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An Examination of Internet Search Behavior and Completed Suicide Rates Across the United States

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AN EXAMINATION OF INTERNET SEARCH BEHAVIOR AND COMPLETED SUICIDE RATES ACROSS THE UNITED STATES

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DISSERTATION APPROVAL

This is to certify that the thesis presented to us by ________Marie Rhoads____________

on the ___14th____ day of ___May_____, 2021, in partial fulfillment of the

requirements for the degree of Doctor of Psychology, has been examined and is

acceptable in both scholarship and literary quality.

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DEDICATION

I’d like to dedicate this dissertation to my mom, Donna DeLia Rhoads. Every day I had with you was a gift. Thank you for teaching me, loving me, and being the best mom I could have ever asked for. Everything I do, I do in your honor and memory.

I’d also like to dedicate this to my brand-new niece, Mia Gabrielle Montes, who is fighting in the NICU. I know you’ve had a rough start in this world, but you have been so brave. You are the first of a new generation in our family and you are so very precious to us. I want you to know that you come from a long line of strong women and you can do anything in this world that you set your mind to.

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ABSTRACT

Suicide remains a leading cause of death in the US (CDC, 2021; Murphy et al., 2018). The literature has shown that individuals seeking information on personal or sensitive topics are likely to utilize the internet (Jacobs et al., 2017; Mok et al., 2015; Pew Research Center, 2019). Research also suggests that internet search behavior can be utilized to track and predict disease outbreak effectively, as well as other public health trends across the nation (Paparrizos et al., 2016; Parker, et al., 2017). Moreover, implicit associations related to suicide have been identified as strong predictors of future suicide (Millner et al., 2018; Nock & Banaji, 2007; Nock et al., 2010). Therefore, internet search behavior related to suicide (especially that which reflects implicit associations between suicide and self) should be explored in order to determine if meaningful relationships exist between search activity and trends in suicide deaths. The purpose of this study was to determine whether a relationship exists between internet search behavior related to suicide and the completed suicide rate throughout the US. Hypotheses for this study were that suicide-related searches are positively predictive of the number of deaths by suicide, while life-affirming searches are negatively predictive of the number of deaths by suicide. In addition, it was hypothesized that frequency of searches for suicide-related terms are higher during the peak suicide month for each state in 2019. Search data from Google trends was statistically analyzed, along with CDC suicide mortality statistics for 2019. Results indicate that the search phrases *how to kill myself* and *painless death* were predictive of completed suicide nationally during 2019. Findings could help to inform future suicide prevention strategies utilizing technology. *Keywords:* suicide, internet search behavior, Google trends.

CHAPTER 1: INTRODUCTION

Statement of the Problem

Current therapeutic interventions rely on patient engagement in traditional psychotherapeutic treatment, which misses much of the population experiencing suicidality. Approximately 50% of individuals considering suicide are not engaged in any type of therapeutic treatment. Of those who are, about half perceive their therapeutic needs as going unmet, despite active engagement in treatment (Han et al., 2014).

The continued high prevalence of completed suicide (CDC, 2021; Murphy et al., 2018) represents a distinct failure by the field of psychology to meet the needs of this population in more adaptive and accessible ways. The development of effective global suicide prevention strategies is one of the most urgent unmet needs in our field, for this is the sole behavioral phenomenon that does not offer additional opportunities for effective intervention. In addition, when a community or family experiences a death by suicide, there are pervasive negative impacts on mental health and functioning for all those affected, as well as a ripple effect for additional suicides for those exposed to the news (Niederkrotenthaler et al., 2010; Ribeiro et al., 2016). It is imperative to begin thinking on a more global scale about ways to identify those in need and to adapt interventions based on what we understand about human behavior preceding suicide.

More global internet-based strategies for identifying suicidal individuals should be explored in this technological age (Christensen et al., 2014). This may potentially help us to identify critical intervention points based on internet behavior and to develop technology-based strategies for offering immediate help in real time if concerning activity is recognized. Overall, this information may aid in the efficient delivery of critical psychological and therapeutic services that we aspire to provide as a field.

Through analysis of internet behavior, we may be able to deepen our understanding of what types of search queries indicate risk of suicide, if there is any potential to intervene during the planning stage of suicide (or other critical intervention points), and if there is any potential for implementation of global prevention strategies using technology.

Purpose of the Study

The purpose of this study was to determine whether a significant and meaningful relationship exists between internet behavior and suicide rate by state in the USA. The literature has shown that individuals are likely to seek information from the internet on topics that are personal or sensitive in nature (e.g., mental health, physical health, etc.) (Jacobs et al., 2017; Mok et al., 2015; Pew Research Center, 2019). Therefore, it is reasonable to assume that individuals who are contemplating suicide are likely to utilize the internet to obtain information. In addition, implicit associations between suicide and the self (reflected in *SI-IAT* outcomes) appear to be associated with high risk of completing suicide six months post-test (Millner et al., 2018; Nock & Banaji, 2007; Nock et al., 2010).

The interplay between these two variables was explored through evaluation of the relationship between internet search behavior and completed suicide statistics. It is important to understand the nature of the relationship between internet behavior and suicide risk in order to identify salient information that may help inform global prevention efforts aimed at reaching more individuals experiencing suicidality who may not be engaged in treatment. It is vital to discover if warning signs of future suicidal behavior can be identified through specific patterns of internet use. If a meaningful relationship between these two variables emerge, it would be important to understand and explore relevant patterns.

There are various implications of potential findings. Information could be utilized to identify geographical regions that might be at higher risk for experiencing local suicide epidemics. Moreover, it may offer opportunities to implement appropriate strategic interventions to ensure that adequate support is accessible to those who need it most. The findings may inform public health initiatives throughout the world.

Hypotheses

The purpose of this study was to determine if a significant relationship exists between internet search behavior and completed suicide rate (examined by state) throughout the USA; if so, what useful information can be derived about the relationship between these two factors? In the current study, suicide-related terms and phrases were examined as they relate to completed suicide rates in a specific geographical region.

The hypotheses for this study are:

1. Suicide-related searches (e.g., *suicide, depression, want to die, how to kill myself, painless death*) are positively predictive of number of deaths, but life-affirming searches (e.g., *alive*, *living*) are negatively predictive of the number of deaths by suicide nationally in 2019.
2. Suicide-related search terms (e.g., *suicide, depression, want to die, how to kill myself, painless death)* are searched more frequently during peak-suicide months (analyzed by state) throughout 2019.

CHAPTER 2: REVIEW OF THE LITERATURE

Introduction

Suicide is a widely recognized public health issue and a leading cause of death both in the United States and internationally. An estimated 800,000 deaths by suicide occur worldwide each year (World Health Organization [WHO], 2021). According to a systematic analysis of mortality, more people die from suicide each year than by homicide and war combined (Lozano et al., 2012).

Based on the *National Vital Statistics System* (NVSS) mortality data for 2019, suicide remains the 10th leading cause of death in the United States (Centers for Disease Control [CDC], 2021; Murphy et al., 2018). Although some fluctuations in suicide rates have been observed in the United States over the decades, frequency of suicide remains a point of clinical concern and national attention, as it is the most common cause of preventable death (Chesney et al., 2014).

Suicide is defined as the infliction of harm to the self with intention to cause death. If the self-inflicted harm ultimately causes death, this is considered a completed suicide. If the individual who intended to die survives, this considered a suicide attempt (CDC, 2020; Klonsky et al., 2016; WHO, 2014).

Despite the high prevalence and concern, suicide remains poorly understood. It is clear that the etiology of this behavioral phenomenon is complex. There are also some confounding features unique to suicide, which have made it particularly challenging to study, such as navigating complex ethical considerations associated with researching vulnerable populations, mitigating errors related to misreporting and disclosure, and the obvious inability to study individuals who have completed suicide (apart from performing psychological autopsies).

In addition, finding appropriate participants for suicide-related research has been challenging, due to the potential for causing additional harm and stigma-related barriers that inhibit engagement. Creative approaches must be explored in order to inform and advance effective prevention and intervention efforts, while simultaneously ensuring protection of our most vulnerable.

Prevalence. As previously stated, suicide remains a leading cause of death in the US. In 2019, there were 47,511 suicide deaths (14.5 per 100,000 population) in the US (National Center for Health Statistics, 2021). In general, suicide rates are reported as the number of people who have died by suicide per 100,000 in the population. This standardization has allowed suicide rates to be more readily comparable between populations of various sizes, as well as tracking trends over time in a specific population relative to population size changes (Chesney et al., 2014; Murphy et al., 2018).

Suicide Methods. Common methods of suicide in the US include self-inflicted gunshot wounds, asphyxiation, and self-poisoning. According to the *National Vital Statistics Report* for 2019, suicide by firearm accounted for 23,941 deaths (7.3 per 100,000). Suicide by suffocation accounted for 13,563 deaths (4.1 per 100,000), and suicide by poisoning accounted for 6,125 deaths (1.9 per 100,000) in the USA (CDC, 2021). In fact, suicide by firearm is higher in the United States than in any other country in the world (Anglemyer et al., 2014).

