between COVID-19 worries and posttraumatic stress symptoms day to day (Messman et al., 2022) and a connection between heart rate variability and momentary worry during COVID-19 (Makovac et al., 2022). Additionally COVID-19 EMA research has shown a connection between pro-active coping through routines and self-care and momentary affect (Zubek et al., 2021). EMA as a method addresses questions of when and in what circumstances which is ideal for considering the connections between environmental and individual coping.

Present Study

This study will consider the relationship between daily changes in the COVID-19 environment at the community level and individual level worry and coping. The COVID-19 environment was measured using ISD of both general coronavirus terms and terms related material resources. Individual level worry and coping was assessed with two weeks of ecological momentary assessment to collect daily self-reports of each construct. A micro-longitudinal within-person approach was used to allow for dynamic changes in the patterns of effect.

Several pre-registered hypotheses guide this work. First, we expected that days in which there is a higher frequency of searches for COVID-19 terms would predict greater worry (hypothesis 1a) and reduced coping self-efficacy (hypothesis 1b). Also, we expected that days in which there was a higher frequency of searches for material resources terms would predict great worry (hypothesis 2a) and reduced coping self-efficacy (hypothesis 2b).

Methods

Preregistration

This paper includes secondary data analysis of individual EMA data with the addition of COVID-19 data. EMA data was part of existing study that predated the on-set of the COVID-19 pandemic and thus was not pre-registered. All hypothesis for this work were preregistered on Open Science Framework (https://osf.io/zfpny), however, prior to any analysis being completed.

Participants

Using online campus recruitment, undergraduates were recruited at a public university in Central California. This study recruited 65 students with 56 (86.2% agreement) consenting to participate in the EMA portion of the study. Analysis of baseline demographics found that EMA participants were consistent with non-EMA participants with the exception of gender, which was included a control variable in all models. Study eligibility included enrolled as current student, over 18 years of age, and self-identified ethnically as Hispanic/Latinx, Asian/ Asian American, or White/Caucasian American. Only EMA participants were included in analysis.

Procedure

During a baseline session in a campus based lab, participants completed informed consent. Demographics collected including gender, race, and ethnicity, as well as additional measures not relevant to the current paper. These measures were collected via Qualtrics. Once participants completed the initial survey, they were invited to participate in 14 days of EMA. EMA participants then completed a training session with a trained research assistant. In this training, participants installed the RealLife Exp application (LifeData, Marion, IN) on their smartphone. Lab provided smart devices were available but were not needed by any participants. Once installed under the guidance of the research assistant, participants completed several EMA practice questions similar to those they would complete during the 14 day assessment. These questions were excluded from study analysis. Once training was complete and participants indicated that they were comfortable with the assessment, the lab session ended. EMA data collection began the following morning. Participants received four device prompts daily to complete measures on their smartphones. Prompts were randomized to initiate between 9-11:30AM, 12:00-2:30PM, 3-5:30PM, 6-8:30PM. Following the device prompt, the participant had a window of 60 minutes to complete assessments of worry and coping self-efficacy, as well as other measures not included in the current paper. After completion of the 14 day EMA, participants completed a short debrief procedure on the LifeData Exp applications to conclude data collection. All participants received course credit and those who participated in EMA also received a $25 Amazon gift card. All procedures were approved by university's institution review board.

Materials

Google Trends Data

Using the framework proposed by Mavragani and Ochoa (2019), internet search data was acquired from February 1 to March 31, 2020 for the local region of Central California where the university is located and where all participants attended school. These dates encompassed the time of EMA data collection. These data were accessed using the Google Trends open access online tool. This tool provides data on aggregate search requests received by Google across platforms. Data through this tool is normalized by Google using the set time range and location of the query. Per Google:

> Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. Otherwise, places with the most search volume would always be ranked highest. The resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion to all searches on all topics. (Google, 2022, para. 4).

This results in a relative search volume (RSV) for each keyword. A topic search was conducted for the keyword *coronavirus* for the general COVID-19 construct. Topic searches were used to include relevant spelling and language variations as well as related terms such as "COVID-19" and "Corona." This results in a COVID-19 RSV value for each day of data collection. The pattern of COVID-19 RSV is illustrated in Figure 3.1.

For the material resources construct, search terms were identified based on significant target items of panic buying behavior and trending material goods during the study period. Due to the functionality of the Google Trends interface, five terms were selected. Then simultaneous topic searches were conducted for the keywords: *toilet paper, bottled water, milk, bread,* and *hand sanitizer*. As with the previous variable, topic searches were conducted to account for spelling and language variations. Because the searches were simultaneous, RSVs were standardized across the same the relative scale for all five terms. Each term returned a value between 0 and 100, with 100 being the highest volume search day of any of the five terms and all other values scaled accordingly. Individual RSVs are illustrated in Figure 3.2a. Then all RSVs were summed for a total RSV for material resources for each day. The shared standardization allows the RSVs to be combined additively. This process resulted in a material resource RSV value for each day of data collection. Pattern of combined material resource RSV is illustrated in Figure 3.2b.

Daily Worry

Worry was assessed at each EMA notification using the question, "How much are you worrying?" Participants indicated their current level of worry using a scale from 0 (*not at all*) to 6 (*extremely*) on their smart phone. A mean was taking for all EMA reports throughout the day to assess the average level of worry each participant reported for the day.

Daily Coping Self-Efficacy

Coping self-efficacy was assessed at each EMA notification using the questions, "Right now, do you feel you could control important things?" and "Right now, do you feel confident in ability to handle problems?" Participants indicated current level of coping efficacy on a scale from 0 (*not at all*) to 6 (*extremely*). At each time point an average was calculated for momentary coping self-efficacy. Then day level coping self-efficacy was calculated as an average across all four measurements.

Analytic Plan

With up to 14 days of EMA and prevalence data per participants there is a two-level structure with days nested within people. Multilevel modeling was used to analyze the data using the PROC MIXED command in SAS 9.4. Separate models were run for worry and coping self-efficacy as outcomes, with each variable separately predicted by COVID-19 RSV and material resources RSV (resulting in a total of four models: hypothesis 1 and 2). Exploratory models for each outcome were run that includes both RSV variables simultaneously to investigate possible unique and shared effects. Additional exploratory models were included using lagged ISD variables, justification to follow. These models included both the current day's RSV as well as the RSV for the previous day in order to investigated delayed relationships with the current days outcome.

Across all models additional control variables were included. To account for potentially systemic difference between weekday and weekend days, a variable to account for weekend days (0 = Saturday or Sunday, 1 = weekday) was included as a control variable. To control for possible person level differences between community influences and individual coping, baseline demographic data were included in the models, gender (1 = man; 0 = woman), race (1 = White; 0 = non-White), and ethnicity (1 = Hispanic/Latino, 0 = non-Hispanic/Latino). Also included was a day level variable to account for timing relative to highest (peak) volume day of each internet search terms (-1 = pre peak, 0 = peak, 1 = post peak). This variable controlled for potential changes over time based on the day during the study period in which the most internet searchers were conducted. Peak day may represent a conceptual shift in the environment and this variable provides insight into that shift. This variable also presents a longer time period perspective to the models.

Random intercepts were modeled to allow for different starting values on the outcomes across participants. Also, an autoregressive covariance structure was specified to account for stronger correlations between outcomes measured closer together in time. Effect size was estimated using a pseudo R^2 statistic calculating the correlation between the observed outcome value and the value that is predicted by the model (Singer & Willett, 2003).

Results

Descriptive Statistics

Participants ethnic and racial demographics were consistent with the school's populations. The majority of participants identifying as ethnically Hispanic/Latino (67.9%) and racially White (58.20%) or Asian (16.4%). Participants ages were consistent with an undergraduate sample (*M* = 20.53 years, *SD* = 2.00). The majority of the sample identified as women (81.80%). Across all moments, participants reported general low worry (*M* = 2.19, *SD* = 1.89) and also low to moderate coping self-efficacy (*M* = 3.69, *SD* = 1.30). Participants completed a total of 2,176 observations during the study period which ended for all participants prior to community and state wide stay-at-home orders. For predictor variables, the mode (peak) of COVID-19 RSVs occurred on March 16, 2020 (*M* = 33.10, *SD* = 31.07, see Figure 2.1) this value was normed to 100. Over time, daily COVID-19 RSV gradually increase in volume thorough February, with a steeper escalation in early March. Similarly the peak of material resources RSV occurred on March 14, 2020 (*M* = 48.59, *SD* = 39.41, see Figure 2.2b) and followed a similar trajectory as COVID-19 RSV. There was more variability in daily material resource RSV values in February and the acceleration to peak RSV in March was more gradual for material resources RSV compared to COVID-19 RSV. There was a strong positive correlations between the two RSVs, r(118) = .91, $p < .001$.

COVID-19

Hypothesis 1a: COVID-19 and Worry

A multilevel regression model tested the effects of daily COVID-19 RSV and timing relative to peak COVID-19 RSV for the study period on daily reports of worry, controlling for weekday, gender, race, and ethnicity. Full results for this model can be found in Table 3.1. Contrary to our prediction, no significant effects were found for COVID-19 RSV ($p = .652$) nor timing relative to peak COVID-19 RSV ($p = .394$) on worry.

Hypothesis 1b: COVID-19 and Coping Self-Efficacy

A multilevel regression model tested the effects of daily COVID-19 RSV and timing relative to peak COVID-19 RSV for the study period on daily reports of coping self-efficacy, controlling for weekday, gender, and race and ethnicity. Full results for this model can be found in Table 3.1. As in hypothesis 1a, no significant effects were found for COVID-19 RSV, ($p = .637$), nor timing relative to peak COVID-19 RSV ($p = .304$) on coping self-efficacy.

Material Resources

Hypothesis 2a: Material Resources and Worry

A multilevel regression model tested the effects of daily material resources RSV and timing relative to peak material resources RSV for the study period on daily reports of worry, controlling for weekday, gender, and race and ethnicity. Full results for this model can be found in Table 3.1. Contrary to our prediction, no significant effects were found for material resources RSV ($p = .647$) nor timing relative to peak material resources RSV, ($p = .865$) on worry.

Hypothesis 2b: Material Resources and Worry

A multilevel regression model tested the effects of daily material resources RSV and timing relative to peak material resources RSV for the study period on daily reports of coping self-efficacy, controlling for weekday, gender, and race and ethnicity. Full results for this model can be found in Table 3.1. As in hypothesis 2a, no significant effects were found for material resources RSV ($p = .896$), nor timing relative to peak material resources RSV ($p = .249$) on coping self-efficacy.

COVID-19 and Material Resources

In a planned exploratory analysis in order to better understand the shared variance and potential unique effects of the RSV predictors, multilevel models were run for worry and coping self-efficacy separately that included both types of RSVs, daily COVID-19 RSV, timing relative to peak COVID-19 RSV, daily material resources RSV, and timing relative to peak material resources RSV as predictors. Full model results can be found in Table 3.2. While no significant effects were found to predict daily worry in the combined model, two significant predictors were found for coping self-efficacy. When the model included both types of RSVs, as well as the control variables used in previous models, the variable for timing relative to peak COVID-19 RSV (p = .011) was a significant predictor such that post peak RSV days related to increased coping self-efficacy. Also in this model timing relative to peak material resources RSV (p = .008) was also a significant predictors such that days post peak material resources RSV was related to decreased coping self-efficacy. However neither the COVID-19 RSV nor material resources RSV predicted coping self-efficacy.

Additional Exploratory Models

To better understand the unique effects of the timing relative to peak RSVs, particularly the opposite directions of the relationships with coping self-efficacy. Two models were run which did not included the RSV values and using both timing relative to peak RSV variables as predictors instead. Worry and coping self-efficacy were tested separately. Full results can be found in Table 3.2. Findings were consistent with the previous combined models. Neither timing relative to peak COVID RSV (p = .412) nor timing relative to peak material resources RSV (p = .784) variable predicted worry. Coping self-efficacy showed the same patterns, with timing relative to peak COVID RSV (p = .025) relating to more coping self- efficacy post peak and timing relative to peak material resources RSV (p = .031) relating to less coping self-efficacy post peak.

