

EMPIRICAL ARTICLE

COVID-19 shifts mortality salience, activities, and values in the United States: Big data analysis of online adaptation

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Email: noahevers@college.harvard.edu**Abstract**

What is the effect of a life-threatening pandemic at the societal level? An expanded Theory of Social Change, Cultural Evolution, and Human Development predicts that, during a period of increasing survival threat and decreasing prosperity, humans will shift toward the psychology and behavior typical of the small-scale, collectivistic, and rural subsistence ecologies in which we evolved. In particular, subjective mortality salience, engagement in subsistence activities, and collectivism will all increase, while the aspiration to be wealthy will decrease. Because coronavirus has forced unprecedented proportions of human activity online, we tested hypotheses derived from the theory by analyzing big data samples for 70 days before and 70 days after the coronavirus pandemic stimulated President Trump to declare a national emergency. Google searches were used for an exploratory study; the exploratory study was followed by three independent replications on Twitter, internet forums, and blogs. Across all four internet platforms, terms related to subjective mortality salience, engagement in subsistence activities, and collectivism showed massive increases. These findings, coupled with prior research testing this theory, indicate that humans may have an evolutionarily conditioned response to the level of death and availability of material resources in society. More specifically, humans may shift their behavior and psychology toward that found in subsistence ecologies under conditions of high mortality and low prosperity or, conversely, toward behavior and psychology found in modern commercial ecologies under conditions of low mortality and high prosperity.

KEYWORDS

American values, big data, blogs, collectivism, coronavirus pandemic, COVID-19, ecology, evolutionary psychology, Google Trends, human behavior, human social behavior, internet, internet forums, mortality salience, social media, social theory, subsistence activities, survival threat, terror management theory, Theory of Social Change, Cultural Evolution, and Human Development, Twitter, values

1 | INTRODUCTION

What is the effect of a life-threatening pandemic on human behavior and cultural values? We have expanded the Theory of Social Change, Cultural Evolution, and Human Development (Greenfield, 2009) to predict that, during a period of increasing survival threat and decreasing prosperity,

humans will shift toward the psychology and behavior typical of the small-scale, rural subsistence ecologies in which human beings evolved (Greenfield & Brown, under revision; Park, Twenge, & Greenfield, 2014).

Our rationale for these predictions is the following: during a period of increasing survival threat and decreasing material resources, an evolutionary instinct causes a psychological shift toward the

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mindset and behavior typical of an earlier form of society, composed of small-scale, rural environments. In such environments, the volatility of day-to-day existence renders scarce resources a considerable concern and mortality highly salient. (We borrow the term mortality salience from Terror Management Theory [Greenberg et al., 1992].)

Therefore, if social conditions suddenly shift toward features of those environments—decreasing material resources and increasing survival threat - it follows that thoughts, behaviors, and values will adjust accordingly. We posited that shifts would be particularly evident in four features that define lifestyles in those ecologies: amplified subjective salience of death, increased engagement in subsistence activities, greater identification with collectivistic values, and reduced aspiration for wealth. Tragically, the societal conditions of the COVID-19 pandemic created a natural experiment in which this theoretical analysis and the empirical hypotheses derived from it could be tested.

Based on the idea that language provides a window into concerns, values, and behavior, we used linguistic terms from Google searches and social media posts in the United States to index the predicted psychological and cultural shifts in the time of coronavirus. An underlying assumption was that the use of linguistic representations on a national level would provide insight into national culture and culture change brought about by the pandemic.

Ironically, because the pandemic transposed much of human activity online, the Internet became a valuable platform for exploring the hypothesis that, in the time of the novel coronavirus, mortality would be more salient, values more collectivistic, subsistence activities more frequent, and wealth less important. Hence, we predicted that, during the pandemic, the frequency of mortality-related terms such as “death” and “cemetery” would increase in Google searches and on social media throughout the United States. We predicted similar increases in terms representing various subsistence activities (e.g., “grow vegetables,” “baking bread”) and collectivistic values (e.g., “sacrifice,” “share”). Because people living in subsistence ecologies have to deal with having enough resources to survive, rather than seeking to accumulate wealth, we also predicted that the use of terms representing materialistic values (e.g., “Rolls Royce”) would decline during the pandemic.

Two big data studies evaluated these predictions by comparing the national prevalence of selected words and phrases on the internet before and after President Trump's declaration that COVID-19 was a national emergency. The first exploratory study used Google searches as the data source. The second confirmatory study used social media. Analyzing data from Twitter, blogs, and internet forums, Study 2 provided three independent replications of Study 1. Our contribution to the literature is to demonstrate the paradox that, on the one hand, adaptation to the pandemic involves concerns, activities, and values associated with a historically earlier way of life, and, on the other hand, that these shifts are expressed on the canvas of the newest emerging technologies.

In the next section we provide background on the theory and empirical findings that led to our predictions.

1.1 | Theory of Social Change, Cultural Evolution, and Human Development

1.1.1 | Sociodemographic ecologies

In the Theory of Social Change, Cultural Evolution, and Human Development, the fundamental determinant of cultural values and behavior consists of sociodemographic variables (Greenfield, 2009, 2016, 2018). The most basic distinction at the sociodemographic level represents subsistence versus commercial ecologies. Subsistence ecologies are characterized by small villages, short life expectancy (including high infant mortality rate), low material resources, collectivism, and basic survival activities—people produce their own food, shelter, and clothing. These are the environments in which human beings evolved. In commercial ecologies—a product of cultural evolution—most people live in urban environments; people have substantially longer life expectancies, access greater material resources, and purchase rather than produce their own food, shelter, and clothing.

Low life expectancy, high mortality rate, and scarce material resources create high survival threat and high mortality salience; these are central features of a subsistence ecology. In contrast, low survival threat and low mortality salience are central to commercial ecologies. However, the commercial ecology of the United States has been impacted by the coronavirus pandemic creating high survival threat. We, therefore, tested the hypothesis that the pandemic's survival threat has made mortality more salient and that online behavior would reflect this increased salience and its downstream effects on activities and values.

1.1.2 | Adaptations to these ecologies

Mortality salience and survival threat

The *municipio* (county) of Zinacantán in the Mexican state of Chiapas exemplifies community response to high mortality and low life expectancy in a subsistence environment. In Zinacantán in the 1960s, families grew their own food, wove their clothing, and constructed their housing. At that time, about 35% of children died before age 4 (Brazelton, Robey, & Collier, 1969). Zinacantecs created elaborate and expensive burial sites and regularly provided food on graves to feed dead family members (Greenfield, 2004). This elaborate cultural structuring of death exemplifies our proposal that high mortality rates and low life expectancy produce mortality salience, a psychological product of intense survival concerns.

In ecologies with low mortality rates and high life expectancy (i.e., low survival threat), we propose that mortality salience is reduced and, correlatively, persistent fear of death and preparations for death are also reduced. For example, in the United States, a highly commercial ecology, focus on a dead body is often minimized through cremation rather than burial, and memorial services, which, by definition, do not include the body, are often structured as celebrations of life rather than opportunities to grieve over death.

Activities

In a subsistence ecology, activities center around subsistence needs, such as food, shelter, and clothing. Many ethnographic field studies evince these priorities (e.g., Bolin, 2006; Bowser & Patton, 2008; Greenfield, 2004; Hewlett, Lamb, Shannon, Leyendecker, & Schölmerich, 1998; Vogt, 1969). In a commercial, high-tech ecology, subsistence needs are most often purchased. For instance, during coronavirus stay-at-home orders, food markets and home construction were considered “essential businesses.” In a commercial ecology, subsistence activities, like food production, are monetized and expanded beyond serving a solely survival purpose.

Values

In subsistence ecologies, the collectivistic values of helping, sharing, and giving are central, and behavior enacts these values. For example, in learning how to weave clothing, the learner relies on help from an older family member (Childs & Greenfield, 1980); in hunting for food, prestige comes from sharing game with other members of the community (Dowling, 1968); in celebrating religious holidays, giving away resources to the whole community, rather than accumulating wealth, is an important source of cachet (Vogt, 1969). Conversely, in a commercial ecology, individual accomplishment, personal property, and accumulation of wealth, rather than helpfulness, sharing, and giving, are dominant values (Raeff, Greenfield, & Quiroz, 2000; Uhls & Greenfield, 2012).

1.1.3 | Social change

Increasing life expectancy, decreasing mortality rates

In subsistence ecologies, life expectancy is short, and survival threats are common. Global life expectancy was age 27 in 1800 and remained at that level for the next hundred years. However, as medicine and science advanced, life expectancies increased (Roser, Ortiz-Espina, & Ritchie, 2013/2019). By 2000, global life expectancy had reached age 65 (Lee, 2003).

In the United States (the geographical area of our study), as a result of advancements in scientific and technological developments in public health and medicine, life expectancy increased, and mortality decreased from 1900 to 2018, with a notable reversal of those trends in 1917 during the Spanish Flu pandemic (National Center for Health Statistics, n.d.).