It is an unfortunate truth that suicide statistics are commonly underreported or misreported based on a range of factors. For example, certain methods of suicide may appear unintentional (e.g., car accidents, drug overdoses) and without additional data (e.g., suicide notes) or the ability to obtain critical information from the individual themselves, intent is impossible to determine. These ambiguous methods can be misinterpreted as accidental deaths, distorting suicide statistics (WHO, 2014).

In addition, the stigma related to suicide may influence the way in which it is reported when methods are ambiguous. For example, family members may be unable to reconcile the possibility of suicide with their memory of a lost loved one, and therefore selectively attend to or rationalize certain circumstances surrounding their loved one’s death. Stigma can also influence professionals involved in determining cause of death (e.g., medical examiners, law enforcement officers), affecting their interpretation of investigation results, and the way in which cases of ambiguous death are conceptualized/ explained (Anglemyer et al., 2014). All these factors create bias in suicide reporting, thereby increasing the likelihood that current statistics do not accurately reflect the true prevalence (Fleischmann & De Leo, 2014).

Epidemiology

Age. Age differences have been observed in suicide deaths. Suicide is the second most common cause of death among 15–29 year-olds globally (WHO, 2018). In the United States, mortality statistics for 2019 reflected that suicide was the second most common cause of death in multiple age cohorts, including ages 10–14, 15–24, and 25–34. In addition, suicide was the fourth most common cause of death for individuals ages 35–44 and 45–54 (CDC, 2021). The rate of suicide increases in adults 75 and older. However, suicide is particularly underreported in older adults, due to a societal tendency to attribute death in older adults to health issues rather than considering other possibilities (WHO, 2014).

Gender. In terms of gender, some differences have been observed in the literature. Completed suicide is more common among men, but suicide attempts are more common among women (Ayers et al., 2013; Nock et al., 2008). This disparity has been observed across adolescence and adulthood (McLoughlin et al., 2015).

Men tend to use more lethal methods when attempting suicide, which has contributed to the higher instance of completed suicide in males (Ayers et al., 2013). In the United States, men are more likely to use a firearm, but women are more likely to self-poison (e.g., overdose, ingest chemicals). Despite more women attempting suicide, their survival rate is higher than among male attempters (Ayers et al., 2013). Nonfatal suicidal behavior appears to be most common in women, particularly in women who are younger, unmarried, or diagnosed with a psychiatric disorder (Nock et al., 2008).

Observed gender differences in completed suicide in the US may also be influenced by social-cultural factors, as this gender disparity is not observed in other areas of the world (e.g., China, India), where women tend to complete suicide more often than men (McLoughlin et al., 2015). Socialization in the US tends to reward aggressive behavior in men, which may influence the likelihood of American men to use more lethal methods when attempting suicide, subsequently leading to higher rates of death by suicide (Lester, 2008).

Race. Suicide rates also vary by race. According to US mortality statistics for 2019, the suicide rate for Native American and Alaska Natives was 22.15 per 100,000, which was the highest of all racial groups. In 2019, suicide rates were 17.83 per 100,000 among Whites, 6.89 per 100,000 among Hispanics, 6.85 per 100,000 among Blacks, and 6.75 per 100,000 among Asian/Pacific Islanders (CDC, 2021).

Disparities in suicide rates relative to race have been observed in research. Suicide rates were compared among five distinct groups: 1) White, non-Hispanic; 2) Blacks, non-Hispanic; 3) Hispanic; 4) Asian or Pacific Islander; and 5) Native American or Alaskan Native. Analysis revealed that suicide rates were highest among the Native American or Alaskan Native population for both males (34.3 deaths per 100,000) and females (9.9 deaths per 100,000) (Jiang et al., 2015).

This means that Native American or Alaskan Native men in particular are more than twice as likely to complete suicide in comparison to any other combination of gender and race (Jiang, et al., 2015). Furthermore, suicide rates among native populations have also been commonly underreported. It is likely that their elevated reported rates are still gross underestimations, indicating an even larger disparity in suicide between Native American and Alaskan native men and other groups (Jiang et al., 2015).

Sexual Orientation & Gender Identity. In the LGBTQ population, suicide risk is significantly higher than in heterosexual or cisgender individuals (CDC, 2021). In fact, individuals who identify as LGBTQ are four to six times more likely to attempt suicide in their lifetime (Aranmolate et al., 2017). Factors that influence risk for this population include familial and societal stigma increasing the risk of homelessness and other psychosocial stressors. In addition, LGBTQ individuals experience higher levels of discrimination and social isolation, amplifying the risk of mental health issues and suicide.

Seasonality. Research has identified patterns of seasonality in suicide. Significantly higher rates of completed suicides occur during the late spring and summer months (Woo et al., 2012). It appears that violent methods of suicide (e.g., hanging, firearms, jumping from heights) are more common during the spring season, especially in men. Violent methods of suicide tend to peak during the spring and summer months and decline during the winter (Woo et al., 2012). Both male and female suicide rates tend to be higher during the spring i.e., April and May, and summer months, i.e., June to August, in comparison to the winter months, i.e., November to February (Woo et al., 2012).

Seasonal patterns also have been observed in individuals seeking suicide-related information online, indicating that individuals are somewhat more likely to seek suicide-related information online in the winter rather than summer months (Ayers et al., 2013).

Risk Factors

Research has identified various factors associated with suicide risk. Recognized risk factors for suicide include mental illness (e.g., depression, bipolar disorder, schizophrenia, borderline personality disorder), previous attempts, self-harm, substance abuse, gambling, exposure to trauma (e.g., childhood abuse, violence, war), medical conditions (e.g., chronic pain, diabetes), and certain psychosocial stressors (e.g., divorce, living alone; Franklin et al., 2017; Kessler et al., 1999; Yoshimasu et al., 2008).

Individualized risk factors. Individualized risk factors include any internal states, traits, or experiences specific to a person that increase risk of suicide.

Mental illness. A variety of mental health issues have been linked to suicide risk. These mental health issues chiefly comprise depression, bipolar disorder, schizophrenia, and borderline personality disorder (Arsenault-Lapierre et al., 2004; Chesney et al., 2014;

Ribeiro et al., 2016; Richard-Devantoy et al., 2014; Walker et al., 2015; Yoshimasu et al., 2008). These specific mental health issues serve to increase the risk of suicide in the individuals who experience them, because the associated symptoms tend to be distressing and disruptive to functioning.

In terms of depression, the commonly experienced symptom, hopelessness, (during a major depressive episode, for example) may elicit suicidality in individuals by blocking their ability to visualize any improvement in their symptoms or circumstances in the future (Richard-Devantoy, et al., 2014). In bipolar disorder, the distinct pattern of extreme mood shifts (i.e., fluctuating from symptoms of mania to depression) may lead to increased suicide risk, especially towards the end of a manic episode, in anticipation of the subsequent depressive episode. This dangerous combination of anticipatory distress and sufficient energy to act before shifting into depression creates the time of highest risk for suicide in individuals with bipolar disorder (Chesney et al., 2014).

Individuals with schizophrenia have an increased risk of suicide if symptoms are unaddressed or poorly managed. Schizophrenia typically includes positive symptoms (i.e., hallucinations, delusions) that can become extremely distressing and overwhelming to individuals without psychopharmacological intervention. Individuals with insight might fear the onset of positive psychotic symptoms during residual times or generally fear the mental disintegration associated with schizophrenia, which increases suicide risk. In addition, those with high levels of agitation and poor adherence to treatment have the highest risk of suicide (Hawton et al., 2005). Conversely, a reduced risk of suicide has been associated with the presence of active hallucinations, which makes sense, because any baseline insight will be diminished during active psychosis (Hawton et al., 2005).

Individuals with the aforementioned diagnoses typically consider suicide as a way to end the pain or escape the distressing symptoms they are experiencing. Suicide might also be considered to reduce the self-perceived burden they put on others (Arsenault-Lapierre et al., 2004; Chesney et al., 2014; Ribeiro et al., 2016; Richard-Devantoy et al., 2014; Walker et al., 2015; Yoshimasu et al., 2008).

Another population with increased risk are those individuals with borderline personality disorder. These individuals are at a higher risk of suicide attempts compared to the general public (Black et al., 2004). This is likely due to extreme difficulty with emotion regulation, inhibitory control, and interpersonal functioning, commonly stemming from neglect, abuse, and/or invalidation during childhood (Black et al., 2004).

However, intent and motivation behind suicidal behavior may be more relational in nature for this population. For example, these individuals may make suicidal gestures or attempts in order to elicit attention, reaction, or for the purposes of retaliation after perceived slights, rejection, or abandonment (Black et al., 2004). This type of gesture is commonly referred to as *parasuicidal* behavior, because death is not the intent. These attempts are typically less lethal and statistically less likely to end in death, as compared to attempts made for the purposes of ending suffering or removing the self-perceived burden imposed on loved ones. However, parasuicide can still lead to death and is a risk factor for eventual suicide completion, so it should be treated with the same level of seriousness as any other attempt (Chesney et al., 2014; Ribeiro et al., 2016; Walker et al., 2015).

