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How did individual differences in neurocognition and health literacy influence the initial uptake and use of health-related information about COVID-19?

Michelle A. Babicz^a, Steven Paul Woods^a, Anastasia Matchanova^a, Luis D. Medina D^a, Kenneth Podell^b, Rheeda L. Walker^a, Adam Fetterman^a, Samina Rahman^a, Briana Johnson^a, Jennifer L. Thompson^a, Kelli L. Sullivan^a, Ilex Beltran-Najera^a, Jasmin Brooks^a, Yenifer Morales^a and Gunes Avci

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ABSTRACT

Introduction: The rapid development of coronavirus disease 2019 (COVID-19) into a pandemic required people to quickly acquire, evaluate, and apply novel complex health-related information about the virus and transmission risks. This study examined the potentially unique and synergistic roles of individual differences in neurocognition and health literacy in the early uptake and use of COVID-19 public health information.

Method: Data were collected between April 23 and 21 May 2020, a period during which 42 out of 50 states were under a stay-at-home order. Participants were 217 healthy adults who completed a telephone-based battery that included standard tests of neurocognition, health literacy, verbal IQ, personality, and anxiety. Participants also completed measures of COVID-19 information-seeking skills, knowledge, prevention intentions, and prevention behaviors.

Results: A series of hierarchical multiple regressions with data-driven covariates showed that neurocognition (viz, episodic verbal memory and executive functions) was independently related to COVID-19 knowledge (e.g. symptoms, risks) at a medium effect size, but not to information-seeking skills, prevention intentions, or prevention behaviors. Health literacy was independently related to all measured aspects of COVID-19 health information and did not interact with neuro-cognition in any COVID-19 health domain.

Conclusions: Individual differences in neurocognition and health literacy played independent and meaningful roles in the initial acquisition of knowledge related to COVID-19, which is a novel human health condition. Future studies might examine whether neurocognitive supports (e.g. spaced retrieval practice, elaboration) can improve COVID-19-related knowledge and health behaviors in vulnerable populations.

Introduction

Due to the moderately contagious nature of coronavirus disease-2019 (COVID-19) and the absence of effective vaccines or targeted therapeutics during its early stages, most public health initiatives initially focused on behavioral measures (e.g. masks, social distancing) as a primary means of slowing the spread of the disease. Even though these behavioral measures can be effective in mitigating the spread of COVID-19 (Ferguson et al., 2020), their use arguably lagged in the United States (Park et al., 2020). Therefore, it is crucial to have a better understanding of the factors that contributed to the early uptake and application of COVID-19 public health information, particularly regarding COVID-19 preventative behaviors.

To help us select and frame determinants of adherence to COVID-19 preventative behaviors, we integrated elements from widely used models of health behavior

described below that were deemed relevant to the intersection of neurocognitive functions, health literacy, and the behavioral management of COVID-19 transmission. A systematic review between 1986 and 2005 revealed over 60 different models of health behavior (Glanz et al., 2008), four of which continue to be widely cited and used in public health initiatives. These four models are the Health Belief Model (HBM; Hochbaum, 1958; Rosenstock, 1990; Rosenstock, Strecher, & Becker, 1988), Social Cognitive Theory (SCT; Bandura, 1977), Transtheoretical Model (TTM; Prochaska, 1984), and Theory of Planned Behavior (Ajzen, 1991; Fishbein, 1967). Acquisition and conceptualization of knowledge that lead to attitude formation regarding health behaviors are highlighted in the HBM, SCT, and TPB models. The TTM and TPB models assert that intention to perform preventative behaviors are a key determinant of carrying out positive health behaviors (or cessation of negative health behaviors). The present

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Neuropsychological assessment; health literacy; coronavirus; disease knowledge; prevention behaviors; health psychology study was thereby informed by (but does not directly test) the following aspects of each of these influential models given their importance to COVID-19 and their relevance to both neurocognition and health literacy: 1) information-seeking; 2) disease-specific knowledge; 3) preventative intentions; and 4) preventative behaviors.

Information-seeking related to COVID-19 increased rapidly in the early part of the pandemic, primarily via online sources (Bento et al., 2020). Such health-related information-seeking may play an important role in the contemplation stage of health behaviors (e.g. "Should I wear a mask?") and is an important determinant of disease-related knowledge. Searching the internet for health-related information can have positive health effects (Fox & Rainie, 2002). Yet online health information is often unregulated, unreliable, and complex to digest (Skierkowski et al., 2019). This variability in online information quality has been particularly challenging in relation to the COVID-19 pandemic (Cuan-Baltazar et al., 2020). Online search behavior is associated with activation in prefrontal and temporal networks (Small et al., 2009) and neurocognitive abilities that they support, including declarative memory and executive functions (Agree et al., 2015). Therefore, we hypothesized that higher neurocognitive abilities would be positively and independently related to more reliable, evidence-based COVID-19 information-seeking behavior.

The acquisition and retention of *disease-specific knowl*edge is also critically important to many health prevention and promotion efforts (Glanz et al., 2008). Early data suggest greater knowledge about COVID-19 transmission, prevention, and clinical management is associated with better compliance with evolving public health recommendations at the individual (Clements, 2020) and population (Lin et al., 2020) levels. Disease-related knowledge is influenced by several factors, including education, race/ethnicity, and health literacy (Jackson et al., 2020). Acquiring new health-related knowledge involves processing, learning, and consolidating oftentimes complex, incomplete, and contradictory information from various sources. A large body of literature shows that neurocognitive abilities in attention, declarative memory, information processing speed, and executive functions are all correlated with disease-specific knowledge (Malow et al., 2012; Wykes et al., 2017). Accordingly, we expected that higher neurocognitive abilities would be independently related to greater COVID-19 knowledge.

