COVID-19 Express Article

Contextualized Knowledge Reduces Misconceived COVID-19 Health Decisions

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How do we resolve conflicting ideas about how to protect our health during a pandemic? Prior knowledge influences our decisions, potentially creating implicit cognitive conflict with new, correct information. COVID-19 provides a natural condition for investigating how an individual's health-specific knowledge (e.g., understanding mask efficacy) and their personal context (e.g., outbreak proximity) influence their protective health behavior endorsement, as information about the virus, its spread, and lethality has changed over time. Using a dual-process-model framework, we investigated the role cognitive conflict has on health decision-making. We used a computer mouse-tracking paradigm alongside geographical information systems (GIS) as a proxy for context. The results support a contextualized-deficit-model framework in which relevant knowledge and context-based factors help individuals override cognitive conflict to make more preventative health decisions. Findings from this study may provide evidence for a more effective way for experts to combat non-adherence due to conflicting health information.

Keywords: Cognitive conflict, Action dynamics, Health behavior, Knowledge, COVID-19, GIS

General Audience Summary

The present study considers how knowledge and context influence COVID-19 health decisions (e.g., decision to maintain social distancing, mask use, etc.). We do this by examining the role positive COVID-19 incidence rates, trust in scientific and medical experts, and knowledge (i.e., germ transmission knowledge, mask knowledge, quantitative reasoning, science change knowledge) have on decision making. Cognitive science suggests that when new information enters the cognitive system, it does not overwrite prior inaccurate information. Rather both new and prior knowledge compete for activation during decision making. We considered whether knowledge and contextual factors

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could help individuals deliberately suppress prior misconceptions (e.g., cloth masks do not reduce COVID-19 spread) in favor of updated information (e.g., cloth masks *do* reduce COVID-19 spread). Results suggest that the more relevant knowledge (in context) individuals had, the easier it was for them to make decisions in line with updated Center for Disease Control and Prevention guidelines, providing evidence for a more effective way for experts to combat non-adherence due to conflicting health information.

How can individuals best protect their health when conflicting ideas exist about health and safety during a pandemic? Under such conditions, experts make predictions and outline guidance for mitigating risk, but these predictions may be inaccurate, necessitating the public to update their prior knowledge as new information accumulates—potentially leading to distrust of experts (Holmes et al., 2009). The term *updating* may be somewhat misleading because new knowledge does not supplant prior knowledge (Murray et al., 2020; Shtulman & Valcarcel, 2012), creating the potential for interference. This interference can be problematic, particularly when prior knowledge is intuitive, implicit, and inaccurate—e.g., cold weather causes the flu. When an individual later learns germs transmit more easily indoors (where winter months are spent), this new knowledge does not replace the prior, intuitive information, creating a phenomenon known as *explanatory coexistence*— multiple theories or beliefs exist to explain the same event (Gelman, 2011). Consequently, accessing these theories creates competition, known as *cognitive conflict* in which concepts, beliefs, and/or processes compete for activation within cognition (Festinger, 1957). Resolving this conflict is mentally demanding, requiring one type of knowledge to be suppressed so that the other can be expressed (Shtulman & Valcarcel, 2012). While some knowledge may be successfully suppressed, it can still influence decision-making implicitly, particularly under conditions of uncertainty (Masson et al., 2014).

Dual process models of information processing (DPM; Evans & Stanovich, 2013; Sherman et al., 2014) broadly suggest decision-making may be driven by two processes: implicit and explicit. Implicit refers to cognitive processes outside of conscious awareness (i.e., cognitive shortcuts; Tversky & Kahneman, 1974), which is particularly helpful in situations that require fast, automatic learning or recognition of information that exceeds working memory capacity (e.g., ensemble perception and cognition; Haberman & Whitney, 2012). However, under novel or uncertain conditions, implicit processing may be based on incomplete or misconceived prior knowledge (e.g., cold weather causes the flu), which sometimes leads to suboptimal decisions (e.g., implicit bias; Gawronski, 2019). Explicit refers to thinking that is deliberate, systematic, and under the conscious control of working memory. Explicit cognition allows for the resolution of conflicts between incorrect information and updated, potentially more accurate, information (e.g., flu is transmitted indoors; Travers et al., 2016). Implicit and explicit processes are concurrently activated, resulting in competition between processes for ultimate control of the final decision (Sloman, 2014). Implicit processes are easier to engage because they require fewer cognitive resources (e.g., working memory); however, failure to engage in explicit processing may solidify and strengthen the endorsement of misconceptions in some cases (Travers et al., 2016) because the new, updated information may not be integrated with prior knowledge.