When individuals receive proper treatment for their respective mental health disorder, fortunately a decrease appears in associated suicide risk (Baldessarini et al., 2006; Hawton et al., 2005). For example, patients diagnosed with bipolar disorder who were engaged in long-term lithium treatment showed a decreased risk for both completed suicide and suicide attempts (Baldessarini et al., 2006).

Previous attempts. Previous attempts have been widely recognized as one of the strongest predictors of future suicide (Beck & Steer, 1989; Franklin et al., 2017). Any past attempts, regardless of the intervening agent (i.e., external, internal, or chance) that led to survival, increased the risk for future suicide (Burke et al., 2016). No difference appeared in lethality of method or intention to die between interrupted /aborted suicide attempters and actual suicide attempters, indicating that any serious suicidal behavior is important to consider when evaluating risk (Burke et al., 2016). Past behavior provides valuable insight into potential future behavior and risk.

Behavior. When other problematic behaviors are present, these can compound suicide risk. For example, increasing substance abuse and compulsive gambling are often associated with higher risk of situational stressors and suicide (Franklin et al., 2017). These behaviors are also often associated with reduced inhibition and diminished impulse control, two factors that considerably increase suicide risk. These problems can be indicative of other trait vulnerabilities that tend to increase risk, namely impulsivity (Beck & Steer, 1989; Franklin et al., 2017; Klonsky et al., 2016).

Hereditability. Hereditability also plays a role in suicide risk. For example, family history of suicide is one factor that increases risk (Brent & Mann, 2005). Magnitude of effect on risk increases with degree of relation. So, the death of first-degree relative by suicide (in comparison to a second-degree relative) puts an individual at a higher risk of suicide (Brent & Mann, 2005; Baldessarini & Hennen, 2004; Qin et al., 2002). Studies have indicated a significantly higher risk of completed suicide among biological, as opposed to adoptive, relatives of suicidal persons (Baldessarini & Hennen, 2004).

Genetics & neurobiology. Genetic influences on suicidal behavior have been investigated in the literature as well. Research in molecular genetics has investigated possible associations between genes required for central serotonergic neurotransmission and suicidal behavior in order to identify suicidal phenotypes (Baldessarini & Hennen, 2004; Brezo et al., 2008). However, much is still unclear about the role genetics play in suicide, due to the complexities of gene-environment interactions (Brezo et al., 2008).

Research into individuals with a history of suicidal behavior implicates the role of the *brain-derived neurotrophic factor* (BDNF) gene, which is a protein that works in the central nervous system to regulate essential processes underlying learning and memory (i.e., *synaptogenesis* and *synaptic plasticity*). Certain variations in BDNF are under investigation to determine what role (if any) this gene plays in relation to the risk of suicidal behavior (Zai et al., 2012). Findings have indicated that for the Met-carrying genotypes and Met allele, the presence of certain markers (i.e., BDNF rs6265 Val66Met) significantly impacted suicide risk. It appears that the makeup and functioning of BDNF Val66Met is involved in some capacity with the expression of suicidality. However, the precise mechanisms of involvement remain unclear. These findings lend support to the hypothesis that certain genotypes may represent a predisposition or vulnerability to suicidal behavior due to their potential implications for cognitive functioning (Zai et al., 2012).

Cognitive functioning. Implications of these genetic vulnerability factors may interfere with cognitive processes essential to reducing risk of suicidal behavior. Memory plays a key role in effective problem solving, learning, coping, and planning (Richard-Devantoy et al., 2015). Impulsivity and problem-solving deficits are commonly observed in individuals with higher risk of suicide. In addition, cognitive functioning deficits in certain areas (e.g., mental flexibility, emotion regulation, inhibitory control, executive function, and perspective taking), as well as the presence of certain cognitive styles (e.g., over-general memory, trait-like maladaptive thinking, polarized thinking) have all appeared to be vulnerability factors associated with suicidality (Richard-Devantoy et al., 2015; Wenzel & Beck, 2008).

External risk factors. In addition, there are many external factors that can influence suicide risk. According to the *Practice Guidelines for the Assessment and Treatment of Patients with Suicidal Behaviors* (APA, 2013) certain interpersonal, social, and societal level factors have been observed to raise an individual's risk.

Stress. Early exposure to stress in the form of adverse childhood experiences can impact an individual's developmental trajectory and increase likelihood of suicide later in life (Sachs-Ericsson et al., 2016). These adverse childhood events include exposure to abuse (e.g., physical, sexual, or emotional), neglect, trauma, toxic stress (i.e., lack of safety, shelter, or sufficient resources to meet basic needs), and parental distress or disfunction (e.g., domestic abuse, substance use, mental health illness, and/or incarceration). It has become clear that this type of exposure impacts developing individuals on a psychosocial level, but it also impacts the physiological functions of the body. Chronic exposure to childhood stress can lead to dysregulated activity in the body's stress response system (i.e., *hypothalamic pituitary adrenal* [HPA] axis), which deleteriously affects cortisol production over a lifetime (O'Connor et al., 2016). Research has indicated that blunted cortisol reactivity to stress in adulthood (commonly the product of exposure to toxic stress during childhood) is associated with suicidal behavior. HPA axis regulation and cortisol production have been identified as serving as a protective factor against suicidal behavior (O'Connor et al., 2016).

Relational and circumstantial. The interpersonal and circumstance-related factors identified as tending to have the most significant influence on suicide risk include lacking social support, living alone, and having poor familial relationships. In addition, certain life experiences or circumstances, such as divorce and unemployment, tend to increase risk (APA, 2013). Other psychosocial stressors acknowledged to increase suicide risk include low socio-economic status, recent break ups, social isolation, major surgery, physical injury and illness, and loss. (Franklin et al., 2017).

Societal. Various societal-level factors may impact risk. These factors can include cultural norms of behavior, religious beliefs, stigma, attitudes toward mental health treatment, and a variety of other overt and covert influences. For example, in certain religions (e.g., Catholicism), suicide is considered a sin, and those who die by suicide are punished in the afterlife (Gearing & Lizardi, 2009; Lester, 2008). Such beliefs commonly influence the thought processes about suicide in individuals exposed to them and ultimately affects suicide risk (Ribeiro et al., 2016).

Due to the variation between religions and their beliefs and practices, it is difficult to reckon reliably how these factors influence risk. In general, a variation in tolerance level of suicide exists, based on dogma. Some religions are ambivalent about suicide, and others even accept suicide. Still other religions explicitly condemn suicide (Stack &

Kposowa, 2011). It is still unclear to researchers how the perceived level of tolerance impacts risk of suicide at an individual level.

Trends in suicide across various religious groups have been observed in the literature, indicating some variation in risk possibly related to religion. In general, suicide rates appear to be lower in religious countries than in secular countries (Gearing & Lizardi, 2009; Hsieh, 2017). In addition, some evidence of slightly lower rates of suicide has been observed in conservative Christian groups (e.g., Catholics, evangelical Baptists) in comparison to other Protestant faiths (Torgler & Schaltegger, 2014). A relatively low suicide rate has been observed among Jews (whose religion traditionally condemns suicide) in both the United States and Israel. However, suicide rates among Jews living in Israel are even lower than in the United States (Cook, 2014; Gearing & Lizardi, 2009).

Variation in suicide rates is likely influenced by a multitude of factors, including regional and local norms, values, and culture, as well as moral interpretation, variation in observance, religious institutional conditions, reporting practices, stigma, etc. (Cook, 2014; Gearing & Lizardi, 2009; Hsieh, 2017; Torgler & Schaltegger, 2014). The intersectional influences of society, culture, and geographical factors are nearly impossible to disentangle, complicated further by the global variations in suicide reporting practices. For all these reasons, it has proved very challenging to interpret these statistics in a meaningful way.

In addition, stigma and attitudes toward mental health treatment can impact risk and reporting. Stigma-related concerns can cause reluctance to seek help in individuals who are experiencing suicidal thoughts, which influences risk (Lester, 2008; McLoughlin et al., 2015; Ribeiro et al., 2016; Wenzel & Beck, 2008).

Access and exposure. Other tertiary factors that increase risk include access to firearms, which is associated with an increased risk for completing suicide, as well as being a victim of homicide (Anglemyer et al., 2014). In addition, exposure to other suicides (of relatives or not), local suicide epidemics, and barriers to mental health treatment increase risk (Ribeiro et al., 2016).

Even with this extensive knowledge of the risk factors for suicide, there has been limited success in utilizing this knowledge to identify at-risk individuals and prevent suicides on a global scale.

Media Reporting & Risk

Media reporting is another factor that can influence suicide risk. Research suggests that media reporting of a celebrity suicide is usually followed by an increased rate of attempted and completed suicides. This effect is particularly salient following high-profile celebrity deaths (Neiderkrotenthaler et al., 2012). The phenomenon of suicide imitation is referred to as the "*Werther Effect*" (Kumar et al., 2015). Discrete periods of increased deaths by suicide following reports of celebrity suicide have been observed all over the world. This spike in subsequent suicides typically lasts anywhere from a few weeks to a month after the media's initial reports about a celebrity (Cheng et al., 2007; Cheng et al., 2007). A limited amount of research indicates that both short-term and long-term increases in suicidal ideation are observed after celebrity suicide among those exposed to media reporting (Fu & Yip, 2007).