Many conceptual models suggest that *intentions* to comply with health behaviors are an important predictor of actual adherence (Glanz et al., 2008). Two COVID-19 era studies suggest that greater self-rated intentions to engage in preventative behaviors (e.g. mask wearing) are associated with better adherence to public health

guidelines for reducing COVID-19 transmission (Barati et al., 2020; Bogg & Milad, preprint). Neurocognitive aspects of intention formation can be conceptualized under the umbrella of prospective memory, which describes one's ability to execute a future intention (Kliegel et al., 2008). Intention formation involves both declarative memory neural networks for encoding (e.g. medial temporal lobe) and executive functions networks for planning and future-oriented processing (e.g. prefrontal cortex; Poppenk et al., 2010). Consistent with these findings, poorer intention formation has been associated with executive dysfunction (Kliegel et al., 2004). Therefore, we hypothesized that higher neurocognitive abilities would be independently associated with stronger intentions to adhere to recommended COVID-19 preventative behaviors.

Adherence to public health recommendations for COVID-19 preventative behaviors is essential to controlling the spread of the virus (Peeples, 2020); however, adherence behaviors themselves are complex and multidetermined (Fisher et al., 2006). The informationmotivation-behavioral skills model suggests that critical determinants of successful adherence include: accurate information regarding disease and treatment, motivation to adhere to a treatment plan or preventative health behavior, and both subjective and objective self-efficacy for treatment behavior (Fisher et al., 2006). Cognitive skills necessary for these critical determinants include aspects of episodic memory (e.g. prospective memory skills) and executive functions (e.g. planning, decisionmaking; Park & Liu, 2007). Indeed, the importance of episodic memory and executive functions has been highlighted both in neurocognitive models of adherence (Park & Liu, 2007) and empirically as predictors of medication adherence among persons with chronic disease (Hinkin et al., 2002). Neurocognition is also associated with adherence to both positive health behaviors (Allan et al., 2016) and engagement in health risk behaviors (Ross et al., 2016). Xie et al. (2020) reported a small, but significant and independent association between adherence to social distancing guidelines and visual working memory and abstract reasoning. We therefore hypothesized that higher neurocognitive abilities would be independently associated with greater self-reported adherence to recommended COVID-19 preventative behaviors.

In addition, we sought to determine whether health literacy, the capacity to obtain, process, understand, and communicate about health-related information to make informed medical decisions (Berkman et al., 2010), may modulate the relationship between neurocognition and COVID-19 health information and behaviors. Lower health literacy is associated with difficulties in seeking out health-related information (Agree et al., 2015), less

disease-specific knowledge (Kalichman et al., 2000), reduced intentions about health prevention (Kim et al., 2019), and suboptimal adherence behaviors (Waldrop-Valverde et al., 2018). Early studies suggest that lower health literacy may be associated with poorer knowledge of COVID-19 symptoms (Wolf et al., 2020), less preparedness (Bailey et al., 2020), and noncompliance with recommended preventative behaviors (Li et al., 2020). Moreover, emerging data show that lower neurocognitive functions may be associated with lower health literacy in both healthy (e.g. Apolinario et al., 2015) and disease populations (e.g. Morgan et al., 2015, 2019; Waldrop-Valverde et al., 2010). In a study of 322 healthy adults, better performance on measures of global cognition, verbal fluency, executive functions, 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 demographics (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 decisionmaking (e.g. Doyle et al., 2016), engagement with healthcare providers (Morgan et al., 2019), and electronic health literacy (e.g. Woods & Sullivan, 2019).

Lower health literacy and poorer neurocognitive functioning have reliably been independently linked with worse medical outcomes (e.g. Becker et al., 2011; Jacks et al., 2015; Kordovski et al., 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), Chin et al. (2017)) suggested that among older adults, better neurocognition (i.e. working memory, processing speed) was associated with higher performance on health tasks for persons with low health literacy, but not for persons with high health literacy. 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 et al., 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: 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.

Overall, the current study aims to examine the role of neurocognition and health literacy in adherence to COVID-19 health behaviors and its determinants including information-seeking behaviors, COVID-19 related knowledge, and intentions to adhere to COVID-19 preventative behaviors. We hypothesize that: 1) neurocognition will be independently associated with each of these primary outcomes and 2) there will be an interaction between health literacy and neurocognitive such that the relationship between neurocognition and COVID-19 information seeking, knowledge, intentions, and prevention behaviors will be strongest among persons with lower levels of health literacy.

Method

Participants

The study was conducted in compliance with the Institutional Review Board of the University of Houston, and the data were gathered between 23 April 2020 and 21 May 2020. A total of 280 participants from 28 different states were recruited via word-of-mouth and postings on social media, 217 of whom (77.5%) completed the study procedures (see Figure 1). There were no significant differences in sex, education, or number of medical comorbidities between the 217 participants who completed the study and the 63 participants who did not (ps>.05). However, participants that completed the assessment were slightly older and had a lower frequency of Black and Hispanic individuals than the participants who were not assessed (ps<.05). Interested participants completed an online screening survey, providing digital, informed consent and confirming that they were: 1) At least 18 years of age; 2) minimally proficient in English; 3) in the United States; and 4) not diagnosed with any major neurological (e.g. seizure disorder) or psychiatric (e.g. psychosis) conditions.