Building further off the findings of the full combined model which indicated a potential delayed effect of RSV on coping self-efficacy as well further consideration of the timing of the search days relative to the timing of the EMA data collection, several additional multilevel models were tested. These models used a lagged approach to better understand the effect of time. In addition to person level control variables (gender, race, ethnicity) and weekend control variable, these models included the RSV and timing relative to peak RSV variables from the previous day as predictors as well as the concurrent day RSV and timing relative to peak RSV as control variables. Previous day variables are referred to as lagged variables. Full model results can be found in Table 3.3. No additional significant predictors emerged for coping self-efficacy in any of the models. However in both the model with COVID-19 RSV only and the model with both COVID-19 RSV and material resources RSV as predictors, lagged COVID-19 RSV significantly predicted daily worry (p = .034, p = .012). On days where there were more COVID-19 searches the previous day, less worry was reported compared to days with less searches. There were also several marginal effects that suggest a pattern of smaller effects. In the model with material resources RSV only as a predictor, lagged material resources RSV predicted less worry (p = .060). Also for coping self-efficacy, when lagged material resources RSV was in the model, concurrent day material resources showed a marginal relationship (p = .099) with more concurrent day material resources searches predicting more coping self-efficacy.

Discussion

The purpose of this study was to consider connections between community daily internet search data as an indicator of community uncertainty and individual experiences of worry and coping in the context of the COVID-19 pandemic. While we expected to find same day relationships between ISD and worry and coping, no such effects were not found. However, from the additional work in this paper, several promising findings suggest that relationships between ISD, as measures of environment, and individual worry and coping may function on a longer time scale than a day to day basis.

Timing Relative to Peak RSV Day

We found that the timing relative to the peak of ISD data during the study period had a unique effect for both COVID-19 RSV and material resources RSV on coping self-efficacy. The day in which the most internet searches were happening represented a change in environment and that change related to changes in the individuals living within that environment. Rather than a driver of that change itself, the RSV peaks could be considered a signpost or indicator of change. The environments people experienced at and after the day of most internet searching was changed in a way that connected to stress and coping. Interestingly those relationships varied considerably by indicator. For searches for COVID-19, days after the peak search volume predicted more self-reports of coping self-efficacy. After the day in which there was the highest level of COVID-19 specific inquiry online, people felt more capable to cope. This could be a demonstration of the transition from uncertainty to certainty. When we consider the type of search that would include a COVID-19 term, such as “what is COVID-19” they are more likely to have a concrete answer and result in some satisfaction based on obtaining the information sought. Therefore, peak search day for this type of term would lead to more people having information and potentially an environment of less uncertainty about this specific issue. Less uncertainty and increased familiarity could influence how threat was perceived and therefore how prepared one felt to cope with challenges (Cori et al., 2020).

In contrast, for internet searches for material resources such as bread, water, and toilet paper, peak search day related to decreased coping self-efficacy. People on and after the day of highest search volume for resources felt less able to cope. To understand this effect two major considerations are needed. First in general the type of searches one might make for a resource like bread is going to be considerably different from COVID-19. During this period it was likely an attempt to procure the resource, e.g., “where can I buy bread” or “how do I make bread,” or to read about ongoing panic buying in these cases the act of reading or view internet content is less likely to satisfy the searcher’s goal or engender confidence in the availability of that resource.

The second consideration relates to the panic buying context of this time period, the spring of 2020. News of impending stay-at-home orders and possible restrictions to address COVID-19 risk led to considerable stockpiling or panic buying of food and other necessities (Leung et al., 2021). When there is a perception of scarcity for a critical resource, individuals often assess their own resources and if those resources do not meet the perceived needs current or future distress may occur. In this context, distress satisfaction using internet searches was much harder to achieve regarding material resources and the highest volume search day could represent the apex of that distress. Also engaging in panic buying has been linked to negative emotions (Huan et al., 2021) and guilt (Prentice et al., 2020). Perhaps the negative effects of post peak days for material resources RSV and the environment of perceived resource scarcity reflects a prolonged pattern of feelings of inability to address everyday needs. That persisted even once interest in the scarcity decreased in post peak days with no added information about resource availability.

It is also notable that the effects of timing relative to RSV peak days only show these effects on coping self-efficacy in the combined models. This suggested that effects occur outside the shared variance of COVID-19 and material resources. There are unique aspects of each environmental influence that notably related to coping in opposite directions. Additionally, given the narrow time period between the peak days for COVID-19 RSV and material resources RSV, this indicates that it was a critical period of time in which considerable shifts were happening environmentally. Applying further context to this brief period of time, while the California statewide stay at home orders would not be used until March 19, 2020, communities and schools were beginning to enact isolation and lockdown policies (Procter, 2021). These changes are highlighted in the RSV patterns.

Lagged COVID-19 RSV

We also found a delayed relationship between COVID-19 RSV and worry, with increased ISD on the previous day predicting decreased worry. With no similar relationship found on same day RSV, this would suggest that additional time is needed for the environment to relate to individual worry. An aspect of this may have related to processing time given the repetitive and intrusive nature of worry. It is interesting that the relationships between COVID-19 RSV and worry is in the opposite direction of what we hypothesized. Similar to the effects of coping self-efficacy, perhaps increased RSV indicates an environment of greater knowledge and therefore less worry rather than one of increased uncertainty. Additionally, there is a possible order issue at play. Frequently worry predicts health information seeking (e.g., Lee & Hawkins, 2016; Seiter & Brophy, 2020). However, less is known about how information seeking predicts worry, although there is evidence of a reciprocal relationship wherein worry leads to information seeking leads to more worry (Chae, 2015; te Poel et al., 2016). However such work has looked at individual information seeking rather than community level information seeking. This is an area for future work with the role of health information seeking during crisis and stress.

Implications

This work expands the research linking community environmental indicators to individual well-being. It also highlights the challenges of identifying optimal indicators, similar to the challenges Knipes et al. (2021) experienced in linking ISD to mental health outcomes. However, rather than demonstrating that ISD, and thus the community environments it indicates, are not useful for understanding daily individual coping this work reveals that the relationships between environments and individual coping are complex. This complexity is most evidence when considering the temporal nature of the relationships. Both the single day lagged effect on worry and the over time effects on coping self-efficacy provide critical insight into the processes of daily life. Coping is an ongoing process as individual adapt to changing threats and resources. Recent work has revealed significant changes in the patterns and manners of coping over the course of the COVID-19 pandemic (Godor & Van der Hallen, 2021). This study provides additional context to those changes.

This work also has further implications on ongoing COVID-19 research. Based on this findings, future research should consider including direct measures of the COVID-19 environment, particularly when investigating stress and coping. Also incorporation of temporal dynamics in considering these relationships is critical. Beyond the COVID-19 context, this work has implications into how we think about the role of environment for other chronic stress and crisis context. The inclusion of dynamic measures like ISD could expand the already well-researched connections between community environments and health and well-being (Taylor et al., 1997). The focus of information and how they change can provide in the moment detail about what a community is concern about. Beyond that this works demonstrates that those community concerns connect to the behavior and well-being of community members. This is vital information to understand the changes in well-being and health of individual and it is likely to fluctuate in both the short and long term time frames.

Limitations and Future Directions

When generalizing and extending the results of this work several limitations should be considered. Because this work relied on a natural experiment opportunity in that it used an ongoing EMA study at the on-set of the COVID-19 pandemic – it was necessary to leverage data that was already being collected to test new questions about this evolving environment. Future dedicated work is needed to expand these results to consider different phases and periods of the COVID-19 pandemic, particularly given the time scale of the effects found in this study. For example, sources of uncertainty likely changed throughout the pandemic. In later phases, concerns for material resources changed from stockpiling of staples like flour and toilet paper to particular mask needs (e.g., N-95 masks) at different phases and worries about financial concerns developed considerably. A more expanded time scale could consider the relationships between these worries and well-being.

This research was conducted over a limited period when considering the full extent of the COVID-19 pandemic (which is ongoing at the time of this paper). We would anticipate that the COVID-19 environment would continue to evolve and change after March 2020. Future work is necessary to look at this environment over an extended period of time or other evolving crisis environments. Additional because of the restricted period, measurements of peak RSV days only reflected the range of study days. While both COVID-19 and material resources RSV were declining at the end of data collections, subsequent escalations in search volume may have more accurately reflected the highest point of interest in the term. This is a promising future direction addressing a more extended time period, allowing for the evaluation of possible a truer peak day and even multiple significantly high RSV days and the possibility of identifying multiple phases of environmental change. Relatedly, this work only addressed two major types of ISD as predictors, however there are multiple other COVID-19 domains that showed elevated interest during this time with varying patterns of escalation (Rotter et al., 2021). Future work should consider these additional domains such as personal safety behavior and social interactions to further understand the environment during this time period and its relationship to coping.

An additional limitation of this work is that it only utilized Google based ISD as an indicator of information seeking environments. Recent research has shown that during COVID-19 multiple information sources were utilized with differing impacts on individuals' well-being and behavior (Entradas 2021; Qiao et al., 2022). While ISD reveals one facet of this environment, the inclusion of other digital information source, particularly social media may improve measurement of the environment either through expanding this aspect or introducing additional distinct aspects to the research. This is particularly true in an undergraduate sample who are frequently and heavy users of social media for information (Kim et al., 2014; Park & Calamaro, 2013). Future work should consider measures of trending terms and hashtags as possible environmental indicators in concert with ISD to address more complex measurements of the environment.

Lastly, individual measures in this study looked at worry and coping as general constructs. However recently work has suggested that COVID-19 specific stress, worry, and coping are related but distinct constructs to general aspects of distress and coping (Green et al., 2022; Thibault et al., 2022). It is possible that the non-specific version of the constructs masked more clear relationships between ISD and individual COVID-19 coping. There may be a more direct connection between the community indicators and efforts to cope with COVID-19 specifically. A promising extension of this work is to relate environmental indicators to even more closely linked individual outcomes.

Conclusion

Both worry and coping self-efficacy during and after COVID-19 are critical aspects of stress and coping but neither is occurring in a vacuum. These findings support both the importance and the complexity of the COVID-19 environment and its relationship to coping efforts. They also begin to disentangle the impact of environments over time and address potential longer timeframe effects using innovated indicators of a community environment during a time of crisis. This extends both the COVID-19 literature and daily life research by connection community ISD with individual coping on a day to day basis.

Chapter 4: General Conclusions and Implications

Environments are dynamic and complex with impacts on health and well-being both immediate and long term. This dissertation further reveals the complex role of the environment in understanding well-being through two studies of the relationships between environments during the onset of the COVI-19 pandemic and individual distress and coping. It extends environmentally grounded research through the consideration of time using a within-person approach to the relationships which allowed for both changes in the environments and changes in the individuals on the day to day level.

Study 1

In Chapter 2 (Study 1), we investigated the relationships between environmental measures of pandemic severity and individual distress. We found that for both severity measures of COVID-19 cases and COVID-19 deaths there were effects on daily distress variability. This pattern suggests that as an environment presents more risk there is a corresponding change in a person's capacity to respond. This means that rather than showing a sensitivity to aspects of daily life (both positive and negative) during times of escalated threat, individuals may instead show less fluctuations around their average or possible trait levels of response. Additionally, this work found that depending on the use of COVID-19 cases or deaths there was an exposure effect - whereas COVID-19 cases show relationships on a day to day basis, COVID-19 deaths predicted distress variability only as an accumulated total. This suggest that aspects of the environment have different relationships with individuals in the environment. This is particularly important when considering intervention efforts. The same thresholds for resource mobilization cannot be applied uniformly to every indicator. Lastly this work can be taken as clear support for the importance of considering environments in daily life. While the COVID-19 pandemic is a novel situation, it is striking to consider that there is a direct and measurable link between surveillance data about infection rates across a large geographic state and the daily distress of undergraduate students.