The influence of media reporting was especially high for males, and for persons who made a prior suicide attempt within the last year (Cheng et al., 2007). Studies also demonstrated that those who were already experiencing active suicidality were the individuals most susceptible to the Werther effect. Some research has emerged that cautions against drawing too direct a linkage between media reporting and peaks in suicide, arguing that the nature of the observed connection is more complex and should not be overgeneralized (Mueller, 2017). Nevertheless, most research on this topic has supported the notion of an association between media reporting and increased suicide rates (Sisask & Varnik, 2012).

The nature of this observed relationship between media reporting and suicide is not well understood; however, it has been theorized that this phenomenon may originate in the modeling effect of social learning. Other theories to explain the relationship cited the effects tradition, observer characteristics, media message comprehension, as well as the meaning making derived from the report (Arendt et al., 2018; Blood & Pirkis, 2001).

A recent study analyzed posts on Twitter in reaction to celebrity suicides covered by media. Subsequent increases in suicide were observed in relation to the number of reaction posts on social media. In celebrity suicide cases that were well covered but did not garner high levels of social media attention (e.g., a high number of Twitter posts reacting to the death), no significant increase in subsequent suicide attempts was observed. A significant increase in suicide was observed only in those cases in which a large number of Twitter posts reacted to a celebrity suicide (Ueda et al., 2017).

Some preliminary investigation has begun into the effects of reporting on positive coping strategies potentially having a negative correlation with copycat suicide

(Niederkrotenthaler et al., 2010). Very limited research in this area has been published as yet, so it is unclear how reporting on positive coping strategies might influence copycat suicide effects.

Guidelines for media outlets on safe reporting practices have been established to reduce risk of imitation suicides (WHO, 2017). These guidelines provide recommendations aimed at reducing the use of sensationalizing or glorifying headlines (or text), the inclusion of pictures, reporting on the method of suicide, and placement of suicide-related headlines. When followed, these guidelines have successfully diminished instances of imitative suicide to varying degrees around the world (Bohanna & Wang, 2012; WHO, 2017). The effectiveness of these guidelines is critically dependent on media sources' awareness, access, and adherence to these responsible reporting guidelines (Bohanna & Wang, 2012).

Interventions

The following is an overview of intervention strategies currently utilized or available in the United States. Evidence concerning the effectiveness of these strategies is presented based on the latest research.

Mental health treatment. According to a national survey, only about 50% of individuals who have had suicidal ideation, plans, or attempts in the past year reported contact with a mental health professional (Stanley et al., 2015). Among those individuals who did receive mental health treatment, about half perceived the persistence of unmet treatment needs, according to a study of mental health treatment patterns among recent suicide attempters in the United States (Han et al., 2014).

Current psychotherapeutic approaches to suicide intervention rely on patient engagement in treatment and therefore fail to reach much of the target population. Compounding the already clear limitation of low patient engagement, only about half of those who received treatment felt that their treatment needs were met (Han et al., 2014).

Furthermore, the successful delivery of psychotherapeutic intervention relies on both patient disclosure/self-report and provider skill, which reciprocally affect one another. A patient's willingness to disclose suicidality depends on a variety of factors, including therapeutic rapport and trust, as well as patient understanding of the therapeutic process (e.g., informed consent and confidentiality) related to safety concerns. Even in cases where a clinician can clearly identify the warning signs associated with suicide and utilize appropriate clinical interventions, the issue of self-report remains. Self-report has not, unfortunately, been a reliable measure of suicidality and is easily influenced by a variety of confounding factors (Barnes et al., 2017), which demonstrates another limitation of current suicide assessment and intervention techniques.

Assessment. If an individual is engaged in treatment and discloses active suicidal ideation, a well-trained mental health professional will begin to conduct a comprehensive suicide assessment. This typically involves gathering data through clinical interviews, as well as the use of an empirically supported instrument to assess suicidality and determine if imminent risk of harm is present (Runeson et al., 2017)

Some widely used assessment tools are available to measure risk of suicide. The *Columbia-Suicide Severity Rating Scale* (C-SSRS) is a commonly utilized suicide assessment tool that can be administered by various professionals, including physicians, psychologists, nurses, social workers, and teachers. In addition, the SAFE-T (*Suicide*

Assessment Five-Step Evaluation & Triage) is a brief screener and tool that helps gauge risk based on a variety of factors. In addition, the *Beck Hopelessness Scale* is also used to assess suicidality and has shown some ability to detect future risk, but with low sensitivity (McMillan et al., 2007). Empirical findings regarding the effectiveness of all these self-report assessment tools are mixed (Bolton et al., 2015).

Due to the mixed evidence regarding the efficacy of these self-report measures, it is important that other options be considered for detecting and assessing suicidality. This is where indirect measures could be useful. One benefit of indirect measures would be that they are less sensitive to self-report biases, at least in theory. Moreover, indirect measures are less reliant on subjective interpretation of experience or insight into one's own mental health.

A brief performance-based test has been investigated as a possible assessment tool for predicting suicidal behavior that is less influenced by self-report biases. The *Self-Injury Implicit Association Test* (SI-IAT) is a measure of implicit associations between self-injury and the self, in which findings are based on reaction time (as opposed to self-report). This measure's intent is to accurately detect and predict suicidal ideation and future attempts (Nock, & Banaji, 2007). This assessment seems to show some promise in its ability to predict future suicide and will be further discussed later in the current study. If no identifiable threat of imminent harm appears to be present after completing a comprehensive risk assessment, then a clinician will likely collaborate with the patient to create a safety plan.

Safety planning. Safety plans serve as a preventative therapeutic tool to use with patients experiencing active or increasing suicidal ideation. These plans typically include predetermined steps and vetted resources for support along with contact information. The reason safety plans can be effective is that they offer suicidal individuals problem-solving support during high-distress times by illuminating options apart from suicide and clear routes for support established prior to crisis (Stanley & Brown, 2012).

Safety plans may also include preemptive measures that create a delay between decision and action (in order to reduce the chance of follow through). Preemptive measures may insert barriers or extra steps into the process (e.g., storing ammunition separately from a gun, giving a trusted friend or family member control of passcodes, keeping medication locked, or having a loved one temporarily manage medications for a suicidal individual) to permit time for higher-level thinking or allow opportunity for social interference (Stanley & Brown, 2012).

Cognitive behavioral therapy. *Cognitive behavioral therapy* (CBT) appears to significantly reduce suicidal behavior in adults when utilized for treatment. According to a meta-analysis intended to evaluate the efficacy of CBT treatment in reducing suicidal behavior, a CBT approach was effective in reducing suicide risk. The positive effects of CBT treatment on suicide risk were observed during active treatment engagement, as well as up to three months post-treatment (Mewton & Andrews, 2016; Tarrier et al., 2008). This indicates that although CBT is an effective treatment method, additional longer-term solutions may be required to supplement the benefits of CBT over time. In addition, CBT treatment for individuals experiencing suicidality appeared to be most effective when delivered to patients individually, as opposed to group settings (Tarrier et. al., 2008). This will be an important factor to consider when developing effective treatment options for this population in the future. In comparison to other treatment approaches, CBT appears to be one of the more promising therapeutic interventions for addressing suicidality yet developed (Mewton & Andrews, 2016).

A third wave CBT psychotherapy called *Dialectical Behavior Therapy* (DBT) is geared toward helping individuals regulate emotions, build interpersonal effectiveness skills, and increase distress tolerance. DBT has proved a particularly effective therapeutic approach for individuals diagnosed with borderline personality disorder and can be effective in reducing suicidal behavior (DeCou, Comtois, & Landes, 2019).

Psychiatric hospitalizations. In the US, one commonly utilized intervention strategy for individuals experiencing active suicidal ideation is psychiatric hospitalization. This can be done voluntarily (i.e., an individual agrees to be hospitalized and enters treatment of their own volition), or involuntarily (i.e., an individual is deemed to pose an imminent risk for harming themselves or others, or, is otherwise unable to establish or maintain personal safety to a reasonable degree). This strategy is only utilized when harm is imminent (e.g., patient has expressed a clear *plan*, has access to lethal *means*, and/or expresses the *intent* to end their life). Psychiatric hospitalizations offer a temporary solution for suicidal individuals. The contemporary aim of psychiatric hospitals is to provide a safe environment for the patient while their mental health is stabilized through short-term care and medication management. After the patient is stabilized (i.e., they can ensure their personal safety outside the hospital), they are transitioned out of inpatient care with a discharge plan (typically comprised of a step-down referral for treatment and instructions for continued care). However, risk of suicide post discharge is high, especially during the months immediately after discharge (Chung et al., 2017). Risk can remain high many years after discharge, and research has struggled to identify exactly which factors might maintain high suicide risk post discharge (Large et al., 2011).

