# Wear a Mask and Don't Drink Bleach: The Role of Neurocognition and Health Literacy in COVID-19 Information Seeking Skills, Knowledge, Prevention Intentions, and Prevention Behaviors

by

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**ABSTRACT**

The rapid development of COVID-19 into a pandemic required people to quickly acquire, evaluate, and apply complex health-related information. The present study examined the possible interplay between neurocognition and health literacy in the early uptake and use of COVID-19 public information. The current study aims were to evaluate: 1) the contribution of neurocognition to COVID-19-related online information seeking skills, knowledge, prevention intentions, and prevention behaviors; and 2) the effects of health literacy on the relationship between neurocognition and these COVID-19 outcomes. Two hundred and seventeen adults completed a telephone-based assessment including standardized measures of neurocognition, health literacy, and COVID-19 health outcomes (i.e., COVID-19 online information seeking skills, knowledge, prevention intentions, and prevention behaviors). Multiple regression models with data-driven covariates revealed that neurocognition, specifically memory and executive functions domains, was independently associated with COVID-19 knowledge, but not COVID-19 online information seeking skills, prevention intentions, or prevention behaviors. A series of hierarchical multiple regressions with data-driven covariates showed that health literacy was independently associated with all measured COVID-19-related outcomes and did not interact with neurocognition for any of these outcomes. These findings suggest that the acquisition of COVID-19 knowledge in the early months of the pandemic was partially explained by individual differences in declarative verbal memory and executive functions. Thus, future studies might examine whether executive functions and memory supports (e.g., spaced retrieval practice) can improve COVID-19-related knowledge in vulnerable populations.

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## INTRODUCTION

The World Health Organization (WHO) first notified the public of a cluster of pneumonia cases in Wuhan, Hubei province on January 4, 2020 (WHO, 2020a). Three months later, on March 11, 2020, the coronavirus disease 2019 (COVID-19) outbreak was declared a pandemic. Globally, over 27.4 million confirmed cases of COVID-19 caused by the 2019 novel coronavirus (SARS-CoV-2) have been reported, including an estimated 894,983 deaths in approximately 200 countries as of September 9, 2020. These estimates include over 6.2 million reported cases and 188,172 deaths in the United States (WHO, 2020b).

SARS-CoV-2 virus primarily affects the respiratory system, although other organ systems can also be involved. Lower respiratory tract infection-related symptoms including fever, dry cough, fatigue, and shortness of breath were reported in the initial case series from Wuhan, China (Huang et al., 2020). The Centers for Disease Control and Prevention (CDC) has since recognized additional symptoms including muscle aches, headache, loss of taste or smell, sore throat, congestion, nausea or vomiting, and diarrhea (CDC, 2020a). It is now widely acknowledged that presentation of COVID-19 is extremely heterogeneous, ranging from asymptomatic (i.e., COVID nucleic acid test positive, without any clinical symptoms and chest imagining is normal) to critical (i.e., acute respiratory distress syndrome [ARDS] with possible shock, encephalopathy, myocardial injury, heart failure, coagulation dysfunction, and/or acute kidney injury; see Yuki, Fujiogi, & Koutsogiannaki, 2020 for review). Available reports have suggested that the time between onset of symptoms and the development of ARDS could be as short as nine days, underscoring the potential of respiratory symptoms to progress rapidly (Huang et al., 2020). COVID-19 is moderately contagious (Liu, Gaule, Wilder-Smith, Rocklöv, 2020) and can be transmitted from human-to-human by multiple means, namely droplets, aerosols, and fomites (Wang & Du, in press).

Early epidemiological studies have suggested that COVID-19 mortalities are higher in older adults (Zhou et al., 2020) and the incidence is lower in children (Wu & McGoogen, 2020). Compared to women, men infected with COVID-19 might have more severe disease symptoms and higher mortality (see Sharma, Volgman, & Michos, in press for review). These demographic trends of COVID-19 cases and deaths are also reported in the United States (CDC, 2020). Persons with certain medical conditions (i.e., chronic kidney disease, chronic obstructive pulmonary disease, immunocompromised state, obesity, heart conditions, sickle cell disease, and type 2 diabetes mellitus) are at increased risk for serious illness from COVID-19 regardless of age (CDC, 2020b). In the United States, people who are Black or Hispanic/Latino are three times as likely to become infected and nearly twice as likely to die from the virus than their White counterparts (Oppel, Gebeloff, Lai, Wright, & Smith, 2020). These outcomes are likely due to longstanding systemic health and social inequities (e.g., William, Mohammed, Leavell, & Collins, 2010) resulting in lower access to services (e.g., Haas et al., 2004) and more underlying health conditions (e.g., CDC, 2013), as well as a higher rate of workers who are Black or Hispanic/Latino employed in services that cannot be provided remotely (Bick, Blandin, & Mertens, 2020).

Current medical management of COVID-19 is supportive in nature, with no targeted treatment therapies available. While there have been clinical trials for several drugs including lipinavir-ritonavir (Cao et al., 2020), remdesivir (Beigel et al., 2020) and hydrochloroquine (e.g., Boulware et al., 2020) none of them have been approved for COVID-19 treatment purposes. Due to its moderately contagious nature, public health initiatives have focused on slowing the spread of the virus in order to “flatten the curve” which refers to slowing the spread of COVID-19 to avoid the healthcare system being overloaded beyond its capacity to treat people. As there is currently no vaccine or specific medication to treat COVID-19, the only direct pathway to “flatten the curve” is through collective behavioral action of the public.

The CDC has provided a number of recommendations (that are frequently updated) aimed at preventing the spread of COVID-19 including: washing hands frequently with soap and water for at least 20 seconds, social distancing from others outside of the home (i.e., put six feet of distance between oneself and people who do not live in your household), covering the mouth and nose with a cloth face cover when around others, covering coughs and sneezes with a tissue, cleaning and disinfecting frequently touched surfaces, and monitoring ones’ health by being alert for symptoms (CDC, 2020c). To comply with these recommendations, many states temporarily closed public schools and businesses have advised employees to work from home if possible; several states also issued “shelter in place” orders, meaning that people should not leave their home except to get essentials like food or medicine (Mervosh, Lu, & Swales, 2020). In combination, these behavioral interventions can be an effective means to control viral transmission (Ferguson et al., 2020), as was demonstrated in earlier epidemics (e.g., Hatchett, Mecher, & Lipsitch, 2007) and the steady decline of COVID-19 cases in areas where these measures were successfully implemented (e.g., New York City; nyc.gov).

Actions taken by citizens in the early stages of a pandemic are critical for slowing down the spread of the virus. While researchers and scientists are working to develop treatments and vaccines for the virus, the current direct responsibility of adhering to preventative health behaviors to slow the spread of the virus rests completely on individuals. Despite the paramount importance of adhering to prevention guidelines, research suggests a potentially worrisome lack of adherence to CDC-recommended COVID-19-related prevention guidelines, particularly among men and young adults (Park, Russell, Fendrich, Finkelstein-Fox, Hutchinson, & Becker, in press). For example, in a survey of 1,015 persons from the United States who reported on their adherence to COVID-19-related health behaviors, only 50% reported wearing a cloth mask when out in public (Park et al., 2020). Therefore, it is crucial to have a better understanding of factors that may contribute to determinants of adherence to COVID-19-related health behaviors, as well as adherence to health COVID-19-related behaviors themselves.

## Models of Health Behaviors

Kanfer and Schefft (1988) observed that "as science and technology advance, the greatest mystery of the universe and the least conquered force of nature remains the human being and his actions…" A systematic review between 1986 and 2005 revealed over 60 different theories and models of health behavior (Glanz, Rimer, & Viswanath, 2008). The same review suggested that the models that continue to be widely cited and used in public health initiatives include: the Health Belief Model (HBM; Hochbaum, 1958; Rosentock, 1960,1974), Social Cognitive Theory (SCT; Bandura, 1977), Transtheoretical Model (TTM; Prochaska, 1984), and Theory of Planned Behavior (Fishbein, 1967; Ajzen, 1991). The present study was informed by (but does not directly test) aspects of each of these influential models, which are described briefly below.

### *Health Belief Model*

The HBM was initially developed in the 1950s by social psychologists in the United States Public Health Service to gain a better understanding of the widespread failure of people to participate in programs and initiatives to prevent and detect disease (Hochbaum, 1958; Rosenstock, 1960, 1974). This model posits that individual beliefs or attitudes (i.e., perceived susceptibility to and severity of disease, benefits of the health behavior, barriers to the health behavior, and self-efficacy for the health behavior) contribute to individual health behaviors, and that modifying factors of these individual beliefs include personality, age, gender, ethnicity, socioeconomics, and knowledge. The effectiveness of HBM to predict and explain behavior has been well-documented in systematic review papers over the past three decades (e.g., Carpenter, 2010; Harrison, Mullen, & Green, 1992; Janz & Becker, 1984; Zimmerman & Vernberg, 1994). A more recent systemic review demonstrated that of 18 eligible studies that utilized HBM in the design of its intervention, 14 reported significant improvements in adherence, with seven showing improvements at medium-to-large effect sizes (Jones, Smith, & Llewellyn, 2014).

***Social Cognitive Theory***

Social Cognitive Theory (SCT; Bandura 1977) was first known as Social Learning Theory, as it was based on the operation of established principles of learning within the human social context. When applied to health behaviors, the theory suggests that six main constructs contribute to behavior: 1) reciprocal determinism (i.e., environmental factors influence individuals and groups, but individuals and groups can also influence the environment and regulate their own behavior); 2) behavioral capacity (i.e., ability to perform a behavior through essential knowledge and skills); 3) observational learning (i.e., learning to perform a behavior by exposure to interpersonal or media displays of that behavior, particularly through peer modeling); 4) internal and external reinforcements (i.e., the use of rewards and punishments to modify behavior); 5) outcome expectations (i.e., anticipated consequences of an individual's behavior); and 6) self-efficacy (i.e., level of an individual's confidence in their ability to successfully perform a behavior). The ability of SCT to explain intention and predict behavior outcomes has been demonstrated across several health behaviors including increased physical activity (Young, Plotnikoff, Collins, Callister, & Morgan, 2014); chronic health condition outcomes (Tougas, Hayden, McGrath, Huguet, & Rozario, 2015), and dietary improvements (e.g., Stacey, James, Chapman, Courneya, & Lubans, 2015).

***Transtheorectical Model***

The TTM emerged from a series of comparative analyses of leading theories of psychotherapy and behavior change (Prochaska, 1984). The TTM includes the term "transtheoretical" because it uses stages of change to integrate processes and principles of change across major theories of intervention. The stages of change include precontemplation (i.e., the individual does not intent to take action in the near future and may be unaware that their behavior is problematic), contemplation (i.e., the individual recognizes that their behavior is problematic and may begin to look at the pros and cons of their continued action), preparation (i.e., the individual is intending to take action in the immediate future and may begin to take small steps towards behavioral change), action (i.e., the individual has made specific, intentional steps towards modifying, reducing, or eliminating their behavior and/or acquiring new health behaviors) and maintenance (i.e., the individual has sustained the action for at least six months and is taking steps to prevent relapse). Processes of change (e.g., consciousness raising through gaining knowledge about the behavior and its consequences, self-liberation or declaring an intention to change, environmental reevaluation), decisional balance (i.e., weighing pros and cons), and self-efficacy are hypothesized to play a role at each stage of the TTM (see Prochaska, Redding, & Evers, 2008 for review). The TTM has been used in intervention studies for a wide number of health behaviors including smoking cessation (e.g., Aveyard et al., 1999; O'Neill, Gillespie, & Slobin, 2006), diet (e.g., Beresford et al., 1997), and exercise (e.g., Rossi et al., 2005) in many different settings including primary care (e.g., Goldstein et al., 1999; Hollis et al., 2005), homes (e.g., Curry et al., 1995; Gold, Anderson, & Serxner, 2000), churches (e.g., Voorhees et al., 1996), and worksites (e.g., Prochaska et al., 2008).

***Theory of Planned Behavior***

The TPB was an extension of the Theory of Reasoned Action (Fishbein, 1967) which was developed to better understand relationships between attitudes, intentions, and behaviors. The theory asserts that the most important determinant of behavior is behavioral intention and that direct determinants of behavioral intention are attitudes towards performing the behavior, subjective norms associated with the behavior, and perceived control over the behavior (i.e., self-efficacy). Modifying factors of attitudes towards the behavior include knowledge and evaluations of behavioral outcomes while modifying factors of subjective norms associated with the behavior include normative beliefs and motivation to comply. External factors hypothesized to contribute to the overall model include individual personality traits and demographics. Several meta-analyses and reviews support the TPB and provide evidence that constructs of attitudes, subjective norms, and perceived control explain a large proportion of variance in intentions for behaviors, and predict a number of behaviors, including health behaviors (e.g., Armitage & Conner, 2001;

Albarracin et al., 2001, 2003, 2004, 2005; Downs & Hausenblau, 2005; Hardeman et al., 2002; Sheeran & Taylor, 1999; Webb & Sheeran, 2006).

**Models of Health Behavior in the Context of COVID-19**

Taken together, these models suggest that behavioral attitudes, risk perceptions, self-efficacy, and intentions have predictive utility for a wide range of health behaviors, and that each of these are heavily impacted by knowledge of the health behavior (Glanz, Rimer, & Viswanath, 2008; Hochbaum, 1958; Rosentock, 1960,1974; Bandura, 1977; Prochaska, 1984; Ajzen, 1991). The present study utilized these models of health behaviors to conceptualize critical determinants of COVID-19-related health behaviors as they intersect with cognition including: online COVID-19-related information-seeking skills, knowledge about COVID-19 and recommended prevention behaviors, and intentions to adhere to COVID-19 health behaviors.

Through using the TTM to stage the contributions of these determinants throughout the process of behavioral change it could be reasoned that: 1) online information-seeking skills would be important during the contemplation stage as individuals begin to realize that their current behavior may be problematic; 2) COVID-19-related knowledge gained from this information-seeking would be important in the contemplative and preparation stages as the individual begins to weigh the pros-and cons of continuing their behavior; 3) intentions to adhere to COVID-19 health behaviors would play a role in the preparation stages in which the individual begins to take small steps towards the behavioral change, and; 4) that these would all contribute to the action and maintenance stages in which the individual successfully carries out and maintains positive COVID-19 health behaviors.

**Cognition and COVID-19 Health Related Behaviors**

It is increasingly important to gain a better understanding of factors that may contribute to adherence to COVID-19-related behaviors. One such factor may be cognition, as aspects of cognition such as executive functions and memory have been demonstrated to impact health behaviors in both healthy (e.g., Allen, McMinn, & McDaly, 2016) and disease populations (e.g., Hinkin et al., 2004), as well as critical determinants of health behavior including online information-seeking (see Woods et al., 2019 for review), health knowledge (e.g., Jones, Cook, Rodriguez, & Waldrop-Valverde, 2012), and intentions to adhere to health behaviors (e.g., Blume, Davis, & Schmaling, 1993). The present study aims to examine the role of cognition in adherence to COVID-19-related health behaviors, as well upstream critical determinants of behavior including: COVID-19-related information-seeking behaviors, COVID-19-related knowledge, and intentions to adhere to COVID-19 behaviors.

### ***Cognition and COVID-19-Related Information Seeking***

In the Munich security conference that occurred on February 15, 2020, Dr. Tedros Adhanom Ghebryesus, the general director of WHO, stated, "We're not just fighting an epidemic; we're fighting an 'infodemic'." Internet searches for "coronavirus" increased by about 36% on the day immediately after the first case announcement in the United States (Bento et al., 2020). COVID-19 (i.e., search terms of "coronavirus" or "COVID-19") was a trending Google topic in the United States and hit its maximum index search score (100/100) on March 12, 2020, the day after COVID-19 was declared a pandemic, according to Google Trends. COVID-19-related search terms trended from March 2, 2020 to April 28, 2020 before the increased level of information seeking faded to about the same level as weather-related Google searches (18/100). It is well-established that searching for and learning information from the internet is complex and relies heavily on cognitive processes (e.g., Kordovski et al, in press; Woods et al., 2020).

Researchers have estimated that 60-80% of Americans use the internet for health-related searches (Nguyen, Mosadeghi, & Almario, 2017; Perrin & Duggan, 2015; Zickuhr & Madden, 2012). While searching the internet for health-related information can have positive health effects, such as improving self-care and treatment decisions (Fox & Rainey, 2002), information on the internet is largely unregulated and often quite difficult to navigate (Skierkowki, Florin, Harlow, Machan, & Ye, 2019). A study by Cuan-Baltazar et al., (2020) provided early evidence of the sheer amount of misinformation and unreliable websites contributing to the COVID-19 "infodemic." Cuen-Baltazat et al. entered the search terms "coronavirus" and "Wuhan" into Google on February 6, 2020 (the authors reported that at the moment these were the most popular keywords at the time as COVID-19 or SARS-CoV-2 were not yet established) and coded the reliability of the first 110 websites obtained by the search (in both Spanish and English) using three different quality assessment instruments. Depending on which quality assessment instrument was used, the percentage of websites that met high quality criteria ranged from 0% to 10% (mean percentage meeting high quality criteria was 4%; Cuen-Baltazat et al., 2020). A similar study was conducted in Brazil among 68 websites in Brazilian Portuguese that demonstrated that COVID-19-related websites were of low-to-moderate quality on average and often contained content at above average reading level, limiting its accessibility (Lins Filho et al., preprint).

Taking into consideration both the vast number of health-related websites and large amount of COVID-19-related misinformation on the internet, one can begin to understand the potential cognitive complexity (and many possible pitfalls) of seeking, identifying, judging, and using the internet for COVID-19-related information. A recent review by

Woods, Kordovski, Tierney, & Babicz (2019) examined the small body of existing literature on the neuropsychology of Internet navigation skills in both healthy and clinical populations. The review suggested that among the 17 articles included, there was a strong association between measures of global neurocognition and performance-based Internet navigation tasks. More specifically, domain-level analyses demonstrated that performance on Internet search skills (i.e., accuracy and/or time to completion, prioritizing accuracy) was associated with measures of episodic memory and executive functions at medium-to-large effect sizes, with visuospatial skills at medium-sized effect sizes, and psychomotor functioning and information processing speed at small-to-medium-sized sizes. Attention and working memory were also related to performance, though less reliably; when effects were present, the strength of the relationship was generally medium-sized. Analyses suggested that the domain of language was inconsistently related to internet search skills at small-to-null effect sizes. The review included both task performance on internet navigation skills within examiner-designed online platforms (e.g., mock travel, bank, and healthcare website) and in naturalistic settings in which the participant freely navigated the live internet to complete tasks.

Within this body of literature about cognition and internet tasks, twelve articles examined the relationship between cognition and performance on naturalistic internet navigation tasks (Agree et al., 2015; Austin, Kaye & Hollingshead, 2017; Chevalier, Dommes and Marquié, 2015; Czaja et al., 2010; Dommes et al., 2011; Goverover et al., 2010, 2014, 2015, 2016, 2017; Sharit et al. 2008, 2015). With the exception of the Goverover et al. studies, all studies within this subset included either search tasks that specifically involved health-related topics such as vaccinations, Multiple Sclerosis, obesity and exercise (e.g., Sharit et al., 2008, 2015), or included at least one health-related query in the internet search task (e.g., Chevalier, Dommes, & Marquié, 2015; "What medical term indicates a jaw deformity?"). Generally, the cognitive correlates of performance on naturalistic internet search tasks within this subset of studies remained similar to above findings (Woods, Kordovski, Tierney, & Babicz, 2019). Specifically, the handful of studies examining cognition and naturalistic internet search in the context of health-related information demonstrated moderate sized relationships between quick and accurate health-related internet searches and measures of visuospatial skills, processing speed, attention, executive functions, and language (Agree et al., 2015, Chevalier, Dommes, & Marquié, 2015; Czaja 2010; Dommes, Chevalier, & Lia, 2011; Sharit, Hernández, Czaja, & Pirolli, 2008; Sharit, Taha, Berkowsky, Profita, & Czaja, 2015). More recently, in a study of 56 young adults, accuracy of responses on a naturalistic online health information search task (i.e., participants were given a list of symptoms and told to use the internet to come up with a plausible diagnosis) was also associated with better performance on measures of episodic and prospective memory at large effects sizes, respectively, while faster time to complete the tasks was associated with better performance on tasks of executive functions at a small effect size (Kordovski, Babicz, Ulrich, & Woods, 2020).

Taken together, these findings suggest that cognition plays an important role in online health information-seeking even among health topics that have been in public discourse for decades and are generally well-understood by the medical community (e.g., seasonal flu vaccinations, Multiple Sclerosis, obesity, and exercise). COVID-19 information seeking on the internet is likely even more complicated (and therefore more cognitive demanding) due to the large surge of information over a short period of time to digest (e.g., Ashrafi-rizi & Kazempour, 2020) and high frequency of misinformation (e.g., Cuan-Baltazar et al., 2020; Lins Filho et al., preprint).

### *Cognition and COVID-19-Related Knowledge*

In the case of COVID-19, misinformation can take many forms from conspiracy theories about 5G wireless networks creating and/or amplifying COVID-19 (see Ahmed, Vidal-Ellabell, Downing, & Seguí, 2020) to claims that drinking alcohol can protect an individual from COVID-19 (WHO, 2020c). Misinformation may cause individuals to turn to ineffective (and potentially harmful) remedies, as well as to either overreact (e.g., by hoarding goods) or, more dangerously, to underreact (e.g., by engaging in risky behavior and spreading the virus). For example, according to the Center for Disease Control and Prevention Morbidity and Mortality Weekly Report published on June 12, 2020 CDC, 39% of the 504 Americans surveyed had done high-risk things with household cleaners in attempts to stay safe from COVID-19 including applying bleach to food items, ingesting cleaning and disinfectant solutions, trying to clean their hands or mist their bodies with household cleaning products, and/or inhaling vapors of household cleaning products (Gharpure et al., 2020).

In contrast, knowledge of accurate COVID-19 information may contribute to increased adherence to COVID-19-related health behaviors. A cross-sectional online study of 1,034 American adults was conducted on March 17, 2020 in which participants completed a 12-item COVID-19 knowledge scale including items regarding clinical characteristics, transmission, and prevention and control of COVID-19 (Clements, 2020). The knowledge questions were scored with one point for each correct answer and a total score was calculated (range 0 to 12), with higher score indicating more knowledge about COVID-19. The participants also answered three questions to determine adherence to CDC-recommended COVID-19-related health behaviors including whether they had refrained from: 1) engaging in hoarding behaviors (i.e., spending more money than usual in the past two weeks on cleaning supplies, personal hygiene products, and food); 2) going to any place in the last five days where there were more than 50 people present (contradicting CDC recommendations to avoid such gatherings); and 3) wearing a medical mask when leaving the home in the past five days (at the time contradicting CDC, NIH, and healthcare guidelines). The study reported that for every point increase in knowledge, the odds of purchasing more goods, attending large gatherings, and using medical masks decreased by 12%, 13%, and 44%, respectively (Clements, 2020). Another recent study demonstrated that Google searches for "wash hands" and "face masks" between the dates of January 19, 2020 to February 18, 2020 were correlated with a lower spreading speed of COVID-19 from February 19, 2020 to March 20, 2020 among 21 countries at a medium effect size (Lin, Liu, & Chiu, 2020) suggesting that accurate knowledge may extend to positive societal effects, as well as increased individual adherence behaviors.