Implications of social change for mortality salience, activities, and values

The dominant direction of social change in our globalized world has been towards ever greater urbanization, commercialization, wealth, and monetization of activity (Greenfield, 2009, 2016). The movement towards a more commercial and wealthy ecology brings with it reduced mortality (Hajat, Kaufman, Rose, Siddiqi, & Thomas, 2011); reduced survival concerns (LeVine, Dixon, Leiderman, Keefer, & Brazelton, 1994); fewer subsistence activities (Greenfield, 2004);

more individualistic values (Santos, Varnum, & Grossmann, 2017); and increased importance of becoming rich (Park et al., 2014).

Even so, social change can go in the opposite direction, as it did in the Great Recession. As wealth decreased, adolescents became more communitarian in their values and less materialistic (Park et al., 2014).

Coronavirus pandemic

Until the coronavirus pandemic, the United States had not, since the 1917 flu pandemic, known survival threat on a mass scale. COVID-19's palpable danger to survival has led to significantly increased mortality salience and fear of death (Cable & Gino, 2020; Menzies & Menzies, 2020). Survival concerns have been caused not only by the coronavirus itself but also by economic retraction. In April, the official unemployment rate reached 14.7%, the highest it has been since the Great Depression, putting 23 million Americans out of jobs and slashing the pay of twice as many workers as the Great Depression (Iacurci, 2020; Long & Van Dam, 2020). This economic devastation left almost one-third of the country unable to pay for subsistence basics like adequate food, medical care, or utility bills (Karpman, Zuckerman, Gonzalez, & Kenney, 2020). Aside from potentiating the increasing survival threat, a hallmark condition of subsistence ecologies, this economic retraction provides the other essential feature of a subsistence ecology: scarcity of material resources.

1.2 | Hypotheses and methodology

These shifts in the direction of a subsistence ecology led us to hypothesize that response to the pandemic would entail (1) increased mortality salience, (2) more engagement in subsistence activities, (3) increased collectivism, and (4) decreased materialism. Study 1 was an exploration; it compared the frequency of relevant terms used in Google searches in the United States before and during the pandemic to produce a list of terms that were representative of the predicted conceptual shifts. Study 2 aimed to replicate the findings of Study 1, drawing data from social media sites in the United States before and during the pandemic. Study 2 provided three independent replications of Study 1 by utilizing national data from three different social media: Twitter, internet forums, and blogs. Approximate estimates indicate 87.3% of Americans use Google (2020), 22% use Twitter (2019), 20% use internet forums (2015), and 10% create blog content (based on 2016 forecast) (Pendry & Salvatore, 2015; Statcounter, 2020; Statista Research Department, 2016; Wojcik & Hughes, 2019). Because of our method of examining whether the predicted trends were consistent across Google, Twitter, internet forums, and blogs, and because such high proportions of the American population use one or more of the analyzed internet platforms, the study was essentially a comprehensive population-level analysis of the United States.

All four hypotheses had been confirmed by survey research carried out during stay-at-home orders in California and Rhode Island (Greenfield & Brown, under revision). With the current research, we test the generality of these findings and explore the extent to which

the internet is a reflection of changing psychological dynamics on a societal level—in this case, psychological reactions to the conditions created by the coronavirus pandemic.

1.2.1 | Methodology background

Language provides a window into the thoughts, feelings, and actions of individuals. Because society is composed of individuals interacting and communicating through language, the study of language on a mass scale provides, in principle, a window into psychological processes on a societal level. So, why has the collection and analysis of massive language datasets in order to develop understandings about human societies emerged only recently? The main reason is that, before the end of the 20th century, existing technology made large-scale word analyses impossible (Pennebaker & Chung, 2014). With the advent of desktop computing and the internet, the linguistic behavior of whole societies could, for the first time, be studied on an unprecedented scale. However, because communication technologies have expanded exponentially, society-wide studies using linguistic data became possible only quite recently as the quantity of data in existence exploded. At the time of our study (2020), 2018–2020 had produced the majority of the world's data (Holst, 2020). Over the same time period, social media users went from being a minority of the world's population to the majority, moving considerable proportions of their social interactions online and recordable for potential analysis (Clement, 2020; Datareportal, 2020). Big data studies on the current research's scale became possible in psychology for the first time; early examples and contributions of big data methodologies to the study of cultural change over historical time are detailed in the next section.

Precedents for studying historical, cultural change through big data sources

Google's digitized collection of roughly 8 million books, 6% of the total books ever published, has been analyzed by numerous scholars to measure historical and cultural changes around the world (e.g., Campbell & Gentile, 2012; Greenfield, 2013; Michel et al., 2011; Skrebyte, Garnett, & Kendal, 2016; Twenge, Campbell, & Gentile, 2012; Zeng & Greenfield, 2015; Younes & Reips, 2019).

Scholars also avail themselves of newspapers for big data. Using a database with millions of newspapers, researchers analyzed U.S. newspapers from 1900 to 2000; they measured historical frequency changes in variables composed of terms associated with specific value categories, a methodology we use in the current research. The researchers established the predictive validity of this methodology in two ways. First, they found that the value-representing variables had a significantly stronger correlation with objective indicators of corresponding value-expressive behavior versus noncorresponding value-expressive behavior. For example, the terms representing the value of stimulation (“excitement,” “novelty,” and “thrill”) highly correlated over time with the number of films released, and the terms representing the value of self-direction (“independence,” “freedom,”

and “liberty”) highly correlated over time with voting participation. Second, they found that the terms correlated with expected behaviors exhibited meaningful variations at expected major time points. For example, the stimulation terms dramatically increased during the roaring twenties and decreased when the Great Depression began. Similarly, the terms representing the value of security (“security,” “safety,” and “protection”) dramatically increased at the start of World War II, dramatically decreased at the end of World War II, and then increased up until the conclusion of the Cold War (Bardi & Calogero, 2008).

Google Trends as a psychological measure of the effect of COVID-19

Many studies have used Google Trends to measure change over time (Jun, Yoo, & Choi, 2018). More specific to our research, Google Trends data have been used to assess the psychological and behavioral effects of COVID-19 in the U.S. population (Goldman, 2020). This research has revealed several COVID-19-induced phenomena, including changes in food-related activities. Evidence of the shift toward a subsistence ecology, search terms related to cooking increased, while searches for restaurants decreased.

“Smaller” studies extract big data from social media in order to measure the effects of COVID-19

As coronavirus forced the greatest proportion of interpersonal relationships in human history from offline interactions to online, several researchers have seen COVID-19 and its effects as a unique opportunity to study psychological changes through big data on social media. These studies used much smaller quantities of data than the present research, but they are still extremely informative. One particularly relevant study analyzed the language used by 17,865 active Chinese users on Weibo, one of the biggest Chinese social media platforms, before and after the Chinese declaration of outbreak of COVID-19, in order to assess several psychological metrics (Li, Wang, Xue, Zhao, & Zhu, 2020). In line with our hypotheses, their results indicate that, based on word frequencies, individuals shifted toward adaptation to a subsistence ecology. For example, Weibo users showed more concern with death after COVID-19 was declared than before the declaration. They also showed more interest in religion, another value that is stronger in rural ecologies than urban societies (Greenfield, 2013).

1.2.2 | Methodological overview of the current research

Study 1 used Google Trends to explore whether Google's variable of search interest for specific words or phrases would shift in the COVID-19 pandemic, as predicted by the Theory of Social Change, Cultural Evolution, and Human Development, now expanded to include mortality salience. Study 2 then replicated findings in three independent analyses using Talkwalker, a powerful social media analytics and monitoring software. Talkwalker analyzes billions of internet conversations and interactions to collect word and phrase frequency data from over 150 million blogs, forums, videos, online newspapers, reviews, and social networks (Talkwalker, n.d.-a, n.d.-b). Whereas

Google Trends data are available in the form of daily relative interest values, which represent what percentage that date's search volume was of the peak search volume over a specified time period and geographic region. Talkwalker data can be extracted as raw daily frequencies of word or phrase mentions in a specified social medium (or media), geographic region, and population.

2 | STUDY 1: GOOGLE SEARCH BEHAVIOR SHIFTS IN THE PANDEMIC

2.1 | Method

2.1.1 | Google Trends

Google Trends is a tool that enables interest analysis of a national population. It provides access to a representative sample of Google searches pulled from the billions of daily Google searches (FAQ about Google Trends data, n.d.). The data are all anonymized, categorized, and aggregated to accurately show Google interest in topics from a worldwide level down to a small-scale city level. The representative sample that Google Trends accesses is almost entirely unfiltered, except for some particular cases where Google purposefully filters out searches to improve its sample's external validity: It filters out searches made by very few people, duplicate searches by the same person in a short period, and searches with apostrophes and other special characters.