Means restriction. One strategy that appears to be effective in reducing suicide is the installation of physical barriers or other structural safety measures at common suicide sites. Research suggests that structural interventions at suicide “hot spots” significantly reduced the occurrence of suicide at those locations. Slight increases in completed suicides were observed at neighboring suicide spots; however, an overall reduction in suicide by jumping was observed across all sites (Pirkis et al., 2013).

In addition, safety measures that restricted access to means or encouraged help-seeking (i.e., signs) both seemed to reduce risk of suicide significantly (Pirkis et al., 2015).

Prevention

Suicides are preventable. The implementation of timely, evidence-based interventions provides an opportunity to reduce the overall incidence of suicide. If we strategize effectively and use the right forums to reach individuals contemplating suicide, we face a clear need for prevention strategies that are more global in reach.

At present, global intervention strategies that identify and reach those who are contemplating suicide are limited at best. More effective, global screening techniques are needed to detect suicidality in the population. The best forum for these screening techniques is online. There are some current E-health interventions aimed at reducing suicide risk that include online screening tools for identifying suicide risk, as well as proactive intervention strategies delivered after identifying individuals at-risk for suicide based on their social media posts (Christensen et al., 2014).

At present, few controlled studies exist regarding the efficacy of online suicide screenings in reducing suicidal behavior or ideation. However, there is evidence that online screenings would be a feasible, promising way to identify individuals experiencing suicidality. The potential of online screenings to reduce suicide, though, requires much more research to determine its effectiveness in suicide prevention (Christensen, Batterham, & O'Dea, 2014).

Studies have also demonstrated the potential for automated analysis of sentiment in social media posts, as well as the prospective use of data mining to identify users at risk of suicide. Social media may be a viable instrument for monitoring suicide risk in real time (on a larger scale). As with most of these developing areas of study, more research is needed to determine the validity of these methods, as well as identifying practical mechanisms for providing support through these forums.

The effectiveness of E-health interventions in managing and reducing suicidal thoughts requires extensive research; however, it appears that web-based interventions have the greatest potential to reach individuals most in need during critical times (Christensen et al., 2014; Sampri et al., 2016).

Implicit Associations and Suicide

The *Implicit-Association Test* (IAT) is a measure designed to detect the strength of automatic associations between mental representations of various concepts in memory (Lane et al., 2007). One subtest of this measure, referred to as the Self-Injury Implicit Association Test (SI-IAT), is designed to reflect implicit associations between self-injury, death, suicide, and the self.

There is evidence that the IAT offers significantly higher predictive validity in comparison to self-report measures, because the IAT is less susceptible to impression-management attempts and other types of self-reporting bias. Self-report measures are particularly skewed when measuring socially sensitive topics (Greenwald et al., 2009), making self-report measures even less likely to accurately reflect suicidality.

According to Harrison, Stritzke, Fay, and Ellison (2014), the SI-IAT was able to significantly predict five out of six indicators of suicide risk (i.e., suicide ideation frequency and intensity, depression, non-suicidal self-harm thought frequency and intensity, and nonsuicidal self-harm attempts), well over the strongest traditional indicators of risk (i.e., history of prior suicide attempts). Implicit associations between self-injury, suicide, and the self were associated with an increased risk of making a suicide attempt in various populations (Barnes et al., 2017; Chiurliza et al., 2018; Kene, et al., 2017; Millner et al., 2018; Nock & Banaji, 2007). In fact, for those who demonstrated an implicit association between suicide and self, risk of making a suicide attempt within six months was approximately six times higher in comparison with those who did not show that implicit association. The literature indicates that implicit associations are strong predictors of suicidal behavior (Nock et al., 2010).

Recently, an extensive replication study was conducted in order to determine if findings regarding implicit associations and suicide would align with those of previous studies. The results demonstrated that implicit associations were stronger in individuals with a history of suicide attempts than in those without a history of suicide attempts). Furthermore, implicit associations appeared to be even stronger among individuals who have had more recent and more lethal suicide attempts (Glenn et al., 2017). These results reinforced a connection between suicidal behavior and implicit associations.

Overall, implicit associations related to self-injury, death, and suicide were associated with risk of suicide (Nock et. al, 2010). In addition, outcomes on the self-injury subtest of the IAT appear to be predictive of suicidal ideation (Ellis et al., 2016; Glashouwer et al., 2010).

Conversely, there has been criticism of the IAT, identifying certain shortcomings that are important to address for the purposes of this study. First, some literature has cited concerns about the reliability of the IAT (Blanton et al., 2009), suggesting that it demonstrates lower test-retest reliability (r = .55) than what is generally deemed acceptable (r = .8). However, this low estimate of test-retest reliability was calculated across various subtests of the IAT, making it difficult to distinguish the reliability of individual subtests. Overall, sufficient investigation into the test-retest reliability of the various subtests of the IAT is lacking, therefore very little empirical data has been gathered to refute or support these claims.

Validity of the IAT has also been challenged by assertions that certain subtests of the IAT may not directly measure what is purported, particularly in reference to the IAT subtest intended to measure implicit bias in racial attitudes/ associations (Oswald et al., 2013; Rezaei, 2011). Concerns have been raised about the IAT's findings of implicit bias not translating to real-world demonstrations of explicitly biased behavior. Therefore, doubt has surfaced regarding the test's ability to predict individual behavior with a useful degree of accuracy (Blanton et al., 2009; Oswald et al., 2013). Last, it has been argued that the results of the IAT may be strongly influenced by familiarity to stimuli, and that the influence of familiarity to stimuli may interfere with the interpretations of IAT findings (Dasgupta et al., 2003; Oswald et al., 2013).

Although concern has persisted regarding the IAT's ability to detect racial bias reliably, to distinguish between implicit association and familiarity, or to predict future biased behavior, this assessment may still be valuable to measure suicidality. The concepts of racism and suicidality differ fundamentally in important ways that impact how they are measured. First, being suicidal is a mood-dependent state that is likely to fluctuate in intensity within in a constricted time frame (e.g., within four hours).

While there may be trait vulnerabilities to experiencing suicidality, it differs radically from implicit racial bias, which is a learned, relatively stable perspective that is likely to remain consistent over time or to change gradually if at all. Therefore, some of the concerns noted about reliability may apply differently to the respective subtests. Subtests should be investigated independently to determine reliability, given the variance in the concepts measured.

Predictive validity for future behavior may differ drastically between overt biased behaviors and suicidal behavior. Demonstrations of overt biased behaviors are heavily influenced by impression management, societal influences, and developmental learning; in contrast, suicidal behavior is typically influenced more by internal experience (e.g., mood, thoughts, impulsivity). In consequence, findings from the IAT might be more successful in predicting the potential for suicidal behavior than other types of behavior.

This subtest of the IAT may yield valuable information about an examinee's current state of mind (i.e., activated schemas mediated by mood), and its findings could be helpful in informing effective treatment by determining level of risk (relative to strength of associations) and by predicting behavioral outcomes.

Internet Use and Suicide

The vast majority of individuals living in the US use the internet. In 2019, 90% of adults in the US reported using the internet. Internet use by gender varied very little: 90% of men and 91% of women in the US. Internet use varied slightly by race. Of those surveyed, 92% of White participants, 85% of Black participants, and 86% of Hispanic participants reported using the internet regularly (Pew Research Center, 2019). In addition, internet use seemed to vary slightly by age. Of those surveyed, 100% of 18-29 year-olds, 97% of 30-49 year-olds, 88% of 50-64 year-olds, and 73% of those 65 or older reported using the internet regularly (Pew Research Center, 2019).

Along with the high prevalence of internet use across gender, age cohorts, and racial groups in the United States, the literature has shown that individuals are highly likely to use the internet to seek out health-related information (Jacobs et al., 2017; Percheski & Hargittai, 2011; Sadasivam et al., 2013) and information related to topics perceived as personal or sensitive in nature (e.g., suicide, sexuality, STD symptoms, reproductive health, etc.) (Kubicek et al., 2011). In this technological age, individuals are much more likely to use the internet to obtain health information than to consult healthcare professionals, friends or family members, or other traditional media sources (i.e., books, etc.) (Jacobs et al., 2017; Wong et al., 2014).

Based on these facts and relevant findings in the literature, there is a high likelihood that individuals seeking information about suicide will utilize the internet to do so. This notion has been supported in the literature thus far, indicating a connection between internet searches related to suicide and suicide trends (Cline & Haynes, 2001; Nuti et al., 2014; Paparrizos et al., 2016). This is likely to be true due to astronomically high rates of internet use in general presently, as well as the tendency for individuals to turn to the internet for information on health-related, sensitive, or personal topics.

Through analysis of internet behavior, a deeper understanding may be established of what types of search queries indicate risk of suicide, if there is any potential to intervene during the planning stage of suicide (or other critical intervention points), and if there is any potential for technology-based prevention strategies.

Suicidality has changed in the age of technology because of the exponential increase in access to suicide-related information via the internet (Biddle et al., 2018; Biddle et al., 2016; Marchant et al., 2017; Mok et al., 2015). This open access provides both pro-suicide information (e.g., methods, support, logistics), as well as mental health treatment information and access to prevention resources (e.g., national suicide prevention lifeline number). The role of the internet in suicide is complicated, because it is simultaneously able to connect individuals to information that encourages suicide and to provide information about mental health treatment (Alao et al., 2006; Sakarya et al., 2013; Tam, et al., 2007). The internet is a means of communication with other suicidal individuals aimed on the one hand at offering support or help, or on the other hand at encouraging suicidal actions (Alao et al., 2006).