Materials and procedures

COVID-19-related measures

Online information-seeking evaluation skills. The COVID-19 Website Evaluation Strategies Questionnaire was adapted from the information

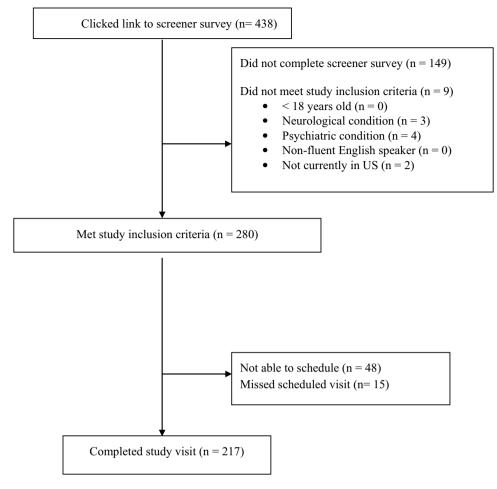


Figure 1. Study flow diagram.

accountability guidelines for the Web established by the American Medical Association (Winker et al., 2000). Participants indicated their use of 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.,'"). Possible total scores ranged from 0 to 16, with higher scores indicating greater self-reported COVID-19 information-seeking evaluative skills (Cronbach's alpha = .81).

Knowledge. Free response and true/false measures developed by the authors were used to assess participant knowledge of COVID-19 information and preventative behaviors based on information and prevention recommendations available on the CDC website as of April 2020 (CDC, 2020a). Participants listed the ways in which health officials said they can help protect themselves from getting COVID-19. Two points were assigned to responses corresponding to one of the eight CDC-recommended prevention measures at the time of evaluation. A *COVID-19 Total Prevention Knowledge Score* was calculated by summing correct responses

(possible range = 0–16). A COVID-19 Prevention Knowledge False Positive score was calculated as a sum of incorrect responses; one point was assigned to any plausible prevention measure response that was not on the CDC website (e.g. disinfect packages) and two points for an unfounded, ineffective prevention measure (e.g. take vitamin C). A randomly selected 10% of the sample was independently coded by a second rater (Intraclass Correlation Coefficient [ICC] = .74, 95% CI = .46,.88).

Participants listed the most common COVID-19 symptoms. Two points were assigned to responses corresponding to one of the four primary symptoms of COVID-19 per the CDC (2020b) at the time of evaluation (i.e. cough, fever, fatigue, shortness of breath), one point for any additional symptoms included on the CDC COVID-19 symptom list (e.g. loss of smell), and zero points for any symptoms not listed by the CDC. A COVID-19 Symptom Knowledge Accuracy score was calculated by the total of these responses. A Total COVID-19 Symptom Knowledge False Positives score was calculated as a sum of incorrect responses; one point was assigned to uncommon but research-supported symptoms (e.g. stroke, cardiac issues) and two points for unfounded COVID-19 symptoms (e.g. loss of teeth). The ICC of a 10% random sample coded by an independent rater was .91(.79,.96).

The COVID-19 General Knowledge Recognition Task included 12 statements about COVID-19. Items were created based on both factual information gathered from reliable sources (e.g. CDC), 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/don'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. "5 g wireless networks weaken the immune system ... "; See Supplementary Table 1). A d prime (d') recognition score was calculated, with higher scores indicating better discrimination.

Participants were asked, "Have you developed a plan for you and your household if you get sick with coronavirus?" Their *COVID-19 Health Plan* was rated on the following 1 to 5 scale: 1) no plan; 2) simple selfisolation; 3) self-isolation with details about the specifics and preparations for at least one aspect of food, dependents, work, or medical care; 4) self-isolation with details about the specifics and preparations for multiple dimensions of care; and 5) detailed self-isolation plan plus higher-level planning for finances, power of attorney, etc. (ICC = .63[.05,.89]).

A continuous COVID-19 Knowledge composite score of the above measures (see Table 2) was derived using principal components analysis (PCA). PCA allows for the reduction of dimensionality in composite scores with several measures by capturing a set of principle components that account for the most variance across the different measures (Gorsuch, 1988). Sampling adequacy was acceptable for these purposes as measured by Kaiser-Myer-Olkin (KMO = 0.527) and Bartlett's test of sphericity $(X^2(15) = 34.5, p = .004)$. All scores except COVID-19 Prevention Knowledge False Positive Score loaded onto a single component in the PCA analysis, accounting for 24.0% of the total variance (Eigenvalue 1.43; Supplementary Table 2). Thus, the composite score used for further analyses accounted for COVID-Prevention Knowledge Accuracy, Symptom 19 Knowledge Accuracy and False Positives, General Knowledge Recognition Task d', and Health Plan Total Score.

Intention to adhere to COVID-19 prevention behaviors. Participants completed eight items indicating their level of intention to adhere to CDC- recommended COVID-19 prevention measures (e.g. "You intend to follow the preventative guidelines in the next few weeks") on a five-point Likert scale (Cheng & Ng, 2006); see Supplementary Table 3. The items from this scale were based on CDC-recommended COVID-19 prevention measures as of 23 April 2020 (CDC, 2020a). Responses were summed to create a COVID-19 Prevention Behavior Intentions Total (range = 8–40), with higher scores indicating higher intent to adhere to preventative guidelines (alpha = .69).

COVID-19 prevention behaviors. Participants completed eight items indicating their adherence to eight CDC-recommended COVID-19 prevention behaviors (e.g. "You never touch your eyes, nose, or mouth with unwashed hands,") on a five-point Likert scale. The items from this scale were based on CDC-recommended COVID-19 prevention measures as of 23 April 2020 (CDC, 2020a). Responses were summed to create a COVID-19 Prevention Behavior Total (range = 8 - 40), with higher scores indicating higher adherence to prevention measures (alpha = .76); see Supplementary Table 4.