2.1.2 | Study design

Google Trends transforms its search frequency for each term in a given region and time period into a metric referred to as “search interest” or just “interest.” The interest metric is a percentage based on a set time frame. Each day's search interest is calculated as a percentage of peak interest during whatever time frame has been selected. For example, an interest value of 100 means that on that date, the search term reached its peak popularity for the time frame, and a value of 50 means that on that date, the term was half as popular as its peak popularity in the same time frame (Google Trends, 2020). Our time frame was the period of January 3, 2020–May 22, 2020. Within this time frame, we compared the 70-day period before President Trump declared COVID-19 an emergency (January 3–March 12) with the 70-day period after the emergency declaration (March 14–May 22). March 13, the day of the emergency declaration, was considered a transitional day and was excluded from the analysis.

Our dependent variables were, for every day of the time frame and for every term searched, the interest value for that term. The independent variable was before versus after Trump's emergency declaration. Our unit of analysis was the day, so that, by means of *t*-tests, 70 daily measurements of search interest before the emergency declaration were compared for every term with 70 daily measurements of search interest after the emergency declaration for the same term.

We considered using both paired-samples and independent-samples *t*-tests and compared them for every dependent variable. All statistically significant shifts were maintained in both the independent-samples and paired-samples *t*-tests. However, we decided to use the independent-samples *t*-tests in reporting results because we had no basis for thinking that Day 1, 70 days before the beginning of the pandemic, would be more similar to Day 1 of the pandemic than it was to other days during the pandemic; no basis for thinking that Day 2, occurring 69 days before the pandemic, would be more similar to Day 2 of the pandemic than to other days during the pandemic, etc. Therefore, we concluded that the two sets of days—70 days before the pandemic and 70 days during the pandemic—were more independent than correlated. Where matching does not produce a substantial correlation, independent-samples *t*-tests are preferred (Zimmerman, 1997).

With *t*-tests performed on time series, the issue of independence of adjacent days arises, as this independence is a required condition for a *t*-test. Because day, rather than person, served as our unit of analysis and because data from adjacent days consisted of input from large but constantly varying samples of internet users all over the United States (rather than data from the same people over a series of days), we considered that our dependent variables met the criterion for the independence of data from adjacent days.

For this exploratory study, we estimated that the time frames of 70 days before and 70 days after President Trump's emergency declaration would be long enough to ensure that the behaviors were stable for both periods, despite day-to-day variability. Because the *n* in our statistical analyses is based on number of days sampled, we estimated that a total *n* of 140 days would provide a reasonable sample for statistical reliability. Based on our exploratory findings in Study 1, we did a power analysis that confirmed this sample size of 140 days to be appropriate for Study 2. Details will be reported in Section 3.1.3.

While it was important to achieve sufficient statistical power by having a large enough sample of days, it was also important to avoid a time sample that was too long. Here the considerations were substantive rather than statistical. Because we conceptualized mortality salience as a key variable, we did not want the time period to be so long that individuals' subjective mortality salience would decrease through factors such as greater understanding of preventative practices, reduced hospital crowding, more widespread testing availability, or lifting of stay-at-home orders. In fact, initial stay-at-home orders were still in full or partial effect in 18 states on the last day of our study period (National Academy for State Health Policy, n.d.); the continuation of stay-at-home orders provided evidence that our pandemic time period had not gone on too long.

2.1.3 | Term selection

For the Google Trends exploration, words and phrases were selected based on three criteria; all of the criteria had been used in prior research (Greenfield, 2013; Zeng & Greenfield, 2015). The first

Term	Before		After		<i>t</i>	<i>df</i>	<i>p</i>	Cohen's <i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>				
Cemeteries	28.3	5.9	39.8	13.9	6.40	92.83	.0000000063	1.12
Survive	44.4	10.1	65.4	11.3	11.59	136.21	<.0000000001	1.97
Cemetery	30.2	2.8	35.6	11.7	3.77	76.65	.0003215304	0.71
Fear of death	49.7	17.9	59.1	16.0	3.28	136.29	.0013202690	0.53
Death	30.5	10.7	36.8	8.1	3.92	128.47	.0001414649	0.74
Bury	51.1	5.3	63.0	10.7	8.40	101.41	<.0000000001	1.43

Note: The above table and all the following tables in Study 1 present each term's mean percentage of the maximum interest for the period encompassing 70 days before March 13, 2020 and 70 days after March 13, 2020, as well as the results of *t*-tests (assuming unequal variance) comparing mean percentage of maximum interest between the two time periods.

criterion was theory relevance. This criterion meant that the guiding principle for selecting particular words was that they represented concepts central to the theoretically-based predictions summarized in the introduction.

The second criterion was that only high-frequency terms were selected. Methodologically, this was a necessary criterion because “[Google] Trends only show data for popular terms” by filtering out data on terms with low search volumes (FAQ about Google Trends data, n.d.). Conceptually, selecting for popular terms meant that the terms would be significantly characteristic of U.S. culture as a whole and not subject to minor influences that would bias the results (Greenfield, 2013).

The third criterion was that the words and phrases had to have a relatively narrow range of meanings, so that they were not ambiguous. Narrowing the semantic interpretations of the words and phrases helped ensure that a particular word or phrase did not have many uses in contexts irrelevant to the psychological or behavioral element that the word or phrase was representing. For example, the term “will” was excluded from the analysis of mortality-related terms because of ambiguous meaning.

2.1.4 | Statistical analysis

Before carrying out *t*-tests, we compared the variances of each word and phrase in the 70 days before Trump's emergency declaration with the variances of the same words and phrases in the 70 days after his emergency declaration. The Levene test for Equality of Variances revealed that 21 out of 30 terms had significantly different variances in the two time periods. If one compares the standard deviations (*SD* column) for the two time periods for each term in Tables 1–4, the unequal variances are apparent. In line with the recommendation of Ruxton (2006), we used Welch's *t*-test, also known as the unequal variance *t*-test, for comparing word and phrase frequencies before and during the pandemic for both the unequal and equal variance cases. Because the unequal variance/Welch's *t*-test factors in the specific standard deviations of the samples being compared, the effective degrees of freedom associated with the Welch's *t*-test can deviate

TABLE 1 Google search interest in mortality before and after President Trump's emergency declaration, March 13, 2020

from that of the equal variance *t*-test where the *df* is always $n - 2$; in this case, $n - 2$ would be 138 (140 days minus 2) (Sawilowsky, 2002). Also, when unequal variances are taken into account, *dfs* have non-integer rather than whole-number values. Thus, in all cases in Tables 1–4, *dfs* show deviations from 138 to varying degrees and have non-integer values. All *t*-tests were two-tailed. The reader may also notice that degrees of freedom differ noticeably from term to term. In the unequal variance *t*-test, degrees of freedom depend on standard deviations and because standard deviations varied dramatically from term to term, degrees of freedom varied from term to term.

We would also like to make two points relating to *p*-values. First, we believe that it is informative to present our *p*-values at the .0000000001 level, rather than cutting them off at the more usual $p < .001$, in order to more accurately demonstrate the unusually high level of statistical significance of our findings. Second, there is a growing body of literature indicating that *p*-values should not carry as much weight with big data studies because, as the sample size grows, the effects become more likely to reach statistical significance (Lin, Lucas Jr, & Shmueli, 2013; Demidenko, 2016). However, in our design, the sample size is relatively small because our unit of analysis is the day. Hence, we compare the 70 days before President Trump's emergency declaration with the 70 days after it. This comparison yields a total sample size of 140. Thus, our study's big data component is the large frequency that each data point is based on, rather than the number of data points. Because of this sample size control, our extraordinarily small *p*-values provide essential information on the results' strength. In order to further demonstrate the strength of the observed effects, we also calculated Cohen's *d* for each before-after comparison in order to provide an estimate of the magnitude of each difference.

2.2 | Results

The expanded Theory of Social Change, Cultural Evolution, and Human Development found support in the Google Trends results for each of the four hypotheses:

TABLE 2 Google search interest in subsistence activities before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Farmland	57.5	10.4	64.1	14.7	3.07	124.53	.0026324136	0.54
Farm	69.7	3.6	83.6	10.2	10.77	86.48	<.0000000001	1.79
Grow vegetables	13.2	4.7	58.6	15.3	23.78	82.00	<.0000000001	4.07
Seeds	40.0	4.5	70.2	11.3	20.76	90.77	<.0000000001	3.49
Shovel	16.5	4.2	27.7	13.0	6.83	83.22	.0000000013	1.24
Garden	35.5	5.8	49.2	12.7	8.23	97.08	<.0000000001	1.32
Grow plants	26.3	4.9	60.0	15.3	17.55	82.96	<.0000000001	2.99
Recipes	49.9	10.4	64.9	11.3	8.16	137.15	<.0000000001	1.38
Baking bread	14.5	3.5	52.9	16.5	19.08	75.07	<.0000000001	3.27
Sourdough	12.7	2.9	61.5	18.6	21.64	72.31	<.0000000001	3.63
Cooking directions	11.0	4.2	17.6	12.2	4.25	85.27	.0000548965	0.72
Cook	26.2	4.7	32.4	9.8	4.72	99.58	.0000077825	0.83
Sewing machine	15.1	1.8	46.4	20.6	12.65	70.08	<.0000000001	2.12
Sew	14.1	1.4	29.9	14.4	9.16	70.24	<.0000000001	1.56
Tools	80.5	6.4	87.4	8.7	5.30	126.37	.0000005029	0.83
Home Depot ^a	34.2	4.6	63.5	13.4	17.4	85.04	<.0000000001	2.95

^aHome Depot is a store chain for purchasing goods related to home repair and home maintenance.