The increased accessibility to suicide-related information has promulgated information about painless lethal methods, even provided practical instruction to aid completion of suicide (e.g., tying an effective noose, the type and quantity of medication to reliably cause a lethal overdose), which has understandably changed the process of planning, attempting, and completing suicide (Biddle et al., 2018; Biddle et al., 2016; Biddle et al, 2012).

With increased access to suicide-related information, a global interest has surfaced in the literature over the past decade concerning tracking suicide-related search queries or internet activity related to the suicide death rate (Arora et al., 2016; Hagihara et al., 2012; Padmanathan et al., 2016; Sueki, 2011). Even patterns of use related to suicide on various social media platforms have been investigated (Aladağ et al., 2018; Chhabra & Bryant, 2016; Jashinsky et al., 2013). Most of these studies have yielded promising but preliminary findings indicating connections between suicide-related internet activity, social media use, and suicide trends.

In addition, a suicide prevention tool called *GoGaurdian Beacon* (powered by Google) has already been developed for schools for identifying students at risk of suicide or possible harm to others (e.g., threats, violence, and bullying) based on online activity (Byars et al., 2020). This tool works across search engines and social media to locate activity that might indicate risk. Since its inception in 2017, schools using GoGuardian have reported anecdotal accounts of successful suicide prevention or identification of at-risk students (Byars et al., 2020). However, these accounts are reported on a case-by-case basis, and publicly available statistical data or peer-reviewed literature about this tool's effectiveness has yet to appear.

In order to investigate this relationship further for the purposes of this study, Google searches have been examined. Google was chosen because it is one of the most popular, heavily utilized search engines among internet users, yielding high volumes of search activity data. Google also makes aggregate search data collected from users publicly accessible for research and trend tracking purposes. The following section explores research already conducted using Google and Google trends and literature on the utility of these types of data sets, commonly referred to as “big data.”

Google trends Search Data

Aggregate search query data from Google searches is publicly accessible through Google trends. Google trends is a website operated by Google that analyzes search-term popularity by collecting data on the top queries entered in Google searches across regions worldwide. The website uses graphs to display and compare the volume of different queries over time. This tool allows one to search ratios by region (e.g., country, state, metro) for any keyword or phrase in any selected time period from 2004 to the present. Google search data (Google trends) has already been used to predict and survey disease outbreaks, identify symptom clusters that predict diagnosis of pancreatic cancer, and forecast premature death (Jun et al., 2018; Ma-Kellams et al., 2016; Nuti et al., 2014; Parker et al., 2017; Solano et al., 2016).

In the present study, Google search query data were assessed to detect patterns in search terminology associated with high-suicide times, according to Centers for Disease Control and Prevention (CDC) 2019 mortality data. The literature has offered some support for the utility of big data in psychological and sociological research (Mooney et al., 2015; Serfass et al., 2017; Vallacher et al., 2017). However, some conflicting opinions are present in the literature regarding the usefulness of Google trends as a tool for understanding global health trends and epidemiological research (Fond et al., 2014; Fond et al., 2015; Tran et al., 2017). According to Cervellin et al. (2017), Google trends has modest reliability for defining the epidemiology of relatively common diseases with minor media coverage, or relatively rare diseases with higher audience. Overall, Google trends seems to be more influenced by the media clamor than by true epidemiological burden

Therefore, media coverage, ‘‘awareness’’ days, and other reporting-related influences appeared to impact data obtained from Google trends. This was an important consideration for this study as a potential confounding variable.

Disease outbreak. Google search queries have been utilized to track certain disease outbreak trends around the world. Web-based tracking of search queries through Google trends has demonstrated some promise in successfully forecasting outbreaks of infectious disease in real-time (Brownstein, et al., 2009; Carneiro & Mylonakis, 2009; Choi & Varian, 2012). If meaningful associations between internet behaviors (i.e., search queries) and health-related states or events can be identified, Google trends and other big data sources may potentially be successfully utilized to detect distress and offer support to our most vulnerable at critical points through effective forecasting of behavior.

Google search data has already been utilized to analyze the movement of influenza throughout the USA and internationally. In fact, Google Flu Trends was published as a tool to provide information on activity of influenza across the world and estimates of outbreak size based on query data. Based on current research, it appears that influenza outbreaks can be successfully tracked and predicted using Google trends, along with measures of ambient temperature (Zhang, et al., 2018). A close relationship appears to exist between those with influenza symptoms and the number of people searching for influenza-related topics (Carneiro & Mylonakis, 2009). Using Google trends and ambient temperature has been helpful in predicting seasonal influenza outbreaks in various geographical locations and in preparing and allocating resources needed to manage those local outbreaks (Ginsberg et al., 2009).

Ebola-related web-based search behavior was also assessed to evaluate correlations between query volume and Ebola cases. High correlations were found between registered Ebola cases and Google trends index for all countries included in the study (Alicino et al., 2015). However, correlations were weaker when countries were assessed individually, indicating some distortion or potential confounding variable (e.g., differences in digital access, media coverage) (Alicino et al., 2015).

Research has also tracked Google Trend inquiries into osteoarthritis (OA) through evaluating over 14 years of search query data. Findings appeared to demonstrate that peak times of inquiry volume correlated most closely with national and global awareness days for OA, as opposed to health trends in diagnosis (Jellison et al., 2018).

Predicting future diagnoses. As previously stated, it is very common for individuals to utilize the internet to seek health-related information (Cline & Haynes, 2001; Nuti et al., 2014; Paparrizos et al., 2016). Because we know this to be the case, research has begun to investigate how that digital activity can be harnessed and utilized for health benefits (e.g., aiding in early detection of health issues, predicting future diagnoses, etc.) (Dehkordy et al., 2014; Paparrizos et al., 2016).

Preliminary studies have been conducted that use web search query information to help screen for early signs and symptoms of pancreatic adenocarcinoma, an aggressive type of cancer that has historically been very difficult to treat (Paparrizos et al., 2016). Early warning signs of pancreatic adenocarcinoma are subtle and ambiguous, which makes them hard to identify. Therefore, this type of cancer is very rarely diagnosed in early stages, when it is much more susceptible to treatment. Early diagnosis of pancreatic adenocarcinoma is critical for successful treatment. An analysis of web search logs showed promise in identifying signs of pancreatic adenocarcinoma up to five months earlier (Paparrizos et al., 2016).

In addition, Google trends was utilized to evaluate trends in Lyme disease, which follows some well-documented geographical and seasonal patterns. Search traffic for “Lyme disease” was highest in cities and states where Lyme was known to be prevalent (Seifter et al., 2010).

Forecasting future diagnosis based on online activity seems has become a promising area of study in the fields of public health and healthcare. The potential for early detection and prediction of future diagnosis will undoubtedly advance the efficiency of the healthcare system and expedite access to appropriate treatment. This also lends credence to the utility of tracking online activity to inform behavioral health trends and early detection of potentially life-threatening symptoms, improving both access to appropriate treatment and overall prognosis.

CHAPTER 3: METHOD

Procedure

This study was an exploration of archival data sets in order to retrospectively identify patterns of internet search behavior and reported rates of death by suicide across time in all states. Frequency information between instances of certain Google inquiries and number of deaths by suicide per region were evaluated for statistical significance. For the purpose of this study, an online search was viewed as one discrete sample of behavior or data point and was analyzed in relation to completed suicide in the corresponding state.

Search engine data were obtained from Google trends, a publicly available source of aggregate user-search history. Using Google trends, search frequencies can be evaluated by interest over time and interest by geographical region. Search phrases included in the current study were obtained from Google trends to analyze relative search volume for each phrase in a specific time period (i.e., per month, throughout 2019) and geographical area (i.e., by state or nationally). Suicide frequency data were obtained from CDC. Mortality statistics from CDC were filtered to represent the number of suicides occurring within each state by month in 2019. Suicide frequency was compared with search query statistics from Google trends for corresponding months and states in order to determine if any meaningful associations existed.

Inclusion and exclusion criteria. All search queries made through the search engine Google within the United States during 2019 were eligible for inclusion. Any death counts of nine or fewer (i.e., < 9 suicides) in any state for any month were not reported by the CDC for the purpose of citizen privacy. Therefore, data were excluded for any state with fewer than 9 suicides in a given month. Last, any search phrases that were less popular in an area/ timeframe and reported as "0" by Google were included as "0" in the analysis.

Design and design justification

This study was a cross-sectional design that explores archival data sets in order to retrospectively identify patterns of internet search behavior and reported rates of death by suicide across time in various geographical locations in the USA. Frequency information between instances of certain Google inquiries and the number of deaths by suicide per region were evaluated for statistical significance. The purpose of the present study was to explore any relationship between search activity and suicide rates in order to determine if certain search activity is associated with higher suicide rates.