Study 2

In Chapter 3 (Study 2), we considered the COVID-19 pandemic environment through a different lens, again linking environmental indicators to individual well-being. Using Google internet search data we found that patterns of community information seeking showed a delayed relationship with individual coping efforts. Rather than predicting coping immediately as we saw in Study 1, community information seeking required more exposure, one day in the case of worry and multiple days for coping self-efficacy. Further, the effects varied by the type of information being sought. While community information seeking about COVID-19 related to improved coping efforts (less worry the next day and more coping self-efficacy as community interest peaked), information seeking about necessary material resources showed the opposite relationship with coping self-efficacy over time. These findings reveal even more complexity in understanding environments and highlight the critical element of time. They also reveal the utility of ISD as a marker for individual experiences. From an intervention standpoint, ISD can provide a nuanced timeline of moments of vulnerability. Study 2 also further supports the need for complex measures of environment that account for multiple dynamic aspects as it was the combined models that revealed unique effects of information seeking environments that were less apparent in the single aspect results.

Implications for Environmentally Grounded Research

Taking together the findings of these studies show considerable promise in including environments as predictors of person level outcomes. It provides models for how to incorporate objective indicators of large environments into individual research, bridging the ecological studies of public health which are concerned with the population or community level with ecological momentary assessment studies of psychology at the individual level.

The COVID-19 environment served a strong environment to demonstrate these models. Most research acknowledges that people are feeling and acting differently during this time period with considerable research demonstrating just how differently (e.g., Andrada et al., 2021; Cervera-Martinex et al., 2021; Gestdottir et al., 2021; Salari et al., 2020). But this dissertation is amongst the first to demonstrate empirically that aspects of the COVID-19 environment can be measurably and significantly predictive of these differences on a person level. At minimum, this provides insight into how one might account for environmental effects when considering data gathered during the COVID-19 period. There is considerable COVID-19 research being conducted across fields (Dinis-Oliveira, 2020). The findings of this dissertation highlight ways to move beyond only indicating that COVID-19 was a factor during the time of data collection in this research. Moreover these findings suggest that the environment itself needs to be a considered as a critical component in this research not just a confounding factor. This is particularly important when considering interventions. As May et al. (2016) indicated in treating context and environment as a confound, researchers are completely discounting the normal condition of life and practices which primes interventions for reduced success.

The findings and approach of this dissertation also provide insight into research during times of crisis. Rather than adding additional burden to participants during such a time, this work shows how the uses of ongoing environmental surveillance can add valuable context to data already being collected, leveraging data to take advantage of natural experimental conditions. These measures also did not rely on perception of participants to measure the COVID-19 environment instead using objective and readily available data to track changes in the environment. By doing so, the dissertation attempted to consider the environment objectively. By doing it expands how research considers and measures environments. In Study 1 COVID-19 cases and deaths were objectively measures and used as proxies for the risk and severity of the COVID-19 environment, a construct that would otherwise have relied on subjective measurement. Similarly in Study 2 community ISD for COVID-19 and material resources were used as proxies for community uncertainty. By the careful selection and identification of objective proxy indicators, this dissertation was able to consider a crisis environment in multiple ways. Similar methods can be used in future work to understand both crisis and non-crisis environments and further inform ongoing research efforts. Additionally future work may look at including both objective and subjective measures in concert to understanding multiple distinct indicators of key aspects.

Environmental Complexity

The complexity of the COVID-19 environment and environments in general is a critical aspect of this dissertation. Findings for both studies indicated surprising and sometimes conflicting relationships with COVID-19 environmental aspects. It is important to remember that rather than acting in isolation, each environmental aspect we measured along with others work in concert to create the environment of any given day during this study. As we found in Study 2, models which included multiple aspects were able to both better predict psychological outcomes but also provided insight into unique effects of the environmental aspects. While research using single aspects of environments are important steps to understanding environments in daily life, this type of approach struggles to address the complexity of environments and as a result may be missing key connections. This dissertation advances the understanding and measurement of complex environments.

Impact of Time

The findings from both studies also highlight the importance of considering the impact of time and the dynamic nature of both environments and individuals. Had either study used a single time point to measure the environment most of the key findings would have been missed. In investigating the relationships between individuals and environment, research is observing an ongoing process. As such, the patterns of such relationships are meaningful. They reveal changes and exposure effects over time. In both studies, a wide range of patterns were found depending on the length of exposure to the environmental aspect. These patterns help researchers to conceptualize even longer term exposure. It also sets up future research to look at more long term patterns and consider possibilities of phases of exposure or critical limits of effect. This work focused on a relative brief interval in the full scope of the current ongoing COVID-19 pandemic. By expanding this work and considering possible longer patterns, it is possible to address if this findings of this dissertation are distinct to the onset of a crisis or is representative of different periods of a crisis or chronic stress. For example COVID-19 death statistics unfortunately continue to increase longitudinally, more work is needed to consider if there continues to be clear relationships to this changes or if perhaps there is a saturation point where the relationships change. Future research is needed to understand how the patterns this dissertation found expand when in the environment continue to change at such rates. From this work it is clear that both environments and the psychological well-being of individuals in them vary and change and that research needs to account for both.

EMA Research

Use of EMA data provides a clear area for further advancement in empirically connecting environment with individuals. A major strength of EMA is that it strives for optimal ecological validity by assessing individuals in their daily life environments (Shiffman et al., 2008). It is a logical and optimal progression then to consider the role of environment in these methods. In both studies, environmental aspects predicted psychological outcomes and these aspects were potentially distally measured at a community and state level. This is promising in two major ways. First it indicates that other dynamic and publicly assessable data can be married to EMA to understand the changing environments, for example climate and weather patterns, traffic and pollution data, or crime instances. Second with advancement in geospatial measurement, EMA data collection methods can include a precise location for participants. This means that research can focus even more specifically on the environment of the moment of data collection. Additionally by included EMA questions that specifically measure aspects of a participants environment from both and an objective and subjective approach, moving beyond simply asking “where are you?,” it is possible to continue to understand the role of environments in psychological well-being and other individual features such as health in a way that accounts for the complexity of these environments.

Conclusion

As a whole this dissertation showed further evidence of the importance of environmental grounded research in understanding individual psychological well-being. It also revealed specifics about the role of the COVID-19 environment in daily experiences at multiple levels of influence, an environment that has generated considerable research and will continue to show lasting effects of everyone who experienced it. This work demonstrated that it is possible to consider both the complex and dynamic nature of both the environment and the individual in a meaningful way. More than possible, the findings for this work that these approaches are necessary to understand daily life and not discount or control for the setting of well-being and health.

References

Abd-Alrazaq, A., Alhuwail, D., Househ, M., Hamdi, M., & Shah, Z. (2020). Top concerns of Tweeters during the COVID-19 pandemic: Infoveillance study. *Journal of Medical Internet Research*, *22*(4), e19016. https://doi.org/10.2196/19016

Adams, R. E., & Boscarino, J. A. (2011). A structural equation model of perievent panic and posttraumatic stress disorder after a community disaster: Perievent panic and PTSD after community disaster. *Journal of Traumatic Stress*, *24*(1), 61–69. https://doi.org/10.1002/jts.20603

Andrada, A., & Ozdemir, U. (2021). COVID 19 and subjective mental well-being: Changes throughout the crisis. *Traumatology*, *27*(4), 444–454. https://doi.org/10.1037/trm0000358

Arendt, F., Markiewitz, A., Mestas, M., & Scherr, S. (2020). COVID-19 pandemic, government responses, and public mental health: Investigating consequences through crisis hotline calls in two countries. *Social Science & Medicine*, *265*, 113532. https://doi.org/10.1016/j.socscimed.2020.113532

Bajaj, S., Blair, K. S., Schwartz, A., Dobbertin, M., & Blair, R. J. R. (2020). Worry and insomnia as risk factors for depression during initial stages of COVID-19 pandemic in India. *PLOS ONE*, *15*(12), e0243527. https://doi.org/10.1371/journal.pone.0243527

Barker, R. G. (1968). *Ecological psychology; concepts and methods for studying the environment of human behavior.* Stanford University Press

Barry, V., Stout, M. E., Lynch, M. E., Mattis, S., Tran, D. Q., Antun, A., Ribeiro, M. J., Stein, S. F., & Kempton, C. L. (2020). The effect of psychological distress on health outcomes: A systematic review and meta-analysis of prospective studies. *Journal of Health Psychology*, *25*(2), 227–239. https://doi.org/10.1177/1359105319842931

Bäuerle, A., Graf, J., Jansen, C., Musche, V., Schweda, A., Hetkamp, M., Weismüller, B., Dörrie, N., Junne, F., Teufel, M., & Skoda, E.-M. (2020). E-mental health mindfulness-based and skills-based ‘CoPE It’ intervention to reduce psychological distress in times of COVID-19: Study protocol for a bicentre longitudinal study. *BMJ Open*, *10*(8), e039646. https://doi.org/10.1136/bmjopen-2020-039646

Benight, C. C., Freyaldenhoven, R. W., Hughes, J., Ruiz, J. M., Zoschke, T. A., & Lovallo, W. R. (2000). Coping self-efficacy and psychological distress following the Oklahoma City bombing. *Journal of Applied Social Psychology*, *30*(7), 1331–1344. https://doi.org/10.1111/j.1559-1816.2000.tb02523.x

Benight, C. C., Swift, E., Sanger, J., Smith, A., & Zeppelin, D. (1999). Coping self-efficacy as a mediator of distress following a natural disaster. *Journal of Applied Social Psychology*, *29*(12), 2443–2464. https://doi.org/10.1111/j.1559-1816.1999.tb00120.x

Bento, A. I., Nguyen, T., Wing, C., Lozano-Rojas, F., Ahn, Y.-Y., & Simon, K. (2020). Evidence from internet search data shows information-seeking responses to news of local COVID-19 cases. *Proceedings of the National Academy of Sciences*, *117*(21), 11220–11222. https://doi.org/10.1073/pnas.2005335117

Berke, E. M., Gottlieb, L. M., Moudon, A. V., & Larson, E. B. (2007). Protective association between neighborhood walkability and depression in older men: Neighborhood and depression in older adults. *Journal of the American Geriatrics Society*, *55*(4), 526–533. https://doi.org/10.1111/j.1532-5415.2007.01108.x

Blix, I., Birkeland, M. S., & Thoresen, S. (2021). Worry and mental health in the Covid-19 pandemic: Vulnerability factors in the general Norwegian population. *BMC Public Health*, *21*(1), 928. https://doi.org/10.1186/s12889-021-10927-1

Breaux, R., Langberg, J. M., Swanson, C. S., Eadeh, H.-M., & Becker, S. P. (2020). Variability in positive and negative affect among adolescents with and without ADHD: Differential associations with functional outcomes. *Journal of Affective Disorders*, *274*, 500–507. https://doi.org/10.1016/j.jad.2020.05.027

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, lockdowns and well-being: Evidence from Google Trends. *Journal of Public Economics*, *193*, 104346. https://doi.org/10.1016/j.jpubeco.2020.104346

Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American Psychologist*, *32*(7), 513–531. https://doi.org/10.1037/0003-066X.32.7.513

Brog, N. A., Hegy, J. K., Berger, T., & Znoj, H. (2021). An internet-based self-help intervention for people with psychological distress due to COVID-19: Study protocol for a randomized controlled trial. *Trials*, *22*(1), 171. https://doi.org/10.1186/s13063-021-05089-9

Brown, L. A., Hamlett, G. E., Zhu, Y., Wiley, J. F., Moore, T. M., DiDomenico, G. E., Visoki, E., Greenberg, D. M., Gur, R. C., Gur, R. E., & Barzilay, R. (2022). Worry about COVID-19 as a predictor of future insomnia. *Journal of Sleep Research*. https://doi.org/10.1111/jsr.13564

Bueno-Notivol, J., Gracia-García, P., Olaya, B., Lasheras, I., López-Antón, R., & Santabárbara, J. (2021). Prevalence of depression during the COVID-19 outbreak: A meta-analysis of community-based studies. *International Journal of Clinical and Health Psychology*, *21*, 100196. https://doi.org/10.1016/j.ijchp.2020.07.007

California Department of Public Health [CDPH], (2021, February 19). Office of Public Affairs: CDPH news releases 2020. https://www.cdph.ca.gov/Programs/OPA/Pages/New-Release-2020.aspx