TABLE 3 Google search interest in collectivistic values before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Sacrifice	52.5	8.4	59.2	10.0	4.26	133.69	.0000380304	0.67
Share	60.5	7.4	81.8	10.6	13.81	123.71	<.0000000001	2.38
Help	78.8	6.9	87.6	7.3	7.35	137.37	<.0000000001	1.22
Give	80.7	4.0	91.2	4.8	14.01	133.85	<.0000000001	2.31

TABLE 4 Google search interest expressing the aspiration to be rich before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Spend	55.8	11.2	47.7	5.7	5.41	103.12	.0000004054	0.93
Lamborghini	72.2	6.1	66.4	12.1	3.62	101.89	.0004676329	0.59
Rolls Royce	64.3	10.0	53.6	9.4	6.51	137.54	.0000000013	1.07
Ferrari	40.3	15.1	25.2	5.8	7.82	88.62	<.0000000001	1.30

2.2.1 | Hypothesis 1: Mortality salience, represented by specific Google search terms, will increase during the pandemic

Compared with before the COVID-19 pandemic, mortality salience has significantly increased during the pandemic; this finding is indicated by a rise in Google searches for many terms related to contemplating and preparing for one's own death or the deaths of others: "cemetery"/"cemeteries," "survive," "fear of death," "death," and "bury" all rose significantly after President Trump's emergency declaration. Effect sizes range from medium to large. Table 1 shows the specific search terms indexing mortality salience with their *t*-values,

degrees of freedom, *p*-values, and effect sizes for every temporal comparison.

2.2.2 | Hypothesis 2: Subsistence activities, as represented by specific Google search terms, will increase during the pandemic

Interest in subsistence activities significantly increased during the pandemic. This conclusion is suggested by a significant increase in Google searches of words related to growing edibles, food preparation, making or repairing clothes, and maintaining one's shelter. The

specific search terms indexing subsistence activities are shown in Table 2. Table 2 also shows *t*-values, degrees of freedom, *p*-values, and effect sizes relevant to each statistical comparison. All effect sizes were in the medium to large range.

2.2.3 | Hypothesis 3: Collectivism, as represented by specific Google search terms, will increase during the pandemic

After the inception of the pandemic, Google searches significantly increased for many words associated with collectivism: “sacrifice,” “share,” “help,” and “give.” Table 3 presents *t*-values, degrees of freedom, *p*-values, and effect sizes associated with each of these comparisons. Again, all effect sizes were in the medium to large range.

In testing the hypothesis of increasing collectivism in the pandemic, we also tried using family terms such as “mother,” “father,” and “grandparents,” given that family values are central to collectivism in subsistence ecologies. However, family terms did not show significant trends during the pandemic, so those data are not shown here.

2.2.4 | Hypothesis 4: Materialism, as represented by specific Google search terms, will decline during the pandemic

Google searches for many words associated with being rich and the aspiration to wealth significantly decreased: “spend,” “Lamborghini,” “Rolls Royce,” and “Ferrari.” For each of these search terms, Table 4 shows *t*-values, degrees of freedom, *p*-values, and effect sizes associated with these comparisons. Again, all effect sizes are in the medium to large range.

3 | STUDY 2: SOCIAL MEDIA BEHAVIOR SHIFTS IN THE PANDEMIC: TWITTER, INTERNET FORUMS, AND BLOGS

3.1 | Method

3.1.1 | Talkwalker analysis of social media

After completing the Google Trends analysis, we used the Talkwalker tool to test whether the theoretically and statistically significant findings from the Google Trends exploration were replicable. This second study was intended to demonstrate that trends in word and phrase frequencies did not reflect the idiosyncrasies of Google searches but captured underlying value and behavior changes that show robust expression throughout the internet. In this way, the Google Trends research is exploratory, whereas the Talkwalker research is predictive and confirmatory.

The Talkwalker tool analyzed word frequencies in three types of social media throughout the United States: Twitter, internet forums,

and blogs. During the time of our study, the Talkwalker database of blogs and forums from which term frequency data were retrieved contained approximately 8 million English language blog posts across almost 1 million blog sites and approximately 10 million English language forum posts from about 240,000 forum domains (Talkwalker Representative, personal communication, August 25, 2020; Talkwalker Representative, personal communication, August 27, 2020; Talkwalker Representative, personal communication, September 9, 2020). For our study, word frequency data came from the same sites for both the “before” and “after” comparison periods (Talkwalker Representative, personal communication, August 19, 2020). See Appendix A for examples of forums and blogs included in the analysis.

3.1.2 | Term selection and Creation of Composite Variables

After we identified the words that emerged with significant predicted shifts from the Google Trends exploration, data on each word's daily mentions on each of three social media types for the specified time frame were collected using the Talkwalker tool. (In one case where two forms of the same root word [“cemetery” and “cemeteries”] showed the same statistically significant directional change in Google searches before and after COVID began, we selected the singular form for the Talkwalker analysis.)

We then grouped the terms into a composite variable for each hypothesis. We averaged the daily mentions of each word comprising the composite variable for each day of the “before” time frame and each day of the “after” time frame. We then averaged the daily averages of each composite variable over the 70 days before Trump's emergency declaration to find the mean daily mentions for that composite variable before the pandemic. In similar fashion, we averaged the daily averages of each composite variable over the 70 days after Trump's emergency declaration to find the mean daily mentions for that composite variable during the pandemic. These scores were then compared statistically as described in Section 3.1.4.

3.1.3 | Study design

The same comparison periods were used in the Talkwalker study as the Google Trends study. In addition to the substantive considerations identified in Study 1, we used the results of our exploratory study of Google searches to confirm that 70 days before and 70 days after President Trump's emergency declaration provided sufficient statistical power. Our calculations indicated that, to achieve a power of .8, the maximum time sample needed to detect an effect at the .05 level of significance for any of the words used in both studies would be 62 days before and 62 days after Trump's emergency declaration (Brant, n.d.). Hence, a sample of 70 days before and 70 days after the declaration provided more than sufficient statistical power.

3.1.4 | Statistical analysis

As in the Google Trends study and for the same reasons, we analyzed the Talkwalker data with two-tailed independent-samples *t*-tests for samples with unequal variances. In this study, we compared mean mentions of each composite variable during the 70 days before Trump's emergency declaration with mean mentions of the same composite variable during the 70 days after Trump's emergency declaration. Thus, the independent variable was before versus after Trump's declaration of a national emergency, or, to state it another way, before versus during the American COVID-19 pandemic.

In the main analysis, the dependent variables were composites consisting of the mean number of mentions per day of words and phrases comprising a particular composite variable. For example, the mortality salience composite variable consisted of mean number of mentions per day of the terms "survive," "cemetery," "fear of death," "death," and "bury." Subsidiary dependent variables were the frequencies of each individual component word and phrase on each day - for example, the individual frequencies of the five terms: "survive," "cemetery," "fear of death," "death," and "bury." Results concerning these individual words and phrases are presented in Appendix B. Unlike the Google Trends search interest metric, which is expressed as a value from 1 to 100, Talkwalker provides frequency data on number of mentions.

The Levene test indicated that 4 out of 12 of the composite variables had significantly unequal variances in the two time periods; these unequal variances are visible in the standard deviations for each *t*-test presented in the text. For individual words and phrases, unequal variances in the two time periods are visible in the *SD* columns of Tables B1-B12; they were significantly unequal in 48 out of 87 cases. Again, we followed the suggestion of Ruxton (2006) and used the unequal variance *t*-test for both the equal and unequal variances cases.

As noted in Study 1, the unequal variance *t*-test is based on effective degrees of freedom that deviate from the equal variance situation of $n - 2$ (140 days minus 2 = 138) and are non-integer values; for the composite variables, the resulting effective degrees of freedom are shown in Section 3.2. For individual words, effective degrees of freedom are seen in the *df* columns of Tables B1-B12.

As in Study 1, the reader may also notice that degrees of freedom differ noticeably from composite variable to composite variable in the text of the Section 3.2 and from term to term in the tables shown in Appendix B. As explained for Study 1, in the unequal variance *t*-test, degrees of freedom depend on standard deviations and because standard deviations varied dramatically from term to term, degrees of freedom varied from term to term.