Neurocognitive measures

All participants were administered an abbreviated neuropsychological test battery (see Table 2) via telephone: Hopkins Verbal Learning Test-Revised (Brandt & Benedict, 2001); Digit Span subtests of the Weschler Adult Intelligence Scale - Fourth Edition (WAIS-IV; Wechsler, 2008a); action fluency (Piatt et al., 1999); Category Switching from the Delis-Kaplan Executive Functions Scale (Delis et al., 2001); Oral Trail Making Test (Ricker & Axelrod, 1994); and a four-target, embedded, focal event-based prospective memory task (Beaver & Schmitter-Edgecombe, 2017; alpha = .80). These specific tests were chosen based on: 1) their potential adaptability for telephone-based administration (e.g. Bunker et al., 2017); 2) evidence of their reliability and validity; 3) the availability of demographically-adjusted normative standards; and 4) their potential relevance to health knowledge and behaviors (e.g. Morgan et al., 2015). A recent paper by Matchanova et al. (2020) using the same sample as the current study, revealed that performance on this battery can be explained by a single factor or by a three-factor solution related to memory, executive functions, and attention. The single cognitive factor was used for all primary analyses. For any significant associations with the primary factor score, we also conducted planned follow-up analyses with these domain-level factor scores. Participants also completed the Information subtest of the WAIS-IV which is a verbal measure that

assesses general fund of knowledge and was used in the current study as a measure of estimated verbal IQ (Weschler, 2008b).

Health literacy measures

The *Brief Health Literacy Screening Tool* (Chew et al., 2008) prompted 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 scale. Higher scores (range 5–15) indicate higher perceived health literacy (alpha = .69).

On the *Subjective Numeracy Scale* (Fagerlin et al., 2007), participants rated the extent to which they agreed with eight statements (e.g. "You are good at working with fractions") on a five-point scale. Higher total scores (range 8-40) indicated higher subjective numeracy (alpha = .73).

The seven-item *Expanded Numeracy Scale* (Lipkus et al., 2001) measures a participant's abilities regarding health-related percentages and proportions (e.g. "If the chance of getting a disease is 20 out of 100, what is the percent chance of getting the disease?"). Higher total correct scores (range 0-7) indicate better numeracy (alpha = .66).

The eight-item *Electronic Health Literacy Scale* (Norman & Skinner, 2006) measures a participant's knowledge and perceived skills at finding, evaluating, and applying electronic health information (e.g. "I know how to find helpful health resources."). Responses were

rated on a one ("Strongly Disagree") to five ("Strongly Agree") scale, with higher total scores (range = 8-40) indicating greater confidence using the Internet for health-related purposes (alpha = .92).

Eight items from the *Health Motivation Questionnaire* (Moorman & Matulich, 1993) were used to assess motivation to adhere to positive health behaviors and monitor health status by asking about an individual's health concerns (e.g. "I try to prevent health problems before I feel any symptoms"). Responses were rated on a scale from one ("Strongly Agree") to five ("Strongly Disagree"), with higher total scores (range = 8-40) suggesting greater health motivation (alpha = .80).

A PCA-derived Health Literacy composite score of the above measures (see Table 2 and *Supplementary Table 5*) explained 36.8% of the variance and showed acceptable sampling adequacy (KMO = 0.61; Bartlett's test of sphericity, $X^2(10) = 105.9$, p < .001). Thus, the factor scores from this single component that included all five measures were used for further analyses.

Other study measures

Participants completed a *Demographic Questionnaire* that included variables that can be associated with performance on neuropsychological measures and health literacy (i.e. sex, age, race/ethnicity, and education level; Heaton, 2004; Paasche-Orlow et al., 2005; see Table 1).

Table 1. Descriptive data on the sociodemographic and clinical characteristics of the study sample (N = 217).

Variables ($N = 217$)	Mean (SD) or %	Sample Range	
Sociodemographics			
Sex (% women)	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		
Education (%)			
High school or equivalent	13.8		
Community college/vocational school	12.4		
Four-year college/university degree	43.8		
Professional/graduate degree	30.0		
WAIS-IV Information (scaled)	11.5 (3.1)	5–19	
Number of medical conditions	0.0 (0.0)	0–3	
Frequency of internet use ⁺ (of 63)	53.9 (14.0)	0–63	
Tested for COVID-19 (%)	5.1		
COVID-19 internet frequency (of 4)	3.4 (0.7)	1–4	
COVID-19-related anxiety (of 5)	3.7 (1.0)	0–5	
COVID-19 pandemic time elapsed (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. ⁺ *N* = 216; ⁺⁺ *N* = 203; GAI-SF = Geriatric Anxiety Inventory – Short Form