Previous literature has suggested that cognition is associated with disease knowledge. In a study of 250 participants with human immunodeficiency virus (HIV) with a history of alcohol abuse, performance on neurocognitive measures of processing speed and executive functions were positively associated with HIV knowledge at a small-to-medium effect sizes (Malow et al., 2012). Similar results have been demonstrated for persons with type 2 diabetes both with and without severe mental illnesses such that better performance on cognitive assessments was associated with higher scores on a diabetes knowledge test with items assessing knowledge of glucose monitoring, diet, and exercise at small-to-medium effect sizes (Nguyen, Gryzwacz, et al., 2010; Wykes, Lee, Bourassa, Kitchen, & McKibbin, 2017; Sartori, Clay, Ovalle, Rothman, & Crowe, 2011). As cognition is associated with knowledge about prevention behaviors and treatments in other diseases, it may similarly impact COVID-19-related knowledge among individuals. Given the increasing individual and societal responsibilities to learn information about COVID-19 and use it to guide behaviors, it is more important than ever to understand the role of cognition in COVID-19-related knowledge.

***Cognition and Intention to Adhere to COVID-19-Related Health Behaviors***

Health behavior models suggest that intentions to adhere to health behaviors have downstream effects on actual adherence to behaviors (e.g., Hochbaum, 1958; Rosentock, 1960,1974; Bandura, 1977; Prochaska, 1984; Fishbein, 1967; Ajzen, 1991). A study of 761 healthcare workers in Iran demonstrated that each increased point in self-reported intention (i.e., rating on a five-point Likert scale to the item "I intend to observe the recommended precautions until the end of the coronavirus epidemic") was associated with a .72 point increase in overall behavior score (i.e., five COVID-19 behavior items, such as washing hands and wearing a mask, rated by a three-point Likert frequency scale of 'always', 'sometimes', or 'never'; Barati et al., 2020). Similarly, a study of predictors of adherence to COVID-19 behaviors among a representative United States sample of 501 participants demonstrated that stronger intentions to adhere to COVID-19-related guidelines was associated with greater adherence (Bogg & Milad, preprint).

Cognition may play a role in forming intentions to adhere to COVID-19-related behaviors. Prospective memory, or the act of "remembering to remember," requires: 1) formation of the intention; 2) delay between the formation of the intention and the occasion for its execution; 3) accurate detection and recognition of the cue; 4) recollection of the intention; and 5) execution of the intention (Carey et al., 2006; Kliegel et al., 2008). Neuroimaging studies suggests the early stages of prospective memory (i.e., intention formation) involve both episodic memory resources (i.e., temporal lobe activation including the hippocampus) and additional executive resources specific to future-oriented processing (i.e., left rostrolateral prefrontal cortex and the right parahippocampal gyrus; Poppenk, Moscovitch, McIntosh, Ozcelik, & Craik, 2010). Lower performance on measures of prospective memory has been associated with higher engagement in a number of health risk behaviors including risky sexual and injection practices among persons with HIV (Martin et al., 2007; Weinborn, Moyle, Bucks, Stritzke, Leighton, & Woods, 2013).

At face value, forming an intention to adhere to COVID-19-related behaviors involves several cognitively-demanding steps including recalling information about COVID-19 ("I read an article last night that we should be wearing cloth masks"), integrating that information to assess personal risks and benefits to adhering to the behaviors ("That sounds uncomfortable, but several sources say it can help protect others around me"), assessing the feasibility of adhering to the behavior ("I don't own a mask, but since it is now a widespread public policy, I could probably easily find one online"), using that information and assessment to make a decision to adhere ("All together, it seems reasonable that I could adhere to this behavior"), generating an action plan ("Now I need to buy a mask"), and creating a cue-intention pairing related to the intention ("Every time I leave my house, I will put my mask on"; e.g., McDaniel & Einstein, 2007). This process involves several aspects of cognition including prospective memory, episodic memory, attention, and executive functions.

### *Cognition and Adherence to COVID-19 Health Behaviors*

The relationship between cognition and health behaviors is well-established in the literature. Better performance on neurocognitive measures, particularly on measures of executive functions and memory, are associated with improved adherence to medications and treatment regiments in the setting of chronic disease management (e.g., HIV and diabetes) at medium effect sizes (Hinkin et al., 2002, 2004; Duke & Harris et al., 2014; Rosen et al., 2003). Cognition has also been associated with increased positive health behaviors including exercise, dieting, and smoking cessation (Allan & McDaly, 2016; Hall et al., 2008, 2014; Duff et al., 2009). On the other hand, lower performance on measures of executive functions are associated with increased risky health behaviors including unprotected sex (see Ross, Duperrouzel, Vega, & Gonzalez, 2016 for review). These studies suggest that in the context of COVID-19, cognitive ability may be associated with adherence to positive health behaviors (e.g., washing hands frequently) and lower participation in risky health behaviors (e.g., gathering in large groups).

Indeed, there is preliminary evidence to suggest that cognition may be associated with individual differences in adherence to COVID-19 prevention measures. A recent study by Xie, Campbell and Zhang (2020) demonstrated an association between working memory capacity and level of adherence to social distancing guidelines. This was a two-part study conducted within the first two weeks following the US federal government's declaration of national emergency due to the COVID-19 pandemic (March 13, 2020 to March 26, 2020). At this time, several states had issued stay-at-home orders and social distancing was widely and vehemently recommended. For Study 1, 397 participants reported their level of compliance to social distancing guidelines and completed a brief working memory task, as well as questionnaires assessing mood, anxiety, and sleep quality between March 20, 2020 and March 22, 2020. For Study 2, 453 participants completed the same measures and tasks in Study 1 (excluding the sleep quality questionnaire) and also additional measures of personality and fluid intelligence and a questionnaire assessing participants' knowledge of costs and benefits of social distancing between March 24, 2020 and March 26, 2020.

For both studies, participants reported how closely they followed a set of social distancing practices (e.g., did not hold social gatherings with friends, cancelled events or plans to go to an event, stopped going to church or attending other community activity, had no handshakes, hugs, or kisses when greeting) in the past week on a scale from 0 "Do not consider following" to 3 "Follow very frequently" (Xie, Campbell, & Zhang, 2020). Across the two studies, higher level of adherence to social distancing guidelines was associated with better performance on a working memory task, at small effect sizes, respectively and lower reported depressed mood and anxiety. In Study 2, in addition to working memory capacity, higher level of adherence was also associated with a non-verbal measure of abstract reasoning at a small effect size and higher agreeableness. Notably, working memory capacity was positively associated with adherence to social distancing guidelines even when controlling for sociodemographics (i.e., age, gender, education, income), mood and anxiety symptoms, and sleep quality in Study 1. These findings were replicated and expanded upon in Study 2 in which working memory capacity was positively associated with adherence to social distancing guidelines when controlling for sociodemographics (i.e., age, gender, education, income), mood and anxiety symptoms, personality traits (i.e., agreeableness, conscientiousness, extraversion, openness, and neuroticism, and performance on a non-verbal abstract reasoning measure. Additional analyses in Study 2 demonstrated that the relationship between working memory and adherence to social distancing guidelines was partially mediated by participants' knowledge of the costs and benefits of social distancing practices. Higher reported compliance to social distancing practices was also associated with other COVID-19-related health behaviors such as lower frequency of leaving home and higher frequency of hand-washing. While this study provided evidence for the role that working memory and non-verbal abstract reasoning may play in COVID-19-related health behaviors, it is still not known how other aspects of cognition, such as memory, may impact adherence to COVID-19 prevention measures.

## Health Literacy

Health literacy is a multidimensional, dynamic construct broadly defined as the degree to which individuals can obtain, process, understand, and communicate about health-related information to make informed medical decisions (Berkman, David, & McCormick, 2010). It is estimated that one-third to one-half of the United States population has either marginal or low health literacy (Paasche-Orlow et al., 2005). Health literacy has emerged over the past 30 years as one of the strongest psychosocial determinants of health disparities by age, race/ethnicity, and socioeconomic status (see Mantwill, Monestel-Umana, & Schulz, 2015 for review).

### *Health Literacy and COVID-19 Information Seeking*

Preliminary research suggests that health-related online navigation skills are associated with health literacy in both the setting of examiner-created experimental platforms (Woods et al., 2016) and during naturalistic searches on the internet (e.g., Agree et al., 2015) at medium effect sizes, respectively. In addition to online search and navigation skills, health literacy and basic literacy may impact the ability to comprehend information on the Internet. A recent study by Szmuda et al. (in press) revealed that the reading-levels of the first 30 results of five COVID-19-related search terms entered into Google on March 13, 2020 ("coronavirus", "COVID-2019", "SARS CoV-2", "2019-nCoV", and "What is coronavirus") were higher than a 5$^{th}$ grade reading level, which is what the United States

Department of Health and Human Services recommends for patient educational information (Cotugna, Vikery, & Carpenter-Haefele, 2005). The lack of reading-level-appropriate resources in combination with the accelerated need for individuals to continually learn new information and un-learn outdated information and resolve contradictions between multiple sources of information suggests that health literacy may play a critical role in accurate COVID-19 information seeking and knowledge acquisition.

### *Health Literacy and COVID-19 Knowledge*

Individuals with low health literacy reliably demonstrate less knowledge about chronic medical conditions (Gazmararian et al., 2003; Schillinger et al., 2002) and preventative health care behaviors, such as prenatal guidelines (Shieh, Mays, McDaniel, & Yum 2009), mammography screenings (Bennet, Chen, Soroui, & White, 2009; White, Chen, & Atchison, 2008), and cervical cancer prevention (Lindau et al., 2002). Similar associations between health literacy and COVID-19 knowledge have emerged in recent literature. For example, a recent study by Wolf et al. (2020) demonstrated that among 630 adults, lower health literacy was associated with poorer knowledge of COVID-19 symptoms.

### *Health Literacy and COVID-19 Intentions*

To date, there have only been two studies that have included analyses investigating the relationship between health literacy and health behavior intentions. In a study of 180 participants recruited from the lobby of a regional healthcare clinic, higher scores on a performance-based measure of health literacy (Newest Vital Sign; Weiss et al., 2005) was associated with higher reported behavioral intentions to follow "healthy heart" recommendations at a small effect size (Crook, Stephens, Pastorek, Mackert, & Donovan, 2016). Another study by Kim, Yoo, Hwang, and Cho (2019) demonstrated that higher scores on an electronic health literacy questionnaire was associated with higher reported intentions to adhere to health-related behaviors. Therefore, health literacy may also play a role in ones' intentions to adhere to COVID-19-related health behaviors.

### *Health Literacy and COVID-19 Health Behaviors*

Suboptimal health literacy is associated with poorer health outcomes (see Berkman et al., 2011 for review), including reduced utilization of preventative medication (Cho, Lee, Arozullah, & Crittenden, 2008; White, Chen, & Atchison, 2008), more emergency room visits (Baker, Gazmararian, & Williams, 2004; Cho, Lee, Arozullah, & Crittenden, 2008), hospitalizations (Baker, Parker, Williams, & Clark, 1998; Baker, Gazmararian et al., 2002), and non-adherence to prescribed medications (Kripilani, Gatti,& Jacobsen, 2010; Murray et al., 2004). In the context of COVID-19, lower health literacy has been associated with lower reported changes in daily routines and plans and higher rates of unpreparedness for COVID-19 (Wolf et al., 2020).

## Health Literacy, Neurocognition, and Health Behaviors

Emerging data shows that lower neurocognitive functions may be associated with lower health literacy in both healthy (e.g., Apolinario, Mansur, Carthery-Goulart, Brucki, & Nitrini, 2015) and disease populations (e.g., Waldrop-Valverde et al., 2010; Morgan et al., 2015). In a study of 322 healthy adults, better performance on measures of global cognition, verbal fluency, executive function, and immediate recall of information was associated with higher scores on a brief measure of health literacy at medium-to-large effect sizes, even when controlling for age, gender, race, childhood residence (urban vs. rural), occupation (manual vs. nonmanual), years of education, and quality of education (Apolinario et al., 2015). Among persons with HIV, neurocognitive impairment has been associated with lower health literacy across several dimensions, ranging from fundamental skills (e.g., literacy and numeracy; Morgan et al., 2015; Waldrop-Valverde et al., 2010) to higher-order capacities, including medical decision-making (e.g., Doyle et al., 2016) and engagement with healthcare providers (Morgan et al., 2019). Recent studies have also demonstrated a positive relationship between neurocognitive abilities and electronic health (eHealth) literacy (e.g., Woods & Sullivan, 2019), which is defined as the ability to search for and understand health information from an electronic source, apply the acquired knowledge, and resolve a health problem, at a medium effect size (Norman & Skinner, 2006).

Lower health literacy and poorer neurocognitive functioning have reliably been independently linked with worse medical outcomes (e.g., Becker, Thames, Castellon, & Hinkin, 2011; Jacks et al., 2015; Kordovski, Woods, Avci, Verduzco, & Morgan, 2017; Rebeiro et al., 2018). However, relatively little is known about the interplay and possible synergistic effects of health literacy and neurocognition in predicting health outcomes. Studies by Chin et al. (2011, 2017) suggested that among older adults, higher neurocognitive abilities (i.e., working memory, processing speed) were associated with better performance on health tasks for persons with low general and health-specific knowledge, but not for persons with high general and health-specific knowledge. Similarly, in a study of 171 persons living with HIV, neurocognitive functioning was associated with treatment management outcomes for persons with low health literacy but not for persons with adequate health literacy (e.g., Fazeli, Woods, Lambert, Waldrop-Valverde, & Vance, 2020). Taken together, these studies suggest that higher health literacy may serve as a protective buffer against the adverse effects of poor neurocognition on health behaviors. The mechanism for this relationship has not yet been explored but may be related to higher health literacy skills allowing for either: 1) comprehension processes dependent on neurocognitive abilities to be more efficient and less resource-consuming and/or; 2) increased utilization of compensatory strategies during health tasks (e.g., double checking sources, seeking additional confirmation of facts). On the other hand, persons with low health literacy may rely more heavily on neurocognitive skills to achieve better health outcomes.

The interaction between neurocognition and health literacy may similarly play a role one's ability to seek out, learn, and apply COVID-19 knowledge. The above findings suggest that the relationships between neurocognitive functioning and COVID-19 outcomes may be amplified for persons with low health literacy. For example, persons with low health literacy may have difficulty accurately interpreting information from a CDC guidelines handout but may be able to gain COVID-19 knowledge through reliance on cognitive skills such as remembering information heard from various sources and using problem-solving skills to deduce the information that has the highest likelihood of being reliable and accurate. Persons with low health literacy with higher neurocognition may also have better awareness (i.e., metacognition) of their difficulty with learning health information than those with lower neurocognition which may allow for greater use of compensatory strategies (e.g., Casaletto et al., 2014). On the other hand, persons with low health literacy and lower neurocognition may be doubly negatively impacted and have more difficulty acquiring COVID-19 knowledge. Persons with high health literacy may have a more "direct" route to COVID-19 information that limits the extent to which higher or lower neurocognition may facilitate or hinder learning COVID-19 information.

The development of COVID-19 into a pandemic over just a few short months has called for the public to acquire and apply health information, and adapt their health behaviors at a rapid pace (Abel & McQueen, in press). As discussed above, health literacy has been implicated in critical determinants of health behaviors including information-seeking skills and knowledge, and has been associated with a number of positive health behaviors. Based on the limited literature available exploring the possible modulatory effect of health literacy on the relationship between neurocognition and health outcomes, it is hypothesized that higher neurocognitive abilities will be associated with COVID-19 information-seeking skills, knowledge, intentions, and behaviors for persons with lower health literacy, but not for persons with higher health literacy

### Study Aims and Hypotheses

The proposed study aimed to investigate the relationship between neurocognition and critical determinants of COVID-19-related health behaviors, as well as the health behaviors themselves. The hypotheses for the present study were:

*Hypothesis 1: Global neurocognition will be positively associated with COVID-19-related online information seeking skills, COVID-19-related knowledge, intentions to adhere to recommended COVID-19 preventative behavior guidelines, and COVID-19 preventative behaviors.*

*Hypothesis 2: The effects of neurocognition on COVID-19 related online information seeking skills, COVID-19-related knowledge, intentions to adhere to recommended COVID-19 preventative behavior guidelines, and COVID-19 preventative behaviors will be larger among persons with lower health literacy.*

## METHOD

### Study Design

The current study was a prospective, cross-sectional, correlational design aimed at examining how neurocognition and health literacy related to COVID-19 information seeking skills, knowledge, intentions to adhere to prevention guidelines, and prevention behaviors. The data were collected and analyzed in compliance with the Institutional Review Board (IRB) of the University of Houston regulations.

**Recruitment and Enrollment**

The study sample was recruited via word-of-mouth and postings including a link to an online screening survey on social media including Facebook, Next Door, and Craigslist. Participants were compensated with a $20 Target gift card after completing the study. Participant recruitment began on April 22, 2020 and participant study completion dates ranged from April 23, 2020 to May 21, 2020. All participants accessed the study via a University of Houston-licensed Qualtrics' secure site.

Upon accessing the online screening survey, participants were presented with the consent form that explained the purpose of the study and potential risks and benefits involved in participation. Participants indicated their consent to participate in the study by clicking "Yes" after reading the statement "I have read and understand the consent information and agree to take part in the research study" and then typing their name. A copy of the consent form was also available to download for the participants' records. Participants then completed a screening questionnaire to ensure that they meet eligibility for the study. The eligibility screener included five yes/no questions about being 18 years or older, being proficient in English, being currently located in the United States, and not being diagnosed with a neurological or severe psychiatric condition(s). If a response indicated that a participant was ineligible, they were re-directed to the end of the survey and told that they did not meet eligibility requirements. Participants also completed a demographic questionnaire indicating their sex, age, race/ethnicity, first language, highest level of education, employment status, and current zip code/state. Finally, they completed the Health Comorbidity Questionnaire (Sangha, Stucki, Liang, Fossel, & Jatz, 2003), a self-report measure that asked about diagnosis of heart disease, lung disease, diabetes, kidney disease, liver disease, cancer, asthma, and immune disease. If the participant indicated that they were diagnosed with a condition they were asked whether they receive treatment for the condition (yes/no) and if it limits their activities (yes/no).

Figure 1 shows that a total of 438 persons accessed the online screening survey. One hundred and forty-nine persons (34%) voluntarily exited out of the screener survey before completing it. Nine persons completed the questionnaire but did not meet study inclusion criteria. There were 280 persons who completed the online screening survey and met study inclusion criteria, 63 of whom were not able to be scheduled for a study phone call. Thus the final sample was 217 eligible participants who completed a one-hour phone-based assessment. Study characteristics for the final study sample ($N = 217$) are displayed in Table 1. The 217 participants that met study criteria and completed the one-hour phone-based assessment were older than the 63 participants that were not assessed, $F(1,278) = 5.15$, $p = .024$, $d = .35$. There was a higher frequency of Black (33%) and Hispanic/Latino (32%) participants versus White (19%) and Asian (13%) participants that were eligible for the study but were not assessed. There were no significant differences on sex, education, or number of medical comorbidities between participants who completed the study and those that were not assessed ($p$s > .05).

**Materials and Procedures**

Persons that completed the online screening survey and met study criteria were contacted by a research assistant via email to schedule the one-hour phone-based assessment. At their scheduled assessment time, participants were contacted via Google Voice by a research assistant to complete the assessment. The participants were tested individually in a single testing session over the telephone. The examiner ensured that the participant was in a quiet, private place to complete the assessment and confirmed that the phone call was not being recorded. The one-hour phone assessment consisted of COVID-19-related measures, a neurocognitive battery, health literacy measures, and personality, mood, and physician trust questionnaires.

### *COVID-19-Related Measures*

**COVID-19 Online Information Seeking Evaluation Skills.** The COVID-19 Website Evaluation Strategies Questionnaire is a self-report measure that assessed participants' competency in evaluating online sources containing COVID-related information. Participants were asked to indicate whether or not they had used 16 different website evaluation strategies in the past month while reading about COVID-19 on the Internet (e.g., "Check that the domain name includes '.gov,' '.org,' or '.edu.,'" "Ensure that the information is not based solely on a 'testimonial' or story given by an individual."). The 16 strategies were adapted from information accountability guidelines for the Web established by the American Medical Association (Winker et al., 2000). Possible total scores for ranged from 0 (participant reported using none of the strategies) to 16 (participant reported using all of the strategies) and in the current sample the range was 0 to 16; Cronbach's alpha was .81.

**COVID-19 Knowledge.**

A continuous COVID-19 Knowledge composite score of the below measures was derived from Principal Components Analysis (PCA) using SPSS (version 26.0; see Table 2).

All scores except the COVID-19 Prevention Knowledge False Positive Score loaded onto a single component in the PCA analysis, which accounted for 24.0% of the total variance (Eigenvalue 1.43). Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for COVID-19 Knowledge was 0.53, suggesting slightly inadequate sampling and utility of the PCA, but still acceptable for the purposes of the analysis (Kaiser, 1974). Bartlett's test of sphericity was significant, approximate $X^2$ (15) = 34.49, $p$ = .004, suggesting sufficient relation between variables to detect an underlying component structure (Snedecor & Cochran, 1989). Thus, the factor scores from this single component that included COVID-19 Total Prevention Knowledge Score, Total COVID-19 Symptom Knowledge Score, Total COVID-19 Symptom Knowledge False Positive Score, COVID-19 Knowledge Recognition Task d', and COVID-19 Plan Total Score were used for further analyses.

***COVID-19 Knowledge Free Recall Task.*** Participants first were asked to list the ways in which health officials said they can help protect themselves from getting COVID-19. Responses were recorded verbatim by the examiner. Each response was scored as two points if it corresponded to one of the eight CDC-recommended prevention measures (e.g., wear a mask, social distance) and zero points for responses that did not. A COVID-19 Total Prevention Knowledge Score was calculated by summing correct responses (two points each).

Any incorrect responses were scored as one point for an ineffective, but plausible prevention measure responses (e.g., wear gloves, disinfect packages) and two points for an unfounded, ineffective prevention measure (e.g., take vitamin C, drink water). A Total COVID-19 Prevention Knowledge False Positive Score was calculated by summing scores for incorrect responses (higher scores indicated increased incorrect information reported). False-positive responses were coded independently by first rater and then a randomly selected 10% of the sample was independently coded by a second rater (Intraclass Correlation Coefficient [ICC] = .74, 95% CI = .46, .88].