Again, similar to Study 1, because of the unusually high levels of statistical significance and our sample size control, we report *p*-values out to 10 decimal places. We have also calculated Cohen's *d* for each Talkwalker before-after comparison in order to provide an estimate of the magnitude of each shift.

3.2 | Results

3.2.1 | Hypothesis 1: The representation of mortality will become more salient on social media during the pandemic

The results confirmed this hypothesis. The terms making up the composite mortality salience variable ("survive," "cemetery," "fear of death," "death," and "bury") showed highly significant increases with large effect sizes on all three types of social media: Twitter, internet forums, and blogs.

On Twitter, the grouped mortality salience terms had 62,093.7 mean daily Twitter mentions (*SD* = 26,260.0) during the 70 days before the COVID-19 pandemic. In comparison, during the 70 days after Trump's emergency declaration, the mortality salience terms had increased to 94,869.1 mean daily mentions (*SD* = 16,095.4). A *t*-test showed this to be a statistically significant effect, $t(114.43) = 8.90$, $p < .000000001$, with a large Cohen's *d* of 1.50. The frequency of all the individual terms rose on Twitter after Trump's emergency declaration on March 13, 2020; three of the five rose to a statistically significant extent, with effect sizes that were either medium or large. (See Table B1 for statistical analyses of the individual terms on Twitter.)

On internet forums, the mean daily mentions for the grouped mortality salience terms were 11,798.9 (*SD* = 2,505.1) during the 70 days before the pandemic was officially recognized on the national level, but 14,554.6 (*SD* = 1,158.7) in the 70 days after President Trump's emergency declaration. A *t*-test and effect size analysis found this change to be statistically significant, $t(97.23) = 8.35$, $p < .000000001$, with a large Cohen's *d* of 1.42. Each individual term rose to a statistically significant extent with three large and two medium effect sizes. (See Table B2 for statistical analyses of the individual terms on internet forums.)

For blogs, the mean daily mentions of the grouped mortality salience terms were 4,344.2 (*SD* = 622.2) for the 70 days before the pandemic was officially recognized on the national level, which increased to 5,284.5 (*SD* = 604.3) for the 70 days after President Trump's emergency declaration. A *t*-test and effect size analysis indicated that this change was significant, $t(137.88) = 9.07$, $p < .000000001$, with a large Cohen's *d* of 1.53. Each individual term rose to a statistically significant extent, with three large effects, one medium effect, and one small effect. (See Table B3 for statistical analyses of the individual terms on blogs.)

3.2.2 | Hypothesis 2: The representation of subsistence activities will increase on social media during the pandemic

This hypothesis was confirmed, as the terms making up the composite subsistence activity variable ("farmland," "farm," "grow vegetables," "seeds," "shovel," "garden," "grow plants," "recipes," "baking bread," "sourdough," "cooking directions," "cook," "sewing machine," "sew,"

“tools,” and “Home Depot”) had significant increases with large effect sizes across Twitter, internet forums, and blogs.

For Twitter, the mean daily mentions for the composite subsistence activities variable were 8,979.3 ($SD = 1,488.5$) for the 70 days before Trump's emergency declaration; they increased to 14,853.5 ($SD = 2,411.7$) for the 70 days after Trump's emergency declaration. A t -test and analysis of effect size found this increase to be significant, $t(114.91) = 17.34$, $p < .0000000001$, with a large Cohen's d of 2.93. Fifteen out of the 16 individual terms rose in mentions; 13 of the 16 rose to a statistically significant extent, with seven large and six medium effect sizes. (See Table B4 for statistical analyses of the individual terms on Twitter.)

On internet forums, the terms making up the composite subsistence activity variable had 2,638.3 ($SD = 232.8$) mean daily mentions during the 70 days before the pandemic was officially recognized on the national level; mentions increased to 3,936.0 ($SD = 551.2$) for the 70 days after official recognition by President Trump. A t -test and effect size analysis indicated that this increase was significant, $t(92.86) = 18.15$, $p < .0000000001$, with a large Cohen's d of 3.07. Fifteen out of the 16 individual terms rose in mentions; 14 rose to a statistically significant extent, with 13 large and 1 medium effect sizes. (See Table B5 for statistical analyses of the individual terms on internet forums.)

On blogs, the mean daily mentions making up the composite subsistence activity variable were 1,553.7 ($SD = 244.4$) during the 70 days before the pandemic was officially recognized on the national level; daily mentions increased to 1,873.1 ($SD = 275.2$) for the 70 days after Trump's emergency declaration. An independent-samples t -test and effect size analysis found this increase to be significant, $t(136.11) = 7.26$, $p < .0000000001$, with a large Cohen's d of 1.23. Fifteen out of the 16 individual terms rose in mentions; 13 of the 16 rose to a statistically significant extent, with 10 large effects and three medium effects. (See Table B6 for statistical analyses of the individual terms on blogs.)

3.2.3 | Hypothesis 3: The representation of collectivism will increase on social media during the pandemic

The data confirmed this hypothesis, with the terms making up the composite collectivism variable (“sacrifice,” “share,” “help,” and “give”) significantly increasing. Almost every term had large effect sizes on all three internet platforms.

On Twitter, the grouped collectivistic terms had 515,721.0 mean daily mentions ($SD = 45,172.7$) during the 70 days before Trump's emergency declaration. This figure increased to 660,776.4 mean daily mentions ($SD = 114,788.3$) during the 70 days after official recognition of the pandemic in the United States. A t -test and effect size analysis indicated that the increase was statistically significant, $t(89.87) = 9.84$, $p < .0000000001$, with a large Cohen's d of 1.66. Each individual term rose to a statistically significant extent, with effect

sizes that were all large. (See Table B7 for statistical analyses of the individual terms on Twitter.)

On internet forums, the composite of collectivism terms had 98,833.1 mean daily mentions ($SD = 6,570.8$) over the 70 days before the pandemic was officially recognized on the national level, which increased to 116,367.6 for the 70 days after President Trump's emergency declaration ($SD = 7,466.7$). A t -test and effect size analysis found that this was a statistically significant increase, $t(135.81) = 14.75$, $p < .0000000001$, with a large Cohen's d of 2.49. Each individual term rose to a statistically significant extent, with effect sizes that were all large. (See Table B8 for statistical analyses of the individual collectivism terms on internet forums.)

For blogs, the composite of collectivistic terms received 31,177.4 mean daily mentions ($SD = 4,694.0$) for the 70 days before the pandemic was officially recognized on the national level, which increased to 35,800.6 mean daily mentions ($SD = 5,390.6$) for the 70 days after the emergency declaration. An independent-samples t -test and effect size analysis deemed this to be a significant increase, $t(135.44) = 5.41$, $p = .0000002766$, with a large Cohen's d of 0.91. Each individual term rose to a statistically significant extent, with three large effects and one small effect. (See Table B9 for statistical analyses of the individual terms on blogs.)

3.2.4 | Hypothesis 4: Materialism. The representation of being rich will decline in importance on social media during the pandemic

The data did not confirm this hypothesis as no social medium showed a significant decrease for the terms composing the aspiration to be rich (“spend,” “Lamborghini,” “Rolls Royce,” and “Ferrari”).

Twitter had 34,074.4 mean daily mentions ($SD = 6,949.1$) for the composite variable representing the aspiration to be rich terms before the emergency declaration. This number increased to 35,233.7 ($SD = 6,481.9$) afterwards. This effect was not significant, $t(137.34) = 1.02$, ns. Nor was there a significant change for any of the individual terms tested. (See Table B10 for statistical analyses of the individual terms on Twitter.)

Similarly, on internet forums, there was no significant change, $t(128.67) = 0.56$, ns, in the mean daily mentions of the grouped aspiration to be rich terms from before the pandemic was officially recognized on the national level ($M = 9,011.0$, $SD = 1,311.0$) to after ($M = 9,121.7$, $SD = 994.8$). None of the individual terms showed a significant change either. (See Table B11 for statistical analyses of the individual terms in internet forums.)

Blogs actually showed a significant increase, $t(137.92) = 3.84$, $p = .0001844935$, from before Trump's emergency declaration ($M = 2,831.3$, $SD = 416.3$) to after ($M = 3,098.5$, $SD = 406.1$). (See Table B12 for statistical analyses of the individual terms on blogs.) The table shows that mentions of “spend” increased significantly, while mentions of “Ferrari” decreased significantly, both with medium effect sizes.

4 | DISCUSSION

In national samples from Google searches, Twitter, internet forums, and blogs, we confirmed theoretically derived predictions that COVID-19 would increase mortality salience, engagement in subsistence activities, and collectivistic values. Given concerns about replicability in psychological science (e.g., Makel, Plucker, & Hegerty, 2012), it is notable that we first carried out an exploratory study and then replicated findings with three independent big data samples. Another notable feature of the results are the many large effect sizes. In fact, many effect sizes are not just unusually large, but huge. These effect sizes testify to the power of the theory to make scientifically important predictions, as well as to the power of the pandemic to lead to socially significant change.