Table 2. Descriptive data for the primary study outcomes $(N = 21)$	Table 2. Descri	ptive data for	r the primar	y study outcom	es (N = 217)
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Variables ($N = 217$)	Mean (SD) or %	Sample Range		
Neurocognition				
Global T-score	53.7 (5.2)	42–71		
Global impairment (1 SD; %)	15.7			
Attention				
HVLT Trial 1 (of 12) ⁺	7.0 (6.0, 9.0)	3–12		
WAIS-IV Digit Span Backward Total ⁺	9.0 (8.0, 11.0)	4-16		
WAIS-IV Digit Span Forward Total +	11.0 (9.0, 13.0)	5–16		
Executive Functions				
Action Fluency Total ⁺	22.0 (19.0, 26.0)	10–40		
DKEFS Verbal Category Switching +	17.0 (15.0, 19.0)	5-26		
Oral Trails Part B (seconds) +	25.0 (19.0, 34.0)	9–225		
Memory		0-8		
Prospective Memory (of 8) +	8.0 (7.0, 8.0)	3-12		
HVLT-R Long Delay Free Recall (of 12) +	10.0 (8.0, 11.0)	7–12		
HVLT-R Recognition (of 12) +	11.0 (11.0, 12.0)			
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		
COVID-19 health				
Information-seeking (of 16)	7.8 (3.7)	0–16		
Symptom knowledge accuracy	6.7 (1.9)	2–13		
False positives	0.5 (0.9)	0–5		
Preventative knowledge accuracy	7.5 (1.7)	4–12		
False positives	0.4 (0.8)	0–4		
General knowledge (d')	2.5 (0.9)	0.2-4.4		
Preventative intentions (of 40)	35.5 (3.2)	21-40		
Preventative behaviors (of 40)	34.2 (4.5)	20-40		
Health plan quality (of 5)	1.8 (1.2)	1–5		

Note. eHEALS = electronic health literacy scale; 3-Brief = Brief Health Literacy Screening Tool; COVID-19 = coronavirus disease 2019. ⁺ median (IQR) reported due to non-normal distribution.

The Geriatric Anxiety Inventory-Short Form (Byrne & Pachana, 2011) was used to assess anxiety symptoms as higher levels of anxiety have been associated with lower adherence to positive health behaviors and worse health outcomes (e.g. Strine et al., 2005). Participants indicated whether they agreed or disagreed with five statements (e.g. "Your own thoughts often make you nervous") and higher scores indicated more anxiety (possible score range = 0-5, current sample range 0-5, current study Cronbach's alpha = .80).

COVID-19-related anxiety was measures a single item in which participants rated the statement "You are worried and nervous about coronavirus" on a fivepoint Likert scale from one ("Strongly Disagree") to five ("Strongly Agree"). The score range in the current sample was from 1–5, with higher scores indicating higher COVID-19-related anxiety.

Participants also indicated the frequency of they were reading about or listening to information about COVID-19 on a four-point scale from "1-Rarely/ Never" to "4-Several Times Per Day," as exposure to information can increase motivation to learn more about the topic (e.g. Ditta et al., in press).

Familiarity and frequency of internet use was assessed used a *General Internet Use Questionnaire*

(see Baggio et al., 2017) given its demonstrated relationship with trust placed on health information learned online, concern for personal health, and perceived usefulness of online health information (e.g. Lemire et al., 2008). Participants were asked 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 (current sample range = 0– 63, current sample Cronbach's alpha = .71).

Participants completed the *Big Five Inventory – 2 Extra-Short Form* (Soto & John, 2017) as recent studies have suggested a relationship between the personality trait of agreeableness (Xie et al., 2020; Zettler et al., preprint; Gotz et al., preprint, c.f., Abdelrahman, in press) with adherence to COVID-19 preventative behaviors. 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 and average Cronbach's alpha for each domain in the current sample was .58 which was comparable to the alphas calculated in the original development and validation paper for the measure (i.e. range .51 to 72; Soto & John, 2017). The first 13 participants were not administered this measure due to a study procedural issue.

Physician trust was assessed using the *Wake Forest Physician Trust Scale* (Hall et al., 2002) given the interest of the present study in how and where participants learned information about COVID-19. 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") on a five-point Likert scale scored from one ("Strongly Disagree") to five ("Strongly Agree"). 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.

Data analyses

Missing values were <5% and were found to be missing completely at random ($\chi^2 = 660.50$, p = .867). The primary neurocognitive, health literacy, and COVID-19 variables were not normally distributed (Shapiro-Wilk ps<.01) and univariate analyses were thus conducted using either Wilcoxon Rank Sums Tests or Spearman's rho. However, the sample size was large and the model residuals did not show major deviations from normal. Hierarchical regressions were used in order to examine the primary hypotheses that: 1) health literacy and neurocognition would be independently associated with each of the COVID-19 outcomes; and 2) that there would be an interaction between health literacy and neurocognitive such that the relationship between neurocognition and the COVID-19 outcome variables would be strongest among persons with lower levels of health literacy. Covariates were selected in a data-driven fashion, whereby only those variables from Table 1 that were uniquely associated with the neurocognitive composite, health literacy composite, and COVID-19 variables at a α = .05 were included (Field-Fote, 2019). Covariates were entered in Step 1, health literacy and neurocognition were entered in Step 2, and the health literacy by neurocognition interaction was entered in Step 3. The first hypothesis was tested by examining the addition of neurocognition and health literacy in Step 2 for each regression. Specifically, the adjusted R^2 change for Step 2 was used to determine the contribution of neurocognition and health literacy collectively to each model, while their individual contributions were determined by examining the unstandardized betas of neurocognition and health literacy in Step 2 of each model. The second hypothesis was tested by examining the unstandardized betas of neurocognition and health literacy in Step 2 of each model. The second hypothesis was tested by examining the unstandardized beta of the neurocognition x health literacy interaction term in Step 3. A Bonferroni correction was utilized to limit Type I error and thus, the adjusted critical alpha was set at .013 (i.e. .05/4 domains of COVID-19 health) and results are accompanied by effect sizes.