Participants were then asked to list the *most common* symptoms of COVID-19. Responses were recorded verbatim by the examiner. Each response was scored as two points if it corresponded to one of the four primary symptoms of COVID-19 (i.e., cough, fever, fatigue, shortness of breath; CDC, 2020), one point for any additional symptoms included on the CDC COVID-19 Symptom list (e.g., headache, loss of smell), and zero points for any symptoms not listed by the CDC. A COVID-19 Total Symptom Knowledge Score was calculated by summing correct responses (two points).

Any incorrect responses were scored as one point for COVID-19 symptoms that were uncommon but research-supported (e.g., stroke, cardiac issues) and two points for unfounded COVID-19 symptoms (e.g., loss of teeth). A Total COVID-19 Symptom Knowledge False Positive Score was calculated by summing scores for incorrect responses (higher scores indicated increased incorrect information reported). False-positive responses were coded independently by first rater and then a randomly selected 10% of the sample was independently coded by a second rater (ICC = .91, 95% CI = .79, .96).

***COVID-19 Knowledge Recognition Task.*** The COVID-19 Knowledge Recognition Task included 12 statements about COVID-19. Items were created based on both factual information gathered from reliable sources (e.g., CDC, WHO), as well as common misconceptions about COVID-19 present in general discourse and media sources. Participants were asked to indicate whether each statement about COVID-19 was true, false, or if they didn't know. The task included six true statements (e.g., "Older adults and persons with lung disease have a high risk of serious illness due to coronavirus") and six false statements (e.g., "5g wireless networks weaken the immune system, making people more likely to contract coronavirus.") A d prime (d') recognition score was calculated such that the hit rate was the proportion of true items endorsed as true by the participant ("hits") and the false alarm rate was the proportion of false items endorsed as true by the participant ("false positives"). COVID-19 Recognition d' range for the current sample was 0.21 to 4.37, with higher scores indicating better discrimination between true and false items. For each item, the percentage of participants that chose the correct response ranged from 56.22% ("Nonsteroidal anti-inflammatory drugs [NSAIDs] like ibuprofen and Advil are proven to worsen the symptoms of coronavirus" – False; and "Everybody needs to be tested for coronavirus" – False) to 99.99% ("Coronavirus may be spread by people who are not showing symptoms" – True).

***COVID-19 Plan.*** Participants were asked, "Have you developed a plan for you and your household if you get sick with coronavirus?" Responses were rated qualitatively on a scale from one to five (1 = no plan; 2 = mention of self-isolation; 3 = mention of self-isolation with details about the specifics and preparations for at least one aspect of food, dependents, work, or medical care; 4 = mention of isolation with details about the specifics and preparations for multiple dimensions of care; 5 = all of the above plus higher-level planning for finances, job, power of attorney, etc.) Scores in the current sample ranged from one to five; ICC = .63, 95% CI = .05, .89.

**Intention to Adhere to COVID-19 Prevention Behaviors.** The COVID-19 Prevention Behavior Intentions questionnaire is a self-report measure that assessed participants' intention to adhere to CDC-recommended COVID-19 prevention measures (adapted from Cheng & Ng, 2006). The measure included eight statements describing intention to adhere to prevention measures (e.g., "You intend to follow the preventative guidelines in the next few weeks," "If you did not follow the preventative guidelines in the next few weeks, you would feel regret."). Participants were asked to indicate on a five-point scale scored from one ("Strongly Disagree") to five ("Strongly Agree") the extent to which they agreed with each statement. The eight item responses were summed to create a COVID-19 Prevention Behavior Intentions Total. Possible scores ranged from 8 to 40 with higher scores indicating higher intent to adhere to preventative guidelines. The range in the current sample was 21 to 40 and the Cronbach's alpha was .69.

**COVID-19 Prevention Behavior.** The COVID-19 Prevention Behavior Questionnaire is a self-report measure that assessed adherence to CDC-recommended COVID-19 prevention behaviors. The measure included eight statements describing CDC-recommended COVID-19 prevention behaviors (e.g., "You never touch your eyes, nose, or mouth with unwashed hands," "You always stay at home except for essential tasks such as grocery shopping or doctor appointments."). Participants were asked to indicate on a five-point scale scored from one ("Strongly Disagree") to five ("Strongly Agree") the extent to which their current behaviors aligned with each statement. The eight item responses were summed to create a COVID-19 Prevention Behavior Total Score. Possible scores ranged from 8 to 40 with higher scores indicating higher adherence to prevention measures. The range in the current sample was 20 to 40 and Cronbach's alpha was .76.

**Other COVID-19 Measures**.

***COVID-19-Related Anxiety.*** COVID-19-related anxiety was assessed with a single-item measure for which participants were asked to indicate on a five-point scale scored from one ("Strongly Disagree") to five ("Strongly Agree") the extent to which they agreed with the statement, "You are worried and nervous about coronavirus." The score range in the current sample was one to five.

***COVID-19-Information Seeking Frequency.*** Participants were asked to describe the frequency of which they were reading about or listening to information about COVID-19 on a four-point scale from "Rarely/Never" to "Several Times Per Day"

***COVID-19 Testing.*** Participants asked to indicate whether they had been tested for COVID-19, and if yes, whether they had tested positive for COVID-19.

***COVID-19 Perceived Risk***. Participant were asked to rate the extent to which they agree with the following statement, "You believe you are at a much higher risk than the average person for developing more serious complications from coronavirus [COVID-19]" on a five-point scale scored from one ("Strongly Disagree") to five ("Strongly Agree"). They were then asked what made them chose their response (e.g., "Why did you chose [Strongly Agree]?") Participant responses were coded verbatim. Participants received one point for each time in their response that they mentioned a metric they used to assess their own risk that corresponded with CDC COVID-19 severe illness risk assessment metrics (CDC, 2020c).

For example, the CDC lists that people 65 years and older are at higher risk for severe illness from COVID-19 so a participant received a point if included in their response that they were either at higher risk due to their older age or lower risk due to younger age. Total COVID-19 Perceived Risk Accuracy Score was calculated by summing number of correct responses. Responses were also rated qualitatively on a scale from one (response was inaccurate or unrelated to question) to five (all reasons given in response corresponded with CDC risk assessment metrics). Responses were coded independently by first rater and then a randomly selected 10% of the sample was independently coded by a second rater (ICC = .78, 95% CI = .52, .91).

### *Neurocognitive Measures*

The neurocognitive measures for this study were chosen both for their reliability and consistency within infectious disease literature, as well as their adaptability to the telephone-administration format (i.e., as informed by video-neuropsychology and tele-neuropsychology literatures). Prior work using the same dataset utilized a confirmatory factor analysis (CFA) to test single, two-, and three-factor models to explain performance on the neurocognitive battery (Matchanova, et al., preprint). The study demonstrated adequate fit for both a one-factor model of global neurocognition (comprised of Hopkins Verbal Learning Test – Revised [HVLT-R] Trial 1, HVLT-R Long Delay Free Recall, HVLT-R Recognition, Prospective Memory total, Delis-Kaplan Executive Function System [DKEFS] Switching, Action Fluency, Oral Trail Making Test Parts A and B, and Digit Span Forward and Backwards subtests of the Weschler Adult Intelligence Scale—Fourth Edition [WAIS-IV) and three-factor model consisting of memory (i.e. HVLT-R Recognition, HVLT-R Long Delay Free Recall and Prospective Memory), executive functioning (i.e. D-KEFS Switching, Action Fluency, OTMT Part B) and attention (i.e. HVLT-R Trial 1, WAIS-IV Digit Span Backward and Forward) domain scores (Matchanova, et al., preprint). The global neurocognitive factor score and three respective neurocognitive domain factor scores from these analyses were used in the present study.

**Hopkins Verbal Learning Test – Revised.** The Hopkins Verbal Learning Test – Revised (HVLT-R; Benedict, Schrentlen, Groninger, & Brandt, 1998; Brandt & Benedict, 2001) is a 12-item list learning task that measures auditory-verbal memory and learning. The supra-span word list contains three groups of semantically related (non-consecutive) words that are read out loud at approximately two-second interstimulus intervals. The HVLT-R includes three learning trials, a 20-25 minute delayed free recall trial (Trial 4), and a recognition yes/no format trial that contains 24 words including the 12 target words from the original list and 12 non-target words. Six of the 12 non-target words are semantically related to words on the original list and the other six are not. Derived scores include HVLT-R, Trial 1, Total Learning (summed number of words recalled from Trials 1, 2, and 3), Delayed Recall (total number of words recalled on Trial 4), and Recognition Discrimination (number of hits minus number of false positives endorsed during the recognition trial). All participants had Recognition Discrimination scores above five, which is the recommended HVLT-R embedded performance validity cut-off (Sawyer, Testa, & Dux, 2017). The literature provides support for the reliability (Benedict et al., 1998; Woods et al., 2005) and construct validity (e.g., Lacritz, Cullum, Weiner, & Rosenberg, 2001) of these standard learning and recall HVLT-R measures. There is also preliminary support for the reliability of scores between telephone and in-person administration methods (Bunker et al., 2016).

**Prospective Memory Task.** Participants completed an event-based prospective memory (PM) task that was embedded into the study protocol (adapted from Beaver & Schmitter-Edgecombe, 2017). During the introduction of the protocol of the one-hour phone-based assessment, participants were told "… several times throughout this call I will say, 'Now we will move on to the next task.' When you hear me say that sentence, I would like you to say the word 'pineapple.' Just to make sure we're on the same page, can you please repeat back those instructions to me?" The examiner then repeated and rephrased instructions, if necessary, to ensure understanding of the task. There were four trials of the PM task embedded in the study protocol during which the participant said the statement "Now we will move on to the next task" then recorded the participants' subsequent responses (or lack thereof). For each trial, the participant response was scored as a two (correct response, correct time), one (incorrect phrase or incorrect time) or zero (did not acknowledge PM task). The PM Task Total Score was calculated by summing the scores from the four trials and the possible range from zero to eight; the current sample range was zero to eight and Cronbach's alpha was .80.

**Digit Span subtests of the WAIS-IV.** The Digit Span Forward subtest of the Weschler Adult Intelligence Scale—Fourth Edition (WAIS-IV; Wechsler, 2008) was used to assess basic auditory attention. For WAIS-IV Digit Span Forward, participants were read a sequence of numbers and asked to repeat back the numbers in the same order. Possible scores ranged from 0 to 16; scores in the current sample ranged from 5 to 16. The Digit Span Backward subtest of the WAIS-IV was used to assess working memory. For WAIS-Digit Span Backwards, the participants were read a sequence of numbers and asked to repeat back the numbers in the backwards order. Possible scores ranged from 0 to 16; scores in the current sample ranged from 4 to 16. Previous studies have utilized WAIS Digit Span subtests in telephone-based neurocognitive assessments (e.g., Unverzagt et al., 2007, Christie et al., 2006) and there is preliminary evidence of reliability between in-person and telephone administration of the WAIS-IV Digit Span subtests (e.g., Taichman et al., 2005; Bunker et al., 2017; Rapp et al., 2012 cf. Mitsis et al., 2010). Reliable Digit Span (RDS; Greiffenstein, Baker, & Gola, 1994) was calculated for each participant by adding their longest span forward and longest span backwards. RDS cutoff score of less than or equal to seven is a well-established embedded measure of performance validity (Boone, 2007; Schroeder, Tqumasi-Ankrag, Baade, & Marshall, 2012) and all participants that completed WAIS-IV Digit Span in the current sample had RDS greater than or equal 7.

**Information subtest of the WAIS-IV.** The Information subtest of the WAIS-IV (WAIS-IV Info; Weschler, 2008) was used to evaluate participants' general fund of knowledge. Participants were asked questions covering a broad range of general knowledge topics. Possible scores ranged from 0 to 26; current sample scores ranged from 4 to 26.

**Action (verb) Fluency.** The action (verbal) fluency test (Piatt, Fields, Paolo, & Tröster, 1999) is a measure of verbally mediated executive functions that required participants to generate as many action words (i.e., verbs) as possible in 60 seconds. The total number of unique words generation in 60 seconds was the total score; current sample total score ranged from 10 to 40. The action fluency task shows adequate test-retest reliability and construct validity (Woods et al., 2005b), convergent validity (e.g., Piatt, Fields, Paolo, & Tröster, 1999; Woods et al., 2005b), and divergent validity (Woods et al., 2005c). While there are no papers to date describing administration of action (verb) fluency over the telephone, there exists preliminary support for the validity of telephone-based assessment of verbal fluency tasks (e.g., Unverzagt et al., 2007; Rapp et al., 2012).

**DKEFS Verbal Fluency – Category Switching.** The Category Switching subtest of DKEFS Verbal Fluency (DKEFS Switching; Delis, Kaplan, & Kramer, 2001) assesses executive abilities including cognitive flexibility, and rule-guided, self-initiated processes commonly associated with frontal systems (e.g., Ho et al., 2002). Participants were told to list as many words as they could in 60 seconds while switching back and forth between naming furniture and fruits. The total number of correct responses was recorded; the total number of correct responses in the current sample ranged from 5 to 26. As described under Action (verb) Fluency), verbal fluency tests are often included in telephone-based cognitive assessments and demonstrate acceptable reliability between telephone and in-person administration modalities (e.g., Unverzagt et al., 2007; Rapp et al., 2012).

**Oral Trail Making Test.** The Oral Trail Making Test (OTMT; Ricker & Axelrod, 1994) consisted of two subtests (OTMT A and OTMT B) that measure processing speed and executive functions, respectively. For OTMT A, examiners timed participants counting from 1 to 25 as quickly as they could. For OTMT B, participants were told to switch back and forth from letter to number as fast as they could without making mistakes (i.e., 1, A, 2, B…) and the time it took them to reach the number 13 was recorded. Total time (in seconds) for OTMT A and OTMT B in the current sample ranged from 5 to 19 and 9 to 225, respectively. The OTMT has been employed in telephone-based assessments previously (e.g., McComb et al., 2010). Only one paper to date has compared performance on OTMT in-person and over the phone and results suggested that there was a discrepancy for OTMT A, but not OTMT B (Mitsis et al., 2009).

***Health Literacy Measure***

A continuous Health Literacy composite score of the below measures was derived from Principal Components Analysis (PCA; see Table 3). One component was extracted from the five health literacy variables (Eigenvalue 1.84), which explained 36.8% of the variance. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for health literacy was 0.61, suggesting slightly inadequate sampling and utility of the PCA, but still acceptable for the purposes of the analysis (Kaiser, 1974). Bartlett's test of sphericity was significant, approximate $X^2$ (10) = 105.89, $p < .001$, suggesting sufficient relation between variables to detect an underlying component structure (Snedecor & Cochran, 1989). Thus, the factor scores from this single component that included the five below measures were used for further analyses.

**Brief Health Literacy Screening Tool (3-BRIEF).** The Brief Health Literacy Screening Tool (3-BRIEF; Chew et al., 2007) is a three-item brief self-report measure of health literacy adequacy. Participants rated the extent to which they agreed with three statements related to health literacy (e.g., “You are confident filling out forms by yourself” on a five-point Likert scale scored from one (“Strongly Disagree”) to five (“Strongly Agree”). Possible scores ranged from 5 to 15 with higher scores indicating higher perceived health literacy; current study scores ranges from 5 to 15 and the Cronbach’s alpha was .69. Participants were considered to have suboptimal levels of health literacy if they endorsed “Disagree” or “Strongly Disagree” to any of the three items.

**Subjective Numeracy Scale.** Participants were administered the Subjective Numeracy Scale (SNS; Fagerlin et al., 2007), an eight-item measure assessing subjective competency with and perceived usefulness of numerical information. Participants were asked to rate the extent to which they agreed with eight statements (e.g., “When you hear a weather forecast, you prefer predictions using percentages rather than predictions using only words,” “You are good at working with fractions”) on a five-point Likert scale scored from one (“Strongly Disagree”) to five (“Strongly Agree). Items were summed to create a total score with higher scores indicating higher subjective numeracy. Possible scores ranged from 8 to 40; in the current sample, scores ranged from 18 to 40 and Cronbach’s alpha was .73.

**Expanded Numeracy Scale.** Participants were administered the Expanded Numeracy Scale (ENS; Lipkus, Samsa, & Rimer, 2001) which assesses participants’ familiarity and competency with health-related percentages and proportions. The measure consists of seven items in which the participant must provide a response to a numerical health-related question (e.g., “If the chance of getting a disease is 20 out of 100, what is the percent change of getting the disease?”). Participants received a score of one (correct) or zero (incorrect) for each item and the seven items were summed to create a total score. Possible scores range from zero to seven; in the current sample scores ranged from zero to seven and the Cronbach’s alpha was .66.

**Electronic Health Literacy.** The eHEALS (Norman & Skinner, 2006) is an eight-item self-report measure of a participant's knowledge and perceived skills at finding, evaluating, and applying electronic health information to health problems (e.g., "I know how to find helpful health resources.") Responses were rated on a five-point Likert scale scored from one ("Strongly Disagree") to five ("Strongly Agree"). This measure evidences good psychometric properties in the young adult sample it was examined in (Norman and Skinner, 2006) and in older adults (Chung & Nahm, 2016). Possible scores range from 0 to 40 with a higher score indicating confidence with utilizing the Internet for health-related purposes. The range of scores in the current sample was 14 to 40 and the Cronbach's alpha was .92.

**Health Motivation Questionnaire.** The Health Motivation Questionnaire assesses motivation to adhere to positive health behaviors and monitor health status. The questionnaire included eight items that were derived from a set of questions first described by Moorman (1993). The set of items extracted from original study included questions about an individual's concern about their health (e.g., "I try to prevent health problems before I feel any symptoms" and "I try to protect myself against health hazards I hear about"). Responses were scored on a five-point Likert scale from one ("Strongly Agree") to five ("Strongly Disagree"). Negative items (e.g., "There are so many things that can hurt you these days, I am not going to worry about them") were reverse coded. Possible scores ranged from 8 to 40 with higher scores suggesting greater health motivation; the current study scores ranged from 16 to 40 and the Cronbach's alpha was .80.

***Possible Covariates***

**Internet Use Questionnaire.** General Internet use was measured utilizing an approach outlined and supported by Baggio Iglesias, Berchtold & Suris (2017). In the present study, participants were asked three questions related to how often they used the Internet in the previous 30 days, how much time they spend on the Internet on an average weekday, and how much time they spend on the Internet on an average weekend day. From these responses, a single score that accounted for quantity and frequency was calculated, which could range from 0 to 63, with a higher score indicated more frequent use. In the current sample, scores ranged from 0 to 63 and the Cronbach's alpha was .71.

**Geriatric Anxiety Inventory-Short Form.** The Geriatric Anxiety Inventory-Short Form (GAI-SF; Bryne & Pachana, 2011) is a five-item self-report measure that assesses common anxiety symptoms. Participants indicated whether they agreed or disagreed with each statement (e.g., "You worry a lot of the time," "Little things bother you a lot"). Possible total scores ranged from zero to five, with higher scores indicating more anxiety. Literature suggests that the measure has strong reliability and construct validity (Bryne & Pachana, 2011). In the current sample, total scores ranged from one to five and the Cronbach's alpha was .80.

**Wake Forest Physician Trust Scale.** The Wake Forest Physician Trust Scale (WFPTS; Hall et al., 2002) is ten-item self-report measure assessing participants' trust in their physician. The scale is modeled on the conceptualization of physician trust as five overlapping domains including fidelity, competence, honesty, confidentiality, and global trust. Participants rated the extent to which they agreed with each statement (e.g., "Your doctor will do whatever it takes to get you all the care you need," "Your doctor is extremely thorough and careful") on a five-point Likert scale scored from one ("Strongly Disagree") to five ("Strongly Agree"). Literature supports the internal consistency and construct validity of the scale (Hall et al., 2002). Possible scores ranged from 10 to 50. In the current study, scores ranged from 17 to 50, with higher scores indicating more trust, and Cronbach's alpha was .91. The first 13 participants were not administered the WFPTS due to a study procedural issue.

**The Big Five Inventory – 2 Extra-Short Form.** Participants completed the Big Five Inventory – 2 Extra-Short Form (BFI-2-XS; Soto & John, 2017) assessing five personality domains. Participants rated the extent to which they agreed with 15 statements describing personality traits on a five-point Likert scale scored from one ("Strongly Disagree") to five ("Strongly Agree"). Domain scores for each of the five personality domains were calculated by summing item scores from three relevant statements for each domain: Extraversion (e.g., "You are someone who tends to be quiet [R]"), Agreeableness (e.g., "You are compassionate, or have a soft heart"), Conscientiousness (e.g., "You are reliable, or can always be counted on"), Negative Emotionality (e.g., "You tend to feel depressed or blue"), and Open-Mindedness (e.g., "You are fascinated by art, music, or literature"). Possible total scores for each domain ranged from 5 to 15. In the current sample, Cronbach's alpha for each domain ranged from .43 (Agreeableness) to .69 (Negative Emotionality); average Cronbach's alpha was .58. These Cronbach alphas were comparable to the alphas calculated in the original development and validation paper for the measure (i.e., range .51 to 72; Soto & John, 2016). Thirteen participants were not administered the BFI-2-XS due to it being a later addition to the study protocol.

**Length of COVID-19 Information Exposure**. The WHO first notified the public of a cluster of pneumonia cases in Wuhan, Hubei province on January 4, 2020 (WHO, 2020d). A length of COVID-19 information exposure variable was created by calculated the number of days between the public being informed and the date of the participant's one-hour phone-based assessment; the current sample range was 109 to 137 days.

**Health Comorbidity Total.** A Health Comorbidity Total was created by summing the number of endorsed medical comorbidities on the Health Comorbidity Questionnaire (Sangha, Stucki, Liang, Fossel, & Jatz, 2003) from the online screening survey. The range of total number of health comorbidities in the current sample was zero to three.

## Data Analyses

Prior to conducting analyses, visual inspection and screening of the data was used to ensure accuracy and identify outliers and other abnormal data points (Van der Broeck, Cunningham, Feckels, & Herbst, 2005). Missing value, correlation, moderation, and regression analyses were conducted using SPSS (version 26.0). Bonferroni adjustment was used for all statistical analysis to control for Type 1 error for the relationship of each variable across four outcome measures (i.e., COVID-19 Online Information Seeking Skills, Knowledge, Intentions, and Behaviors, respectively) and thus, alpha was set at .013 for all primary analyses.

***Hypothesis 1:*** *Cognition will be related to COVID-19-related online information seeking skills, COVID-19-related knowledge, intentions to adhere to recommended COVID-19 preventative behavior guidelines, and COVID-19 preventative behaviors.*

All COVID-19 outcome variables were non-normally distributed (Shapiro-Wilk test for normality $p$s < .05; Royston, 1995) thus, non-parametric Spearman's rank correlations were used to evaluate the univariate relationship between neurocognition and each of the respective COVID-19 outcomes.