Indeed, this research may be the largest analysis of socio-cultural change, using behavioral data, ever published in psychology. The results, furthermore, have tremendous ecological validity because individuals from across the United States were interacting naturally in familiar online environments. These are environments, moreover, in which people do not explicitly think that their interactions are being recorded. For this reason, we believe that the expanded Theory of Social Change, Cultural Evolution, and Human Development is valid and generalizable to the U.S. population or, at the very least, to the internet-using population in the United States.

The theory provided a comprehensive model for predicting the observed shifts in activities and values – shifts that are difficult to explain comprehensively without it. One can explain away the significant rise in mortality salience (thinking about one's death and others' deaths) as an obvious response to the increased danger present in daily life. However, the simultaneous rise of subsistence activities in a variety of seemingly distinct contexts (growing edibles, food preparation, making or repairing clothes, and maintaining one's shelter) and of collectivistic values is far from obvious and immediately conjures up an image of a small-scale, rural society.

At the outset of coronavirus, the dramatic shift toward collectivism would have been quite challenging to predict, and there were actually substantial behavioral indications that the pandemic would make Americans more individualistic. Hoarding, a distinctly individualistic behavior, taking more than necessary from the common good and keeping it for oneself, was predominant. Even before Trump declared COVID-19 a national emergency, the nation was in a “grocery-hoarding frenzy (D'Innocenzio & The Associated Press, 2020).” The news was full of iconic images of shoppers in long lines at supermarkets waiting to get in right when they opened, and supermarket shelves were wiped out of essentials (Manning-Schaffel, 2020; Zagorsky, 2020). On the flip side, sellers were using it as a time to engage in the most brute capitalism they could: In response to the increased demand, N95 mask listings went from \$18.20 in mid-January to \$199.99 at the end of February; a dozen Purell bottles selling at \$30 in January skyrocketed to \$159.99 by March 3; and shoppers were being quoted astronomical shipping fees up to \$5,000 for next-day air (Tyko, 2020).

What transformed Americans from the hyper-individualists of the onset of the pandemic to valuing collectivism as documented in our study? We would argue that they adapted to living in a society with a high mortality rate. At the time of Trump's announcement, a little over 50 people in the United States had died from coronavirus, 10 times less than would have died by the next week, and nothing compared to the 2,770 that became America's peak death rate in the 70 days following the emergency declaration (Centers for Disease Control and Prevention, 2020; The COVID Tracking Project, 2020). This massive increase in societal mortality appears to have caused death to become significantly more salient in the American mind, as indicated by this study. Our theory predicted that this salience would cause an adaptive shift resulting in a traditionally individualistic society shifting significantly toward collectivistic values.

The Theory of Social Change, Cultural Evolution, and Human Development is also unique in being able to predict the significant increase in subsistence activities. Aside from the initial panic and hoarding of toilet paper and water, there was never any time during the pandemic when there might be a real need to become self-sufficient. Food delivery never stopped; no shortage of water ever occurred; supermarkets and home repairs were deemed essential services; almost everything was available online. Taking a big-picture approach, we conclude that the only major difference in our society's commercial functions was that an unprecedented number of transactions moved online, and goods came as deliveries. Nonetheless, the American people engaged in significantly increased subsistence activities across various domains. Because these shifts happened so quickly—within the span of a couple of months—we conclude that these responses reflect evolutionarily conserved instinctual adaptations to changing environmental conditions.

4.1 | “The Largest Movement in U.S. History” in light of this study's findings

During the pandemic, America witnessed the “largest movement in U.S. History” (Buchanan, Bui, & Patel, 2020). Catalyzed by video footage going viral of a white police officer, Derek Chauvin, with his knee on George Floyd's neck, and Floyd stating that he could not breathe more than 20 times, followed by reports explaining that Floyd was pronounced dead less than 30 minutes later, hundreds of demonstrators took to the streets of Minneapolis to protest the murder of unarmed blacks by police officers (BBC, 2020). From there, the Black Lives Matter protests exploded across the country, with surveys reporting that about 15–26 million adults demonstrated (Buchanan et al., 2020). This turnout for a single continuous protest on a particular issue far surpassed the Women's March of 2017, which had been the largest protest movement prior with three to five million participants (Buchanan et al., 2020; Waddell, 2017). What makes this record-breaking movement so interesting is its unusual timing. It all occurred amid the coronavirus pandemic, so, despite Americans being significantly more concerned about death, they put their lives at risk by participating in a mass protest in record numbers. Further, it is also

important to question why George Floyd's death catalyzed this movement as the terrible fact of the matter is that George Floyd was not the first or last black man or woman to be unjustly murdered by police or even to have their unjust murder filmed.

Perhaps the answer to this question is that the American shift toward the collectivistic values inherent in subsistence ecologies created optimal conditions for mass protest. The significant increases found in this study of Americans valuing the group's welfare may have made substantial proportions of Americans more inclined to put aside their daily obligations and reduce the extent of their self-protective coronavirus measures to improve the welfare of black individuals that they saw as part of their community.

This reasoning aligns particularly well with the data on the protests. Unlike prior Black Lives Matter protests, which were majority black and could be interpreted as more individualistic responses to bettering one's own welfare, almost 95% of the American counties, which participated in the recent Black Lives Matter protest, were majority white, indicating an increased collectivistic desire to help others (Buchanan et al., 2020).

4.2 | Implications of our findings for the expanded Theory of Social Change, Cultural Evolution, and Human Development

Our findings show the dramatic COVID-19-induced shift in ecological conditions corresponded with dramatic increases in mortality salience, engagement in subsistence activities, and identification with collectivistic values occurring in quite a short time (70 days). For comparison, a big data study of millions of books digitized by Google showed that collectivistic values declined in the United States over a period of 200 years, a rate of change that was drastically slower than what occurred in the present study (Greenfield, 2013). The most obvious difference between these two situations was the rate of ecological change in societal mortality and material resources: 200 years of slowly declining death rate and increasing economic prosperity, versus several weeks of dramatically increasing mortality rates and economic retraction. The extraordinary speed with which values and activities changed is indicative of an evolutionary adaptation established long ago in human history: This adaptation allows humans to respond with extraordinary speed to changes in the two most critical features of their environment - survival threats and resource scarcity.

How lasting are these changes? Residents of the United States adapted quickly to the sudden COVID-19-induced change in ecological conditions. Therefore, when these conditions reverse, they will likely adapt in the opposite direction, at a rate dependent on the speed of the ecological reversal. In order to test this prediction, this study should be replicated after the United States recovers from the pandemic. The study design will have to be a bit different as the country will likely have a slow recovery, so that researchers would not measure whether there were significant changes in a short 10-week period as we did, but would, instead, examine the rate of psychological and behavioral change as the United States recovers

over a longer period of time. However, despite our prediction that the population as a whole will readapt to the commercial ecology as it previously existed, prior research has shown that economic conditions present in one's adolescence and emerging adulthood have a lifelong impact on people's values (Bianchi, 2016). Hence, we predict that the ecological conditions created by the COVID-19 pandemic will leave an enduring effect on American adolescents and young adults.

4.3 | The prediction that the aspiration to be rich would decline did not replicate on social media

It surprised us that the aspiration to be wealthy did not replicate on social media because, in Greenfield and Brown's surveys in Rhode Island and California, participants reported that their interest in becoming rich declined after the pandemic began (Greenfield & Brown, under revision); and, in our first study, aspiring to be rich seemed to decline so significantly in Google searches. The most likely explanation for these seemingly paradoxical findings is that the search terms representing the aspiration to be rich were not a valid representation of the concept as a whole. They were "spend," "Lamborghini," "Rolls Royce," and "Ferrari." "Spend" does not necessarily represent being rich, but rather the purchasing of goods, which Americans still had to do at a generally unchanged level as the subsistence activities they were participating in would not provide sufficient goods for their family.

As for "Lamborghini," "Rolls Royce," and "Ferrari," these do represent the aspiration to be rich as they are blatant status symbols. However, buying luxury cars only represents one specific way to aspire to be rich, and if the majority of the population does not care much about cars, then the behavior of those words would not reflect on the aspiration to be rich as a concept. This American lack of interest in luxury cars may be the case, as "Lamborghini," "Rolls Royce," and "Ferrari" were substantially less used terms even before the pandemic compared with other variables. For example, before COVID-19, those three words had 2,298.8 average daily mentions on Twitter, compared to the 8,979.3 average daily Twitter mentions for the subsistence activities terms or the 515,721.0 average daily Twitter mentions for the collectivistic terms. Perhaps this comparative analysis shows that luxury car brands were not items of interest to most people and that they may not, therefore, have been ideal indicators, even if there was, in fact, an actual decline in the aspiration to be rich.