Results

Univariable relationships between the primary study variables

Neurocognition showed broadly medium positive associations with both health literacy ($\rho = .26$, p < .001) and COVID-19 Knowledge ($\rho = .31$, p < .001), as well as a small negative correlation with COVID-19 Preventative Behaviors ($\rho = -.17$, p = .010; Table 3). Health literacy additionally had broadly medium positive associations with COVID-19 Online Information-Seeking Skills ($\rho = .26$, p < .001), Knowledge ($\rho = .32$, p < .001), and Preventative intentions ($\rho = .41$, p < .001). COVID-19 Preventative Behaviors was associated with Online Information-Seeking Skills ($\rho = .26$, p < .001) and Preventative Intentions ($\rho = .41$, p < .001) at small-tomedium effect sizes. COVID-19 Knowledge was associated with Preventative Intentions at a small effect size ($\rho = .23$, p = .001).

COVID-19 online information-seeking evaluation skills

WAIS-IV Information, the only variable that met criteria for inclusion as a covariate, was entered in Step 1 and accounted for a significant amount of variance in

 Table 3. Correlations between the primary predictors and outcome variables.

	1	2	3	4	5
1. Neurocognition	-	-	-	-	-
2. Health literacy	.26	-	-	-	-
3. COVID-19 information-seeking	05	.26	-	-	-
4. COVID-19 knowledge	.31	.32	.11	-	-
5. COVID-19 preventative intentions	.03	.41	.14	.23	-
6. COVID-19 preventative behaviors	17	.15	.26	.03	.41

Note: Table values are Spearman's rho correlation coefficients. **Bold** indicates p < .013. COVID-19 = coronavirus disease 2019

COVID-19 Online Information-Seeking Evaluation Skills (adjusted $R^2 = .02$, p = .012; Table 4). The entry of neurocognition and health literacy in Step 2 accounted for additional variance (adjusted $R^2 = .06$, p = .001), which was primarily attributable to health literacy (p < .001). After accounting for health literacy, neither global neurocognition nor WAIS-IV Information were significant contributors (ps>.013). Inclusion of the interaction term in Step 3 did not explain any additional variance in COVID-19 Online Information-Seeking Evaluation Skills (adjusted $R^2 = .07$, p = .548).

COVID-19 knowledge

Education and WAIS-IV Information were the only variables that met criteria for inclusion as covariates (ps<.05). These covariates were entered in Step 1 of the model, which was significant (adjusted $R^2 = .09$, p < .001; Table 4). The entry of global neurocognition and health literacy in Step 2 contributed a significant amount of variance (adjusted $R^2 = .15$, p < .001), attributable to both global neurocognition (p = .005) and health literacy (p = .012), but not WAIS-IV Information or education (ps>.013). The addition of the interaction term between global neurocognition and health literacy in Step 3 did not explain

a significant amount of additional variance in COVID-19 Knowledge (adjusted $R^2 = .16$, p = .032).

A series of planned post-hoc multiple regression analyses were conducted predicting COVID-19 Knowledge from the domains of attention, executive functions and memory, controlling for education, WAIS-IV Information, and health literacy. All three omnibus models were significant (ps<.001) and revealed significant, independent effects of memory (b = 0.47[0.15,0.78], t[211] = 2.93, p = .004) and executive functions (b = 0.04[0.01,0.07], t[211] = 2.72, p = .007), but not attention (p = .111).

In addition, a reviewer recommended that we repeat the above analyses of interactions between neurocognition and health literacy in an exploratory fashion by replacing global neurocognition with the domains of attention, executive functions, and memory. We used an adjusted critical $\alpha = .004$ (i.e. .05/4 domains of COVID-19 health/3 additional analyses) for these exploratory analyses. None of the interaction terms between health literacy and the domains of attention ((b = .18, p = .107; adjusted $R^2 = .13, F$ of $R^2\Delta = 2.63,$ p = .107), executive functions (b = .03, p = .008; adjusted $R^2 = .17, F$ of $R^2\Delta = 7.22, p = .008$), or memory (b = .28, p = .046; adjusted $R^2 = .16, F$ of $R^2\Delta = 4.04$,

Table 4. Stepwise regression results for neurocognition, health literacy, and data-driven covariates predicting COVID-19 health information (N = 217).

		Model 1		Model 2			Model 3		
Variable	b	SE b	β	b	SE b	β	b	SE b	β
Outcome: COVID-19 Info-Seeking									
WAIS-IV Info	0.13	.05	.17	.09	.06	.11	0.09	.06	.12
Global Neurocognition				-1.19	.68	13	-1.29	0.70	14
Health Literacy				0.96	.27	.26	0.95	.28	.25
Global Neurocognition x HL							-0.39	.60	05
adjusted R ²	.02			.06			.07		
F for change in R^2	6.38			6.70			0.43		
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; COVID = coronavirus disease 2019; WAIS-IV Info = Wechsler Adult Intelligence Scale – fourth edition Information subtest; HL = health literacy

p = .046) met were statistically significant according the adjusted critical α .

COVID-19 preventative intentions

No variable met criteria for inclusion as a covariate. Global neurocognition and health literacy accounted for a significant amount of variance in COVID-19 Intentions (adjusted $R^2 = .15$, p < .001; Table 4). This result was primarily attributable to health literacy (p < .001) rather than global neurocognition (p = .255). Addition of the interaction term between global neurocognition and health literacy did not account for more variance in COVID-19 Intentions (adjusted $R^2 = .14$, p = .701).

COVID-19 preventative behaviors

WAIS-IV Information alone met criteria for inclusion as a covariate and accounted for a significant amount of variance in COVID-19 Preventative Behaviors (adjusted $R^2 = .02$, p = .012; Table 4). In Step 2, global neurocognition and health literacy contributed a significant amount of variance (adjusted $R^2 = .08$, p = .001). This result was primarily attributable to health literacy (p < .001) and WAIS-IV Information (p = .003), rather than global neurocognition (p = .099). The addition of the neurocognition x health literacy interaction term did not account for more variance in this model (adjusted $R^2 = .08$, p = .682).