To determine the need for covariates, univariate analyses were conducted using Wilcoxon/Mann-Whitney, and Spearman's rank correlations. Variables in Table 1 were evaluated as possible covariates. Any variable that was significantly related to both the main predictor (i.e., global cognition) and criterion variable of interest (i.e., COVID-19-related online information seeking skills, COVID-19-related knowledge, intention to adhere to COVID-19 preventative behaviors, and COVID-19 preventative behaviors, respectively) using a liberal critical alpha of 0.10 was considered as a possible covariate. In order to reduce collinearity and burden on the final models, if more than one possible covariate emerged, possible covariates were put into a regression predicting the relevant outcome and any variables that remained independently associated with the relevant outcome ($p < .05$) were included in the final model. SPSS software was used to generate diagnostic plots that revealed that the data meet multiple regression assumptions for linearity, normality of residuals, and homoscedasticity. A correlation matrix among all continuous independent variables was be used to determine that there was no multicollinearity among independent variables ($r$s < .80). A power analysis conducted using the program *G*Power* (version 3.1.9.6; Faul, Erdfelder, Lang, & Buchner, 2009) revealed that the power was acceptable (.98) to detect a medium effect size ($f^2$= .15, Cohen, 1977) using a critical alpha of .0125 with a sample size of 217 and up to five predictors. The final multivariable models included the neurocognitive variable of interest (i.e., global neurocognition, attention/working memory, executive functions, or memory) and relevant covariates predicting the respective COVID-19 outcome.

***Hypothesis 2:*** *The effects of neurocognition on COVID-19 related online information seeking skills, COVID-19-related knowledge, intentions to adhere to recommended COVID-19 preventative behavior guidelines, and COVID-19 preventative behaviors will be larger among persons with lower health literacy.*

Hierarchical regression analyses were conducted to evaluate main and interactive effects of global neurocognitive (independent variable) and the health literacy composite (moderator), on each of the respective COVID-19 outcomes (dependent variable). All models met assumptions for causality, linearity, homogeneity of variance, and measurement error. Overall significance of the predictors was interpreted at $p < .013$. A power analysis conducted using the program *G**Power (version 3.1.9.3; Faul, Erdfelder, Lang, & Buchner, 2009) revealed that the power was acceptable (.98) to detect a medium effect size ($f^2 = .15$, Cohen, 1977) using a critical alpha of .0125 with a sample size of 217 and up to five predictors. Relevant covariates, determined through the data-driven method described above, were entered in the first step of each model. Global neurocognition and health literacy were then entered simultaneously in the second step of the mode. Finally, the interaction of global neurocognition and health literacy was added in the third step.

## RESULTS

### Association Between Neurocognition, Health Literacy, and COVID-19 Outcome Measures

Descriptive statistics for participant performance on neurocognitive, health literacy and COVID-19 outcome measures were reported in Table 4. See Table 5 for univariate correlations between neurocognition, health literacy and COVID-19 outcome measures (i.e., online COVID-19 information seeking skills, COVID-19 knowledge, intentions to adhere to COVID-19 preventative behaviors, and self-reported adherence to COVID-19 behaviors.

### Cognition and COVID-19 Online Information Seeking Evaluation Skills

Global neurocognition was not associated with COVID-19 Online Information Seeking Evaluation Skills at the univariate level (Spearman's rho = -.05, $p = .482$). None of the individual cognitive domains (i.e., Attention, Executive Functions or Memory) were associated with COVID-19 Online Information Seeking Evaluation Skills at the univariate level (*p*s > .013).

## Cognition and COVID-19 Knowledge

### *Global Neurocognition*

Global neurocognition scores were positively associated with COVID-19 Knowledge at a medium effect size (Spearman's rho = .31, $p < .001$). Education, race/ethnicity, length of COVID-19 exposure, and WAIS-IV Information were associated with both Global Cognition and COVID-19 Knowledge and thus, were considered as possible covariates (*p*s < .10). There were no other Table 1 variables that were associated with both Global Cognition and COVID-19 Knowledge (*p*s > .10). When a multiple regression with education, race/ethnicity, length of COVID-19 exposure, and WAIS-IV Information predicting COVID-19 Knowledge was conducted, only race/ethnicity and education were associated with COVID-19 Knowledge (*p*s < .05) and thus, were included as covariates in the final multivariable model.

A multiple regression was conducted with global cognition, education, and race/ethnicity predicting COVID-19 Knowledge. The overall model was significant $F(3, 210) = 10.82$, $p < .001$, adjusted $R^2 = .12$. Global Neurocognition ($b = 0.64$, $b$ 95% CI = 0.31, 0.97, $t[210] = 3.82$, $p < .001$) and education ($b = 0.10$, $b$ 95% CI = 0.03, 0.17, $t[210] = 2.97$, $p = .003$) were significant predictors of COVID-19 Knowledge. Race/ethnicity was not a significant predictor of COVID-19 Knowledge ($p = .772$).

### *Attention/Working Memory*

Attention/Working Memory was positively associated with COVID-19 Knowledge at a small effect size (Spearman's rho = .23, $p = .001$). Education, race/ethnicity, and WAIS-

IV Information were associated with both Attention/Working Memory and COVID-19 Knowledge (*p*s < .10). There were no other Table 1 variables that were associated with both Attention/Working Memory and COVID-19 Knowledge (*p*s > .10). When a multiple regression with education, race/ethnicity, and WAIS-IV Information predicting COVID-19 Knowledge was conducted, only education and WAIS-IV Information were associated with COVID-19 Knowledge (*p*s < .05) and thus, were included as covariates.

A multiple regression was conducted with Attention/Working Memory, WAIS-IV Information, and education predicting COVID-19 Knowledge. The overall model was significant $F(3, 212) = 9.12$, $p < .001$, adjusted $R^2 = .10$. Education ($b = 0.11$, $b$ 95% CI = 0.04, 0.17, $t[212] = 3.04$, $p = .003$) was the only significant predictor of COVID-19 Knowledge. Attention/Working Memory and WAIS-IV Information were not associated with COVID-19 Knowledge (*p*s > .013).

### *Executive Functions*

Executive Functions (Spearman's rho = .33, $p = .001$) were positively associated with COVID-19 Knowledge at a medium effect size. Education, race/ethnicity, length of COVID-19 exposure, and WAIS-IV Information were associated with both Executive Functions and COVID-19 Knowledge (*p*s < .10). There were no other Table 1 variables that were associated with both Executive Functions and COVID-19 Knowledge (*p*s > .10). When a multiple regression with education, race/ethnicity, length of COVID-19 exposure, and WAIS-IV Information predicting COVID-19 Knowledge was conducted, only education and WAIS-IV Information were associated with COVID-19 Knowledge (*p*s < .05) and thus, were included as covariates.

A multiple regression was conducted with Executive Functions, education, and WAIS-IV Information predicting COVID-19 Knowledge. The overall model was significant

$F(3, 212) = 11.13$, $p < .001$, adjusted $R^2 = .12$. Executive Functions ($b = 0.04$, $b$ 95% CI = 0.01, 0.07, $t[212] = 2.94$, $p = .004$) and education ($b = 0.09$, $b$ 95% CI = 0.02, 0.16, $t[212] = 2.62$, $p = .010$) were significant predictors of COVID-19 Knowledge. WAIS-IV Information was not a significant predictor of COVID-19 Knowledge ($p = .351$).

***Memory***

Memory (Spearman's rho = .31, $p < .001$) was positively associated with COVID-19 Knowledge at a medium effect size. Education, race/ethnicity, length of COVID-19 exposure, and WAIS-IV Information were associated with both Memory and COVID-19 Knowledge (*p*s < .10). There were no other Table 1 variables that were associated with both Memory and COVID-19 Knowledge (*p*s > .10). When a multiple regression with education, race/ethnicity, length of COVID-19 exposure, and WAIS-IV Information predicting COVID-19 Knowledge was conducted, only education and WAIS-IV Information were associated with COVID-19 Knowledge (*p*s < .05) and thus, were included as covariates.

A multiple regression was conducted with Memory, education, and WAIS-IV Information predicting COVID-19 Knowledge. The overall model was significant $F(3, 212) = 11.56$, $p < .001$, adjusted $R^2 = .13$. Memory ($b = 0.50$, $b$ 95% CI = 0.19, 0.82, $t[212] = 3.11$, $p = .002$) and education ($b = 0.10$, $b$ 95% CI = 0.02, 0.16, $t[212] = 2.62$, $p = .009$) were significant predictors of COVID-19 Knowledge. WAIS-IV Information was not a significant predictor of COVID-19 Knowledge ($p = .190$).

**Cognition and Intentions to Adhere to COVID-19 Preventative Behaviors**

Global neurocognition was not associated with Intentions to Adhere to COVID-19 Preventative Behaviors at the univariate level (Spearman's rho = .03, $p = .621$). None of the individual neurocognitive domains (i.e., Attention, Executive Functions or Memory) were associated with COVID-19 Online Information Seeking Evaluation Skills at the univariate level ($p$s > .013).

## Cognition and COVID-19 Preventative Behaviors

### *Global Neurocognition*

At the univariate level, higher global neurocognition was associated with *lower* reported adherence to COVID-19 Preventative Behaviors at a small effect size (Spearman's rho = -.17, $p$ = .010). WAIS-IV Information and Agreeableness were associated with both global neurocognition and COVID-19 Preventative Behaviors ($p$s < .10). There were no other Table 1 variables that were associated with both global neurocognition and COVID-19 Preventative Behaviors ($p$s > .10). When a multiple regression with WAIS-IV Information and Agreeableness predicting COVID-19 Preventative Behaviors was conducted, only WAIS-IV Information was associated with COVID-19 Preventative Behaviors ($p$s < .05) and thus, was included as a covariate.

A multiple regression was conducted with global neurocognition and WAIS-IV Information predicting COVID-19 Preventative Behaviors. The overall model was not significant, $F(2, 213) = 3.82$, $p = .023$, adjusted $R^2 = .03$. Neither global neurocognition nor WAIS-IV Information was associated with COVID-19 Preventative Behaviors ($p$s > .013).

### *Attention/Working Memory*

Attention/Working Memory scores were not associated with lower reported adherence to COVID-19 Preventative Behaviors at a significant level (Spearman's rho = -.16, $p$ = .019)**.**

### *Executive Functions*

Higher executive functions were associated with lower reported adherence to COVID-19 Preventative Behaviors at a small effect size (Spearman's rho = -.22, $p$ = .001). WAIS-IV Information and Agreeableness were associated with both Executive Functions and COVID-19 Preventative Behaviors ($p$s < .10). There were no other Table 1 variables that were associated with both Executive Functions and COVID-19 Preventative Behaviors ($p$s > .10). When a multiple regression with WAIS-IV Information and Agreeableness predicting COVID-19 Knowledge was conducted, only WAIS-IV Information was associated with COVID-19 Preventative Behaviors ($p$ < .05) and thus, was included as a covariate.

A multiple regression was conducted with Executive Functions and WAIS-IV Information predicting COVID-19 Preventative Behaviors. The overall model was significant, $F(2, 213) = 4.97$, $p = .008$, adjusted $R^2 = .04$. Neither Executive Functions nor WAIS-IV Information, was associated with COVID-19 Preventative Behaviors ($p$s > .013).

### *Memory*

Memory scores were associated with reported adherence to COVID-19 Preventative Behaviors at the univariate level (Spearman's rho = -.16, $p$ = .017).

## Health Literacy as Moderator of Neurocognition and COVID-19 Health Outcomes

### *Health Literacy as a Moderator of Neurocognition and COVID-19 Information-Seeking Evaluation Skills*

WAIS-IV Information was associated with global neurocognition, health literacy, and COVID-19 Online Information-Seeking Evaluation Skills ($p$s < .05) and thus, was included as a covariate. WAIS-IV Information entered in the first step accounted for a significant amount of variance in COVID-19 Online Information-Seeking Evaluation Skills,

$R^2adj = .03$, $F(1,214) = 6.38$, $p = .012$. The entry of global neurocognition and health literacy in step two accounted for a significant amount of variance above and beyond step one ($\Delta R^2 = .061$, $\Delta F(2,212) = 7.11$, $p = .001$), which was primarily attributable to health literacy, $b = 0.95$, $b$ 95% CI = 0.42, 1.49 $t[212] = 3.57$, $p < .001$; global neurocognition, $b = -1.19$, $b$ 95% CI = -2.54, 0.15, $t[212] = -1.72$, $p =.088$. The addition of the interaction term between global neurocognition and health literacy in step three did not account for more variance in COVID-19 Information-Seeking Evaluation Skills ($\Delta R^2 = .002$, $\Delta F(1,211) = 0.36$, $p = .548$; see *Table 6*).

***Health Literacy as a Mediator of Cognition and COVID-19 Knowledge***

Education, race/ethnicity, length of COVID-19 information exposure, and WAIS-IV Information were associated with Global Neurocognition, health literacy, and COVID-19 Knowledge ($p$s < .10). When a multiple regression with education, race/ethnicity, length of COVID-19 information exposure, and WAIS-IV Information predicting COVID-19 Knowledge was conducted, only education and WAIS-IV Information were associated with COVID-19 Knowledge ($p$s < .05).

WAIS-IV Information and education entered in the first step accounted for a significant amount of variance in COVID-19 Knowledge $R^2adj = .09$, $F(2,213) = 11.96$, $p < .001$. The entry of global neurocognition and health literacy in step two accounted for a significant amount of variance above and beyond step one ($\Delta R^2 = .06$, $\Delta F(2,211) = 8.07$, $p < .001$), which was attributable to both global neurocognition, $b = 0.55$, $b$ 95% CI = 0.21, 0.91, $t[211] = 2.95$, $p = .005$, and health literacy, $b = 0.22$, $b$ 95% CI = 0.08, 0.36 $t[211] = 2.52$, $p =.012$; WAIS-IV Information and education $p$s > .013. The addition of the interaction term between global neurocognition and health literacy in step three did not account for more variance in COVID-19 Knowledge ($p > .013$; see *Table 6*).

***Health Literacy as a Moderator of Cognition and COVID-19 Intentions***

Education and length of COVID-19 exposure were associated with Global Neurocognition, health literacy, and COVID-19 Intentions (*p*s < .10). When a multiple regression with education and length of COVID-19 exposure predicting COVID-19 Intentions was conducted, neither education nor length of COVID-19 exposure were associated with COVID-19 Intentions (*p*s > .05), thus no covariates were included in the model.

Global neurocognition and health literacy entered in the first step accounted for a significant amount of variance in COVID-19 Intentions, $R^2adj = .15$, $F(2,214) = 19.35$, $p < .001$, which was primarily attributable to health literacy, $b = 1.31$, $b$ 95% CI = 0.89, 1.73, $t[214] = 6.17$, $p < .001$; global neurocognition $p > .013$. The addition of the interaction term between global neurocognition and health literacy in step two did not account for more variance in COVID-19 Intentions ($p > .013$; see *Table 6*).

***Health Literacy as a Moderator of Cognition and COVID-19 Preventative Behaviors***

WAIS-IV Information and Agreeableness were the only Table 1 variables associated with Global Neurocognition, health literacy, and COVID-19 Preventative Behaviors (*p*s < .10). When a multiple regression with WAIS-IV Information and Agreeableness predicting COVID-19 Preventative Behaviors was conducted, only WAIS-IV Information remained a significant predictor of COVID-19 Preventative Behaviors ($p < .05$) and thus, was included as a covariate in the final model.

WAIS-IV Information was entered in the first step and accounted for a significant amount of variance in COVID-19 Behaviors $R^2adj = .02$, $F(1,214) = 6.39$, $p = .012$. The entry of global neurocognition and health literacy in step two accounted for a significant amount of variance above and beyond step 1 ($\Delta R^2 = .06$, $\Delta F(2,212) = 7.42$, $p = .001$), which was primarily attributable to health literacy, $b = 1.21$, $b$ 95% CI = 0.56, 1.86, $t[212] = 3.69$, $p < .001$, and WAIS-IV Information, $b = -0.21$, $b$ 95% CI = -0.35, -0.07, $t[212] = -3.00$, $p = .003$; global neurocognition $p > .013$. The addition of the interaction term between global neurocognition and health literacy in step three did not account for more variance in COVID-19 Behaviors ($p > .013$; see *Table 6*).

## Discussion

In just a few short months, COVID-19 evolved from an isolated cluster of pneumonia cases in China to a pandemic that has brought many countries to a standstill, pushed some hospital systems to the brink, and dragged the global economy into a recession. Immediate determinable effects of COVID-19 include hundreds of thousands of lives lost around the world (WHO, 2020b), unprecedented unemployment rates (US Bureau of Labor Statistics, 2020), school closures, cancelled social events, and a general shift in social norms. Its long-term medical, societal, and psychological effects are likely substantial, but are yet to be determined. The data from the current study captured a distinct period of time in which government-regulated COVID-19 restrictions were at their height in the US; for example, when data collection began on April 23, 2020, 42 out of 50 states were under a stay-at-home order (CDC, 2020e). The one-month window of data collection during this critical period allowed for a unique opportunity to assess the contributions of cognition and health literacy to the acquisition and implementation of novel disease-related information seeking, knowledge, intentions, and behavior.

### Neurocognition and COVID-19 Knowledge

Findings from the current study suggested that global neurocognition was positively associated with COVID-19 knowledge at a medium effect size. That is, individuals with higher neurocognitive ability had higher scores on a COVID-19-related knowledge composite that included free recall of COVID-19 symptoms and preventative measures, recognition discrimination of true and false statements regarding COVID-19, and quality of a household plan if they contracted COVID-19. The association between global neurocognition and COVID-19 knowledge remained significant even when controlling for the data-driven covariates of race/ethnicity and education. These results were consistent with previous studies that have demonstrated a positive association between cognition and infectious disease transmission knowledge among persons with HIV (Malow et al., 2012), and disease management and treatment knowledge among persons with type 2 diabetes (Nguyen, Gryzwacz, et al., 2010; Wykes, Lee, Bourassa, Kitchen, & McKibbin, 2017; Sartori, Clay, Ovalle, Rothman, & Crowe, 2011).

Between January 2020 and May 2020, COVID-19 went from a virtually unknown respiratory illness to the central topic of most news cycles and household conversations as the public grappled with how to best protect themselves, their families, and their communities from the virus. The responsibility of slowing down the spread of the virus rested largely on individuals' abilities to learn new health-related information. The present study is the first to identify the independent role of neurocognition in this process of quickly acquiring, comprehending and recalling critical information about COVID-19 (e.g., identification and appropriate response to symptoms, prevention measures). At the immediately relevant level, these results suggest that individuals with lower neurocognition may be at increased risk for believing misinformation about COVID-19 and/or not having knowledge of COVID-19 information, either of which could have serious implications for public health. Taking a step back, the present study also afforded a unique glimpse of the importance of neurocognition in the early acquisition of disease knowledge in the context of a virus that was novel to both researchers and the general public and had an immediate impact on most Americans.

Previous studies have operationalized neurocognition function either using a single measure (i.e., Color Trails; Malow et al., 2012) or using brief screeners (e.g., Wykes et al., 2017; Sartori et al., 2011). As the current study utilized a brief clinical battery of neuropsychological tests across several domains, the relationship between neurocognition and COVID-19-related knowledge could be explored at the domain level. At the univariate level, all neurocognitive domains (i.e., attention/working memory, executive functions, and memory) were positively associated with COVID-19 Knowledge at small-to-medium effect sizes. When controlling for relevant covariates, executive functions and memory, but not attention/working memory, were associated with COVID-19 Knowledge. Notably, post-hoc analyses revealed that executive function and memory were associated with COVID-19 Knowledge independently of attention/working memory, suggesting that these associations were not an artifact of more basic attentional processes.

Executive functions likely play a role both in the process of learning and recalling new information about COVID-19. The process of learning new information, particularly in the Internet age, relies heavily on gathering information from multiple sources and performing iterative processes of both updating knowledge as new information becomes available and un-learning information that is no longer relevant (e.g., Ford, 2004). Executive functions assessed in the current study that may contribute to learning about COVID-19 through these processes include speeded auditory-verbal set-shifting (e.g., switching between information sources) and cognitively flexibility (e.g., updating knowledge based on new information). It is also well-established that executive functions contribute to encoding and retrieval aspects of episodic memory (e.g., Moscovitch, 1992; Stuss et al., 1994), suggesting that executive functions may have also contributed to the recall of COVID-19 related information through enhancement of strategic aspects of encoding (e.g., use of higher-order organization, personalization) at the learning stage (e.g., Sullivan, Babicz, & Woods, in press). Previous studies have also demonstrated a relationship between learning new information about health behaviors (e.g., proper medication management) and aspects of executive functions that were not measured in the current study including planning (e.g., Cattie et al., 2012; Waldrop-Valverde, Jones et al., 2010), novel problem-solving (e.g., Patton et al., 2012), and inhibition (e.g., Thames et al., 2011, 2013). Future studies should draw from modern theories of executive functions (e.g., Anderson, 2008) to include more comprehensive measures of these diverse abilities in an effort to better delineate which aspects of executive functions are most relevant to learning COVID-19 knowledge.

Declarative memory abilities may play an important role in acquiring new health-related knowledge, a process that can be complex and challenging (Brown & Park, 2002). Even among healthy young adults, forgetting and inaccurate recall of complex information is quite typical (e.g., Bergman & Roediger, 1999). There are a variety of possible contributors that may interfere with encoding and/or retrieval of health-related information (see Kessels et al., 2003 for review) including prior knowledge that conflicts with new information to be learned (e.g., Rice & Okun, 1994), mood state while learning the information (e.g., Loeffler, Myrtek, & Peper, 2013), perceived importance of the information (e.g., Kliegal et al., 2001), and format of presented information (e.g., written versus spoken). Forgetting and/or erroneous recall of COVID-19 information may interfere with the iterative process described above of updating information (i.e., when the previous information is not able to be recalled or is recalled inaccurately). While the current study included measures of episodic retrospective and prospective memory, it did not include any measures of source memory. Source memory is an aspect of declarative memory that describes ones' ability to recall the characteristics, conditions, or context related to a particular episodic memory (e.g., Glisky, Polster, & Routhieaux, 1995). As sources of COVID-19 information vary widely in reliability and quality, source memory may play an important role in learning and recalling accurate information about COVID-19. For example, one may remember reading that coconut oil is protective against COVID-19 but have difficulty remembering whether that information was learned from the CDC website or a Facebook advertisement for a health food store. Future studies should investigate not only the quality of reported sources of COVID-19 information for participants, but also assess source memory ability using available standardized measures (e.g., California Verbal Learning Test; Babicz, Sheppard, Morgan, & Woods, 2020).