Cervera-Martínez, J., Atienza-Carbonell, B., Mota, J. C., Bobes-Bascarán, T., Crespo-Facorro, B., Esteban, C., García-Portilla, M. P., Gomes-da-Costa, S., González-Pinto, A., Jaén-Moreno, M. J., Sarramea, F., Vieta, E., Zorrilla, I., Tabarés-Seisdedos, R., Kapczinski, F., De Boni, R. B., & Balanzá-Martínez, V. (2021). Lifestyle changes and mental health during the COVID-19 pandemic: A repeated, cross-sectional web survey. *Journal of Affective Disorders*, *295*, 173–182. https://doi.org/10.1016/j.jad.2021.08.020

Chae, J. (2015). Online cancer information seeking increases cancer worry. *Computers in Human Behavior*, *52*, 144–150. https://doi.org/10.1016/j.chb.2015.05.019

Choli, M., & Kuss, D. J. (2021). Perceptions of blame on social media during the coronavirus pandemic. *Computers in Human Behavior*, *124*, 106895. https://doi.org/10.1016/j.chb.2021.106895

Chou, W. Y. S. & Gaysynsky A. (2021). Racism and xenophobia in a pandemic: Interactions of online and offline worlds. *American Journal of Public Health*, *111*(5), 773–775. https://doi.org/10.2105/AJPH.2021.306230

Cori, L., Bianchi, F., Cadum, E., & Anthonj, C. (2020). Risk perception and COVID-19. *International Journal of Environmental Research and Public Health*, *17*(9), 3114. https://doi.org/10.3390/ijerph17093114

Daly, M., & Robinson, E. (2021). Psychological distress and adaptation to the COVID-19 crisis in the United States. *Journal of Psychiatric Research*, *136*, 603–609. https://doi.org/10.1016/j.jpsychires.2020.10.035

Dinis-Oliveira, R. J. (2020). COVID-19 research: Pandemic *versus* “paperdemic”, integrity, values and risks of the “speed science.” *Forensic Sciences Research*, *5*(2), 174–187. https://doi.org/10.1080/20961790.2020.1767754

Douglas, O. B., & Holland, B. F. (1938). *Fundamentals of educational psychology*. MacMillan Co. https://doi.org/10.1037/14910-000

Dyer, J., & Kolic, B. (2020). Public risk perception and emotion on Twitter during the Covid-19 pandemic. *Applied Network Science*, *5*(1), 99. https://doi.org/10.1007/s41109-020-00334-7

Eid, M., & Diener, E. (1999). Intraindividual variability in affect: Reliability, validity, and personality correlates. *Journal of Personality and Social Psychology*, *76*(4), 662–676. https://doi.org/10.1037/0022-3514.76.4.662

Entradas, M. (2021). In science we trust: The effects of information sources on COVID-19 risk perceptions. *Health Communication*, 1–9. https://doi.org/10.1080/10410236.2021.1914915

Fang, Q., Burger, J., Meijers, R., & Van Berkel, K. (2021). The role of time, weather and Google Trends in understanding and predicting web survey response. *Survey Research Methods*, 1-25 Pages. https://doi.org/10.18148/SRM/2021.V15I1.7633

Fiksdal, A., Hanlin, L., Kuras, Y., Gianferante, D., Chen, X., Thoma, M. V., & Rohleder, N. (2019). Associations between symptoms of depression and anxiety and cortisol responses to and recovery from acute stress. *Psychoneuroendocrinology*, *102*, 44–52. https://doi.org/10.1016/j.psyneuen.2018.11.035

Flett, G. L., Vredenburg, K., & Krames, L. (1995). The stability of depressive symptoms in college students: An empirical demonstration of regression to the mean. *Journal of Psychopathology and Behavioral Assessment*, *17*(4), 403–408. https://doi.org/10.1007/BF02229059

Frank, L. D., Schmid, T. L., Sallis, J. F., Chapman, J., & Saelens, B. E. (2005). Linking objectively measured physical activity with objectively measured urban form. *American Journal of Preventive Medicine*, *28*(2), 117–125. https://doi.org/10.1016/j.amepre.2004.11.001

Fu, S. (Qiang), Greco, L. M., Lennard, A. C., & Dimotakis, N. (2021). Anxiety responses to the unfolding COVID-19 crisis: Patterns of change in the experience of prolonged exposure to stressors. *Journal of Applied Psychology*, *106*(1), 48–61. https://doi.org/10.1037/apl0000855

Gestsdottir, S., Gisladottir, T., Stefansdottir, R., Johannsson, E., Jakobsdottir, G., & Rognvaldsdottir, V. (2021). Health and well-being of university students before and during COVID-19 pandemic: A gender comparison. *PLOS ONE*, *16*(12), e0261346. https://doi.org/10.1371/journal.pone.0261346

Glowacz, F., & Schmits, E. (2020). Psychological distress during the COVID-19 lockdown: The young adults most at risk. *Psychiatry Research*, *293*, 113486. https://doi.org/10.1016/j.psychres.2020.113486

Godor, B. P., & Van der Hallen, R. (2022). Investigating the susceptibility to change of coping and resiliency during COVID-19. *Scandinavian Journal of Psychology*, *63*(3), 238–245. https://doi.org/10.1111/sjop.12787

Google. (2022). *FAQ about Google Trends data*. https://support.google.com/trends/answer/4365533?hl=en

Green, S. M., Furtado, M., Inness, B. E., Frey, B. N., & McCabe, R. E. (2022). Characterizing worry content and impact in pregnant and postpartum women with anxiety disorders during COVID-19. *Clinical Psychology & Psychotherapy*, *29*(3), 1144–1157. https://doi.org/10.1002/cpp.2703

Guan, M., Li, Y., Scoles, J. D., & Zhu, Y. (2022). COVID-19 message fatigue: How does it predict preventive behavioral intentions and what types of information are people tired of hearing about? *Health Communication*, 1–10. https://doi.org/10.1080/10410236.2021.2023385

Guidotti, E., & Ardia, D. (2020). COVID-19 Data Hub. *Journal of Open Source Software*, *5*(51), 2376. https://doi.org/10.21105/joss.02376

Gyurcsik, N. C., Brawley, L. R., & Langhout, N. (2002). Acute thoughts, exercise consistency, and coping self-efficacy. *Journal of Applied Social Psychology*, *32*(10), 2134–2153. https://doi.org/10.1111/j.1559-1816.2002.tb02067.x

Henry, J. D., & Crawford, J. R. (2005). The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample. *British Journal of Clinical Psychology*, *44*(2), 227–239. https://doi.org/10.1348/014466505X29657

Holingue, C., Kalb, L. G., Riehm, K. E., Bennett, D., Kapteyn, A., Veldhuis, C. B., Johnson, R. M., Fallin, M. D., Kreuter, F., Stuart, E. A., & Thrul, J. (2020). Mental distress in the United States at the beginning of the COVID-19 pandemic. *American Journal of Public Health*, *110*(11), 1628–1634. https://doi.org/10.2105/AJPH.2020.305857

Hollenstein, T., Lichtwarck-Aschoff, A., & Potworowski, G. (2013). A model of socioemotional flexibility at three time scales. *Emotion Review*, *5*(4), 397–405. https://doi.org/10.1177/1754073913484181

Huan, C., Park, S., & Kang, J. (2021). Panic buying: Modeling what drives it and how it deteriorates emotional well-being. *Family and Consumer Sciences Research Journal*, *50*(2), 150–164. https://doi.org/10.1111/fcsr.12421

Islam, T., Pitafi, A. H., Arya, V., Wang, Y., Akhtar, N., Mubarik, S., & Xiaobei, L. (2021). Panic buying in the COVID-19 pandemic: A multi-country examination. *Journal of Retailing and Consumer Services*, *59*, 102357. https://doi.org/10.1016/j.jretconser.2020.102357

Jenkins, B. N., Hunter, J. F., Cross, M. P., Acevedo, A. M., & Pressman, S. D. (2018). When is affect variability bad for health? The association between affect variability and immune response to the influenza vaccination. *Journal of*

Psychosomatic Research, *104*, 41–47. https://doi.org/10.1016/j.jpsychores.2017.11.002

Jongeneel-Grimen, B., Droomers, M., van Oers, H. A. M., Stronks, K., & Kunst, A. E. (2014). The relationship between physical activity and the living environment: A multi-level analyses focusing on changes over time in environmental factors. *Health & Place*, *26*, 149–160. https://doi.org/10.1016/j.healthplace.2013.12.003

Kim, K. S., Sin, S. C. J., & Yoo-Lee, E. Y. (2014). Undergraduates' use of social media as information sources. *College & Research Libraries*, *75*(4), 442-457. https://doi.org/10.5860/crl.75.4.442

Kleiman, E. M., Yeager, A. L., Grove, J. L., Kellerman, J. K., & Kim, J. S. (2020). Real-time mental health impact of the COVID-19 pandemic on college students: Ecological momentary assessment study. *JMIR Mental Health*, *7*(12), e24815. https://doi.org/10.2196/24815

Knipe, D., Gunnell, D., Evans, H., John, A., & Fancourt, D. (2021). Is Google Trends a useful tool for tracking mental and social distress during a public health emergency? A time–series analysis. *Journal of Affective Disorders*, *294*, 737–744. https://doi.org/10.1016/j.jad.2021.06.086

Koffman, J., Gross, J., Etkind, S. N., & Selman, L. (2020). Uncertainty and COVID-19: How are we to respond? *Journal of the Royal Society of Medicine*, *113*(6), 211–216. https://doi.org/10.1177/0141076820930665

Kumar, S., Quinn, S. C., Kim, K. H., Musa, D., Hilyard, K. M., & Freimuth, V. S. (2012). The Social Ecological Model as a framework for determinants of 2009 H1N1 influenza vaccine uptake in the United States. *Health Education & Behavior*, *39*(2), 229–243. https://doi.org/10.1177/1090198111415105

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. New York: Springer.

Lee, J., Kwan, Y., Lee, J. Y., Shin, J. I., Lee, K. H., Hong, S. H., Han, Y. J., Kronbichler, A., Smith, L., Koyanagi, A., Jacob, L., Choi, S., Ghayda, R. A., & Park, M.-B. (2021). Public interest in immunity and the justification for intervention in the early stages of the COVID-19 pandemic: Analysis of Google Trends data. *Journal of Medical Internet Research*, *23*(6), e26368. https://doi.org/10.2196/26368

Lee, S. Y., & Hawkins, R. P. (2016). Worry as an uncertainty-associated emotion: Exploring the role of worry in health information seeking. *Health Communication*, *31*(8), 926–933. https://doi.org/10.1080/10410236.2015.1018701

Leger, K. A., Charles, S. T., & Fingerman, K. L. (2019). Affect variability and sleep: Emotional ups and downs are related to a poorer night's rest. *Journal of Psychosomatic Research*, *124*, 109758. https://doi.org/10.1016/j.jpsychores.2019.109758

Leung, J., Chung, J. Y. C., Tisdale, C., Chiu, V., Lim, C. C. W., & Chan, G. (2021). Anxiety and panic buying behaviour during COVID-19 pandemic: A qualitative analysis of toilet paper hoarding contents on Twitter. *International Journal of Environmental Research and Public Health*, *18*(3), 1127. https://doi.org/10.3390/ijerph18031127

Lin, Y.-H., Liu, C.-H., & Chiu, Y.-C. (2020). Google searches for the keywords of "wash hands" predict the speed of national spread of COVID-19 outbreak among 21 countries. *Brain, Behavior, and Immunity*, *87*, 30–32. https://doi.org/10.1016/j.bbi.2020.04.020

Lodder, G. M. A., Van Halem, S., Bülow, A., van Scheppingen, M. A., Weller, J., & Reitz, A. K. (2021). Daily fluctuations in occupation with and worry about COVID-19. *Personality and Individual Differences*, *182*, 111078. https://doi.org/10.1016/j.paid.2021.111078