Aggregate search query data from Google searches is publicly accessible through Google trends. Google trends is a website by Google that analyzes search-term popularity by collecting data on the top queries entered in Google searches across regions worldwide. The website uses graphs to display and compare the search volume of different queries over time. This tool allows one to search ratios by region (e.g., country, state, metro) for any keyword or phrase within any specified time period from 2004 to the present. Google search query data were assessed to identify and analyze patterns in search terminology in times of high suicide and in times of low suicide according to Centers for Disease Control and Prevention (CDC) 2019 statistics.

Data on suicides rates were collected from the CDC, which tracks mortality data nationally and makes that data available to the public for purposes of research. An interactive archive of this data called CDC Wonder provides statistical information on the number of deaths per state per month by suicide and intentional self-harm. To protect citizen privacy, total suicides of nine or fewer (i.e., < 9 suicides) in any state for any month are not reported. This proved to be an important data consideration for the purposes of this study. This process of data collection accrues a lag, so CDC mortality data were available only through 2019 at this time. Therefore, statistical information on suicides from 2019 were analyzed for the purposes of this study.

Data were obtained from Google trends regarding each phrases' search query frequency by state during each month of 2019. Obtaining this specific data will allow for fine-grain analysis of suicide frequency in each state, to be analyzed in relation to search query frequencies from Google trends for corresponding states and months. Analysis of suicide rate and search query data in specific geographical regions over the course of a year will facilitate identification of any significant patterns that emerge between variables over time.

Terminology

For the purposes of this study, terminology from the self-injury Implicit Association Test (IAT), which is intended to measure implicit associations between self-injury, death, suicide, and the self, was used to construct hypothesized search phrases. The popularity of search queries including these phrases were investigated using Google trends in order to determine dissemination over time across a geographical location.

The implicit-association test (IAT) detects the strength of automatic associations between mental representations of various concepts in memory. Findings from the Self-Injury IAT subtest appear to be effective in predicting five out of six indicators of suicide risk over the strongest traditional indicators (i.e., history of prior suicide attempts)

(Harrison et al., 2014). In addition, implicit associations between self-injury, death, suicide, and oneself are associated with an increased risk of attempting suicide within six months. Overall, research suggests that implicit cognitions are a strong predictor of suicidal behavior (Nock et al., 2010). Therefore, terminology from the IAT was utilized to construct search phrases hypothesized to be associated with suicide risk when searched online or “googled.”

Search Phrases

Phrases constructed for the purposes of this study were created from terms utilized in the Self-Injury Implicit Association Test (SI-IAT) to represent the constructs of suicide (e.g., suicide, depression), life (e.g., alive, living), and me (e.g., myself, self).

Suicide-related terms:

suicide

want to die

how to kill myself

painless death

depression

Life-affirming terms:

living

alive

CHAPTER 4: RESULTS

Statistical analyses were computed using the Statistical Package for the Social Sciences.

Multiple Regression

Hypothesis 1: A multiple linear regression was conducted to predict deaths by suicide across the United States in 2019. It was hypothesized that death-related searches would be significantly positively predictive of the number of deaths, and life-affirming searches would be significantly negatively predictive of the number of deaths. Table 1 presents the means and standard deviations for deaths and search terms.

Table 1

Descriptives for Predictor Variables for Deaths (n = 50)

Predictor Variables	*M*	*SD*
Want to die	28.27	6.58
Suicide	66.06	6.50
How to kill myself	16.05	13.03
Depression	72.07	5.08
Painless death	3.43	10.17
Living	78.05	5.39
Alive	70.30	6.26
Outcome Variable	*M*	*SD*
Total Deaths	79.62	75.71

Note. Averages for total deaths were calculated for each state in the year 2019

Averages were calculated for state death rates and search term selection rates over 2019. There are missing data for some months for two reasons: 1) The CDC does not report any deaths by suicide in a given month/state if total deaths are fewer than nine (for the purposes of citizen privacy); 2) For infrequently chosen search terms, Google will report “0” for a term, if it is the least chosen to search compared to the other terms in the designated time scale/geographic area. Although there may have been some searches for these phrases during those times in those areas, Google represents it as “0.” Lacking this data, averages for each state were calculated for the most accurate representation of trends. A multiple linear regression requires a continuous dependent variable, as well as two or more independent variables. Test assumptions include normality, a linear relationship between dependent and independent variables, independence of observations, no multicollinearity, no significant outliers, homoscedasticity, and normal distribution of residuals (Fields, 2013).

The assumption that residuals were normally distributed was tested with a *Normal P-P Plot of Regression Standardized Residual* chart. Upon visual inspection, slight deviations from the regression line were observed, indicating *kurtosis* (i.e., leptokurtic distribution). This condition highlights some non-normality in the data between expected and observed cumulative probably of deaths.

The assumption of no multicollinearity was satisfied through the *variance inflation factor* (VIF), which indicated no collinearity across variables (< 2.5). In addition, a scatterplot of the standardized residuals alongside each independent variable was created in order to test the assumption of homoscedasticity. Upon visual inspection of the scatterplot, no heteroscedasticity was observed, and therefore this assumption was satisfied. Durban Watson (DW = 2.23) indicated no autocorrelation was detected in the given sample, completing the demonstration that all assumptions required for multiple regression had been met. The multiple regression analysis demonstrated statistically significant findings, F (7, 42) = 12.43, $p < .001$, with $R^2 = .67$, indicating that the phrase *how to kill myself* ($p < .001$) and *painless death* ($p < .000$) were both significant predictors. In fact, these search phrases appear to explain approximately 67% of unique variance in average death rates. This means that higher rates of searches for *how to kill myself* and *painless death* were predictive of higher rates of completed suicide nationally during 2019. None of the life-affirming search terms, however, were significantly predictive of death. Tables 2 and 3 present correlations and coefficients respectively.

Table 2

Correlations of Dependent and Independent Variables

	1	2	3	4	5	6	7	8
1- Deaths	1.000	---	---	---	---	---	---	---
2- want to die	.034	1.000	---	---	---	---	---	---
3- suicide	-.425	-.005	1.000	---	---	---	---	---
4- how to kill myself	***.527	.152	-.408	1.000	---	---	---	---
5- painless death	***.689	-.050	-.340	.140	1.000	---	---	---
6- depression	-.506	.180	.384	-.364	-.424	1.000	---	---
7- alive	-.292	.091	.096	-.004	-.436	.474	1.000	---
8- living	.052	.107	.195	.298	-.101	-.021	.204	1.000

Note: * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 3

Coefficients for Suicide-Related and Life-Affirming Search Terms

		b	*SE b*	*Β*
	(Constant)	159.54	156.95	
Suicide-related terms	*Want to die*	0.29	1.06	.025
	Suicide	-0.20	1.30	-.017
	How to kill myself	2.28	.65	.393***
	Painless death	4.37	.78	.587***
	Depression	-1.88	1.78	-.126
Life-affirming terms	*Alive*	.33	1.34	.027
	Living	-.18	1.43	-.013

Note: R^2 = .674. * p < .05, ** p < .01, *** p < .001.

MANOVA

Hypothesis 2: A one-way MANOVA was calculated to explore differences in searches between peak and nonpeak months for number of deaths by state. It is hypothesized that a higher number of searches will be made for suicide-related terms during peak months compared to non-peak months. A peak month is defined as the month with the highest number of deaths by suicide in 2019 in each state (*N* = 50). Nonpeak months include all other months in 2019 for each state (*N* = 550), in which suicide deaths were lower than in the peak month.

A one-way MANOVA can be used to explore differences between groups (peak and nonpeak) across a variety of outcome measures (search terms) by creating a linear composite on which to compare groups. The following assumptions must be met in order to use MANOVA: 1) independent random sampling, 2) categorical data for independent variables (IVs) and continuous data for dependent variables (DVs), 3) normal distribution, 4) no multicollinearity, and 5) homogeneity of variance (Fields, 2013).

A normal distribution refers to a common phenomenon in most data in which observations generally cluster around a central peak and values taper off, as they move further away from the mean due to decreasing probability. This tapering occurs equally in both directions as the probability decreases indefinitely, creating a bell-shaped curve. Normality of data and other assumptions must be satisfied to ensure data are appropriate for parametric statistics (Fields, 2013). For the purposes of this study, all assumptions were satisfied excepting homogeneity of variance.

In testing the assumption of homogeneity of variance, Levene's Test of Equality of Variance, which examines variance between independent variable groups in order to ensure equality, was also significant for *painless death* (p = .013), indicating unequal variance between groups. In addition, the Box's Test of Equality of Covariances Matrices was significant (p < .001) suggesting heterogeneity of covariances. The equality of covariance matrices assumes that the dependent variables vary in equal measure across the range of independent variables, and the Box's M must not be significant in order to ensure integrity of analysis.

In order to rectify these violations, data for the term *painless death* was removed, and the analysis was run with *want to die, suicide, how to kill myself,* and *depression*. Table 4 presents the descriptive statistics for suicide-related search terms during peak and nonpeak months, omitting *painless death*.