### ***Additional COVID-19 Knowledge Correlates***

In addition to neurocognition, COVID-19 Knowledge scores were positively associated at a univariate level with education and length of COVID-19 epidemic at small effect sizes, respectively. COVID-19 Knowledge scores were also associated with race/ethnicity; post-hoc analyses revealed that COVID-19 Knowledge scores were significantly higher for White participants compared to Black participants and did not differ significantly for comparisons between any other race/ethnicity groups (*p*s < .05). Education and race/ethnicity, but not length of COVID-19 exposure, were also associated with global neurocognition and thus, were included in the final multivariate model. This data driven approach was utilized in order to increase statistical power and minimize Type I error. Results from the multivariable model with global neurocognition, race/ethnicity, and education predicting COVID-19 Knowledge suggested that education and global neurocognition were independently associated with COVID-19 Knowledge while race/ethnicity was not a significant predictor.

Previous studies have also demonstrated lower performance on infectious disease knowledge for Black Americans compared to White Americans (e.g., Ebrahim, Anderson, Weidle, & Purcell, 2004; Garofalo, Gayles, Bottone, Ryan, Kuhns, & Mustanski, 2015). In current study, the effects of race/ethnicity on COVID-19 knowledge were no longer significant after controlling for education and global neurocognition, suggesting that this association may be partially attributable to systemic discrimination resulting in lower access to higher educational opportunities for Black Americans compared to White Americans (McFarland et al., 2019). Future studies should use a community-based participatory research approach to translate COVID-19 information into locally relevant and culturally appropriate language and constructs for Black Americans (e.g., boot camp translation; Norman et al., 2013).

It is worth noting that the contribution of education to COVID-19 knowledge was significant even though the current sample had a restricted, high range of education, which may suggest that the signal might be even stronger in a sample with broader educational backgrounds. These findings are in line with previous studies that established education as a consistent predictor of disease knowledge across conditions of interest such as cancers (Ramirez, Suarez, Laufman, Barroso, & Chalela, 2000; Tseng et al., 2009; Deibert et al., 2007; Harmon, Castro & Coe, 1996; Viswanath et al., 2006), diabetes (e.g., Firestone et al., 2004), hypertension (Sanne et al., 2008); dementia (Werner et al., 2001; Edwards, Cherry, & Peterson, 2000), and chronic kidney disease (e.g., Nunes, Wallston, Eden, Shintani, Ikizler, & Cavanaugh, 2011). Several possible, likely complementary, explanations exist for the relationship between education and COVID-19 knowledge. Higher levels of education may be associated with greater access to sources of information such as periodicals, professional journals, television and the Internet. Additionally, the relationship between higher levels of education and higher levels of health literacy have been well-established (e.g., Sorensen et al. 2012, Manganello, 2008; Nutbeam, 2000), thus education may also contribute to COVID-19 knowledge through its relationship with health literacy. Indeed, a post-hoc regression analysis with education and health literacy predicting COVID-19 knowledge revealed that the effect of education on COVID-19 knowledge became non-significant when controlling for health literacy.

**Neurocognition and Adherence to COVID-19 Preventative Behaviors**

Contrary to hypotheses, global neurocognition was *negatively* associated with self-reported adherence to COVID-19 preventative behaviors at the univariate level at a small effect size; however, this association was no longer significant after controlling for relevant covariates (e.g., WAIS-IV Information). At the neurocognitive domain level, only executive functions (but not attention/working memory or memory) was negatively associated with COVID-19 Behaviors at the univariate level at a small effect size (and likewise, this association was no longer significant after controlling for relevant covariates). These results were inconsistent with a recent study that suggested that performance on a measure of working memory was positively associated with self-reported adherence to COVID-19 social distancing guidelines in healthy adults at a small effect size (Xie et al., 2020). The discrepancy in findings may be due to differences in how neurocognition was assessed (i.e., single measure of working memory versus a neurocognitive battery) and how COVID-19 behaviors were assessed (i.e., self-report measure of COVID-19 social distancing compliance versus self-report measure of several COVID-19 preventative behaviors.)

However, a post-hoc analysis in the current study of the univariate relationship between performance on a measure of working memory (i.e., WAIS-IV Digits Backwards) and a single-item measure of COVID-19 social distancing compliance (i.e., on a scale from 1 *Strongly Disagree* to 5 *Strongly Agree* rate the statement 'You always avoid close contact with other people by staying at least 6 feet apart) suggested that working memory was negatively associated with social distance compliance at a small effect size.

One possible explanation for the negative univariable relationship between neurocognition and adherence to COVID-19 preventative behaviors in the current study may be that persons with higher neurocognition are less likely to "blindly" follow instructions given by an authority figure (e.g., local and state officials). Previous studies have demonstrated that cognitive flexibility is associated with "intellectual humility" (see Zmigrod, Zmigrod, Rentfrow, & Robbins, 2019 for review). Intellectual humility refers to the understanding of one's limitations and biases when making evidence-based decisions and has been positively correlated with self-reported openness to alternative ideas and values, and negatively correlated with dogmatism and intolerance of ambiguity (Leary et al., 2017). For example, among religious individuals, persons with higher cognitive flexibility were associated with religious disbelief and reduced religious practices (e.g., Zmigrod, Rentfrow, Zmigrod, & Robbins, 2019). Similarly, persons with higher cognition may be less likely to adhere to COVID-19 preventative behaviors without proper evaluation of all relevant information, rather than directly obeying local and state orders and recommendations. One important limitation to this study is that our measures did not capture the source from which participants were receiving their information about COVID-19. Therefore, we were not able to ascertain whether non-compliance with COVID-19 recommendations was associated with rejection of recommendations provided by a reliable information source (e.g., the CDC) or acceptance of ambivalence towards COVID-19 recommendations by authority figures (e.g., President Donald Trump; New York Times, 2020).

### ***Additional COVID-19 Preventative Behavior Correlates***

WAIS-IV Information was negatively associated with COVID-19 preventative behaviors at a small effect size such that persons with higher general funds of knowledge were less adherent to COVID-19 preventative behaviors. The significant relationship between WAIS-IV Information and COVID-19 preventative behaviors remained significant and negative in the multivariable model that included health literacy and global neurocognition. To further explore this finding, a post-hoc exploratory factor analysis of the COVID-19 Preventative Behaviors items was conducted and revealed a two-factor solution of items that were associated with: 1) personal and home hygiene (i.e., frequently washing hands, avoiding touching face, covering coughs and sneezes, disinfecting the home) and 2) social hygiene practices (i.e., social distancing, wearing a mask, staying home, avoiding touching common areas in public). Higher general funds of knowledge were associated at a significant level with lower adherence to personal and home hygiene behaviors at a small effect size (Spearman's rho = -.15) but not social hygiene practices (Spearman's rho = .10). While these personal and home hygiene practices continue to be recommended by the CDC (CDC, 2020), the CDC clarified on their website on May 22, 2020 that increasing evidence suggested that surface transmission of COVID-19 (i.e., touching a surface or object that has the virus on it and then touching their own mouth, nose, or eyes) is not thought to be the main way the virus spreads and may have originally been overinflated in earlier recommendations (CDC, 2020). It is possible that persons with a higher general fund of knowledge may have already began digesting relevant articles and information containing evidence against the likelihood of contracting COVID-19 via surface transmission and had become more lax about precautions targeting surface transmission (e.g., disinfecting surfaces, not touching one's face, washing hands frequently). Thereby, it is possible that the negative relationship between neurocognition and adherence to COVID-19 health behaviors may also be a consequence of research and information outpacing study measures and COVID-19 behavior recommendations.

Adherence to COVID-19 preventative behaviors was also positively associated with age, agreeableness, conscientiousness, extraversion, open-mindedness and self-reported trust in physicians, at small effect sizes, respectively. Previous studies have reliably demonstrated positive associations between agreeableness and adherence to COVID-19 preventative behaviors (e.g., Xie, Campbell, & Zhang, 2020; Zajenkowski, Jonason, Leniarska, & Kozakiewicz, 2020, Zettler et al., preprint, Gotz, Gvritz, Galinsky, & Jachimowicz preprint, cf. Abdelrahman, in press). Persons high in agreeableness generally tend to be compassionate and caring (e.g., McRae & Costa, 2008). COVID-19 preventative behaviors require personal cost (e.g., not socializing in person, working from home, wearing a mask, etc.) for the protection of others that the person may or may not know. Persons who are agreeable also have a generalized disposition toward helping others (e.g., Matthews, 2009) and are prosocial in nature (e.g., Wilkowski, Robinson, & Meier, 2006) which may factor into the weighing of pros and cons of COVID-19 guideline compliance. The present findings also support the well-established role of conscientiousness in adherence and maintenance of health behaviors (see Bogg and Roberts, 2004 for review). Future studies may wish to prospectively examine the importance of personality factors such as agreeableness, conscientiousness, and open-mindedness in adherence to COVID-19 guidelines.

**Neurocognition and Online COVID-19-related Information Seeking Skills**

Global neurocognition was not associated with online COVID-19 related information seeking skills. It is unlikely that the lack of significant findings were due to Type II error, as the current study sample of 217 participants was well-powered to detect medium effect sizes. That neurocognition was not associated with online COVID-19-related information seeking skills in the present study was surprising, as other studies have demonstrated a reliable association between global neurocognition and electronic health literacy (e.g., Woods & Sullivan, 2019), as well as performance on naturalistic online search tasks (Woods et al., 2019; Kordovski et al., 2020). One potential reason for these findings was that the present study was limited to a brief telephone-administered neuropsychological battery. The current study did not include measures of visuospatial speed or language, which have both been associated with performance on naturalistic health-related internet search tasks at moderate effect sizes (see Woods et al., 2019 for review). It is also possible that the outcome measure of the number of strategies used to evaluate COVID-19 online sources of information may not account for other aspects of online health-related information-seeking that could be more cognitively demanding such as generating a search term, navigating between different websites, and consolidating information from various sources.

***Additional Online COVID-19 Information Seeking Skill Correlates***

Online COVID-19 related information seeking skills were associated at the univariate level with open-mindedness at a small effect size (Spearman's rho = .22) such that people who were more open-minded used more strategies when evaluating the reliability of a website with COVID-19 information. As open-mindedness was not associated with neurocognition, it was not included in the multivariable model. The increased use of strategies may be protective for people who are open-minded and thereby, may visit more websites or a wider range of websites varying in reliability when searching for information. Future studies should further investigate the role of neurocognition on COVID-related online information seeking skills using a battery that includes measures of visuospatial and language skills and a performance-based measure of online COVID-19 information seeking skills (e.g., Kordovski, Babicz, Ulrich, & Woods, 2020).

**Neurocognition and Intentions to Adhere to COVID-19 Preventative Behaviors**

Global neurocognition was not associated with intentions to adhere to COVID-19 preventative behaviors. The relationship between neurocognition and intentions to adhere to COVID-19 preventative behavior was hypothesized primarily due to cognitive underpinnings of prospective memory which have been shown to play a role in intention formation (e.g., McDaniel & Einstein, 2007). Therefore, it was somewhat unexpected that the memory domain was not associated with intentions to adhere to COVID-19 preventative behaviors. In a post-hoc analysis, the prospective memory measure was also not associated with COVID-19 Intentions. These findings may be due to the possible ceiling effects of the prospective memory measure used (i.e., 80% of participants earned perfect scores on the prospective memory measure). Post-hoc analyses revealed that intentions to adhere to COVID-19 preventative measures was associated with agreeableness and open-mindedness at small effect sizes. Future studies may wish to future examine these personality traits in association with measures of attitudes, subjective norms, and perceived control which have been reliably demonstrated to explain a large proportion of variance in intentions for behaviors (e.g., Armitage & Conner, 2001; Albarracin et al., 2001, 2003, 2004, 2005; Downs & Hausenblau, 2005; Hardeman et al., 2002; Sheeran & Taylor, 1999; Webb & Sheeran, 2006). Consistent with models of health behaviors (e.g., Hochbaum, 1958; Rosenstock, 1960, 1974; Prochaska 1984), intentions to adhere to health behaviors was associated with adherence to health behaviors at a medium effect size and with knowledge at a small effect size. Future studies may wish to evaluate the role of prospective memory on intentions to adhere to health behaviors using laboratory-based measures that assess multiple facets of prospective memory.

**Relationship Between Health Literacy, Neurocognition, and COVID-19 Outcomes**

The hypothesis that health literacy was a moderating variable in the relationship between neurocognition and the COVID-19 outcomes was not supported by present study findings. While health literacy and global neurocognition were correlated at a small effect size, the present findings suggest that their relationship to COVID-19 outcomes are largely independent of one another. Results suggested that global cognition and health literacy both independently contributed to a significant amount of variance of COVID-19 knowledge. However, for all other COVID-19 outcomes (i.e., online COVID-19 information seeking skills, intentions to adhere to COVID-19 behaviors, and self-reported adherence to COVID-19 preventative behaviors), when health literacy and global neurocognition were entered into the model simultaneously, health literacy remained the only significant driving factor of the COVID-19 outcomes.

The contributions of health literacy to these COVID-19 outcome is not surprising, given that the pandemic has called for people to acquire, comprehend, and apply health information presented at a rapid pace (Sorenson et al., 2012). In the present study health literacy was assessed using measures of subjective and objective numeracy, self-report of electronic health literacy, and reported motivation to adhere to positive health behaviors and monitor health status. As evidenced in these findings, health literacy may contribute to one's ability to utilize tools to distinguish between reliable and unreliable information, attain and recall COVID-19-related knowledge, weigh the pros and cons of that knowledge to form intentions to adhere to preventative behaviors, and carry out the intended behavior. The relationship of health literacy with COVID-19 outcomes is made more robust when considering that the present study sample was also overrepresented for persons with higher education degrees compared to the general United States population (United States Census Bureau, 2019).While several papers have discussed the theoretical importance of health literacy in the COVID-19 pandemic (e.g., Paakari & Okan, 2020; Abel & McQueen, 2020), the current paper is the first to empirically investigate the role of health literacy in COVID-19 outcomes using well-validated measures of health literacy.

## Health Literacy and COVID-19 Outcomes

### *Health Literacy and Online COVID-19 Information Seeking Skills*

The regression analyses revealed that health literacy was associated with online COVID-19 information seeking skills independent of neurocognition. Additionally, post-hoc analyses suggested that higher health literacy was associated with increased use of strategies to evaluate online COVID-19 information even when controlling for relevant covariates. These findings are consistent with prior studies reliably demonstrating a positive relationship between health literacy and the ability to evaluate online health information (see Diviana, vas den Putte, Giani, & van Weert, 2015 for review). Persons with low health literacy have been shown to rely on ineffective strategies to evaluate online sources of health information such as the position of a website in search results, the quality of images, and general mistrust of government health-related sources (e.g., Mackert, Kahlow, Tyler, & Gustafson, 2009; Lawson, Forbes, & Williams, 2011). In the present study, increased use of the health-website evaluation criteria recommended by the American Medical Association (Winker et al., 2000) was associated with increased adherence to COVID-19 preventative measures at a small effect size. Future interventions aimed at increasing adherence to COVID-19 preventative behaviors may benefit from identifying website evaluation skills as a possible target for intervention, as persons with low health literacy have been shown to receive benefit from Internet health education (e.g., Robinson & Graham, 2010)

***Health Literacy and COVID-19 Knowledge***

The regression analyses revealed that health literacy was positively associated with COVID-19 knowledge even when controlling for relevant covariates. Given that health knowledge is often treated as an outcome of health literacy (e.g., Berkman et al., 2011), and the association between health literacy and health knowledge in both clinical and healthy populations has been well-established the current findings were not surprising. The role of health literacy in acquiring COVID-19 information may be particularly important compared to other diseases for several reasons including the novelty of the virus, the rapid pace at which the public is expected to consume information, and the multitude of information sources (varying in reliability). Recent studies have shown that at the beginning stages of the pandemic, a significant proportion of healthcare professionals and medical students had poor knowledge of COVID-19 transmission and symptom onset (e.g., Bhagavathula, Aldhaleei, Rahmani, Mahabadi, & Bandari, preprint; Khasawneh et al., 2020). It is therefore expected that if persons presumed to have high aspects of health literacy had trouble learning about

COVID-19 information, the task is even more daunting for laypersons who may have lower levels of health literacy.

***Health Literacy and Intentions to Adhere to COVID-19 Preventative Behaviors***

Health literacy was also positively associated with intentions to adhere to COVID-19 preventative behaviors even when controlling for relevant covariates. These findings were consistent with the two other studies to date that reported a positive relationship between health literacy and health behavior intentions (Crook, Stephens, Pastorek, Mackert, & Donovan, 2016; Kim, Yoo, Hwang, & Cho, 2019). Health literacy may play an important role in the weighing of pros and cons to form an intention to adhere to COVID-19 preventative behaviors, as the process requires integrating previously learned information and evaluating how one would apply the learned information to their everyday life.

***Health Literacy and Adherence to COVID-19 Preventative Behaviors***

Post-hoc analyses revealed that health literacy was positively associated with adherence to COVID-19 preventative behaviors even when controlling for relevant covariates. It was theorized by Paakkari and Okan (2020) that non-adherence to COVID-19 preventative measures may be associated with a misperception of risk or other personal priorities that may allow for a “free rider” problem (Buchanan, 1968). In other words, “free riders” may feel a false sense of invincibility and safety while participating in non-compliant behaviors (e.g., travelling, being in large groups, not wearing masks) because of their confidence in others complying with given guidelines (e.g., Gunia, 2020). Health literacy may serve to prevent the “free rider” mentality by contributing to people’s ability to grasp the reasons behind COVID-19-related recommendations and reflect on the outcomes of their possible actions. Paakari and Oman (2020) argue that taking social responsibility, thinking beyond personal interests, and understanding how people make choices (e.g., ethical viewpoints and behavioral insights) fall under the umbrella of health literacy. This viewpoint is in line with the Sorensen (2012) model of health literacy that includes fundamental skills (e.g., literacy, numeracy), as well as critical skills (i.e., the ability to obtain, process, evaluate, and act upon information that is needed to make health decisions that benefit the community) and civic orientation (i.e., ability to evaluate who disproportionally benefits and who is harmed by public health efforts).

**Study Limitations and Conclusions**

The present study has a number of limitations that are important to consider. Compared to the most recent United States census demographics, the present sample was relatively well-matched in terms of race/ethnicity distributions, with a slight overrepresentation of Asian participants and underrepresentation of Hispanic/Latino participants (United States Census Bureau, 2019). However, as the COVID-19 pandemic has been demonstrated to disproportionally affect Black and Hispanic/Latino communities (e.g., Oppel, Gebeloff, Lai, Wright, & Smith, 2020), future research should develop studies aimed at better understanding predictors of COVID-19 outcomes and developing interventions for improving COVID-19 outcomes in these ethnorocial groups. Second, as noted above, due to COVID-19 restrictions, neurocognitive abilities were assessed using only measures that could be administered over the telephone. Given the telephone-administration format and the relatively brief time frame, the study not able to assess non-verbal domains of cognitive functions and possibly relevant aspects of executive functions including abstract reasoning and novel problem-solving. Future studies may wish to incorporate video-assessment into future studies that may allow for more comprehensive cognitive batteries including measures that require visual stimuli. Third, assessment of COVID-19 knowledge and behavior was determined using novel measurements developed by the authors. The analyses in the present study revealed that all but one COVID-19 knowledge measure loaded on a single factor, and that the factor scores were related to predictor variables. Future studies may wish to use COVID-19 knowledge assessments that have been demonstrated to be reliable and valid across one or more studies (e.g., Zhong et al., 2020; Clements et al., 2020). Adherence to COVID-19 preventative behavior measures also was assessed in the current sample using a novel self-report measure. Future studies may wish to use ecological momentary assessment tools such as text messages or diaries to measure COVID-19-related behaviors over time without the presence of an examiner. While we used English proficiency as an inclusion criteria and collected data regarding participant's first language, about 10% of our sample was Hispanic/Latino and our study would have benefitted from collecting measure of other aspects that could contribute to performance on neuropsychological tests and/or responses to COVID-19 guidelines among this group (e.g., acculturation). Finally, the present study used internet-based recruiting and required completion of an online internet survey which excluded persons without internet access.

These data represent a pivotal time during the early stages of the COVID-19 pandemic during which local, state, and national governing bodies were recommending (and in some cases, actively enforcing) guidelines to prevent the spread of COVID-19 that impacted several aspects of day-to-day life for the majority of Americans. While the present findings provide important insight into predictors of COVID-19 information seeking skills, knowledge, prevention intentions, and prevention behaviors at the early stages of the COVID-19 pandemic, it is likely that as the COVID-19 pandemic (and subsequent personal-, community-, and governmental-level responses to it) changes over time that the predictors of these COVID-19 outcomes may differ as well. Longitudinal studies targeting the assessment of relevant COVID-19 outcome predictors over time may be warranted to inform public health messaging and initiatives while keeping pace with the evolving nature of the pandemic.

Despite these limitations, findings from the present study have practical relevance. The findings suggest that persons with lower neurocognitive abilities, particularly in the areas of executive functions and memory, may be at higher risk for difficulty learning new information about COVID-19. Interventions aimed at incorporating mnemonic devices that aid strategic processes of learning and memory for health information grounded in applied cognitive psychology paradigms (e.g., spaced practice retrieval; Avci et al., 2017; Woods et al., preprint) may improve COVID-19 knowledge in individuals. Health literacy was also found to be independently associated with online COVID-19 information seeking skills, COVID-19 knowledge, intentions to adhere to COVID-19 behaviors, and self-reported adherence to COVID-19 behaviors. These findings suggest that interventions aimed at promoting health literacy may help improve these COVID-19 outcomes regardless of cognitive status (see Sheridan et al., 2011 for review).

## REFERENCES


Abdelrahman, M. (in press). Personality traits, risk perception, and protective behaviors of Arab residents of Qatar during the COVID-19 pandemic. *International Journal of Mental Health and Addiction*.

Abel, T., & McQueen, D. (in press). Critical health literacy and the COVID-19 crisis. *Health Promotion International*.

Agree, E. M., King, A. C., Castro, C. M., Wiley, A., & Borzekowski, D. L. (2015). "It's got to be on this page": Age and cognitive style in a study of online health information seeking. Journal of Medical Internet Research, 17(3), e79.

Ahmed, W., Vidal-Alaball, J., Downing, J., & Seguí, F. L. (2020). COVID-19 and the 5G conspiracy theory: social network analysis of Twitter data. *Journal of Medical Internet Research*, *22*(5), e19458.

Albarracin, D., Fishbein, M., & De Muchinik, E. G. (1997). Seeking social support in old age as reasoned action: Structural and volitional determinants in a middle-aged sample of Argentinean women 1. *Journal of Applied Social Psychology, 27*(6), 463-476.

Albarracin, D., Johnson, B. T., Fishbein, M., & Muellerleile, P. A. (2001). Theories of reasoned action and planned behavior as models of condom use: a meta-analysis. *Psychological Bulletin, 127*(1), 142-161.

Albarracín, D., McNatt, P. S., Klein, C. T., Ho, R. M., Mitchell, A. L., & Kumkale, G. T. (2003). Persuasive communications to change actions: an analysis of behavioral and cognitive impact in HIV prevention. *Health Psychology, 22*(2), 166-177.