Equally or more important, Google and social media have different uses. This usage difference was beneficial to our study because a phenomenon has more generality if it exists across different contexts. However, testing each composite variable on platforms with slightly different uses opens up the possibility that terms may be a reasonable measure of their represented value, but only in one of their usage contexts. More specifically, Google is often used with the intent to purchase, whereas Twitter, internet forums, and blogs are not. Hence, luxury cars may have been a reasonable measure of

the importance of wealth in Google searches, but not on social media.

Greenfield and Brown's surveys of the effect of the pandemic on California and Rhode Island residents found a significant self-reported decline in the importance of becoming wealthy (Greenfield & Brown, under revision). However, the limited breadth of selected terms in our study representing the aspiration to be rich, coupled with a method of analysis that puts much pressure on whether the selected terms comprehensively represent their designated element of human psychology, may have led to a scenario where, despite a probable actual decline in the aspiration to be rich, the terms used to represent that aspiration were not good enough indicators to show significant effects for both experimental analyses.

4.4 | Limitations and conclusion

This study measured the effects of the novel coronavirus through frequency changes in words and phrases used on the internet. The use of such frequencies to represent aspects of human psychology and behavior has been validated in other studies and has substantial precedent; however, that does not mean that analyzing frequencies of linguistic terms is a foolproof method. The method is still an indirect measure. Although we believe that the method has advantages over the direct collection of self-reports because of the number of people we could access and the ecological validity of the responses, it is, nonetheless, an approximation of changes in psychology and behavior. Furthermore, although this study comes close to being a population-level analysis of the United States, individuals are being left out. For example, almost 13% of Americans do not use Google, our most popular data source (Statcounter, 2020). In addition, the results skew toward internet users who are actively writing content because we measure word and phrase frequencies. The users who write on the internet may be slightly different from the rest of the population. That said, we believe the study to have accurately measured the human capacity for rapid, dramatic psychological and behavioral adaptations to shifting societal conditions on the continuum from the subsistence ecologies in which our species evolved to the commercial ecologies of today's world.

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CONFLICT OF INTEREST

We have no known conflict of interest to disclose.

PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1002/hbe2.251>.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in openICPSR COVID-19 Data Repository at <https://doi.org/10.3886/E130646V2>.

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Social Psychology, and the Boesch Prize from the German Society of Cultural Psychology. Her books include *Mind and Media: The Effects of Television, Video Games, and Computers*, which was translated into nine languages and appeared in 2015 as a 30th anniversary classic edition. With Genavee Brown, she has coauthored a second article in this special issue: “Staying connected during stay-at-home: Communication with family and friends and its association with well-being.”



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APPENDIX A

Examples of forums from which word frequency data was extracted for the social media analysis

- <http://ramailoforum.com/>
- <https://www.reddit.com/>
- <http://stubbyhub.community/>
- <https://forddaily.net/>
- <https://www.eng-tips.com/>
- <http://boards.4chan.org/>
- <https://community.tableau.com/s/>
- <http://www.raginpagin.com/>
- <https://www.4chan.org/>
- <https://slickdeals.net/>
- <http://forum.garyjuang.com/>
- <http://community.sephora.com/>
- <https://community.myfitnesspal.com/en/>
- <https://www.cardschat.com/>
- <https://theshaveden.com/forums/portal/>
- <https://wcrpforums.com/>
- <https://odyesports.com/>
- <https://myapnea.org/>
- <https://www.excelforum.com/>
- <https://rathena.org/>
- <http://forum.cog-online.org/>

- <https://forum.tz-uk.com/forum.php?s=59647c0c598b1f18880deaef0b61718f>
 - <https://www.parentune.com/>
 - <https://lpvforum.com/>
 - <http://forums.rakard-kingdoms.com/>
 - <https://forums.contribs.org/>
 - <https://www.team-bhp.com/>
 - <https://www.crownofthegods.com/>
 - <https://lamborghinichat.com/forum/home>
 - <https://forum.workibox.com/>
 - <https://mouthfulsfood.com/forums/>
 - <https://www.survivalmonkey.com/>
 - <https://why.org/>
 - <https://forums.oneplus.com/>
 - <https://forums.storm8.com/forum.php?s=383dcd218f27d06adc60ec8af31fae59>
 - <http://www.trans-girls.com/>
 - <https://psoriasisclub.org/>
 - <https://www.pokecommunity.com/>
 - <https://www.expat.com/>
 - <https://forums.elderscrollsonline.com/en>
 - <http://www.gopbriefingroom.com/>
 - <https://pixelcountstudios.com/>
 - <https://www.spacetimestudios.com/>
 - <https://www.waguns.org/>
 - <https://www1.flightrising.com/>
 - <https://www.rv.net/>
 - <https://www.desidime.com/>
 - <http://forums.trovegame.com/>
 - <https://www.veganforum.org/>
 - <https://hypixel.net/>
- Examples of blogs from which word frequency data was extracted for the social media analysis.*
- <https://medium.com/>
 - <https://www.surrenderat20.net/>
 - <https://variety.com/>
 - <https://spectator.org/>
 - <https://www.weaselzipper.us/>
 - <https://www.mediaite.com/>
 - <https://www.teslarati.com/>
 - <https://www.earthlymission.com/>
 - <http://raconteurreport.blogspot.com/>
 - <http://edsources.org/>
 - <https://blog.ticketmaster.com/>
 - <https://thegregjarrett.com/>
 - <https://thefederalist.com/>
 - <https://www.ineteconomics.org/>
 - <https://scitechdaily.com/>
 - <https://www.koreaboo.com/>
 - <https://www.thegatewaypundit.com/>
 - <https://www.businessinsider.com/>
 - <https://saraacarter.com/>
 - <http://ladyfreethinker.org/>
 - <https://veganyackattack.com/>
 - <https://freebeacon.com/>
 - <https://babylonbee.com/>
 - <https://www.sidneypowell.com/>
 - <https://therightscoop.com/>
 - <https://www.mostlyblogging.com/>
 - <https://thepoliticalinsider.com/>
 - <https://blog.thesocialms.com/>
 - <https://thehardtimes.net/>
 - <https://boingboing.net/>
 - <https://thenationalpulse.com/>
 - <https://voiceofeurope.com/farewell.html>
 - <https://hannity.com/>
 - <https://www.cbpp.org/>
 - <https://www.sxsw.com/>
 - <https://bongino.com/>
 - <https://wccftech.com/>
 - <https://cleantechnica.com/>
 - <https://berniesanders.com/>
 - <https://www.zerohedge.com/>
 - <http://blogs.mercurynews.com/>
 - <https://www.thenation.com/>
 - <https://thebulwark.com/>
 - <https://headlineplanet.com/home/>
 - <https://americanindependent.com/>
 - <https://nationalfile.com/>
 - <https://www.themarysue.com/>
 - <https://uncoverdc.com/>
 - <https://www.judicialwatch.org/>
 - <https://thecoconutwhisperer.blogspot.com/>

APPENDIX B

TABLE B1 Comparison of daily Twitter mentions for individual mortality salience terms before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Survive	44,070.8	18,081.5	74,183.9	28,452.9	7.47	116.92	<.0000000001	1.26
Cemetery	3,108.3	1,395.4	3,627.1	2,109.2	1.72	119.69	ns	0.29
Fear of death	1,359.2	1,981.1	2,919.8	3,109.6	3.54	117.09	.0005728233	0.60
Death	251,264.0	124,789.5	382,646.2	72,279.4	7.62	110.61	<.0000000001	1.29
Bury	10,666.1	7,157.1	10,968.7	4,290.0	0.30	112.91	ns	0.05

Note: The above table and all the following tables present each term's mean daily mentions for the period before President Trump's emergency declaration (70 days before March 13, 2020) and the period after President Trump's emergency declaration (70 days after March 13, 2020), as well as the results of t-tests (assuming unequal variance) comparing the mean daily mentions between the two time periods.