Table 4

Descriptive Statistics for Suicide-Related Search Terms during Peak and Nonpeak months

	Terms	Mean	*SD*	*n*
Peak Months	Want to die	30.72	20.07	50
	Suicide	67.22	12.56	50
	How to kill myself	19.54	28.26	50
	Depression	74.64	10.40	50
Nonpeak Months	Want to die	29.36	22.41	550
	Suicide	65.97	12.10	550
	How to kill myself	16.21	25.93	550
	Depression	71.77	11.08	550

Note: *SD*=Standard Deviation, *n*=number of participants

The one-way MANOVA did not demonstrate statistically significant differences in searches for suicide-related terms during peak and nonpeak months (based on death rates), F (4, 595) = 1.167, p = .324, Wilk's Λ = .043, partial η^2 = .008. This means that searches for suicide-related terms were not significantly higher during peak months for suicide deaths than in nonpeak months.

CHAPTER 5: DISCUSSION

Based on the current study's findings, it appears that the search phrases *how to kill myself* and *painless death* were predictive of completed suicide nationally during 2019. In other words, when the terms *how to kill myself* and *painless death* were searched more frequently, deaths by suicide were higher. A combination of searches for to *how to kill myself* and *painless death* explain 67% of the variance in deaths, indicating these terms are strong predictors of completed suicides at the national level.

In order to predict the number of completed suicide deaths across states, it may be important to monitor searches for the identified phrases in specific areas. It is possible that these phrases represent individuals that have moved from a contemplative or information-gathering stage of suicidal ideation to an action or planning stage of the process, indicating higher risk suicidal actions.

For individuals experiencing suicidal ideation, factors of volition and motivation appear to influence the shift from ideation to action. When terms involving physical pain sensitivity or planning specific methods of suicide are discovered, it may be more indicative of intention to carry out suicidal behavior (Klonsky et al., 2018; Wetherall et al., 2018). Therefore, monitoring search queries for language indicating pain level or plans could be important in prevention.

After analysis of search queries during peak suicide months (by state) in 2019, no significant difference appeared between suicide-related terms searched during peak suicide months and nonpeak suicide months.

Limitations

There are many potential liabilities in using large datasets, such as Google trends. These liabilities should be considered when interpreting the findings of this study and other studies using data on a similar scale.

First, in order to support the ability to make comparisons between terms, Google trends normalizes search data to the time and location of a query; each data point is divided by the total searches in the area during the time period it represents in order to compare relative popularity. Resulting quantities are then scaled from 0 to 100 based on a category of queries proportion to all searches on every topic in that area/ timeframe. Because Google performs billions of searches each day, data can be heavily normalized, which influences data outcomes. This specific process of normalization on such a large data set can distort or oversimplify data, which should be considered in research design, methods, and statistical analysis. Frequencies for less popular searches in our data were represented as “0,” despite the raw number of searches for these terms being higher. Data were normalized for the purposes of comparing terms, and more common searches can bury patterns for more specific/relatively uncommon searches due to the disparity in frequency.

In addition, sources of irregular activity can interfere with data. For example, software programmed to repeat or duplicate searches in order to promote certain webpages, products, etc. Google trends currently uses a fail-safe to detect irregular activity or duplicitous searches by the same entity, which is often indicative of a program or bot. This fail-safe is aimed at reducing undue influence of irregular activity on search data. However, these malicious influences are a reality of the internet and can impact aggregate search data. These programs can be a confounding variable that artificially inflates the frequency of certain search terms. It is impossible to know if these safeguards were able to prevent all undue influence from similar programs on the data used for this study, which is another limitation of this data.

Another clear limitation of the use of aggregate data, is the anonymous/ deidentified nature of the data. This leads to the inability to distinguish multiple searches by one individual from those by discrete individuals. Due to the nature of the data, it is impossible to say if those engaged in search behavior have completed suicide in those regions during that time.

Last, if media events (e.g., celebrity suicide deaths) occur that generate high interest in certain areas (or nationally), this could distort (or bury) search patterns. Overall, when using big data sets like Google trends, there will always be considerations regarding generalizability due to the potential influence of confounding variables.

In part, the data sources utilized in this study limited the scope of analysis. Although Google trends can offer a more fine-grained look at interest over time (down to the day/hour) and interest by geographical region (down to metro/county), the CDC only releases mortality statistics by month at the state level in order to protect citizen privacy. Therefore, this prevents a more fine-grained look at morality statistics or zooming in tighter for more specific analysis of localized matches between search terms and suicide rates.

Without specific permission, research in this area is limited to using frequency data as opposed to tracking progression of searches over time at the individual level (based on IP addresses, for example) due to the clear privacy implications of accessing such data. If a safe and ethical method is developed in the future that protects or deidentifies this type of data, more precise tools may be available for research purposes. At present, no such option exists.

For these reasons, this exploratory study is limited to identifying broader patterns based on frequency data on search activity and suicide rates by region in the hope of gleaning pertinent information for future prevention efforts.

Implications & Future Directions

In the future, these findings could be the foundation for identifying additional search terms/phrases connected to completed suicide. This information ultimately can inform global suicide prevention efforts using technology or public health initiatives. For example, any useful information derived from this study could eventually inform an algorithm created to identify alarming patterns of search behavior that may indicate high risk of suicide and to respond by offering immediate options for help (in real-time) as part of a global suicide prevention effort. One common criticism of this idea may be that individuals would feel monitored or intruded upon. In addition, individuals may believe a safeguard like this infringes on personal autonomy. These concerns are valid and fair.

However, tracking can also be useful and potentially life-saving. As previously discussed, research has begun to investigate how digital activity can be harnessed and utilized for health benefits (e.g., aiding in early detection of health issues, predicting future diagnoses, etc.) (Dehkordy et al., 2014; Paparrizos et al., 2016). Digital activity has already demonstrated some value in the early detection of warning signs of certain illness or diseases up to five months earlier in some preliminary studies (Paparrizos et al, 2016).

It is possible that this model could be applied to detecting early warning signs of certain mental health issues or risk of harm with more research.

Forecasting diagnoses based on online activity continues to be a promising area of study for the field of public health and healthcare, which can potentially be expanded to the field of psychology to address prosocial interests. This hinges on the ability of researchers with expertise in fields related to behavioral health to take an interest and study this information constructively and objectively.

The potential for early detection and prediction of future diagnoses will certainly advance the efficiency of the healthcare system and expedite access to appropriate treatment. This prospect lends credence to the utility of tracking online activity to inform behavioral health trends and early detection of potentially life-threatening symptoms, subsequently improving both access to appropriate treatment and overall prognosis.

One response to these concerns would be that an ideal solution would preserve anonymity while monitoring general patterns of activity (in much the same way as internet use already is) that indicate a safety issue and prompt an immediate option for connection with services. This hypothetical solution would deidentify search queries with the goal of flagging high-risk search patterns or behaviors. Individuals who may be having a mental health crisis would be offered immediate support in the moment, which they could decline (i.e., informed consent). Any individual in the general population experiencing suicidality who turns to the internet would encounter (at least) one opportunity to be connected to help, offered automatically as a safeguard.

There have certainly been other attempts in our society to protect vulnerable populations using online monitoring; it can be worth the breach of privacy to prevent or interdict criminal behavior and/or protect society's more vulnerable members (i.e., children) (Shivayogi, 2013; Tiffin et al., 2019). The use of this information for maximum benefit with limited risk of harms is growing topic of research; it is difficult balance the competing values of privacy and safety in society (Tiffin et al., 2019).

In this technological age, companies utilize data about our online activity to tailor marketing in the form of ads, which we can choose to click on or ignore. In addition, many online forums will issue pop-up warnings for safety purposes. For example, WebMD will issue a pop-up warning that urges users to go to the emergency room or see a doctor if symptoms indicate a medical emergency. Our internet behavior is already being collected, monitored, and utilized for a variety of purposes, which typically aim at monetizing our time and attention. Occasionally, this information is used for our benefit to inform us of potential dangers or connect us with help or support. It is reasonable to project that in the future this data could also be utilized for pro-social efforts, including immediate access to online help during mental health crises. The suicide prevention lifeline is an excellent means for individuals experiencing a mental health crisis to seek immediate help. Follow-up with individuals who called the suicide prevention lifeline during a mental health crisis revealed that approximately 50% of individuals were utilizing mental health care referrals post-call (Gould et al., 2018; Gould et al., 2012). However, based on changes in the way we interact with technology, the Suicide Preventions Lifeline may soon become antiquated in the coming years.

An option that aligns more with current expectations of immediacy and accessibility is needed, especially for younger individuals. In addition, an option should be available during crisis moments that requires less extensive steps or effort on the part of the individual in crisis. For example, finding and dialing a phone number may not always be feasible expectation for an individual in crisis, who may well feel ambivalent about help. There is a clear need for internet-based prevention efforts with global reach to keep up with changing times and to continue improving strategies of effective suicide prevention.

Specific future directions in this research could include studies that replicate the current study to support the reliability of the findings. In addition, future studies may potentially explore additional suicide-related terms or phrases in relation to death rates, in order to increase knowledge about specific terminology associated with suicide that may be important to track.

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