Albarracín, D., Gillette, J. C., Earl, A. N., Glasman, L. R., Durantini, M. R., & Ho, M. H. (2005). A test of major assumptions about behavior change: a comprehensive look at the effects of passive and active HIV-prevention interventions since the beginning of the epidemic. *Psychological Bulletin, 131*(6), 856-897.

Allan, J. L., McMinn, D., & Daly, M. (2016). A bidirectional relationship between executive function and health behavior: evidence, implications, and future directions. *Frontiers in Neuroscience, 10*, 386-392.

Anderson, P. J. (2008). Towards a developmental model of executive function. In V. Anderson, R. Jacobs, & P. J. Anderson (Eds.), *Executive functions and the frontal lobes: A lifespan perspective*. Taylor & Francis.

Apolinario, D., Mansur, L. L., Carthery-Goulart, M. T., Brucki, S. M., & Nitrini, R. (2015). Cognitive predictors of limited health literacy in adults with heterogeneous socioeconomic backgrounds. *Journal of Health Psychology*, *20*(12), 1613-1625.

Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. *British Journal of Social Psychology, 40*(4), 471-499.

Ashrafi-rizi, H., & Kazempour, Z. (2020). Information diet in covid-19 crisis; a commentary. *Archives of Academic Emergency Medicine, 8*(1).

Austin, J., Hollingshead, K., & Kaye, J. (2017). Internet searches and their relationship to cognitive function in older adults: Cross-sectional analysis. *Journal of Medical Internet Research, 19*(9), e307.

Avci, G., Woods, S. P., Verduzco, M., Sheppard, D. P., Sumowski, J. F., Chiaravalloti, N., ... & HIV Neurobehavioral Research Program (HNRP) Group. (2017). The Effect of

Retrieval Practice on Short-Term and Long-Term Retention in HIV+ Individuals. *Journal of the International Neuropsychological Society*, *23*(3), 214.

Aveyard, P., Cheng, K. K., Almond, J., Sherratt, E., Lancashire, R., Lawrence, T., ... & Evans, O. (1999). Cluster randomised controlled trial of expert system based on the transtheoretical ("stages of change") model for smoking prevention and cessation in schools. *British Journal of Medicine*, *319*(7215), 948-953.

Azjen, I. & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice Hall.

Babicz, M. A., Sheppard, D. P., Morgan, E. E., & Paul Woods, S. (2020). Where have I heard that before? A validity study of source memory indices from the California Verbal Learning Test–Second edition. *The Clinical Neuropsychologist*, *34*(3), 541-560.

Baggio, S., Iglesias, K., Berchtold, A., & Suris, J. C. (2017). Measuring internet use: comparisons of different assessments and with internet addiction. *Addiction Research & Theory*, *25*(2), 114-120.

Baker, D. W., Parker, R. M., Williams, M. V., & Clark, W. S. (1998). Health literacy and the risk of hospital admission. *Journal of General Internal Medicine*, *13*(12), 791-798.

Baker, D. W., Gazmararian, J. A., Williams, M. V., Scott, T., Parker, R. M., Green, D., ... & Peel, J. (2002). Functional health literacy and the risk of hospital admission among Medicare managed care enrollees. *American Journal of Public Health*, *92*(8), 1278-1283.

Baker, D. W., Gazmararian, J. A., Williams, M. V., Scott, T., Parker, R. M., Green, D., ... & Peel, J. (2004). Health literacy and use of outpatient physician services by medicare managed care enrollees. *Journal of General Internal Medicine*, *19*(3), 215-220.

Bandura, A. (1977). *Self-efficacy: The exercise of control*. W. H. Freeman.

Barati, M., Bashirian, S., Jenabi, E., Khazaei, S., Karimi-Shahanjarini, A., Zareian, S., ... & Moeini, B. (in press). Factors associated with preventive behaviours of COVID-19 among hospital staff in Iran in 2020: An application of the protection motivation theory. *Journal of Hospital Infection*.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173.

Beaver, J., & Schmitter-Edgecombe, M. (2017). Multiple types of memory and everyday functional assessment in older adults. *Archives of Clinical Neuropsychology*, *32*(4), 413-426.

Becker, B. W., Thames, A. D., Woo, E., Castellon, S. A., & Hinkin, C. H. (2011). Longitudinal change in cognitive function and medication adherence in HIV-infected adults. *AIDS and Behavior*, *15*(8), 1888-1894.

Benedict, R. H., Schretlen, D., Groninger, L., & Brandt, J. (1998). Hopkins Verbal Learning Test–Revised: Normative data and analysis of inter-form and test-retest reliability. *The Clinical Neuropsychologist*, *12*(1), 43-55.

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

Bennett, I. M., Chen, J., Soroui, J. S., & White, S. (2009). The contribution of health literacy to disparities in self-rated health status and preventive health behaviors in older adults. *The Annals of Family Medicine*, *7*(3), 204-211.

Beresford, S. A., Curry, S. J., Kristal, A. R., Lazovich, D., Feng, Z., & Wagner, E. H. (1997). A dietary intervention in primary care practice: the Eating Patterns Study. *American Journal of Public Health, 87*(4), 610-616.

Bergman, E. T., & Roediger, H. L. (1999). Can Bartlett's repeated reproduction experiments be replicated? *Memory & Cognition, 27*(6), 937–947.

Berkman, N. D., Davis, T. C., & McCormack, L. (2010). Health literacy: what is it?. *Journal of Health Communication*, *15*(S2), 9-19.

Berkman, N. D., Sheridan, S. L., Donahue, K. E., Halpern, D. J., & Crotty, K. (2011). Low health literacy and health outcomes: an updated systematic review. *Annals of Internal Medicine*, *155*(2), 97-107.

Bhagavathula, A. S., Aldhaleei, W. A., Rahmani, J., Mahabadi, M. A., & Bandari, D. K. (preprint). Novel coronavirus (COVID-19) knowledge and perceptions: a survey on healthcare workers.

Bick, A., Blandin, A., & Mertens, K. (2020, June 9). *Work from home after the COVID-19 outbreak.* Federal Reserve Bank of Dallas. https://doi.org/10.24149/wp2017

Beigel, J. H., Tomashek, K. M., Dodd, L. E., Mehta, A. K., Zingman, B. S., Kalil, A. C., ... & Lopez de Castilla, D. (in press). Remdesivir for the treatment of Covid-19—preliminary report. *New England Journal of Medicine*.

Berkman, N. D., Sheridan, S. L., Donahue, K. E., Halpern, D. J., & Crotty, K. (2011). Low health literacy and health outcomes: an updated systematic review. *Annals of Internal Medicine*, *155*(2), 97-107.

Blume, A. W., Davis, J. M., & Schmaling, K. B. (1999). Neurocognitive dysfunction in dually- diagnosed patients: a potential roadblock to motivating behavior change. *Journal of Psychoactive Drugs, 31*(2), 111-115.

Bogg, T., & Milad, E. (pre-print). Slowing the Spread of COVID-19: Demographic, personality, and social cognition predictors of guideline adherence in a representative US sample.

Bogg, T., & Roberts, B. W. (2004). Conscientiousness and health-related behaviors: a meta-analysis of the leading behavioral contributors to mortality. *Psychological Bulletin*, *130*(6), 887.

Bohrnstedt, G. W., & Carter, T. M. (1971). Robustness in regression analysis. *Sociological Methodology*, *3*, 118-146.

Boulware, D. R., Pullen, M. F., Bangdiwala, A. S., Pastick, K. A., Lofgren, S. M., Okafor, E. C., ... & Engen, N. W. (in press). A randomized trial of hydroxychloroquine as postexposure prophylaxis for Covid-19. *New England Journal of Medicine.*

Brandt, J., & Benedict, R. H. B. (2001). Hopkins Verbal Learning Test-Revised (HVLT-R) Psychological Assessment Resources. *Lutz, FL, USA*.

Brown, P. H., & Park, A. (2002). Roles of age and familiarity in learning health information. *Educational Gerontology, 28*(8), 695-710.

Buchanan, J. M. (1968). *The demand and supply of public goods.* Chicago: Rand McNally.

Bunker, L., Hshieh, T. T., Wong, B., Schmitt, E. M., Travison, T., Yee, J., ... & Inouye, S. K. (2017). The SAGES telephone neuropsychological battery: correlation with in-person measures. *International journal of geriatric psychiatry*, *32*(9), 991-999.

Bureau of Labor Statistics. *The Economics Daily: Unemployment rates down over the past month in 38 states in May 2020.* United States Department of Labor. https://www.bls.gov/opub/ted/2020/unemployment-rates-down-over-the-month-in-38-states-in-may-2020.htm

Byrne, G. J., & Pachana, N. A. (2011). Development and validation of a short form of the Geriatric Anxiety Inventory-the GAI-SF. *International Psychogeriatrics*, *23*(1), 125-131.

Cao, B., Wang, Y., Wen, D., Liu, W., Wang, J., Fan, G., ... & Li, X. (2020). A trial of lopinavir–ritonavir in adults hospitalized with severe Covid-19. *New England Journal of Medicine*, *382*, 1787-1799.

Carey, C. L., Paul Woods, S., Rippeth, J. D., Heaton, R. K., Grant, I., & HIV Neurobehavioral Research Center (HNRC) Group. (2006). Prospective memory in HIV-1 infection. *Journal of Clinical and Experimental Neuropsychology*, *28*(4), 536-548.

Carpenter, C. J. (2010). A meta-analysis of the effectiveness of health belief model variables in predicting behavior. *Health Communication*, *25*(8), 661-669.

Casaletto, K. B., Doyle, K. L., Weber, E., Woods, S. P., Heaton, R. K., Grant, I., ... & Marquie-Beck, J. (2014). Self-predictions of prospective memory in HIV-associated neurocognitive disorders: evidence of a metamemory deficit. *Archives of Clinical Neuropsychology*, *29*(8), 818-827.

Cattie, J. E., Doyle, K., Weber, E., Grant, I., Woods, S. P., & HIV Neurobehavioral Research Program (HNRP) Group. (2012). Planning deficits in HIV-associated neurocognitive disorders: component processes, cognitive correlates, and implications for everyday functioning. *Journal of Clinical and Experimental Neuropsychology*, *34*(9), 906-918.

Centers for Disease Control and Prevention (2013). CDC health disparities and inequalities reports – United States, 2013, *Morbidity and Mortality Weekly Report, 62*(3).

Center for Disease Control and Prevention. (2020, May 13). *Coronavirus Disease 2019 (COVID-19): Symptoms of Coronavirus.* Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/symptoms.html

Centers for Disease Control and Prevention. (2020, June 25). *Coronavirus Disease 2019 (COVID-19): People who are at increased risk for severe illness*. Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-at-increased-risk.html

Centers for Disease Control and Prevention. (2020, April 24). *Coronavirus Disease 2019 (COVID-19): How to protect yourself and others*. Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html

Centers for Disease Control and Prevention. (2020, March 25). *Coronavirus Disease 2019 (COVID-19): Household checklist.* World Health Organization. https://www.cdc.gov/coronavirus/2019-ncov/daily-life-coping/checklist-household-ready.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fdaily-life-coping%2Fget-your-household-ready-for-COVID-19.html

Centers for Disease Control and Prevention. (2020). Timing of state and territorial COVID-19 stay-at-home orders and changes in population movement – United States, March 1 to May 31, 2020, *Morbidity and Mortality Weekly Report, 62*(3).

Centers for Disease Control and Prevention. (2020, May 22). CDC updates to COVID-19 transmission webpage to clarify information about types of spread.

https://www.cdc.gov/media/releases/2020/s0522-cdc-updates-covid transmission.html

Chevalier, A., Dommes, A., & Marquié, J. C. (2015). Strategy and accuracy during information search on the Web: Effects of age and complexity of the search questions. *Computers in Human Behavior, 53*, 305-315.

Chew, L. D., Bradley, K. A., & Boyko, E. J. (2008). Chew LD, Griffin JM, Partin MR, Noorbaloochi S, Grill JP, Snyder A, et al. Validation of screening questions for limited health literacy in a large VA outpatients population. *Journal General Internal Medicine, 23*, 561-566.

Chin, J., Madison, A., Gao, X., Graumlich, J. F., Conner-Garcia, T., Murray, M. D. et al. (2017). Cognition and health literacy in older Adults' recall of self-care information. *Gerontologist*, 57(2), 261–268.

Chin, J., Morrow, D. G., Stine-Morrow, E. A., Conner-Garcia, T., Graumlich, J. F., & Murray, M. D. (2011). The process-knowledge model of health literacy: Evidence from a componential analysis of two commonly used measures. *Journal of Health Communication*, *16*(Suppl 3), 222–241.

Cho, Y. I., Lee, S. Y. D., Arozullah, A. M., & Crittenden, K. S. (2008). Effects of health literacy on health status and health service utilization amongst the elderly. *Social Science & Medicine*, *66*(8), 1809-1816.

Christie, J. D., Biester, R. C. P., Taichman, D. B., Shull Jr, W. H., Hansen-Flaschen, J., Shea, J. A., & Hopkins, R. O. (2006). Formation and validation of a telephone battery to assess cognitive function in acute respiratory distress syndrome survivors. *Journal of Critical Care*, *21*(2), 125-132.

Chung, S. Y., & Nahm, E. S. (2015). Testing reliability and validity of the eHealth Literacy Scale (eHEALS) for older adults recruited online. *Computers, Informatics, Nursing: CIN*, *33*(4), 150-156.

Clements, J. M. (2020). Knowledge and Behaviors Toward COVID-19 Among US Residents During the Early Days of the Pandemic: Cross-Sectional Online Questionnaire. *Journal Medical Internet Research Public Health and Surveillance*, *6*(2), e19161.

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research, and Evaluation*, *10*(1), 7.

Cotugna, N., Vickery, C. E., & Carpenter-Haefele, K. M. (2005). Evaluation of literacy level of patient education pages in health-related journals. *Journal of Community Health*, *30*(3), 213-219.

Crook, B., Stephens, K. K., Pastorek, A. E., Mackert, M., & Donovan, E. E. (2016). Sharing health information and influencing behavioral intentions: The role of health literacy, information overload, and the Internet in the diffusion of healthy heart information. *Health Communication*, *31*(1), 60-71.

Cuan-Baltazar, J. Y., Muñoz-Perez, M. J., Robledo-Vega, C., Pérez-Zepeda, M. F., & Soto-Vega, E. (2020). Misinformation of COVID-19 on the internet: infodemiology study. *Journal of Medical Internet Research Public Health and Surveillance, 6*(2), e18444.

Curry, S. J., McBride, C., Grothaus, L. C., Louie, D., & Wagner, E. H. (1995). A randomized trial of self-help materials, personalized feedback, and telephone counseling with nonvolunteer smokers. *Journal of Consulting and Clinical Psychology, 63*(6), 1005-1014.

Czaja, S. J., Sharit, J., Lee, C. C., Nair, S. N., Hernández, M. A., Arana, N., & Fu, S. H. (2013). Factors influencing use of an e-health website in a community sample of older adults. *Journal of the American Medical Informatics Association, 20*(2), 277-284.

Deibert, C. M., Maliski, S., Kwan, L., Fink, A., Connor, S. E., & Litwin, M. S. (2007). Prostate cancer knowledge among low income minority men. *The Journal of Urology*, *177*(5), 1851-1855.

Delis, D. C., Kaplan, E., & Kramer, J. H. (2001). Delis-Kaplan executive function system.

Devraj, R., Herndon, C. M., & Griffin, J. (2013). Pain awareness and medication knowledge: a health literacy evaluation. *Journal of Pain & Palliative Care Pharmacotherapy*, *27*(1), 19-27.

Diviani, N., van den Putte, B., Giani, S., & van Weert, J. C. (2015). Low health literacy and evaluation of online health information: a systematic review of the literature. *Journal of medical Internet research*, *17*(5), e112.

Dommes, A., Chevalier, A., & Lia, S. (2011). The role of cognitive flexibility and vocabulary abilities of younger and older users in searching for information on the web. *Applied Cognitive Psychology, 25*(5), 717-726.

Downs, D. S., & Hausenblas, H. A. (2005). Elicitation studies and the theory of planned behavior: A systematic review of exercise beliefs. *Psychology of Sport and Exercise, 6*(1), 1-31.

Duff, K., Mold, J. W., & Gidron, Y. (2009). Cognitive functioning predicts survival in the elderly. *Journal of Clinical and Experimental Neuropsychology*, *31*(1), 90-95.

Duke, D. C., & Harris, M. A. (2014). Executive function, adherence, and glycemic control in adolescents with type 1 diabetes: a literature review. *Current Diabetes Reports*, *14*(10), 532.

Edwards, A. B., Cherry, R. L., & Peterson, J. (2000). Predictors of misconceptions of Alzheimer's disease among community dwelling elderly. *American Journal of Alzheimer's Disease*, *15*(1), 27-35.

Fagerlin, A., Zikmund-Fisher, B. J., Ubel, P. A., Jankovic, A., Derry, H. A., & Smith, D. M. (2007). Measuring numeracy without a math test: development of the Subjective Numeracy Scale. *Medical Decision Making*, *27*(5), 672-680.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149-1160.

Fazeli, P. L., Woods, S. P., Lambert, C. C., Waldrop-Valverde, D., & Vance, D. E. (2020). Neurocognitive functioning is associated with self-reported and performance-based treatment management abilities in people living with HIV with low health literacy. *Archives of Clinical Neuropsychology, 35*(5), 517-527.

Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., ... &

Dighe, A. (2020). Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. *Imperial College COVID-19 Response Team*. https://doi.org/10.25561/77482

Fishbein, M. & Azjen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Floyd, F. J., & Widaman, K. F. (1995). Factor analysis in the development and refinement of clinical assessment instruments. *Psychological Assessment*, *7*(3), 286.

Ford, N. (2004). Towards a model of learning for educational informatics. *Journal of Documentation, 60*(2), 183-225.

Fox, S., & Rainie, L. (2002). Vital decisions: A Pew Internet health report. *Pew Research Center*.

Ferguson, N. M., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., ... & Dighe, A. (2020, March 16). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. *Imperial College COVID-19 Response Team*, *10*, 77482.

Firestone, D. N., Jiménez-Briceño, L., Reimann, J. O., Talavera, G. A., Polonsky, W. H., & Edelman, S. V. (2004). Predictors of diabetes-specific knowledge and treatment satisfaction among Costa Ricans. *The Diabetes Educator*, *30*(2), 281-292.

Fritz, M. S., & MacKinnon, D. P. (2008). A graphical representation of the mediated effect. *Behavior Research Methods*, *40*(1), 55-60.

Gazmararian, J. A., Williams, M. V., Peel, J., & Baker, D. W. (2003). Health literacy and knowledge of chronic disease. *Patient Education and Counseling*, *51*(3), 267-275.

Gharpure, R., Hunter, C. M., Schnall, A. H., Barrett, C. E., Kirby, A. E., Kunz, J., Berling, K.… Garcia-Williams, A. G. (2020). Knowledge and practices regarding safe household cleaning and disinfection for COVID-19 Prevention – United States, May 2020. *Morbidity and Mortality Weekly Report, 68*, 705-709.

Glanz, K., Rimer, B. K., & Viswanath, K. (2008). The scope of health behavior and health education. In Glanz, K., Rimer, B. K., & Viswanath, K (Eds.) *Health behavior and health education: Theory, research, and practice* (pp. 3-18). Jossey-Bass: A Wiley Imprint.

Glisky, E. L., Polster, M. R., & Routhieaux, B. C. (1995). Double dissociation between item and source memory. *Neuropsychology*, *9*(2), 229.

Glorfeld, L. W. (1995). An improvement on Horn's parallel analysis methodology for selecting the correct number of factors to retain. *Educational and Psychological Measurement, 55*(3), 377-393.

Gold, D. B., Anderson, D. R., & Serxner, S. A. (2000). Impact of a telephone-based intervention on the reduction of health risks. *American Journal of Health Promotion, 15*(2), 97-106.

Goldstein, M. G., Pinto, B. M., Marcus, B. H., Lynn, H., Jette, A. M., Rakowski, W., ... & Tennstedt, S. (1999). Physician-based physical activity counseling for middle-aged and older adults: a randomized trial. *Annals of Behavioral Medicine, 21*(1), 40-47.

Götz, F., Gvirtz, A., Galinsky, A., & Jachimowicz, J. (preprint). How personality and policy predict pandemic behavior: Understanding sheltering-in-place in 55 countries at the onset of COVID-19.

Goverover, Y., O'Brien, A. R., Moore, N. B., & DeLuca, J. (2010). Actual reality: A new approach to functional assessment in persons with multiple sclerosis. *Archives of Physical Medicine and Rehabilitation*, *91*(2), 252-260.

Goverover, Y., Genova, H., Griswold, H., Chiaravalloti, N., & Deluca, J. (2014). Metacognitive knowledge and online awareness in persons with multiple sclerosis. *NeuroRehabilitation, 35*(2), 315–323

Goverover, Y., & DeLuca, J. (2015). Actual reality: Using the Internet to assess everyday functioning after traumatic brain injury. *Brain Injury, 29*, 715–721.

Goverover, Y., Chiaravalloti, N., & DeLuca, J. (2016). Brief International Cognitive Assessment for Multiple Sclerosis (BICAMS) and performance of everyday life tasks: Actual reality. *Multiple Sclerosis Journal, 22*, 544–550.

Goverover, Y., Sandroff, B. M., & DeLuca J. (2018). Dual task of fine motor skill and problem solving in individuals with multiple sclerosis: A pilot study. *Archives of Physical Medicine and Rehabilitation, 99*(4), 635–640.

Gunia, A. (2020, March, 20). Millenials aren't taking coronavirus seriously, a top WHO official warns. *Times*.

Haas, J. S., Phillips, K. A., Sonneborn, D., McCulloch, C. E., Baker, L. C., Kaplan, C. P., ... & Liang, S. Y. (2004). Variation in access to health care for different racial/ethnic groups by the racial/ethnic composition of an individual's county of residence. *Medical Care*, *24*(7), 707-714.

Hall, M. A., Zheng, B., Dugan, E., Camacho, F., Kidd, K. E., Mishra, A., & Balkrishnan, R. (2002). Measuring patients' trust in their primary care providers. *Medical Care Research and Review*, *59*(3), 293-318.

Hall, P. A., Fong, G. T., Epp, L. J., & Elias, L. J. (2008). Executive function moderates the intention-behavior link for physical activity and dietary behavior. *Psychology & Health*, *23*(3), 309-326.

Hall, P. A., & Marteau, T. M. (2014). Executive function in the context of chronic disease prevention: theory, research and practice. *Preventive Medicine*, *68*, 44-50.

Hardeman, W., Johnston, M., Johnston, D., Bonetti, D., Wareham, N., & Kinmonth, A. L. (2002). Application of the theory of planned behaviour in behaviour change interventions: A systematic review. *Psychology and Health, 17*(2), 123-158.