Post-hoc analysis

In contemplating the unexpected negative relationship between estimated verbal IQ and COVID-19 Preventative Behavior, we posited that perhaps participants with higher IQs may have been at the forefront of digesting emerging information about the reduced risk of surface transmission. We derived two subscales of COVID-19 preventative behaviors, with three items measuring dynamic preventative behaviors related to surface transmission (e.g. frequent cleaning home and surfaces) and three items measuring persistent preventative behaviors (e.g. social distancing, masks). A CFA supported this two-factor solution ($X^2(19) = 15.9, p = .045$; RMSEA = 0.07 (0.10,0.12); CFI = 0.97; SMMR = 0.04). Using a median split of evaluation date, WAIS-IV Information was negatively associated with the dynamic surface transmission COVID-19 preventative behaviors among participants assessed May 6 to 20 May 2020 at a small effect size (r_s = -.28, p = .003), but not among those assessed earlier in the pandemic ($r_s = -.11$, p = .267). The difference between these correlation coefficients was significant (z = 1.83, p = .033). WAIS-IV Information was not related to

persistent COVID-19 preventative behaviors in either epoch (*ps>*.10).

Discussion

We examined the unique and combined roles of individual differences in neurocognition and health literacy in the initial uptake and use of health-related information about COVID-19 during the Spring of 2020. Consistent with our initial hypotheses, univariable results suggest that individuals with higher neurocognitive ability had greater knowledge of the symptoms, preventative measures, and associated health factors related to COVID-19 at a medium effect size. Importantly, the association between neurocognition and COVID-19 knowledge remained significant when controlling for education, estimated verbal IQ, and health literacy. Findings are consistent with the positive association between neurocognition and disease-specific knowledge in chronic medical illnesses (Malow et al., 2012) and extend that work in the context of novel, evolving infectious disease knowledge acquisition and recall. Given that disease prevention and health promotion often begin with knowledge (Link & Phelan, 1995), individuals with lower neurocognitive ability may be at risk for acquiring and using misinformation about COVID-19, which could have downstream implications for both personal and public health.

At the domain level, better executive functions and episodic memory, but not attention/working memory, were uniquely associated with higher COVID-19 knowledge. The episodic memory findings are intuitive and align with research showing that individual differences in episodic memory play an independent role in learning the content and context of novel health-related information about infectious disease (Morgan et al., in press). Future studies might examine other relevant aspects of declarative memory (e.g. source memory) and the extent to which memory-based supports such as self-generation, elaboration, and spaced retrieval practice can enhance the acquisition of health-related knowledge (Roediger III & Karpicke, 2006). The process of learning new health-related information, particularly in the digital age, is complex (Ford, 2004). Executive functions can influence the encoding and retrieval aspects of episodic memory (Moscovitch, 1992). Thus, executive functions may have also contributed to the acquisition of COVID-19 knowledge by influencing the use of higher-order organization and retrieval strategies (e.g. clustering), as has been shown in relation to other aspects of health literacy (Sullivan et al., 2021). Future studies are encouraged to include more specific measures and to use experimental approaches to delineate whether providing executive supports (e.g. scaffolding, clustering)

can enhance COVID-19 knowledge acquisition in persons with neurocognitive disorders.

Contrary to our hypotheses, neurocognition was negatively associated with self-reported adherence to COVID-19 preventative behaviors; however, this association was no longer significant after controlling for relevant covariates, most notably estimated verbal IQ. These results are inconsistent with a recent study that suggested that working memory was positively associated with self-reported adherence to COVID-19 social distancing guidelines in healthy adults (Xie et al., 2020). The discrepancy in findings may be due to differences in how both constructs were assessed; however, a post-hoc correlation between WAIS-IV Digits Backwards and a single-item measure of COVID-19 social distancing compliance that was akin to Xie et al. (2020) was also small and negative. Regardless, the finding may be of tertiary importance because global neurocognition was no longer a significant predictor of COVID-19 preventative behaviors when the model was covaried for estimated verbal IQ, which was also negatively associated with COVID-19 preventative behaviors. Post-hoc analyses showed that estimated verbal IQ was specifically negatively related to personal home and hygiene factors during the latter part of the study period, at which time evidence was emerging against surface transmission. Thus, it is plausible that people with higher funds of knowledge were modifying their behavior based on digesting the evolving information about the less effective preventative measures (CDC, 2020c). These findings may underscore a limitation of the current study as COVID-19 measures developed by the authors were based on information and recommendations at a single time point (i.e. late April) and did not account for the rapidly developing COVID-19 information over the month-long course of the study. Prospective, hypothesis-driven studies may help to shed further light on these post-hoc observations.

Contrary to our initial hypothesis, neurocognition was not associated with online COVID-19 related information seeking skills. It is unlikely that the lack of significant findings was due to Type II error, as the current study sample of 217 participants was wellpowered to detect small-to-medium effect sizes. These results were surprising, as other studies have demonstrated an association between neurocognition and electronic health literacy (e.g. Woods & Sullivan, 2019), as well as performance on naturalistic online search tasks (Woods et al., 2019). Neurocognitive domains not assessed (e.g. spatial cognition, visual problem-solving) may still play an important role in information-seeking skills. Although our measure of COVID-19 information-seeking skills was internally consistent, associated with preventative behaviors and health literacy (see Table 3), and adapted from well-validated measure, it was nevertheless a single self-report measure that does not encompass other potentially important neurocognitive aspects of the construct that might be the focus of future studies (e.g. source biases, search term generation, and internet navigation skills).