TABLE B2 Comparison of daily mentions on internet forums for individual mortality salience terms before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Survive	9,039.6	1,489.3	11,959.6	2,023.4	9.72	126.80	<.0000000001	1.64
Cemetery	467.4	120.3	632.0	275.5	4.58	94.37	.0000142752	0.79
Fear of death	281.1	88.7	372.0	188.7	3.65	98.11	.0004276281	0.62
Death	47,684.1	11,697.0	57,959.7	5,257.0	6.70	95.78	.0000000014	1.13
Bury	1,522.5	218.1	1,849.9	285.8	7.62	129.02	<.0000000001	1.29

TABLE B3 Comparison of daily blog mentions for individual mortality salience terms before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Survive	3,540.7	477.0	5,247.9	826.5	14.97	110.38	<.0000000001	2.53
Cemetery	607.7	119.4	660.5	117.9	2.63	137.98	.0094239443	0.44
Fear of death	183.9	44.4	309.7	71.1	12.55	115.65	<.0000000001	2.13
Death	16,866.9	2,845.9	19,591.7	2,202.4	6.33	129.83	.0000000036	1.07
Bury	521.6	113.0	612.7	122.3	4.57	137.14	.0000105758	0.77

TABLE B4 Comparison of daily Twitter mentions for individual subsistence activities terms before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Farmland	522.0	243.3	651.7	625.4	1.62	89.41	ns	0.27
Farm	22,448.8	7,017.1	30,868.0	10,601.9	5.54	119.72	.0000001814	0.94
Grow vegetables	142.2	143.2	287.3	276.4	3.90	103.57	.0001704624	0.66
Seeds	8,960.8	4,673.7	14,380.4	10,846.4	3.84	93.77	.0002236973	0.65
Shovel	4,107.5	7,009.0	3,743.3	2,912.0	0.40	92.13	ns	0.07
Garden	27,591.4	7,050.5	56,935.6	19,604.9	11.78	86.55	<.0000000001	1.99
Grow plants	433.8	247.7	686.3	447.0	4.13	107.71	.0000707846	0.70
Recipes	7,333.0	1,215.9	15,614.1	4,497.8	14.87	79.03	<.0000000001	0.53
Baking bread	403.3	1,315.9	1,832.1	2,496.4	4.24	104.60	.0000489715	0.72
Sourdough	605.3	430.1	3,392.7	1,797.6	12.62	76.87	<.0000000001	2.13
Cooking directions	8.0	11.5	26.5	87.9	1.75	71.38	ns	0.30
Cook	43,583.8	17,402.8	61,402.9	15,231.8	6.45	135.62	.0000000018	1.09
Sewing machine	628.6	335.1	1,894.9	1,888.0	5.53	73.34	.0000004820	0.93
Sew	2,754.0	1,984.2	8,342.1	11,628.6	3.96	73.01	.0001705039	0.67
Tools	21,841.9	6,587.4	29,157.6	5,594.9	7.08	134.48	<.0000000001	1.20
Home Depot ^a	2,304.7	1,105.0	8,439.9	7,270.9	6.98	72.19	.0000000012	1.18

^aHome Depot is a store chain for purchasing goods related to home repair and home maintenance.

TABLE B5 Comparison of daily mentions on internet forums for individual subsistence activities terms before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Farmland	233.4	163.2	216.8	98.0	0.73	113.08	ns	0.12
Farm	10,403.7	1,163.8	12,287.4	1,573.5	8.05	127.10	<.0000000001	1.36
Grow vegetables	39.0	14.0	82.2	65.7	5.38	75.26	.0000008079	0.91
Seeds	3,027.2	448.6	5,211.2	1,485.2	11.78	81.49	<.0000000001	1.99
Shovel	1,030.3	326.2	1,213.1	267.6	3.63	132.91	.0004095065	0.61
Garden	5,318.1	866.7	11,871.3	2,755.1	18.98	82.52	<.0000000001	3.21
Grow plants	327.6	53.7	486.8	259.8	5.02	74.89	.0000033834	0.85
Recipes	2,701.4	468.3	7,119.5	2,969.4	12.30	72.43	<.0000000001	2.08
Baking bread	107.9	48.4	286.3	125.1	11.13	89.19	<.0000000001	1.88
Sourdough	466.4	108.8	1,476.0	401.1	20.32	79.09	<.0000000001	3.44
Cooking directions	4.2	3.5	9.7	23.4	1.96	72.11	ns	0.33
Cook	7,494.9	1,682.7	9,023.7	1,172.4	6.24	123.21	.0000000066	1.05
Sewing machine	191.3	51.9	422.2	125.6	14.2	91.90	<.0000000001	2.40
Sew	486.3	101.3	791.1	279.8	8.57	86.78	<.0000000001	1.45
Tools	9,441.0	943.5	11,031.2	1,130.4	9.04	133.72	<.0000000001	1.53
Home Depot	939.5	179.2	1,448.2	261.1	13.44	122.22	<.0000000001	2.27

TABLE B6 Comparison of daily blog mentions for individual subsistence activities terms before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Farmland	175.6	52.8	144.3	44.1	3.81	133.82	.0002144122	0.66
Farm	3,073.9	540.0	3,138.9	572.5	0.69	137.53	ns	0.12
Grow vegetables	47.3	13.3	82.5	28.5	9.39	97.93	<.0000000001	1.59
Seeds	1,615.7	214.5	1,988.0	251.8	9.42	134.60	<.0000000001	1.59
Shovel	252.3	60.6	254.9	79.3	0.22	129.12	ns	0.04
Garden	4,405.3	500.2	5,733.0	559.2	14.81	136.32	<.0000000001	2.50
Grow plants	234.9	91.5	255.8	71.1	1.51	130.04	ns	0.25
Recipes	2,291.3	290.6	2,862.7	417.2	9.40	123.20	<.0000000001	1.59
Baking bread	81.2	17.2	224.6	72.6	16.07	76.74	<.0000000001	2.72
Sourdough	93.1	31.4	278.4	84.5	17.19	87.65	<.0000000001	2.91
Cooking directions	10.1	4.1	14.5	4.9	5.78	133.38	.0000000513	0.98
Cook	3,211.1	459.7	4,019.1	579.1	9.14	131.24	<.0000000001	1.55
Sewing machine	126.8	65.4	192.9	84.4	5.18	129.90	.0000008131	0.88
Sew	322.1	50.4	609.0	204.1	11.42	77.37	<.0000000001	1.93
Tools	8,576.3	2,081.1	9,786.6	2,217.9	3.33	137.44	.0011180035	0.56
Home Depot	342.9	76.0	384.5	85.1	3.05	136.28	.0027330810	0.52

TABLE B7 Comparison of daily Twitter mentions for individual terms expressing collectivism before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Sacrifice	22,530.6	6,065.0	47,732.8	35,050.7	5.93	73.13	.0000000939	1.00
Share	305,403.5	39,472.6	378,792.3	68,218.3	7.79	110.55	<.0000000001	1.32
Help	855,104.6	109,113.7	1,175,278.1	266,499.8	9.30	91.50	<.0000000001	1.57
Give	879,845.5	81,087.8	1,041,302.5	168,637.5	7.22	99.29	.0000000011	1.22

TABLE B8 Comparison of daily mentions on internet forums for individual terms expressing collectivism before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Sacrifice	4,074.5	665.5	5,869.4	1,519.3	9.05	94.54	<.0000000001	1.53
Share	46,222.3	4,826.3	55,910.6	5,455.6	11.13	135.98	<.0000000001	1.88
Help	206,099.4	13,084.3	246,181.6	14,499.2	17.17	136.57	<.0000000001	2.90
Give	138,936.2	10,523.3	157,508.9	13,013.2	9.28	132.21	<.0000000001	1.57

TABLE B9 Comparison of daily blog mentions for individual terms expressing collectivism before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Sacrifice	1,696.0	220.4	2,193.6	385.1	9.38	109.84	<.0000000001	1.59
Share	29,304.0	5,145.7	34,052.2	5,243.3	5.41	137.95	.0000002737	0.91
Help	55,564.5	9,296.1	67,034.8	11,834.9	6.38	130.67	.0000000029	1.08
Give	38,145.1	4,483.7	39,921.8	4,817.0	2.26	137.30	.0254760853	0.38

TABLE B10 Comparison of daily Twitter mentions for individual terms representing the aspiration to be rich before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Spend	129,401.3	26,843.9	133,682.4	24,928.7	0.98	137.25	ns	0.17
Lamborghini	1,568.7	531.9	1,980.6	1,326.4	2.41	90.63	ns	0.41
Rolls Royce	1,121.9	784.4	878.5	772.8	1.85	137.97	ns	0.31
Ferrari	4,205.7	3,248.7	4,393.3	4,053.0	0.30	131.76	ns	0.05

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Spend	33,264.8	4,948.1	33,755.0	3,140.1	0.70	116.82	ns	0.12
Lamborghini	583.0	829.5	489.3	377.3	0.86	96.37	ns	0.15
Rolls Royce	176.4	190.9	133.3	52.1	1.82	79.24	ns	0.31
Ferrari	2,019.7	906.8	2,109.2	1,599.6	0.41	109.20	ns	0.07

TABLE B11 Comparison of daily mentions on internet forums for individual terms representing the aspiration to be rich before and after President Trump's emergency declaration, March 13, 2020**TABLE B12** Comparison of the daily blog mentions for individual terms representing the aspiration to be rich before and after President Trump's emergency declaration, March 13, 2020

Term	Before		After		t	df	p	Cohen's d
	M	SD	M	SD				
Spend	10,487.2	1,576.1	11,712.6	1,549.6	4.64	137.96	.0000080652	0.78
Lamborghini	179.3	42.5	162.2	74.8	1.66	109.41	ns	0.28
Rolls Royce	129.0	38.9	137.5	62.9	0.97	115.03	ns	0.16
Ferrari	529.9	221.3	381.7	112.3	5.00	102.34	.0000024355	0.84