Harmon, M. P., Castro, F. G., & Coe, K. (1997). Acculturation and cervical cancer: knowledge, beliefs, and behaviors of Hispanic women. *Women & Health*, *24*(3), 37-57.

Harrison, J. A., Mullen, P. D., & Green, L. W. (1992). A meta-analysis of studies of the health belief model with adults. *Health Education Research*, *7*(1), 107-116.

Hatchett, R. J., Mecher, C. E., & Lipsitch, M. (2007). Public health interventions and epidemic intensity during the 1918 influenza pandemic. *Proceedings of the National Academy of Sciences*, *104*(18), 7582-7587.

Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal*, *25*(1), 76-81.

Hinkin, C. H., Castellon, S. A., Durvasula, R. S., Hardy, D. J., Lam, M. N., Mason, K. I., ... & Stefaniak, M. (2002). Medication adherence among HIV+ adults: effects of cognitive dysfunction and regimen complexity. *Neurology*, *59*(12), 1944-1950.

Hinkin, C. H., Hardy, D. J., Mason, K. I., Castellon, S. A., Durvasula, R. S., Lam, M. N., & Stefaniak, M. (2004). Medication adherence in HIV-infected adults: effect of patient age, cognitive status, and substance abuse. *AIDS, 18*(1), S19.

Ho, A. K., Sahakian, B. J., Robbins, T. W., Barker, R. A., Rosser, A. E., & Hodges, J. R. (2002). Verbal fluency in Huntington's disease: A longitudinal analysis of phonemic and semantic clustering and switching. *Neuropsychologia, 40*, 1277–1284

Hochbaum, G. (1958) *Public participation in medical screening programs: A sociopsychological study.* Public Health Service Publication, no. 572.

Hollis, J. F., Polen, M. R., Whitlock, E. P., Lichtenstein, E., Mullooly, J. P., Velicer, W. F., & Redding, C. A. (2005). Teen reach: outcomes from a randomized, controlled trial of a tobacco reduction program for teens seen in primary medical care. *Pediatrics, 115*(4), 981-989.

Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., ... & Cheng, Z. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet, 395*(10223), 497-506.

Jacks, A., Salazar, L., Grimes, R., York, M., Strutt, A. M., Shahani, L., ... & Hasbun, R. (2015). Neurocognitive deficits increase risk of poor retention in care among older adults with newly diagnosed HIV infection. *AIDS*, *29*(13), 1711-1714.

Janz, N. K., & Becker, M. H. (1984). The health belief model: A decade later. *Health Education Quarterly*, *11*(1), 1-47.

Jones, D., Cook, R., Rodriguez, A., & Waldrop-Valverde, D. (2013). Personal HIV knowledge, appointment adherence and HIV outcomes. *AIDS and Behavior, 17*(1), 242-249.

Jones, C. J., Smith, H., & Llewellyn, C. (2014). Evaluating the effectiveness of health belief model interventions in improving adherence: a systematic review. *Health Psychology Review*, *8*(3), 253-269.

Kanfer, F. H. & Schefft, B. K. (1988). *Guiding the process of therapeutic change*. Research Press.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement, 20*, 141–151.

Kessels, R. P. (2003). Patients' memory for medical information. *Journal of the Royal Society of Medicine*, *96*(5), 219-222.

Khasawneh, A. I., Humeidan, A. A., Alsulaiman, J. W., Bloukh, S., Ramadan, M., Al-Shatanawi, T. N., ... & Saleh, T. (2020). Medical students and COVID-19:

Knowledge, attitudes, and precautionary measures. A descriptive study from Jordan. *Frontiers in Public Health*, *8*.

Kim, M. N., Yoo, Y. S., Hwang, K. H., & Cho, O. H. (2019). The effects of office workers' attitudes to internet health information, e-health literacy on health information seeking behavior and health-related behavioral intention. *Journal of Digital Convergence*, *17*(11), 357-367.

Kirton, J. W., Soble, J. R., Marceaux, J. C., Messerly, J., Bain, K. M., Webber, T. A., ... & McCoy, K. J. (2019). Comparison of models of premorbid IQ estimation using the TOPF, OPIE-3, and Barona equation, with corrections for the Flynn effect. *Neuropsychology*, *34*(1), 43-52.

Kliegel, M., Jager, T., Altgasen, M., & Shum, D. (2008). *Clinical neuropsychology of prospective memory.* In M. Kliegel, M. A. McDaniel, & G. O. Einstein (Eds.), Prospective memory: Cognitive, neuroscience, developmental, and applied perspectives (pp. 283–308). Taylor & Francis Group/ Lawrence Erlbaum Associates.

Kliegel, M., Martin, M., McDaniel, M. A., & Einstein, G. O. (2001). Varying the importance of a prospective memory task: Differential effects across time-and event-based prospective memory. *Memory*, *9*(1), 1-11.

Kordovski, V. M., Woods, S. P., Avci, G., Verduzco, M., & Morgan, E. E. (2017). Is the newest vital sign a useful measure of health literacy in HIV disease?. *Journal of the International Association of Providers of AIDS Care (JIAPAC)*, *16*(6), 595-602.

Kordovski VM, Babicz MA, Ulrich N, Woods SP. (2020) Neurocognitive correlates of Internet search skills for eHealth fact and symptom information in a young adult sample. *Perceptual and Motor Skills*, *127*(5), 960-979.

Kripalani, S., Gatti, M. E., & Jacobson, T. A. (2010). Association of age, health literacy, and medication management strategies with cardiovascular medication adherence. *Patient Education and Counseling*, *81*(2), 177-181.

Lacritz, L. H., Cullum, C. M., Weiner, M. F., & Rosenberg, R. N. (2001). Comparison of the Hopkins Verbal Learning Test-Revised to the California Verbal Learning Test in Alzheimer's disease. *Applied Neuropsychology*, *8*(3), 180-184.

Lawson, R., Forbes, S., & Williams, J. (2011). Patterns of trust in sources of health information. *New Zealand Medical Journal*, *124*(1328), 98-105.

Leary, M. R., Diebels, K. J., Davisson, E. K., Jongman-Sereno, K. P., Isherwood, J. C., Raimi, K. T., ... & Hoyle, R. H. (2017). Cognitive and interpersonal features of intellectual humility. *Personality and Social Psychology Bulletin*, *43*(6), 793-813.

Lin, Y. H., Liu, C. H., & Chiu, Y. C. (in press). Google searches for the keywords of “wash hands” predict the speed of national spread of COVID-19 outbreak among 21 countries. *Brain, Behavior, and Immunity*.

Lindau, S. T., Tomori, C., Lyons, T., Langseth, L., Bennett, C. L., & Garcia, P. (2002). The association of health literacy with cervical cancer prevention knowledge and health behaviors in a multiethnic cohort of women. *American Journal of Obstetrics and Gynecology*, *186*(5), 938-943.

Lins Filho, P. C., de Macedo, T. S., Ferreira, A. K. A., de Melo, M. C. F., de Araujo, M. M. S., de Melo Freitas, J. L., ... & de Franca Caldas, A. (preprint). Assessing the quality, readability and reliability of online information on COVID-19: an infoveillance observational study.

Lipkus, I. M., Samsa, G., & Rimer, B. K. (2001). General performance on a numeracy scale among highly educated samples. *Medical Decision Making*, *21*(1), 37-44.

Little, R. J. A. 1988. A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*, 1198–1202.

Liu, Y., Gayle, A. A., Wilder-Smith, A., & Rocklöv, J. (2020). The reproductive number of COVID-19 is higher compared to SARS coronavirus. *Journal of Travel Medicine, 27*(2).

Loeffler, S. N., Myrtek, M., & Peper, M. (2013). Mood-congruent memory in daily life: Evidence from interactive ambulatory monitoring. *Biological Psychology*, *93*(2), 308-315.

Mackert, M., Kahlor, L., Tyler, D., & Gustafson, J. (2009). Designing e-health interventions for low-health-literate culturally diverse parents: addressing the obesity epidemic. *Telemedicine and e-Health*, *15*(7), 672-677.

Malow, R. M., Dévieux, J. G., Stein, J. A., Rosenberg, R., Lerner, B. G., Attonito, J., & Villalba, K. (2012). Neurological function, information–motivation–behavioral skills factors, and risk behaviors among HIV-positive alcohol users. *AIDS and Behavior*, *16*(8), 2297-2308.

Manganello, J. A. (2008). Health literacy and adolescents: a framework and agenda for future research. *Health Education Research*, *23*(5), 840-847.

Mantwill, S., Monestel-Umaña, S., & Schulz, P. J. (2015). The relationship between health literacy and health disparities: a systematic review. *PLoS One*, *10*(12), e0145455.

Martin, E. M., Nixon, H., Pitrak, D. L., Weddington, W., Rains, N. A., Nunnally, G., ... & Bechara, A. (2007). Characteristics of prospective memory deficits in HIV-seropositive substance-dependent individuals: Preliminary observations. *Journal of Clinical and Experimental Neuropsychology*, *29*(5), 496-504.

McRae, R. R. & Costa, P. T. (2008). The five-factor theory of personality. In O. P. John, R. W. Robins, & L. A. Pervins (Eds.). *Handbook of personality: Theory and research.* (pp. 159-181). (3rd ed.). New York, NY: Guilford.

McDaniel, M. A., & Einstein, G. O. (2007). *Prospective memory: An overview and synthesis of an emerging field*. Sage Publications.

McComb, E., Brewster, P., Chou, P. H., Crossley, M., Simard, M., & Tuokko, H. (2010). Telephone administration of the mental alternation test: Sensitivity to cognitive decline and practice effects across midlife and late life. *Neuroepidemiology, 35*(4), 298–302.

McFarland, J., Hussar, B., Zhang, J., Wang, X., Hein, S., Diliberti, M., Forrest Cataldi, E…Barmer, A. (2019) *The condition of education 2019*. U.S. Department of Education. Washington, DC: National Center for Education Statistics.

Mervosh, S., Lu, D., & Swales, V. (2020, April 20). See which state sand cities have told residents to stay home. *New York Times.* https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

Mitsis, E. M., Jacobs, D., Luo, X., Andrews, H., Andrews, K., & Sano, M. (2010). Evaluating cognition in an elderly cohort via telephone assessment. *International Journal of Geriatric Psychiatry: A Journal of the Psychiatry of Late Life and Allied Sciences*, *25*(5), 531-539.

Moorman, C., & Matulich, E. (1993). A model of consumers' preventive health behaviors: The role of health motivation and health ability. *Journal of Consumer Research*, *20*(2), 208-228.

Morgan, E. E., Iudicello, J. E., Cattie, J. E., Blackstone, K., Grant, I., Woods, S. P., & HIV Neurobehavioral Research Program (HNRP) Group. (2015). Neurocognitive impairment is associated with lower health literacy among persons living with HIV infection. *AIDS and Behavior*, *19*(1), 166-177.

Moscovitch, M. (1992). Memory and working-with-memory: A component process model based on modules and central systems. *Journal of Cognitive Neuroscience*, *4*(3), 257-267.

Murray, M. D., Morrow, D. G., Weiner, M., Tu, W., Deer, M. M., Brater, D. C., & Weinberger, M. (2004). A conceptual framework to study medication adherence in older adults. *The American Journal of Geriatric Pharmacotherapy*, *2*(1), 36-43.

New York City Health. (2020, July 11). *COVID-19: Data*. https://www1.nyc.gov/site/doh/covid/covid-19-data.page

Nguyen, A., Mosadeghi, S., & Almario, C. V. (2017). Persistent digital divide in access to and use of the Internet as a resource for health information: Results from a California population-based study. *International Journal of Medical Informatics, 103*, 49-54.

Nguyen, H. T., Grzywacz, J. G., Arcury, T. A., Chapman, C., Kirk, J. K., Ip, E. H., ... & Quandt, S. A. (2010). Linking glycemic control and executive function in rural older adults with diabetes mellitus. *Journal of the American Geriatrics Society*, *58*(6), 1123-1127.

Norman, C. D., & Skinner, H. A. (2006). eHEALS: the eHealth literacy scale. *Journal of Medical Internet Research*, *8*(4), e27.

Nunes, J. A. W., Wallston, K. A., Eden, S. K., Shintani, A. K., Ikizler, T. A., & Cavanaugh, K. L. (2011). Associations among perceived and objective disease knowledge and satisfaction with physician communication in patients with chronic kidney disease. *Kidney International*, *80*(12), 1344-1351.

Nutbeam, D. (2000). Health literacy as a public health goal: a challenge for contemporary health education and communication strategies into the 21st century. *Health Promotion International*, *15*(3), 259-267.

O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behavior Research Methods, Instruments, & Computers*, *32*(3), 396-402.

O'Neill, H. K., Gillespie, M. A., & Slobin, K. (2000). Stages of change and smoking cessation: A computer administered intervention program for young adults. *American Journal of Health Promotion, 15*(2), 93-96.

Oppel, R. A., Gebeloff, R., Lai, K. K. R., Wright, W., & Smith, M. (2020, July 5). The fullest look yet at the racial inequity of coronavirus. *New York Times.* https://www.nytimes.com/interactive/2020/07/05/us/coronavirus-latinos-african-americans-cdc-data.html

Paakkari, L., & Okan, O. (2020). COVID-19: Health literacy is an underestimated problem. *The Lancet Public Health*, *5*(5), e249-e250.

Paasche-Orlow, M. K., Parker, R. M., Gazmararian, J. A., Nielsen-Bohlman, L. T., & Rudd, R. R. (2005). The prevalence of limited health literacy. *Journal of General Internal Medicine*, *20*(2), 175-184.

Park, C. L., Russell, B. S., Fendrich, M., Finkelstein-Fox, L., Hutchison, M., & Becker, J. (in press). Americans' COVID-19 Stress, Coping, and Adherence to CDC Guidelines. *Journal of General Internal Medicine*.

Patton, D. E., Woods, S. P., Franklin, D., Cattie, J. E., Heaton, R. K., Collier, A. C., ... & Morgello, S. (2012). Relationship of Medication Management Test-Revised (MMT-

R) performance to neuropsychological functioning and antiretroviral adherence in adults with HIV. *AIDS and Behavior*, *16*(8), 2286-2296.

Perrin, A., & Duggan, M. (2015). Americans' internet access: 2000-2015. *Pew Research Center*, *26*(6), 1-12.

Piatt, A. L., Fields, J. A., Paolo, A. M., & Tröster, A. I. (1999). Action (verb naming) fluency as an executive function measure: convergent and divergent evidence of validity. *Neuropsychologia*, *37*(13), 1499-1503.

Poppenk, J., Moscovitch, M., McIntosh, A. R., Ozcelik, E., & Craik, F. I. M. (2010). Encoding the future: Successful processing of intentions engages predictive brain networks. *Neuroimage, 49*(1), 905-913.

Prochaska, J. O. (1984) *Systems of psychotherapy: A transtheoretical analysis.* (*2nd ed.).:* Brooks-Cole.

Prochaska, J. O., DiClemente, C. C., Celicer, W. F., & Rossi, J. S. (1993). Standardized, individualized, interaction, and personalized self-help programs for smoking cessation. *Health Psychology, 12*, 399-405.

Prochaska, J. O., Redding, C. A., & Evers, K. E. (2008). The transtheoretical model and stages of change. In Glanz, K., Lewis, F. M., Rimer, B. K. (Eds.) *Health Behavior and Health Education: Theory, Research, and Practice*. Jossey-Bass.

Ramirez, A. G., Suarez, L., Laufman, L., Barroso, C., & Chalela, P. (2000). Hispanic women's breast and cervical cancer knowledge, attitudes, and screening behaviors. *American Journal of Health Promotion*, *14*(5), 292-300.

Rapp, S. R., Legault, C., Espeland, M. A., Resnick, S. M., Hogan, P. E., Coker, L. H., ... & CAT Study Group. (2012). Validation of a cognitive assessment battery administered over the telephone. *Journal of the American Geriatrics Society*, *60*(9), 1616-1623.

Rebeiro, P. F., McPherson, T. D., Goggins, K. M., Turner, M., Bebawy, S. S., Rogers, W. B., ... & Pettit, A. C. (2018). Health literacy and demographic disparities in HIV care continuum outcomes. *AIDS and Behavior*, *22*(8), 2604-2614.

Rice, G. E., & Okun, M. A. (1994). Older readers' processing of medical information that contradicts their beliefs. *Journal of gerontology*, *49*(3), 119-128.

Ricker, J. H., & Axelrod, B. N. (1994). Analysis of an oral paradigm for the Trail Making Test. *Assessment*, *1*(1), 47-51.

Robinson, C., & Graham, J. (2010). Perceived Internet health literacy of HIV-positive people through the provision of a computer and Internet health education intervention. *Health Information & Libraries Journal*, *27*(4), 295-303.

Rosen, M. I., Beauvais, J. E., Rigsby, M. O., Salahi, J. T., Ryan, C. E., & Cramer, J. A. (2003). Neuropsychological correlates of suboptimal adherence to metformin. *Journal of Behavioral Medicine*, *26*(4), 349-360.

Rosenstock, I. M. (1990). The past, present, and future of health education. In Glanz, K., Lewis, F. M., Rimer, B. K. (Eds.) *Health Behavior and Health Education: Theory, Research, and Practice*. Jossey-Bass.

Rosenstock, I. M., Strecher, V. J., & Becker, M. H. (1988). Social learning theory and the health belief model. *Health Education Quarterly, 15*(2), 82-93.

Ross, J. M., Duperrouzel, J., Vega, M., & Gonzalez, R. (2016). The neuropsychology of risky sexual behavior. *Journal of the International Neuropsychological society*, *22*(6), 586-594.

Rossi, J. S., Clark, P., Greaney, M., Riebe, D., Greene, G., Saunders, S., & Nigg, C. (2005). Effectiveness of transtheoretical model–based interventions on exercise and fruit and vegetable consumption in older adults. *Annals of Behavioral Medicine, 29*, S134.

Royston, J. P. (1995). Shapiro-Wilk normality test and P-value. *Applied Statistics*, *44*(4), 547-551.

Sanne, S., Muntner, P., Kawasaki, L., Hyre, A., & DeSalvo, K. B. (2008). Hypertension knowledge among patients from an urban clinic. *Ethnicity and Disease*, *18*(1), 42.

Sangha, O., Stucki, G., Liang, M. H., Fossel, A. H., & Katz, J. N. (2003). The Self-Administered Comorbidity Questionnaire: a new method to assess comorbidity for clinical and health services research. *Arthritis Care & Research: Official Journal of the American College of Rheumatology*, *49*(2), 156-163.

Sartori, A., Clay, O., Ovalle, F., Rothman, R., & Crowe, M. (2011). Age and cognitive function are associated with diabetes knowledge. *Archives of Clinical Neuropsychology*, *26*(6), 470-567.

Schillinger, D., Grumbach, K., Piette, J., Wang, F., Osmond, D., Daher, C., ... & Bindman, A. B. (2002). Association of health literacy with diabetes outcomes. *JAMA*, *288*(4), 475-482.

Sharit, J., Hernández, M. A., Czaja, S. J., & Pirolli, P. (2008). Investigating the roles of knowledge and cognitive abilities in older adult information seeking on the web. *ACM Transactions on Computer-Human Interaction, 15*(1), 1-25.

Sharit, J., Taha, J., Berkowsky, R. W., Profita, H., & Czaja, S. J. (2015). Online information search performance and search strategies in a health problem-solving scenario. *Journal of Cognitive Engineering and Decision Making*, *9*(3), 211-228.

Sharma, G., Santos Volgman, A., & Michos, E. D. (in press). Sex differences in mortality from COVID-19 pandemic: Are men vulnerable and women protected? *JACC: Case Reports*.

Shear, M. D., & Kaplan, S. (2020, April 3). A debate over masks uncovers deep white house divisions. *The New York Times.*

Sheeran, P., & Taylor, S. (1999). Predicting intentions to use condoms: a meta-analysis and comparison of the theories of reasoned action and planned behavior. *Journal of Applied Social Psychology, 29*(8), 1624-1675.

Sheridan, S. L., Halpern, D. J., Viera, A. J., Berkman, N. D., Donahue, K. E., & Crotty, K. (2011). Interventions for individuals with low health literacy: a systematic review. *Journal of Health Communication*, *16*(sup3), 30-54.

Shieh, C., Mays, R., McDaniel, A., & Yu, J. (2009). Health literacy and its association with the use of information sources and with barriers to information seeking in clinic-based pregnant women. *Health Care for Women International*, *30*(11), 971-988.

Skierkowski, D. D., Florin, P., Harlow, L. L., Machan, J., & Ye, Y. (2019). A readability analysis of online mental health resources. *American Psychologist, 74*(4), 474.

Sørensen, K., Van den Broucke, S., Fullam, J., Doyle, G., Pelikan, J., Slonska, Z., & Brand, H. (2012). Health literacy and public health: a systematic review and integration of definitions and models. *BioMed Central Public Health*, *12*(1), 80.

Soto, C. J., & John, O. P. (2017). Short and extra-short forms of the Big Five Inventory–2: The BFI-2-S and BFI-2-XS. *Journal of Research in Personality*, *68*, 69-81.

Stacey, F. G., James, E. L., Chapman, K., Courneya, K. S., & Lubans, D. R. (2015). A systematic review and meta-analysis of social cognitive theory-based physical activity and/or nutrition behavior change interventions for cancer survivors. *Journal of Cancer Survivorship*, *9*(2), 305-338.

Stuss, D. T., Alexander, M. P., Palumbo, C. L., Buckle, L., Sayer, L., & Pogue, J. (1994). Organizational strategies with unilateral or bilateral frontal lobe injury in word learning tasks. *Neuropsychology*, *8*(3), 355.

Sullivan, K. L., Babicz, M. A., & Woods, S. P. (in press). Verbal learning mediates the relationship between executive functions and a laboratory task of medication management in HIV disease. *Archives of Clinical Neuropsychology.*

Szmuda, T., Özdemir, C., Ali, S., Singh, A., Syed, M. T., & Słoniewski, P. (in press). Readability of Online Patient Education Material for the Novel Coronavirus Disease (COVID-19): A Cross-sectional Health Literacy Study. *Public Health*.

Taichman, D. B., Christie, J., Biester, R., Mortensen, J., White, J., Kaplan, S., ... & Hopkins, R. O. (2005). Validation of a brief telephone battery for neurocognitive assessment of patients with pulmonary arterial hypertension. *Respiratory Research*, *6*(1), 1-7.

Thames, A. D., Arentoft, A., Rivera-Mindt, M., & Hinkin, C. H. (2013). Functional disability in medication management and driving among individuals with HIV: A 1-year follow-up study. *Journal of Clinical and Experimental Neuropsychology*, *35*(1), 49-58.

Thames, A. D., Kim, M. S., Becker, B. W., Foley, J. M., Hines, L. J., Singer, E. J., ... & Hinkin, C. H. (2011). Medication and finance management among HIV-infected adults: the impact of age and cognition. *Journal of Clinical and Experimental Neuropsychology, 33*(2), 200-209.