Neurocognition was also not associated with selfreported intentions to adhere to COVID-19 preventative guidelines which was contrary to our initial hypothesis. A positive relationship was hypothesized primarily based on theory and empirical evidence for the roles of attention, retrospective memory encoding, and executive functions in the formation of intentions (Kliegel et al., 2008). Intention formation is a critical aspect of prospective memory, yet a post-hoc analysis showed that even our focal, event-based prospective memory measure was not specifically associated with COVID-19 intentions ($r_s = -.10$). It nevertheless remains possible that other aspects of prospective memory might relate to COVID-19 intentions, including more strategically-demanding tasks (e.g. timebased), naturalistic measures (Rendell & Thomson, 1999), or approaches that allow for the isolation of the encoding and planning aspects of intentions (Kliegel et al., 2001). Despite the null associations with the aspects of neurocognition measured in this study, intentions to adhere to COVID-19 guidelines were internally consistent and showed small-tomedium associations with COVID-19 knowledge and self-reported behavioral practices, as well as health literacy.

The hypothesis that health literacy was a moderating variable in the relationship between neurocognition and the COVID-19 outcomes was not supported; rather, findings suggest that the effects of health literacy and neurocognition are largely independent of one another. Global cognition and health literacy independently contributed to a significant amount of variance of COVID-19 knowledge. However, health literacy emerged as the only significant driving factor of the other COVID-19 outcomes. While the theoretical importance of health literacy in the COVID-19 pandemic has been discussed (Abel & McQueen, 2020; Paakkari & Okan, 2020), this is the first study to investigate its role using well-validated measures. Future studies might examine the role of a broader range of fundamental (e.g. health reading comprehension) and critical (e.g. health-related decision-making) aspects of health literacy in relation to COVID-19 health outcomes. Furthermore, future studies are needed to determine whether the relationship between health literacy and COVID-19 health knowledge and behaviors (and potential mediators and

moderators) are also present among persons of lower socioeconomic status.

These data were gathered at a pivotal time during the early stages of the COVID-19 pandemic during which many governing bodies were recommending guidelines to prevent the spread of COVID-19 that impacted several aspects of day-to-day life for the majority of Americans. Thus, while the present findings provide important insight into predictors of COVID-19 health-related factors at the early stages of the pandemic, it is plausible that these relationships may evolve over time as the dynamics of the pandemic itself change. Another important limitation was that this study was focused on examining the neurocognitive and health literacy aspects of COVID-19 and therefore treated many potentially influential factors as confounds (e.g. personality) and did not assess some other potentially important predictors such as identity and political affiliation (Clements, 2020; Pedersen & Favero, 2020; c.f., Masters et al., 2020). Thus, it is plausible that people with higher funds of knowledge were modifying their behavior based on digesting the evolving information about the less effective preventative measures (CDC, 2020c). The current study used hierarchical regressions for the primary analyses, which limited our ability to account for the theoretical temporal relationships between COVID-19 knowledge, intentions, and prevention behaviors. Future studies may wish to apply more advanced statistical techniques to examine the complex relationships between cognition, health literacy, and COVID-19 (e.g. structural equation models, mediation). Use of longitudinal data would allow for testing of mediation effects that could further elucidate relationship between neurocognition and COVID-19 online information-seeking evaluation skills, intentions to adhere to COVID-19 preventative behaviors, and adherence to COVID-19 preventative behaviors. Indeed, it is possible that despite the current findings provide support against the relationship between neurocognition and these COVID-19 outcomes that health literacy is a possible mediating variable between them which may explain these unexpected null results. Finally, the assessment of COVID-19 health knowledge and behaviors is rapidly evolving and although the current measures showed adequate psychometric properties for this study, future work on this topic may benefit from the use of standardized, reliable, and ideally performance-based measures that are emerging (e.g. Clements, 2020; Zhong et al., 2020).

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 emerging public health threats such as 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, in press) may improve knowledge of emerging public health issues like COVID-19. Health literacy was also 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 neurocognitive status among healthy individuals (see Sheridan et al., 2011 for review). Finally, the critical period of data collection for this study at the early stages of the COVID-19 pandemic 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. Although this study was conducted in the early stages of the emergency of COVID-19, several aspects of the findings are relevant to the evolving pandemic and other health conditions. Indeed, the information and recommendations regarding COVID-19 are constantly evolving and require the public to learn and integrate new health information in order to keep themselves and others safe and healthy. For example, the demonstrated contributions of neurocognition and health literary to COVID-19 knowledge in this study may be helpful in identifying persons at risk for misinformation regarding new vaccine recommendations and updated mask policies. Our findings may also help with the development and targeting of information campaigns as new public health crises inevitably emerge. For example, based on the study findings we suggest that these campaigns focus on the translation of scientific evidence-based guidelines and recommendations into constructs and language that are accessible to persons with low levels of health literacy, perhaps through community-based participatory research approaches (e.g. Boot Camp Translation; Norman et al., 2013). The study also underscores the importance of the use of health literacy assessments in clinic to help identify persons with low health literacy that may be at a higher risk for misinformation about diseases and/or health conditions that are novel to them. While there is no current "gold standard" measurement of health literacy, wellvalidated performance based measures that can quickly and easily be implemented into clinical practice and have been demonstrated to correlate with health behaviors include the Newest Vital Sign (Weiss et al., 2005) and the Rapid Estimate of Adult Literacy in Medicine (REALM; Murphy et al., 1993).

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Consent

All participants provided digitally recorded consent to the inclusion of materials pertaining to themselves and acknowledged that they cannot be identified via the paper. The authors have fully anonymized the participants.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

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