Explanatory coexistence (Gelman, 2011; Legare & Visala, 2011; Shtulman & Legare, 2020) may explain why competition could exist between implicit/explicit processes as a direct result of imperfect learning and remain in cognition to fill context-specific needs (Shtulman & Lombrozo, 2016). Because of this, implicit/intuitive theories *may* become resilient in cognition and resistant to supplantation because they require overt inhibition to override, providing a potential explanation for why misconceptions form (Shtulman & Valcarcel, 2012; Rich et al., 2017). Thus, individuals may inadvertently make decisions in line with intuitive, implicit, and/or misconceived knowledge because it is an easier *cognitive* decision.

The COVID-19 pandemic fomented uncertainty and conflicting information, as experts rushed to better understand the novel coronavirus, its lethality, and spread based on limited information. We use COVID-19 as a case to examine DPM because the pandemic created natural conditions in which information changed in real-time, resulting in *authentic* explanatory coexistence and the need to inhibit prior information in light of new evidence. For instance, it may be the case that the knowledge individuals held prior to the pandemic (e.g., only symptomatic individuals spread germs) or at the outset of the pandemic (e.g., cloth masks do not reduce spread) was deeply rooted in cognition and driving implicit processes. Consequently, individuals may rely on automatic heuristics for decision-making rather than dedicate limited cognitive resources to engage explicit cognitive processes to inhibit implicit, prior knowledge in favor of more up-to-date information (i.e., cloth masks *do* reduce symptomatic/asymptomatic spread; Pachur et al., 2012).

When explicit processes are engaged, cognitive conflict likely burdens decision-making because it competes with automatic heuristics based on prior information (Pachur et al., 2012). To avoid relying on implicit processes that may not be informed by the most up-to-date information, one solution could be to reduce the amount of information the public consumes—at least until more *complete* knowledge is available. However, the contextualized deficit model (CDM; Allum et al., 2008; Sturgis & Allum, 2004) suggests this proposition would likely be problematic. This model highlights that the understanding of scientific knowledge is two-fold. First, uncer-

tainty and skepticism are typically caused by the lack of sufficient knowledge. Lower knowledge levels are associated with a lower likelihood of endorsing scientific guidelines/findings because they may directly contradict already-held intuitive theories (Allum et al., 2008; Čavojová et al., 2020; Sturgis & Allum, 2004). Second, adequate contextualized knowledge should help overcome knowledge deficits because it provides relevant situational information that may ease decision-making, particularly when context supports knowledge. Further, when contextual information is salient (e.g., health officials reporting spikes in local incidence rates, calling for increased protective behavior), individuals may be more likely to rely on this information because it is more easily recalled. Pachur et al. (2012) explain that if something is recalled, it is assumed to be important (e.g., local spikes in positive cases cueing protective behaviors) or at least more important than other solutions that are not easily retrieved (i.e., availability-by-recall heuristic).

Contextualized knowledge likely affects the recall of information to shape decision-making. We investigate the following research questions (RQ) associated with knowledge (germs, mask facts, science as change, quantitative reasoning) and context (incidence rate, trust in scientific/medical experts) on explicit, implicit, and prospective COVID-19 decisions. We used computer mouse-tracking to measure these processes because it permits the evaluation of action dynamics (i.e., body movements) to reveal the dual, parallel cognitive processes (i.e., implicit/explicit) that are activated simultaneously during decision-making (McKinstry et al., 2008).