Lucan, S. C., & Mitra, N. (2012). Perceptions of the food environment are associated with fast-food (not fruit-and-vegetable) consumption: Findings from multi-level models. *International Journal of Public Health*, *57*(3), 599–608. https://doi.org/10.1007/s00038-011-0276-2

Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R., & Sanbonmatsu, L. (2012). Neighborhood effects on the long-term well-being of low-income adults. *Science*, *337*(6101), 1505–1510. https://doi.org/10.1126/science.1224648

MacNeil, L., Esposito-Smythers, C., Mehlenbeck, R., & Weismoore, J. (2012). The effects of avoidance coping and coping self-efficacy on eating disorder attitudes and behaviors: A stress-diathesis model. *Eating Behaviors*, *13*(4), 293–296. https://doi.org/10.1016/j.eatbeh.2012.06.005

Makovac, E., Carnevali, L., Medina, S., Sgoifo, A., Petrocchi, N., & Ottaviani, C. (2022). Safe in my heart: Resting heart rate variability longitudinally predicts emotion regulation, worry, and sense of safeness during COVID-19 lockdown. *Stress*, *25*(1), 9–13. https://doi.org/10.1080/10253890.2021.1999408

Mavragani, A., & Gkillas, K. (2020). COVID-19 predictability in the United States using Google Trends time series. *Scientific Reports*, *10*(1), 20693. https://doi.org/10.1038/s41598-020-77275-9

Mavragani, A., & Ochoa, G. (2019). Google Trends in infodemiology and infoveillance: Methodology framework. *JMIR Public Health and Surveillance*, *5*(2), e13439. https://doi.org/10.2196/13439

May, C. R., Johnson, M., & Finch, T. (2016). Implementation, context and complexity. *Implementation Science*, *11*(1), 141. https://doi.org/10.1186/s13012-016-0506-3

McClain, C., Vogels, E. A., Perrin, A., Sechopoulos, S. & Rainie, L. (2021) The Internet and the pandemic. *PEW Research Center*. https://www.pewresearch.org/internet/2021/09/01/the-internet-and-the-pandemic/

Messman, B. A., Rafiuddin, H. S., Slavish, D. C., Weiss, N. H., & Contractor, A. A. (2022). Examination of daily-level associations between posttraumatic stress disorder symptoms and COVID-19 worries. *Psychological Trauma: Theory, Research, Practice, and Policy*, *14*(3), 497–506. https://doi.org/10.1037/tra0001170

Mills, S. D., Fox, R. S., Bohan, S., Roesch, S. C., Sadler, G. R., & Malcarne, V. L. (2020). Psychosocial and neighborhood correlates of health-related quality of life: A multi-level study among Hispanic adults. *Cultural Diversity and Ethnic Minority Psychology*, *26*(1), 1–10. https://doi.org/10.1037/cdp0000274

Mohr, C. D., Arpin, S., & McCabe, C. T. (2015). Daily affect variability and context-specific alcohol consumption: Affect variability and drinking. *Drug and Alcohol Review*, *34*(6), 581–587. https://doi.org/10.1111/dar.12253

Moore, K. A., & Lucas, J. J. (2021). *COVID-19* distress and worries: The role of attitudes, social support, and positive coping during social isolation. *Psychology and Psychotherapy: Theory, Research and Practice*, *94*(2), 365–370. https://doi.org/10.1111/papt.12308

Nuti, S. V., Wayda, B., Ranasinghe, I., Wang, S., Dreyer, R. P., Chen, S. I., & Murugiah, K. (2014). The use of Google Trends in health care research: A systematic review. *PLoS ONE*, *9*(10), e109583. https://doi.org/10.1371/journal.pone.0109583

Okifuji, A., Bradshaw, D. H., Donaldson, G. W., & Turk, D. C. (2011). Sequential analyses of daily symptoms in women with fibromyalgia syndrome. *The Journal of Pain*, *12*(1), 84–93. https://doi.org/10.1016/j.jpain.2010.05.003

Park, B. K., & Calamaro, C. (2013). A systematic review of social networking sites: innovative platforms for health research targeting adolescents and young adults. *Journal of Nursing Scholarship*, *45*(3), 256-264. https://doi.org/10.1111/jnu.12032

Peng, A. C., Schaubroeck, J. M., & Xie, J. L. (2015). When confidence comes and goes: How variation in self-efficacy moderates stressor–strain relationships. *Journal of Occupational Health Psychology*, *20*(3), 359–376. https://doi.org/10.1037/a0038588

Pepper, C. M., & Coyne, J. C. (1996). The predictable instability of psychological distress in college students: A comment on Flett, Vredenburg, and Krames. *Journal of Psychopathology and Behavioral Assessment*, *18*(2), 183–186. https://doi.org/10.1007/BF02229116

Procter, R. (2021, March 4) *Remember when? Time marks key events in California's year-long grind.* CalMatters. https://calmatters.org/health/coronavirus/2021/03/timeline-california-pandemic-year-key-points/

Prentice, C., Quach, S., & Thaichon, P. (2022). Antecedents and consequences of panic buying: The case of COVID-19. *International Journal of Consumer Studies*, *46*(1), 132–146. https://doi.org/10.1111/ijcs.12649

Qiao, S., Friedman, D. B., Tam, C. C., Zeng, C., & Li, X. (2022). COVID-19 vaccine acceptance among college students in South Carolina: Do information sources and trust in information matter? *Journal of American College Health*, 1–10. https://doi.org/10.1080/07448481.2022.2059375

Rees-Punia, E., Hathaway, E. D., & Gay, J. L. (2018). Crime, perceived safety, and physical activity: A meta-analysis. *Preventive Medicine*, *111*, 307–313. https://doi.org/10.1016/j.ypmed.2017.11.017

Ridner, S. H. (2004). Psychological distress: Concept analysis. *Journal of Advanced Nursing*, *45*(5), 536–545. https://doi.org/10.1046/j.1365-2648.2003.02938.x

Rios, R., Aiken, L. S., & Zautra, A. J. (2012). Neighborhood contexts and the mediating role of neighborhood social cohesion on health and psychological distress among Hispanic and non-Hispanic residents. *Annals of Behavioral Medicine*, *43*(1), 50–61. https://doi.org/10.1007/s12160-011-9306-9

Riva, G., Bernardelli, L., Castelnuovo, G., Di Lernia, D., Tuena, C., Clementi, A., Pedroli, E., Malighetti, C., Sforza, F., Wiederhold, B. K., & Serino, S. (2021). A virtual reality-based self-help intervention for dealing with the psychological distress associated with the COVID-19 lockdown: An effectiveness study with a two-week follow-up. *International Journal of Environmental Research and Public Health*, *18*(15), 8188. https://doi.org/10.3390/ijerph18158188

Rhodes, R. E., Zhang, R., & Zhang, C. (2020). Direct and indirect relationships between the built environment and individual-level perceptions of physical activity: A systematic review. *Annals of Behavioral Medicine*, *54*(7), 495-509. https://doi.org/10.1093/abm/kaz068

Romiti, G. F., & Talerico, G. (2021). Embracing the uncertainty: An important lesson from COVID-19. *Journal of General Internal Medicine*, *36*(11), 3562–3564. https://doi.org/10.1007/s11606-021-06809-2

Rotter, D., Doebler, P., & Schmitz, F. (2021). Interests, motives, and psychological burdens in times of crisis and lockdown: Google Trends analysis to inform policy makers. *Journal of Medical Internet Research*, *23*(6), e26385. https://doi.org/10.2196/26385

Salari, N., Hosseinian-Far, A., Jalali, R., Vaisi-Raygani, A., Rasoulpoor, S., Mohammadi, M., Rasoulpoor, S., & Khaledi-Paveh, B. (2020). Prevalence of stress, anxiety, depression among the general population during the COVID-19 pandemic: A systematic review and meta-analysis. *Globalization and Health*, *16*(1), 57. https://doi.org/10.1186/s12992-020-00589-w

Scheitle, C. P., Moule, R. K., & Fox, B. H. (2019). Googling in fear: Measuring moral panic using internet searches before and after Obama's 2008 election. *Deviant Behavior*, *40*(11), 1333–1348. https://doi.org/10.1080/01639625.2018.1511945

Schreier, H. M. C., & Chen, E. (2013). Socioeconomic status and the health of youth: A multilevel, multidomain approach to conceptualizing pathways. *Psychological Bulletin*, *139*(3), 606–654. https://doi.org/10.1037/a0029416

Schulz, P. J., Andersson, E. M., Bizzotto, N., & Norberg, M. (2021). Using ecological momentary assessment to study the development of COVID-19 worries in Sweden: Longitudinal study. *Journal of Medical Internet Research*, *23*(11), e26743. https://doi.org/10.2196/26743

Scott, S. B., Sliwinski, M. J., Zawadzki, M., Stawski, R. S., Kim, J., Marcusson-Clavertz, D., Lanza, S. T., Conroy, D. E., Buxton, O., Almeida, D. M., & Smyth, J. M. (2020). A coordinated analysis of variance in affect in daily life. *Assessment*, *27*(8), 1683–1698. https://doi.org/10.1177/1073191118799460

Sim, K., Chua, H. C., Vieta, E., & Fernandez, G. (2020). The anatomy of panic buying related to the current COVID-19 pandemic. *Psychiatry Research*, *288*, 113015. https://doi.org/10.1016/j.psychres.2020.113015

Singer, J. D., & Willett, J. B. (2003). *Applied Longitudinal Data Analysis*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195152968.001.0001

Schilling, O. K., Gerstorf, D., Lücke, A. J., Katzorreck, M., Wahl, H.-W., Diehl, M., & Kunzmann, U. (2022). Emotional reactivity to daily stressors: Does stressor pile-up within a day matter for young-old and very old adults? *Psychology and Aging*, *37*(2), 149–162. https://doi.org/10.1037/pag0000667

Schoggen, P. (1989). *Behavior settings: A revision and extension of Roger G. Barker's "Ecological Psychology"*. Stanford University Press.

Seiter, C. R., & Brophy, N. S. (2020). Worry as a mechanism to motivate information seeking about protective end-of-life communication behaviors. *Journal of Health Communication*, *25*(5), 353–360. https://doi.org/10.1080/10810730.2020.1765222

Shahrour, G., & Dardas, L. A. (2020). Acute stress disorder, coping self-efficacy and subsequent psychological distress among nurses amid COVID-19. *Journal of Nursing Management*, *28*(7), 1686–1695. https://doi.org/10.1111/jonm.13124

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Sobkow, A., Zaleskiewicz, T., Petrova, D., Garcia-Retamero, R., & Traczyk, J. (2020). Worry, risk perception, and controllability predict intentions toward COVID-19 preventive behaviors. *Frontiers in Psychology*, *11*, 582720. https://doi.org/10.3389/fpsyg.2020.582720

Stainback, K., Hearne, B. N., & Trieu, M. M. (2020). COVID-19 and the 24/7 news cycle: Does COVID-19 news exposure affect mental health? *Socius: Sociological Research for a Dynamic World*, *6*, 237802312096933. https://doi.org/10.1177/2378023120969339

Su, L., Zhou, S., Kwan, M.-P., Chai, Y., & Zhang, X. (2022). The impact of immediate urban environments on people's momentary happiness. *Urban Studies*, *59*(1), 140–160. https://doi.org/10.1177/0042098020986499

Taylor, S., Landry, C. A., Paluszek, M. M., Rachor, G. S., & Asmundson, G. J. G. (2020). Worry, avoidance, and coping during the COVID-19 pandemic: A comprehensive network analysis. *Journal of Anxiety Disorders*, *76*, 102327. https://doi.org/10.1016/j.janxdis.2020.102327

Taylor, S. E., Repetti, R. L., & Seeman, T. (1997). Health psychology: What is an unhealthy environment and how does it get under the skin? *Annual Review of Psychology*, *48*(1), 411–447. https://doi.org/10.1146/annurev.psych.48.1.411

te Poel, F., Baumgartner, S. E., Hartmann, T., & Tanis, M. (2016). The curious case of cyberchondria: A longitudinal study on the reciprocal relationship between health anxiety and online health information seeking. *Journal of Anxiety Disorders*, *43*, 32–40. https://doi.org/10.1016/j.janxdis.2016.07.009