Tougas, M. E., Hayden, J. A., McGrath, P. J., Huguet, A., & Rozario, S. (2015). A systematic review exploring the social cognitive theory of self-regulation as a framework for chronic health condition interventions. *PloS one*, *10*(8), e0134977.

Tseng, T. S., Holt, C. L., Shipp, M., Eloubeidi, M., Britt, K., Norena, M., & Fouad, M. N. (2009). Predictors of colorectal cancer knowledge and screening among church-attending African Americans and Whites in the Deep South. *Journal of Community Health*, *34*(2), 90-97.

Unverzagt, F. W., Monahan, P. O., Moser, L. R., Zhao, Q., Carpenter, J. S., Sledge Jr, G. W., & Champion, V. L. (2007). The Indiana University telephone-based assessment of neuropsychological status: a new method for large scale neuropsychological assessment. *Journal of the International Neuropsychological Society: JINS*, *13*(5), 799-806.

Van den Broeck, J., Cunningham, S. A., Eeckels, R., & Herbst, K. (2005). Data cleaning: Detecting, diagnosing, and editing data abnormalities. *PLoS Med*, *2*(10), e267.

Viswanath, K., Breen, N., Meissner, H., Moser, R. P., Hesse, B., Steele, W. R., & Rakowski, W. (2006). Cancer knowledge and disparities in the information age. *Journal of Health Communication*, *11*(S1), 1-17.

Voorhees, C. C., Stillman, F. A., Swank, R. T., Heagerty, P. J., Levine, D. M., & Becker, D. M. (1996). Heart, body, and soul: impact of church-based smoking cessation interventions on readiness to quit. *Preventive Medicine, 25*(3), 277-285.

Waldrop-Valverde, D., Jones, D. L., Gould, F., Kumar, M., & Ownby, R. L. (2010). Neurocognition, health-related reading literacy, and numeracy in medication management for HIV infection. *AIDS Patient Care and STDs*, *24*(8), 477-484.

Wang, J., & Du, G.. (in press) COVID-19 may transmit through aerosol. *Irish Journal School of Medical Science*.

Webb, T. L., & Sheeran, P. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological Bulletin, 132*(2), 249.

Wechsler, D. (2008). Wechsler adult intelligence scale–Fourth Edition (WAIS–IV). *San Antonio, TX: NCS Pearson*, *22*(498), 1.

Weinborn, M., Moyle, J., Bucks, R. S., Stritzke, W., Leighton, A., & Woods, S. P. (2013). Time- based prospective memory predicts engagement in risk behaviors amongst substance users: Results from clinical and nonclinical samples. *Journal of the International Neuropsychological Society*, *19*(3), 284.

Werner, P. (2001). Correlates of family caregivers' knowledge about Alzheimer's disease. *International Journal of Geriatric Psychiatry*, *16*(1), 32-38.

White, S., Chen, J., & Atchison, R. (2008). Relationship of preventive health practices and health literacy: a national study. *American Journal of Health Behavior*, *32*(3), 227-242.

Wilkowski, B. M., Robinson, M. D., & Meier, B. P. (2006). Agreeableness and the prolonged spatial processing of antisocial and prosocial information. *Journal of Research in Personality, 40,* 1152-1168.

Williams, D. R., Mohammed, S. A., Leavell, J., & Collins, C. (2010). Race, socioeconomic status and health: Complexities, ongoing challenges and research opportunities. *Annals of the New York Academy of Sciences*, *1186*, 69-101.

Williams, M. N., Grajales, C. A. G., & Kurkiewicz, D. (2013). Assumptions of multiple regression: Correcting two misconceptions. *Practical Assessment, Research, and Evaluation*, *18*(1), 11.

Winker, M. A., Flanagin, A., Chi-Lum, B., White, J., Andrews, K., Kennett, R. L., ... & Musacchio, R. A. (2000). Guidelines for medical and health information sites on the internet: principles governing AMA web sites. *JAMA*, *283*(12), 1600-1606.

Wolf, M. S., Serper, M., Opsasnick, L., O'Conor, R. M., Curtis, L. M., Benavente, J. Y., ... & Russell, A. (in press). Awareness, attitudes, and actions related to COVID-19 among adults with chronic conditions at the onset of the US outbreak: a cross-sectional survey. *Annals of Internal Medicine*.

Woods, S. P., Babicz, M. A., Matchanova, A. M., Sullivan, K. L., Avci, G., Hasbun, R., Giordano, T. P…Morgan, E. E. (preprint). A clinical pilot study of spaced retrieval practice to improve health-related memory in persons with HIV disease.

Woods, S. P., Scott, J. C., Dawson, M. S., Morgan, E. E., Carey, C. L., Heaton, R. K., ... & HIV Neurobehavioral Research Center (HNRC) Group. (2005). Construct validity of Hopkins Verbal Learning Test—Revised component process measures in an HIV-1 sample. *Archives of Clinical Neuropsychology*, *20*(8), 1061-1071.

Woods, S. P., Scott, J. C., Sires, D. A., Grant, I., Heaton, R. K., Troster, A. I., & HIV Neurobehavioral Research Center (HNRC) Group. (2005). Action (verb) fluency: Test-retest reliability, normative standards, and construct validity. *Journal of the International Neuropsychological Society: JINS*, *11*(4), 408.

Woods, S. P., Carey, C. L., Tröster, A. I., Grant, I., & HIV Neurobehavioral Research Center (HNRC) Group. (2005). Action (verb) generation in HIV-1 infection. *Neuropsychologia, 43*(8), 1144-1151.

Woods, S. P., Kordovski, V. M., Tierney, S. M., & Babicz, M. A. (2019). The neuropsychological aspects of performance-based Internet navigation skills: A brief review of an emerging literature. *The Clinical Neuropsychologist, 33*(2), 305-326.

Woods, S. P., & Sullivan, K. L. (2019). Lower neurocognitive functioning disrupts the effective use of internet-based health resources in HIV disease: The mediating effects of general health literacy capacity. *AIDS and Behavior*, *23*(3), 676-683.

World Health Organization (2020, April 27). *WHO Timeline – COVID 19*. World Health Organization. https://www.who.int/news-room/detail/27-04-2020-who-timeline---covid-19

World Health Organization (2020, September 9). *WHO Coronavirus (COVID-19) Dashboard*. World Health Organization. https://covid19.who.int/

World Health Organization. (2020). *Coronavirus disease (COVID-19) advice for the public: Mythbusters*. World Health Organization. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/myth-busters

World Health Organization (2020, April 27). *WHO timeline: COVID-19.* World Health Organization. https://www.who.int/news-room/detail/27-04-2020-who-timeline---covid-19

Wykes, T. L., Lee, A. A., Bourassa, K., Kitchen, K. A., & McKibbin, C. L. (2017). Diabetes knowledge among adults with serious mental illness and comorbid diabetes mellitus. *Archives of psychiatric nursing*, *31*(2), 190-196.

Wu, Z., & McGoogen, J. M. (2020). Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: Summary of a report of

72314 cases from the Chinese Center for Disease Control and Prevention. *JAMA, 323*(13), 1239-1242.

Xie, W., Campbell, S., & Zhang, W. (in press). Working memory capacity predicts individual differences in social distancing compliance during the COVID-19 pandemic in the US. *PNAS.*

Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology*, *9*(2), 79-94.

Young, M. D., Plotnikoff, R. C., Collins, C. E., Callister, R., & Morgan, P. J. (2014). Social cognitive theory and physical activity: a systematic review and meta-analysis. *Obesity Reviews*, *15*(12), 983-995.

Yuki, K., Fujiogi, M., & Koutsogiannaki, S. (2020). COVID-19 pathophysiology: A review. *Clinical Immunology,* 108427.

Zajenkowski, M., Jonason, P. K., Leniarska, M., & Kozakiewicz, Z. (2020). Who complies with the restrictions to reduce the spread of COVID-19?: personality and perceptions of the COVID-19 situation. *Personality and individual differences*, *166*.

Zettler, I., Schild, C., Lilleholt, L., & Böhm, R. (preprint). Individual differences in accepting personal restrictions to fight the COVID-19 pandemic: Results from a Danish adult sample.

Zhou, F., Yu, T., Du, R., Fan, G., Liu, Y., Liu, Z.…& Cao, B. (2020). Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: A retrospective cohort study. *The Lancet, 395*(10229), 1054-1062.

Zickuhr, K., & Madden, M. (2012). Older adults and internet use. *Pew Internet & American Life Project*.

Zimmerman, R. S., & Vernberg, D. (1994). Models of preventive health behavior: Comparison, critique, and meta-analysis. *Advances in Medical Sociology*, *4*, 45-67.

Zmigrod, L., Rentfrow, P. J., Zmigrod, S., & Robbins, T. W. (2019). Cognitive flexibility and Religious Disbelief. *Psychological research*, *83*(8), 1749-1759.

Zmigrod, L., Zmigrod, S., Rentfrow, P. J., & Robbins, T. W. (2019). The psychological roots of intellectual humility: The role of intelligence and cognitive flexibility. *Personality and Individual Differences*, *141*, 200-208.

## Figure and Tables

Figure 1. Study flow diagram.

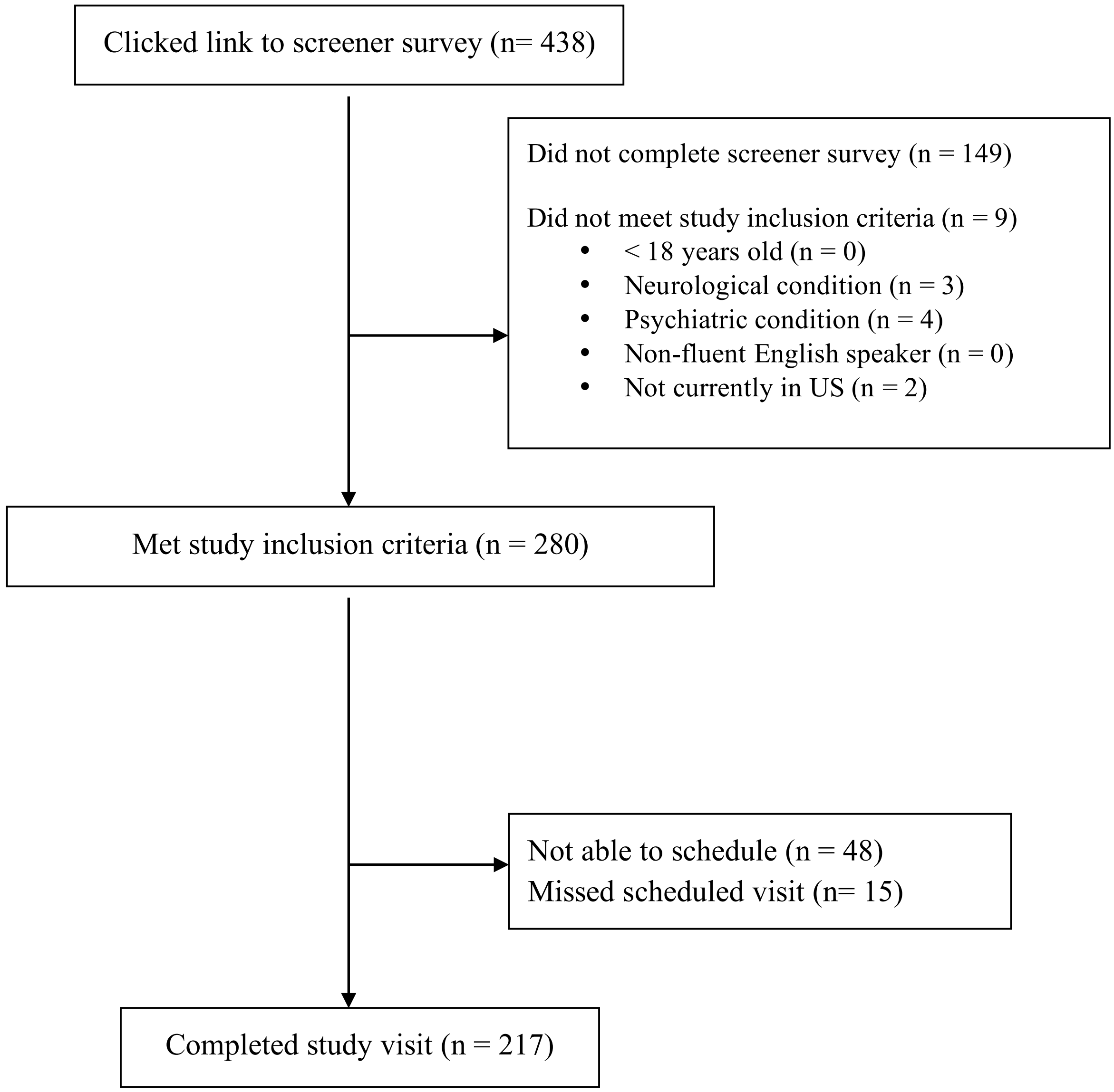

Table 1. Participant characteristics.

| Variables ($N$ = 217) | Mean (SD) or % | Sample Range |
|---|---|---|
| **Sociodemographics** | | |
| Sex (% female) | 74.7 | |
| Age (years) | 35.1 (14.7) | 18-77 |
| Race/Ethnicity (%)^ | | |
| Asian | 12.4 | |
| Black | 15.7 | |
| Hispanic | 9.7 | |
| White | 60.8 | |
| Other | 9.2 | |
| English First-Language | 88.0 | |
| Education (%) | | |
| High School or Equivalent | 13.8 | |
| Community College/Vocational School | 12.4 | |
| Four-Year College/University Degree | 43.8 | |
| Professional Degree/Graduate School | 30.0 | |
| WAIS-IV Information subtest | 15.8 (4.9) | 4-26 |
| **Health Literacy (% suboptimal)** | 8.8 | |
| **Number of Medical Conditions**+ | 0.0 (0.0) | 0-3 |
| **Frequency of Internet Use**+ | 63.0 (14.0) | 0-63 |
| **COVID-19-Related Anxiety** | 3.7 (1.0) | 0-5 |
| **COVID-19 Exposure Period (days)** | 122.4 (7.4) | 109-137 |
| **GAI-SF** (of 5) | 2.2 (1.8) | 0-5 |
| **Big Five Personality Domains*** | | |
| Extraversion (of 15) | 10.2 (2.3) | 5-15 |
| Agreeableness (of 15) | 11.4 (1.8) | 6-15 |
| Conscientiousness (of 15) | 11.3 (2.2) | 6-15 |
| Negative Emotionality (of 15) | 7.7 (2.3) | 3-14 |
| Open-Mindedness (of 15) | 11.6 (1.8) | 6-15 |
| **Wake Forest Physician Trust Scale*** (of 50) | 38.6 (6.2) | 17-50 |

*Note*: ^ = data from three participants were missing; * = data from 14 participants were missing; + = median (IQR) reported due not non-normal distribution; GAI-SF = Geriatric Anxiety Inventory – Short Form; COVID-19 = coronavirus 2019

Table 2. Results from the Principle Components Analysis of the COVID-19 Knowledge Component

| Test | | Intercorrelations | | | |
|---|---|---|---|---|---|
| | Factor Loading | COVID Prevent | COVID Symp | COVID Symp FP | COVID Recog |
| COVID Prevention Knowledge Total | .47 | – | – | – | – |
| COVID Symptom Knowledge Total | .74 | .17 | – | – | – |
| COVID Symptom Knowledge FP | .43 | .08 | .09 | – | – |
| COVID Recognition | .48 | .01 | .25 | .06 | – |
| COVID Plan | .49 | .08 | .17 | .12 | .00 |

*Note*: COVID = coronavirus 2019; COVID Prevent = COVID Prevention Knowledge Total; COVID Symp = COVID Symptom Knowledge Total; COVID Symp FP = COVID Symptom Knowledge Total False Positives; COVID Recog = COVID Recognition d’

Table 3. Results from the Principle Components Analysis of the Health Literacy Component

| Test | | Intercorrelations | | | |
|---|---|---|---|---|---|
| | Factor Loading | eHEALS Total | SNS Total | ENS Total | 3Brief Total |
| eHEALS Total | .68 | – | – | – | – |
| Subjective Numeracy Scale Total | .67 | .22 | – | – | – |
| Expanded Numeracy Scale Total | .63 | .19 | .42 | – | – |
| 3Brief Total | .57 | .26 | .17 | .21 | – |
| Health Motivation Total | .44 | .34 | .10 | .00 | .13 |

*Note*: eHEALS = Electronic Health Literacy Scale; SNS = Subjective Numeracy Scale; ENS = Expanded Numeracy Scale

Table 4. Predictor and outcome variables

| Variables ($N = 217$) | Mean (SD) | Sample Range |
|---|---|---|
| **COVID-19 Outcomes** | | |
| *Online Information Seeking Skills (of 16)* | 7.8 (3.7) | 0-16 |
| *Knowledge* | | |
| Prevention Free Recall Total | 7.4 (1.7) | 4-12 |
| Symptoms Free Recall Total | 6.7 (1.9) | 2-13 |
| Symptoms Free Recall False Positives | 0.5 (0.9) | 0-5 |
| Recognition d’ | 2.5 (0.9) | 0.2-4.4 |
| Plan Quality (of 5) | 1.8 (1.2) | 1-5 |
| *Prevention Intentions (of 40)* | 35.5 (3.2) | 21-40 |
| *Prevention Behaviors (of 40)* | 34.2 (4.5) | 20-40 |
| **Neurocognition** | | |
| *Attention/Working Memory* | | |
| HVLT-R T1 (of 12)* | 7.4 (1.8) | 3-12 |
| WAIS-IV Digit Span Forwards* | 11.1 (2.5) | 5-16 |
| WAIS-IV Digit Span Backward* | 9.8 (2.6) | 4-16 |
| *Executive Functions* | | |
| DKEFS Verbal Switching$^{+}$ | 16.8 (3.3) | 5-26 |
| Action Fluency* | 22.5 (6.1) | 10-40 |
| OTMT Part B* | 30.3 (20.9) | 9-225 |
| *Memory* | | |
| HVLT-R Recognition Discrimination (of 12)* | 11.13 (1.1) | 7-12 |
| HVLT-R Long Delay Free Recall (of 12)* | 9.7 (2.0) | 3-12 |
| Prospective Memory (of 8)* | 7.0 (2.0) | 0-8 |
| **Health Literacy** | | |
| Health Motivation (of 40) | 32.2 (4.3) | 16-40 |
| Expanded Numeracy Scale (of 7) | 5.5 (1.5) | 0-7 |
| Subjective Numeracy Scale (of 40) | 30.1 (4.4) | 18-40 |
| 3-Brief (of 15) | 13.9 (1.5) | 5-15 |
| eHEALS (of 40)* | 33.4 (4.4) | 14-40 |

*Note*: * = data from one participant were missing; $^{+}$ = data from two participants were missing; COVID-19 = coronavirus 2019; HVLT-R = Hopkins Verbal Learning Test – Revised; WAIS-IV = Wechsler Adult Intelligence Scale – Fourth Edition; DKEFS = Delis-Kaplan Executive Function System; OTMT = Oral Trails Making Test; eHEALS = Electronic Health Literacy Scale.

Table 5. Correlations between Main Predictors and Outcome Variables

| *Main Predictor and Outcome Variables* | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. Global Neurocognition | – | – | – | – | – |
| 2. Health Literacy | **.26** | – | – | – | – |
| 3. COVID-19 Online Information Seeking | -.05 | **.26** | – | – | – |
| 4. COVID-19 Knowledge | **.31** | **.32** | .11 | – | – |
| 5. COVID-19 Intentions | .03 | **.41** | .14 | **.23** | – |
| 6. COVID-19 Behaviors | -.17 | .15 | **.26** | .03 | **.41** |

*Note:* Table values indicate Spearman's rho. **bold** indicates $p < .013$; COVID-19 = coronavirus 2019.

Table 6. Hierarchical Regression Models

| | Model 1 | | | Model 2 | | | Model 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Outcome: COVID-19 Info-Seeking** | | | | | | | | | |
| Variable | *b* | SE *b* | *β* | *b* | SE *b* | *β* | *b* | SE *b* | *β* |
| WAIS-IV Info | **0.13** | **.05** | **.17** | .09 | .06 | .11 | 0.09 | .06 | .11 |
| Global Neurocognition | | | | -1.17 | .68 | -.13 | -1.26 | 0.70 | -.14 |
| Health Literacy | | | | **0.97** | **.27** | **.26** | **0.95** | **.28** | **.25** |
| Global Neurocognition x HL | | | | | | | -0.36 | .60 | -.04 |
| adjusted $R^2$ | .02 | | | .08 | | | .07 | | |
| $F$ for change in $R^2$ | **6.38** | | | **7.11** | | | 0.36 | | |
| **Outcome: COVID-19 Knowledge** | | | | | | | | | |
| WAIS-IV Info | **0.04** | **.01** | **.18** | 0.01 | .02 | .03 | 0.01 | .02 | .04 |
| Education | **0.11** | **0.04** | **0.22** | 0.07 | .04 | .13 | 0.07 | .04 | .13 |
| Global Neurocognition | | | | **0.51** | **.18** | **.20** | **0.59** | **.18** | **.24** |
| Health Literacy | | | | **0.18** | **.07** | **.18** | **0.21** | **.07** | **.21** |
| Global Neurocognition x HL | | | | | | | 0.33 | .15 | .14 |
| adjusted $R^2$ | .09 | | | .15 | | | .16 | | |
| $F$ for change in $R^2$ | **11.96** | | | **8.07** | | | 4.66 | | |
| **Outcome: COVID-19 Intentions** | | | | | | | | | |
| Global Neurocognition | -0.60 | .52 | -.08 | -0.55 | .54 | -.07 | | | |
| Health Literacy | **1.30** | **.21** | **.41** | **1.31** | **.21** | **.41** | | | |
| Global Neurocognition x HL | | | | 0.19 | .50 | .03 | | | |
| adjusted $R^2$ | .15 | | | .14 | | | | | |
| $F$ for change in $R^2$ | **18.36** | | | 0.15 | | | | | |
| **Outcome: COVID-19 Behaviors** | | | | | | | | | |
| WAIS-IV Info | **-0.15** | **.06** | **-.17** | **-0.21** | **.07** | **-.23** | **-0.21** | **.07** | **-.23** |
| Global Neurocognition | | | | -1.36 | .82 | -.12 | -1.29 | .84 | -.11 |
| Health Literacy | | | | **1.19** | **.33** | **.27** | **1.21** | **.33** | **.27** |
| Global Neurocognition x HL | | | | | | | 0.29 | .72 | .03 |
| adjusted $R^2$ | .02 | | | .08 | | | .08 | | |
| $F$ for change in $R^2$ | **6.38** | | | **7.27** | | | 0.17 | | |

Note: **bold** < .013; WAIS-IV Info = Wechsler Adult Intelligence Scale – fourth edition Information subtest; HL = health literacy