RQ.1: How do knowledge and contextual factors influence *explicit* COVID-19 behavioral decisions? When knowledge and context are in alignment, accuracy should increase because the knowledge types support each other (i.e., CDM)—because the information in their local environment (e.g., low incidence rate) may support updated scientifically accurate information (e.g., wearing masks protects against COVID-19 spread) creating a synergic relationship between context and knowledge to prevent the spread of COVID-19.

RQ.2: How do knowledge and contextual factors influence cognitive conflict underlying decisions (i.e., *implicit* COVID-19 behavioral decisions)? When context supports knowledge (i.e., when knowledge and contexts are aligned), decision-making will be easier (i.e., availability-by-recall heuristic, creating less cognitive conflict in the cognitive system—implicit process). However, if these factors are in conflict (i.e., explanatory coexistence), more cognitive conflict should be observed as individuals decide whether or not to inhibit prior knowledge in favor of updated information (i.e., parallel-competitive DPM; Travers et al., 2016).

RQ.3: How do knowledge and contextual factors influence *prospective* COVID-19 behavioral decisions? Differential vaccine-endorsement decisions should be observed based on whether participants rely on context or knowledge to shape their behavior. If participants rely more on knowledge than context, then they should endorse the vaccine when available.

However, if endorsement is driven by context (e.g., trust in experts), participants should be less likely to endorse the vaccine, as context at the time of testing predominantly advocated mask-usage over the vaccine in clinical trials.

Method

Participants

Participants (*N* = 306) were recruited from Amazon's Mechanical Turk (MTurk; *n* = 270) and an undergraduate participant pool (*n* = 24). No differences in the level of agreement associated with COVID-19 behavior were observed (*p* > .05) between the samples. Samples were combined for analyses. All participants were U.S. residents (women = 129, men = 175, non-binary = 2; M_{age} = 37.83 years, *SD* = 12.5). At the time of data collection, most participants (83%) had never received a positive COVID-19 diagnosis (Supplemental Table 1), with our sample having a slightly higher positivity rate than the U.S. national average. Data were collected prior to the U.S. presidential election between October 27 and November 2, 2020.

Only participants who reported their zip codes were included in the analysis (*n* = 294) because zip code was used to calculate local incidence rate for each participant (see Measures). These participants were overwhelmingly located in metropolitan areas—73.5% were located in Urbanized Areas, 7.8% were located in Urban Clusters, and 18.7% were located in rural areas (see Supplemental Figure 1).

Experimental Platform and Stimuli

FindingFive

Data were collected in a single session remotely using the FindingFive platform (FindingFive, 2019). FindingFive permits collection of computer mouse *x* and *y* coordinates (i.e., calculated proportion of participant screen pixel size) during mouse-tracking and psychological tasks. The Mousetrap package (Kieslich et al., 2019) in R (R Development Core Team, 2012) was used to process the raw data (proportional x, y coordinates to control for screen size variation) from FindingFive to produce the initiation times and maximum deviation measure.

Stimuli

Participants responded to 60 statements, representing five constructs (12 per construct; Table 1): COVID-19 behaviors, mask knowledge, germ theory, change in science, and quantitative reasoning (see Supplemental Materials OSF). COVID-19 behavioral statements indicated protective or non-protective behaviors and mask knowledge included factual/false statements based on CDC (2020) recommendations at the time of data collection. Germ theory included scientific (empirically based explanations) and naïve theory (inaccurate, observation-based explanation) statements regarding germ transmission and infection (from Shtulman & Valcarcel, 2012). The science-change category included factual/false