Thibault, T., Thompson, K., Keough, M., Krank, M., Conrod, P., Moore, M., & Stewart, S. H. (2022). Psychometric properties of a brief version of the COVID-19 Stress Scales (CSS-B) in young adult undergraduates. *Stress and Health*, smi.3175. https://doi.org/10.1002/smi.3175

Thompson, R. J., Berenbaum, H., & Bredemeier, K. (2011). Cross-sectional and longitudinal relations between affective instability and depression. *Journal of Affective Disorders*, *130*(1–2), 53–59. https://doi.org/10.1016/j.jad.2010.09.021

Twenge, J. M., & Joiner, T. E. (2020). Mental distress among U.S. adults during the COVID-19 pandemic. *Journal of Clinical Psychology*, *76*(12), 2170–2182. https://doi.org/10.1002/jclp.23064

Van Damme, W., Dahake, R., Delamou, A., Ingelbeen, B., Wouters, E., Vanham, G., van de Pas, R., Dossou, J.-P., Ir, P., Abimbola, S., Van der Borght, S., Narayanan, D., Bloom, G., Van Engelgem, I., Ag Ahmed, M. A., Kiendrébéogo, J. A., Verdonck, K., De Brouwere, V., Bello, K., … Assefa, Y. (2020). The COVID-19 pandemic:

Diverse contexts; different epidemics—how and why? *BMJ Global Health*, *5*(7), e003098. https://doi.org/10.1136/bmjgh-2020-003098

Walker, A., Hopkins, C., & Surda, P. (2020). Use of Google Trends to investigate loss-of-smell–related searches during the COVID-19 outbreak. *International Forum of Allergy & Rhinology*, *10*(7), 839–847. https://doi.org/10.1002/alr.22580

Walker, M. D., & Sulyok, M. (2020). Online behavioural patterns for Coronavirus disease 2019 (COVID-19) in the United Kingdom. *Epidemiology and Infection*, *148*, e110. https://doi.org/10.1017/S0950268820001193

Wang, C., Havewala, M., & Zhu, Q. (2022). COVID-19 stressful life events and mental health: Personality and coping styles as moderators. *Journal of American College Health*, 1–10. https://doi.org/10.1080/07448481.2022.2066977

Weaver, K. E., Palmer, N., Lu, L., Case, L. D., & Geiger, A. M. (2013). Rural–urban differences in health behaviors and implications for health status among US cancer survivors. *Cancer Causes & Control*, *24*(8), 1481–1490. https://doi.org/10.1007/s10552-013-0225-x

Wise, T., Zbozinek, T. D., Michelini, G., Hagan, C. C., & Mobbs, D. (2020). Changes in risk perception and self-reported protective behaviour during the first week of the COVID-19 pandemic in the United States. *Royal Society Open Science*, *7*(9), 200742. https://doi.org/10.1098/rsos.200742

World Health Organization (WHO) (2020). Mental health and psychosocial considerations during the COVID-19 outbreak. *World Health Organization*, 1-6. https://www.who.int/docs/default-source/coronaviruse/mental-health-considerations.pdf

Yardley, P., McCall, A., Savage, A., & Newton, R. (2019). Effectiveness of a brief intervention aimed at increasing distress tolerance for individuals in crisis or at risk of self-harm. *Australasian Psychiatry*, *27*(6), 565–568. https://doi.org/10.1177/1039856219848835

Zawadzki, M. J., Scott, S. B., Almeida, D. M., Lanza, S. T., Conroy, D. E., Sliwinski, M. J., Kim, J., Marcusson-Clavertz, D., Stawski, R. S., Green, P. M., Sciamanna, C. N., Johnson, J. A., & Smyth, J. M. (2019). Understanding stress reports in daily life: A coordinated analysis of factors associated with the frequency of reporting stress. *Journal of Behavioral Medicine*, *42*(3), 545–560. https://doi.org/10.1007/s10865-018-00008-x

Zhao, Y., & Chung, P.-K. (2017). Neighborhood environment walkability and health-related quality of life among older adults in Hong Kong. *Archives of Gerontology and Geriatrics*, *73*, 182–186. https://doi.org/10.1016/j.archger.2017.08.003

Zimmer, Z., Wen, M., & Kaneda, T. (2010). A multi-level analysis of urban/rural and socioeconomic differences in functional health status transition among older Chinese. *Social Science & Medicine*, *71*(3), 559–567. https://doi.org/10.1016/j.socscimed.2010.03.048

Zubek, J., Ziembowicz, K., Pokropski, M., Gwiaździński, P., Denkiewicz, M., & Boros, A. (2022). Rhythms of the day: How electronic media and daily routines influence mood during COVID-19 pandemic. *Applied Psychology: Health and Well-Being*, *14*(2), 519–536. https://doi.org/10.1111/aphw.12317

Table 2.1

Multilevel Models Testing the Relationship between the COVID-19 Severity (Cases) and Daily Psychological Distress

	Daily Psychological Distress	
	H1: Mean	H2: Variability (*SD*)
	b (*SE*)	*b* (*SE*)
Fixed Effects		
Intercept	**1.18 (.43)**	**.70 (.12)**
Gender	.61 (.47)	.01 (.12)
Weekend	**.22 (.07)**	.07 (.05)
Daily Total COVID-19 Cases	-.01 (.22)	-.23 (.13)
Cumulative Total COVID-19 Cases	-.01 (.05)	.01 (.03)
Random Effects		
Intercept	.67 (.49)	**.06 (.02)**
Variance	**.80 (.45)**	--
Autoregression	**.88 (.10)**	--
Residual	**.34 (.53)**	**.22 (.01)**
Model Effects		
Pseudo r^2	.02	.01

Note. Bold coefficients indicate $p < .05$. H = hypothesis 1, gender (0 = man ; 1 = woman), weekend (0 = Saturday or Sunday, 1 = weekday), COVID-19 cases are per 100. *SD* = standard deviation. -- Indicates term was not included due to a model not using an autoregressive structure.

Table 2.2

Multilevel Models Testing the Relationship between the COVID-19 Severity (Cases), Progression of the Pandemic, and Daily Psychological Distress

	Daily Psychological Distress	
	Mean	Variability (*SD*)
	b (*SE*)	*b* (*SE*)
Fixed Effects		
Intercept	**1.14 (.45)**	**.67 (.12)**
Gender	.62 (.46)	.01 (.12)
Weekend	**.22 (.07)**	.07 (.05)
Daily Total COVID-19 Cases	.05 (.39)	**-.43 (.21)**
Cumulative Total COVID-19 Cases	.01 (.05)	-.01 (.03)
Progression of the Pandemic (Cases)	.07 (.34)	**.22 (.09)**
Daily Total*Progression	-.04 (.22)	.14 (.10)
Random Effects		
Intercept	.67 (.51)	**.05 (.02)**
Variance	**.82 (.47)**	--
Autoregression	**.88 (.10)**	--
Residual	**.03 (.05)**	**.22 (.02)**
Model Effects		
Pseudo r^2	.02	.04

Note. Bold coefficients indicate $p < .05$. Gender (0 = man ; 1 = woman), weekend (0 = Saturday or Sunday, 1 = weekday), COVID-19 cases are per 100, progression of the pandemic is a person-level variable of the cumulative total COVID-19 cases at EMA day 0. *SD* = standard deviation. -- Indicates term was not included due to a model not using an autoregressive structure.

Table 2.3

Multilevel Models Testing the Relationship Between the COVID-19 Severity (Deaths), Progression of the Pandemic and Daily Psychological Distress

	Daily Psychological Distress	
	H3: Mean	H4: Variability (*SD*)
	b (*SE*)	*b* (*SE*)
Fixed Effects		
Intercept	**1.19 (.43)**	**.69 (.12)**
Gender	.61 (.46)	.01 (.12)
Weekend	**.22 (.07)**	.08 (.05)
Daily Total COVID-19 Deaths	.87 (4.87)	.25 (3.19)
Cumulative Total COVID-19 Deaths	-.98 (1.77)	-1.60 (.84)+
Random Effects		
Intercept	.67 (.48)	**.06 (.02)**
Variance	**.79 (.43)**	**--**
Autoregression	**.88 (.10)**	**--**
Residual	**.34 (.05)**	**.22 (.01)**
Model Effects		
Pseudo r^2	.02	.01

Note. Bold coefficients indicate $p < .05$. + indicates $p < .10$. H = hypothesis 1, gender (0 = man ; 1 = woman), weekend (0 = Saturday or Sunday, 1 = weekday), COVID-19 deaths are per 100. *SD* = standard deviation. -- Indicates model did not have an autoregressive structure specified.

Table 2.4

Multilevel Models Testing the Relationship Between the COVID-19 Severity (Deaths), Progression of the Pandemic and Daily Psychological Distress

	Daily Psychological Distress	
	Mean	Variability (*SD*)
	b (*SE*)	*b* (*SE*)
Fixed Effects		
Intercept	**1.20 (.44)**	**.68 (.11)**
Gender	.59 (.46)	-.01 (.12)
Weekend	**.23 (.07)**	.09 (.48)
Daily Total COVID-19 Deaths	-4.57 (8.76)	-5.51 (-5.29)
Cumulative Total COVID-19 Deaths	-1.07 (1.89)	**-2.60 (.91)**
Progression of the Pandemic (Deaths)	.46 (15.07)	**10.85 (4.08)**
Daily Total*Progression	141.74 (.45)	168.42 (105.24)
Random Effects		
Intercept	.72 (.47)	**.05 (.02)**
Variance	**.78 (.42)**	**--**
Autoregression	**.87 (.10)**	**--**
Residual	**.34 (.05)**	**.22 (.01)**
Model Effects		
Pseudo r^2	.03	.04

Note. Bold coefficients indicate $p < .05$. Gender (0 = man ; 1 = woman), weekend (0 = Saturday or Sunday, 1 = weekday), COVID-19 deaths are per 100, progression of the pandemic is a person-level variable of the cumulative total COVID-19 deaths at EMA day 0. *SD* = standard deviation. -- Indicates model did not have an autoregressive structure specified.

Table 2.5

Explanatory Multilevel Models Testing the Relationship Between the COVID-19 Severity, Person Level Distress, and Daily Psychological Distress

	Daily Psychological Distress Variability (*SD*)	
	b (*SE*)	*b* (*SE*)
Fixed Effects		
Intercept	**.68 (.14)**	**.71 (.13)**
Gender	.06 (.11)	.04 (.11)
Weekend	.07 (.05)	.08 (.05) +
Depression	-.003 (.01)	-.002 (.01)
Stress	**.02 (.01)**	.02 (.008) +
Anxiety	**-.02 (.01)**	**-.02 (.01)**
Daily Total COVID-19 Cases	**-.44 (.21)**	-
Cumulative Total COVID-19 Cases	-.01 (.03)	-
Progression of the Pandemic (Cases)	**.19 (.09)**	-
Daily Total Cases*Progression (Cases)	.14 (.10)	-
Daily Total COVID-19 Deaths	-	-6.01 (5.30)
Cumulative Total COVID-19 Deaths	-	**-2.58 (.91)**
Progression of the Pandemic (Deaths)	-	**9.28 (4.05)**
Daily Total Deaths*Progression (Cases)	-	178.91 (106) +
Random Effects		
Intercept	**.05 (.01)**	**.05 (.02)**
Residual	**.22 (.01)**	**.22 (.01)**
Model Effects		
Pseudo r^2	.07	.07

Note. Bold coefficients indicate $p < .05$. + indicates $p < .10$. Gender (0 = man ; 1 = woman), weekend (0 = Saturday or Sunday, 1 = weekday), COVID-19 deaths are per 100, progression of the pandemic is a person-level variable of the cumulative total COVID-19 deaths or cases at EMA day 0. *SD* = standard deviation. - Indicates term was not included in current model.

Table 2.6

Exploratory Multilevel Models Testing the Relationship Between the COVID-19 Severity (Deaths) and Daily Psychological Distress Excluding Days with 0 Value Cumulative Deaths

	Daily Psychological Distress	
	Mean	Variability (*SD*)
	b (*SE*)	*b* (*SE*)
Fixed Effects		
Intercept	1.09 (.65)	**.87 (.15)**
Gender	.63 (.68)	-.25 (.14)
Weekend	.21 (.14)	.08 (.08)
Daily Total COVID-19 Deaths	-5.00 (10.67)	-5.55 (5.75)
Cumulative Total COVID-19 Deaths	-.82 (1.68)	**-2.63 (.92)**
Progression of the Pandemic (Deaths)	4.61 (.79)	**11.38 (4.03)**
Daily Total*Progression	84.75 (214.87)	174.39 (4.03)
Random Effects		
Intercept	**1.48 (.47)**	**.04 (.02)**
Residual	**.71 (.08)**	**.22 (.02)**
Model Effects		
Pseudo r^2	.03	.10

Note. Bold coefficients indicate $p < .05$. Gender (0 = man; 1 = woman), weekend (0 = Saturday or Sunday, 1 = weekday), COVID-19 deaths are per 100, progression of the pandemic is a person-level variable of the cumulative total COVID-19 deaths at EMA day 0. *SD* = standard deviation.

Table 3.1

Multilevel Models Testing the Relationship Between the COVID-19 and Material Resources Relative Search Volume and Daily Worry and Coping

Outcome	COVID-19 RSV		Material Resources RSV	
	H1a: Worry	H1b: Coping	H2a: Worry	H2b: Coping
	b (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)
Fixed Effects				
Intercept	**2.20 (.37)**	**3.84 (.27)**	**2.04 (.37)**	**3.70 (.27)**
Weekend	**.23 (.08)**	-.03 (.05)	**.25 (.08)**	-.03 (.05)
Gender	-.38 (.52)	.14 (.39)	-.39 (.52)	.15 (.39)
Hispanic	.33 (.37)	-.13 (.28)	.32 (.38)	-.15 (.28)
Race	-.34 (.36)	-.03 (.27)	-.35 (.36)	-.03 (.27)
COVID-19 RSV	-.001 (.003)	.001 (.002)	-	-
COVID-19 RSV Peak	.11 (.13)	.08 (.08)	-	-
Resources RSV	-	-	.001 (.002)	.001 (.001)
Resources RSV Peak	-	-	.02 (.11)	-.08 (.07)
Random Effects				
Intercept	**1.23 (.36)**	**.81 (.18)**	**1.26 (.36)**	**.81 (.18)**
Variance	**.80 (.19)**	**.30 (.04)**	**.77 (.17)**	**.29 (.04)**
Autoregression	**.92 (.03)**	**.80 (.05)**	**.92 (.04)**	**.81 (.05)**
Residual	**1.50 (.07)**	**.55 (.03)**	**1.50 (.07)**	**.56 (.03)**
Model Effects				
Pseudo r^2	.03	.01	.02	.004

Note. Bold coefficients indicate $p < .05$. RSV = Google Trends relative search volume for 2/1/2020-3/31/2020, H = hypothesis, weekend (0 = Saturday or Sunday, 1 = weekday), gender (1 = man; 0 = woman), race (1 = White; 0 = non-White) Hispanic (1 = Hispanic/Latino, 0 = non-Hispanic/Latino), COVID-19 RSV peak = timing relative to highest RSV day for COVID-19 search term (-1 = pre peak, 0 = peak, 1 = post peak), resources RSV peak = timing relative to highest RSV day for material resources search terms (-1 = pre peak, 0 = peak, 1 = post peak).

Table 3.2

Multilevel Models Testing the Relationship Between Both COVID-19 and Material Resources Relative Search Volume and Daily Worry and Coping

Outcome	COVID-19 and Material Resources RSV		Timing Relative to Peak RSV	
	Worry	Coping	Worry	Coping
	b (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)
Fixed Effects				
Intercept	**2.16 (.38)**	**3.75 (.27)**	**2.15 (.36)**	**3.87 (.26)**
Weekend	**.24 (.08)**	-.07 (.06)	**.23 (.08)**	-.07 (.05)
Gender	-.38 (.52)	.13 (.39)	-.39 (.52)	.15 (.05)
Hispanic	.34 (.37)	-.15 (.28)	.33 (.37)	-.14 (.39)
Race	-.34 (.36)	-.03 (.27)	-.34 (.36)	-.03 (.27)
COVID-19 RSV	-.004 (.004)	.003 (.003)	-	-
COVID-19 RSV Peak	.11 (.15)	**.26 (.10)**	.13 (.15)	**.22 (.10)**
Resources RSV	.002 (.002)	.0002 (.002)	-	-
Resources RSV Peak	.01 (.15)	**-.26 (.10)**	-.04 (.13)	**-.19 (.09)**
Random Effects				
Intercept	**1.24 (.36)**	**.81 (.18)**	**1.24 (.36)**	**.82 (.18)**
Variance	**.80 (.18)**	**.29 (.04)**	**.79 (.18)**	**.29 (.04)**
Autoregression	**.92 (.03)**	**.79 (.05)**	**.92 (.03)**	**.79 (.05)**
Residual	**1.50 (.07)**	**.55 (.03)**	**1.50 (.07)**	**.55 (.03)**
Model Effects				
Pseudo r^2	.03	.01	.02	.002

Note. Bold coefficients indicate $p < .05$. RSV = Google Trends relative search volume for 2/1/2020-3/31/2020, weekend (0 = Saturday or Sunday, 1 = weekday), gender (1 = man; 0 = woman), race (1 = White; 0 = non-White) Hispanic (1 = Hispanic/Latino, 0 = non-Hispanic/Latino), COVID-19 RSV peak = timing relative to highest RSV day for COVID-19 search term (-1 = pre peak, 0 = peak, 1 = post peak), resources RSV peak = timing relative to highest RSV day for material resources search terms (-1 = pre peak, 0 = peak, 1 = post peak).

Table 3.3

Multilevel Models Testing the Relationship Between the Lagged Relative Search Volumes and Daily Worry and Coping

	COVID-19 RSV		Material Resources RSV		COVID-19 and Material Resources RSV	
	Worry	*Coping*	*Worry*	*Coping*	*Worry*	*Coping*
	b (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)
Fixed Effects						
Intercept	**2.37 (.38)**	**3.92 (.27)**	**2.25 (.38)**	**3.75 (.28)**	**2.34 (.39)**	**3.82 (.28)**
Weekend	**.23 (.08)**	-.02 (.05)	**.26 (.08)**	-.06 (.06)	**.28 (.08)**	-.06 (.06)
Gender	-.36 (.52)	.14 (.39)	-.36 (.52)	.14 (.39)	-.35 (.52)	.13 (.39)
Hispanic	.33 (.37)	-.13 (.28)	.32 (.37)	-.15 (.28)	.35 (.37)	-.15 (.28)
Race	-.35 (.36)	-.03 (.27)	-.34 (.36)	-.03 (.27)	-.36 (.36)	-.02 (.27)
COVID-19 RSV (lag)	**-.01 (.005)**	-.004 (.003)	-	-	**-.02 (.01)**	.00003 (.005)
COVID-19 RSV Peak (lag)	-.01 (.24)	.23 (.16)	-	-	-.50 (.35	.32 (.22)
COVID-19 RSV	.005 (.005)	.004 (.003)	-	-	.004 (.01)	.01 (.004)
COVID-19 RSV Peak	.22 (.23)	-.08 (.16)	-	-	.98 (.52)+	-.02 (.34)
Resources RSV (lag)	-	-	-.004 (.002)+	-.0004 (.002)	.002 (.004)	-.001 (.002)
Resources RSV Peak (lag)	-	-	-.16 (.25)	.31 (.16)+	-.67 (.004)	.02 (.32)
Resources RSV	-	-	.002 (.002)	.002 (.001)+	.003 (.004)	-.001 (.002)
Resources RSV Peak	-	-	.28 (.26)	-.33 (.18)+	.43 (.29)	-.25 (.19)
Random Effects						
Intercept	**1.14 (.38)**	**.81 (.18)**	**1.23 (.36)**	**.82 (.18)**	**1.17 (.37)**	**.81 (.18)**
Variance	**.85 (.24)**	**.29 (.04)**	**.78 (.18)**	**.29 (.04)**	**.83 (.22)**	**.29 (.04)**
Auto regression	**.94 (.03)**	**.80 (.05)**	**.92 (.03)**	**.79 (.05)**	**.93 (.03)**	**.79 (.05)**
Residual	**1.51 (.06)**	**.55 (.03)**	**1.50 (.07)**	**.55 (.03)**	**1.51 (.06)**	**.55 (.03)**
Model Effects						
Pseudo r^2	.03	.01	.03	.001	.04	.02

Note. Bold coefficients indicate $p < .05$. + indicates $p < .10$. RSV = Google Trends relative search volume for 2/1/2020-3/31/2020, weekend (0 = Saturday or Sunday, 1 = weekday), gender (1 = man; 0 = woman), race (1 = White; 0 = non-White) Hispanic (1 = Hispanic/Latino, 0 = non-Hispanic/Latino), COVID-19 RSV peak = timing relative to highest RSV day for COVID-19 search term (-1 = pre peak, 0 = peak, 1 = post peak), resources RSV peak = timing relative to highest RSV day for material resources search terms (-1 = pre peak, 0 = peak, 1 = post peak). Lag indicates data from the preceding day as a predictor.

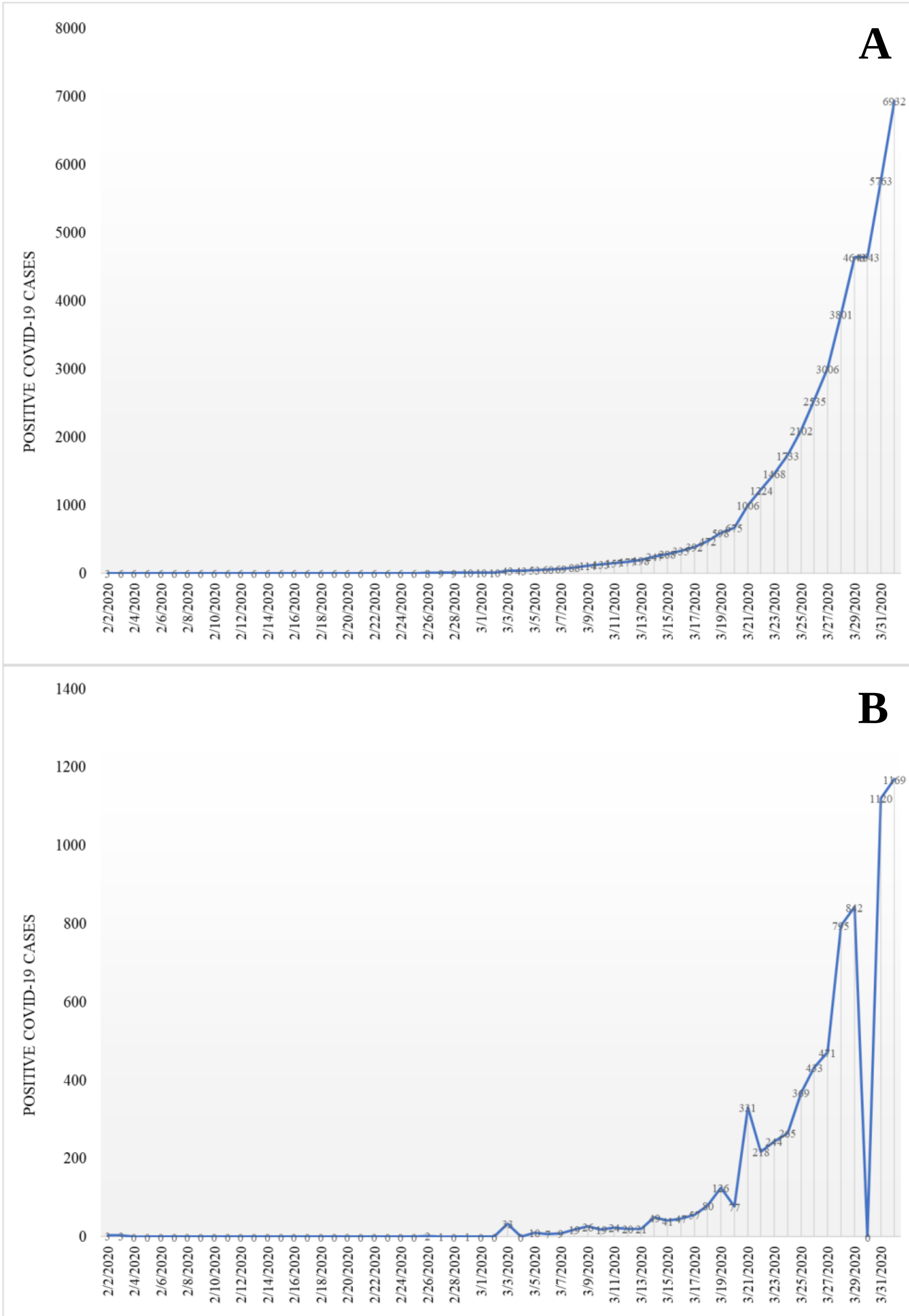

Figure 2.1. *California COVID-19 Cases Cumulative Total (A) and Daily Total (B) February-March 2020*

Note. No data was reported for 3/30/2020 by the California Department of Public Health.

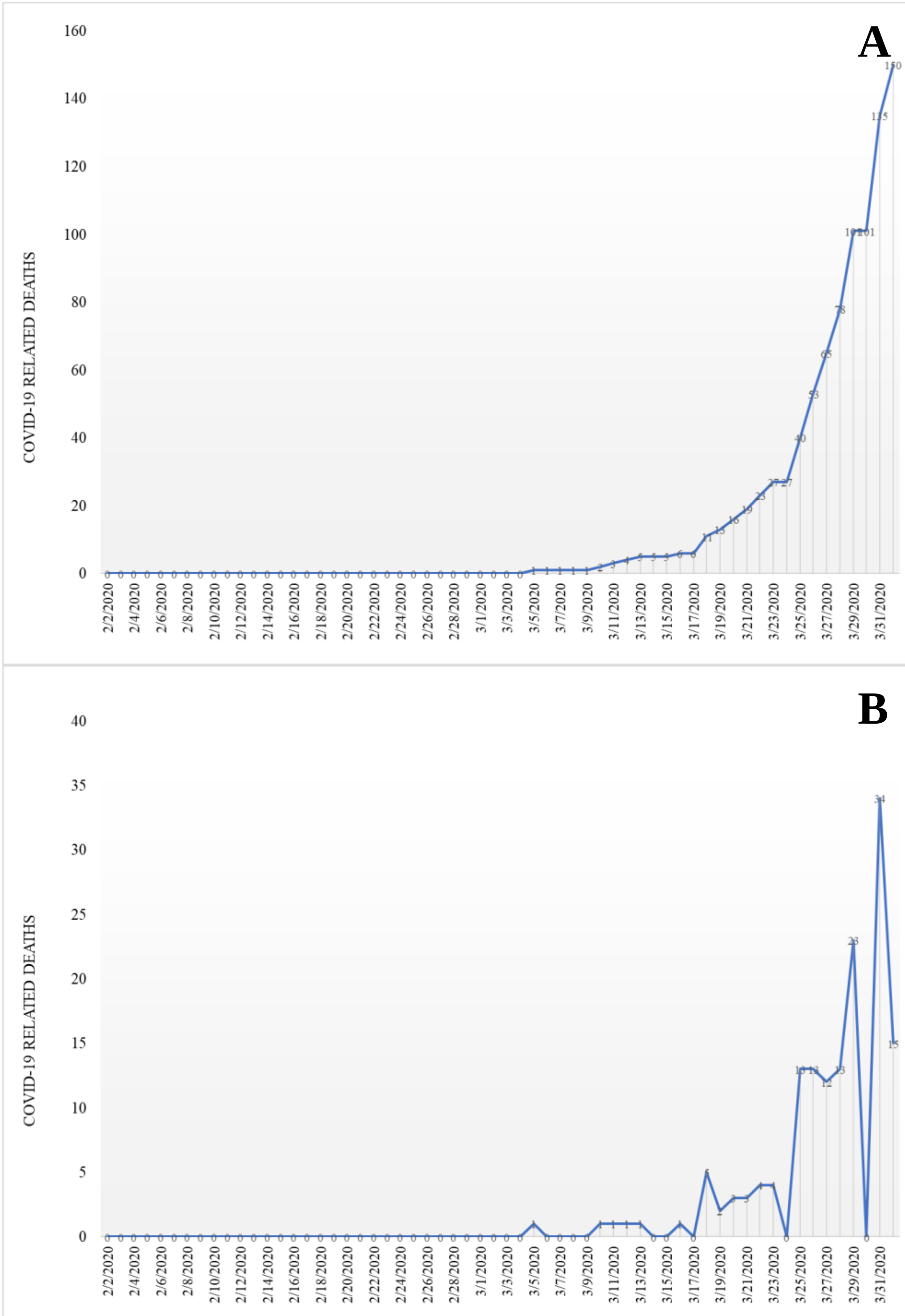

Figure 2.2. *California COVID-19 Deaths Cumulative Total (A) and Daily Total (B) February-March 2020*

Note. No data was reported for 03/30/2020 by the California Department of Public Health.

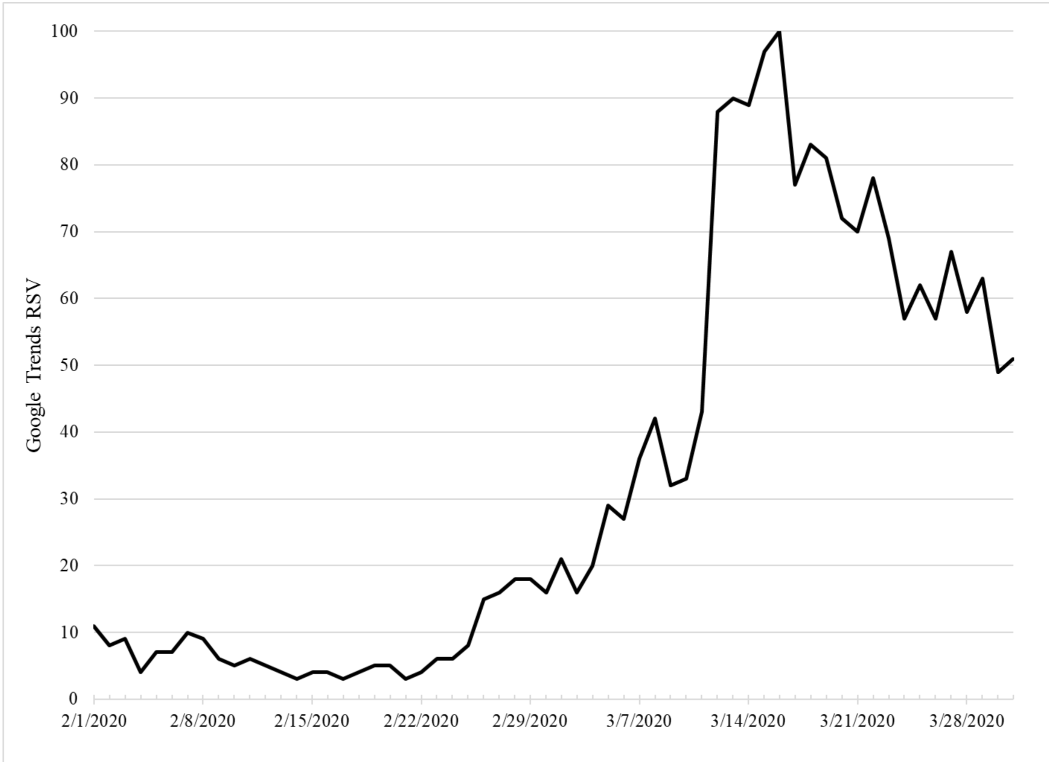

Figure 3.1. G*oogle Trends Relative Search Volume for COVID-19 Central California Region 2/1/2020 Thru 3/31/2020*

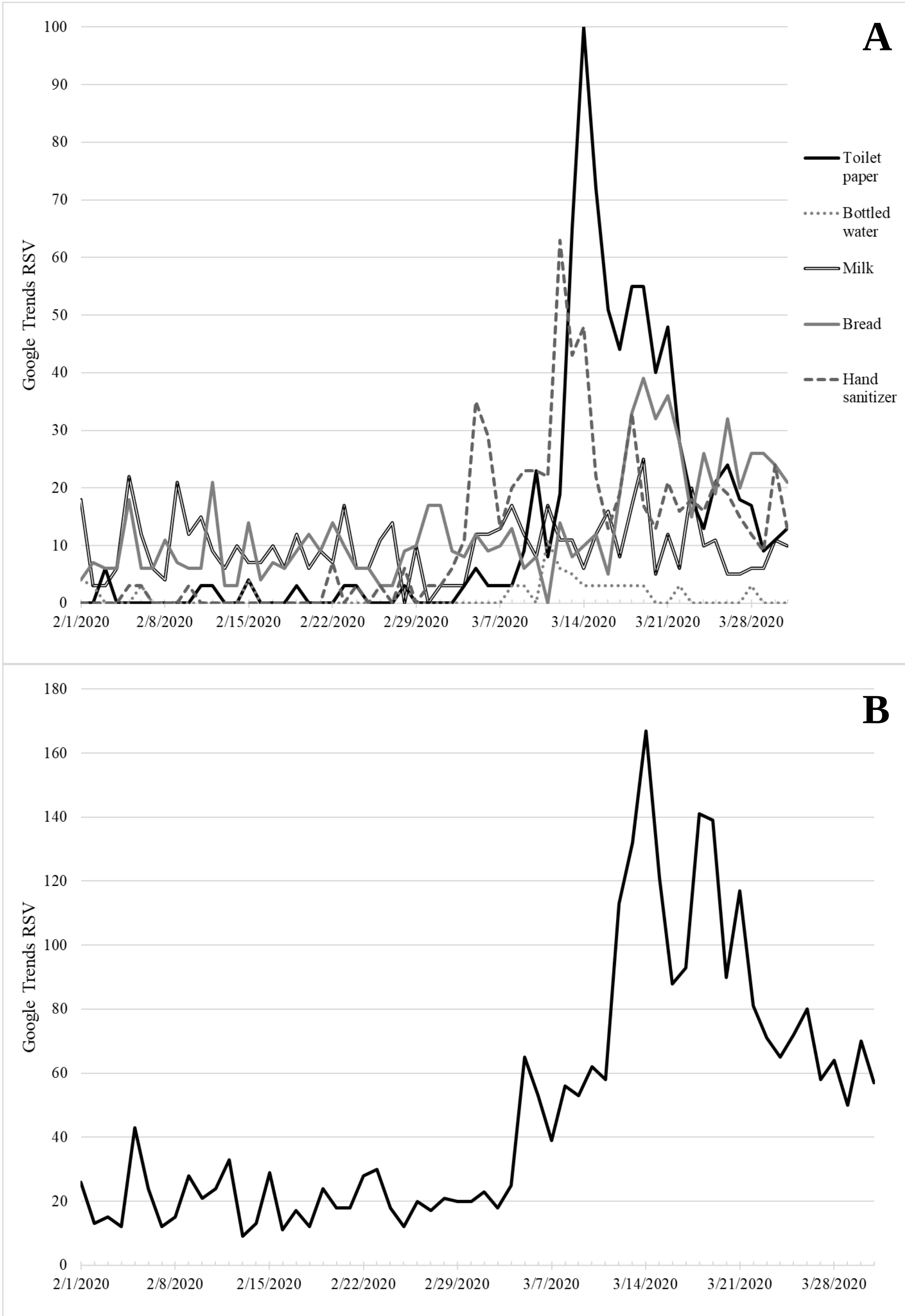

Figure 3.2. *Google Trends Relative Search Volumes for Material Resources - Individual terms (A) and Combined Terms (B) Central California Region 2/1/2020 Thru 3/31/2020*