Table 1

Sample Questions Presented to Participants Across the Five Question Constructs

Construct	Type	Sample statement
COVID-19 behaviors	Protective	I wear a mask every time I leave the house.
	Non-protective	I wear a mask only when it's enforced by others.
Mask effectiveness	Fact	Cloth masks work to prevent the spread of coronavirus.
	Myth	Prolonged mask usage may cause oxygen deficiency.
Germ theory	Scientific	Dish sponges contain germs.
	Naïve	Being cold can make a person sick.
Science change	Fact	Scientific evidence is constantly changing.
	Myth	Scientific evidence is relatively stable.
Quantitative reasoning	COVID-19 Word Problem	In Pickaway County, Ohio (population 57,400) there are 3,011 cases of COVID-19. In Queens County, NY (population 2.3 million) there are 75,000 confirmed cases. Which county has the highest rate of confirmed cases?
	Generic Word Problem	The International Society for Arboriculture surveyed 465,000 deciduous trees in Northeastern Ohio. Of the deciduous trees, 181,772 are maple trees. The Society also surveyed 126,000 coniferous trees. Of the coniferous trees, 56,000 are pine trees. Northeastern Ohio has a higher rate of which type of tree?
	COVID-19 Graph	Which graph had the highest COVID-19 case peak?
	Generic Graphs	Which graph had the highest sales of Ford automobiles: 2010 vs 2020?

*Note.* See OSF for the full list of items.

statements about how scientific knowledge is revised as evidence accumulates and concepts typically taught in research method courses. Quantitative reasoning items assessed participants' ability to interpret graphs or numeric word problems (similar to Kahan, 2017). All experimental items were presented during the mouse-tracking portion of the experiment. Twelve demographic questions were asked without mouse-tracking (see Supplemental Materials).

Design and Procedure

A within-subjects design was used. A computer mouse (not a trackpad) was required for participation—all participants self-reported that they were using a computer mouse. Experimental trials (*n* = 60) were presented in a traditional, computer mouse-tracking paradigm in which participants saw a statement paired with two-alternative, forced-choice response options (Figure 1). All (6) question blocks occurred in a fixed order (demographics, COVID-19 behavior, mask, germ theory, science change, quantitative reasoning questions); however, the questions were randomized within each block.

Experimental trials began with a primer statement (e.g., *In light of the COVID-19 pandemic*) or a blank screen and participants were then required to click a *Continue* button in the bottom, middle of the computer screen to initiate mouse-tracking. The experimental statement was then presented for 1,000 ms (to allow time to read the statement). After 1,000 ms, FindingFive presented two categorical response options (see Measures). Participants were reminded to only begin moving their cursor once the response options appeared on their screen to ensure all participants' cursors began at the same time and location (proportional *x* and *y* coordinate on the screen).
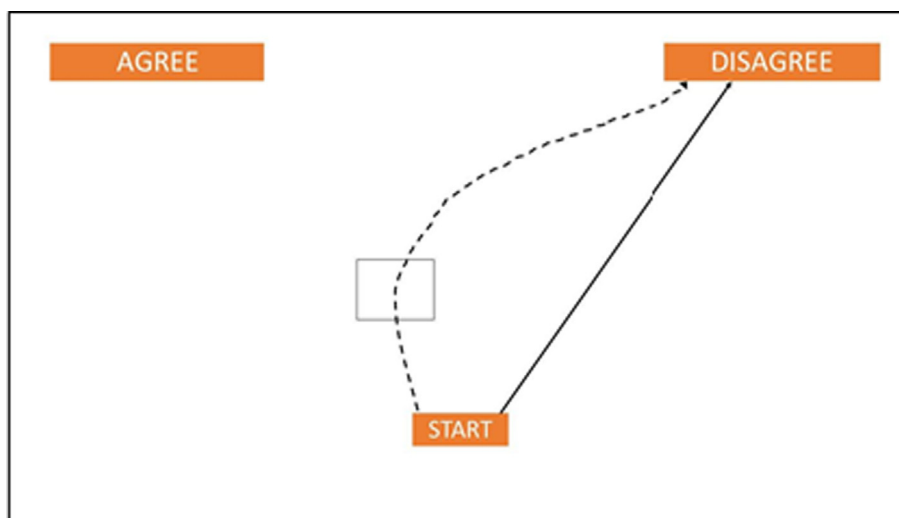
Figure 1. Schematic representation of the Finding Five response selection screen. The solid line indicates the ideal cursor trajectory in which no cognitive pull toward the alternative response option occurs. The dashed line indicates a simulated trajectory in which cognitive pull does occur. The box around a portion of the dotted line shows the furthest x-cursor position to a simulated maximum deviation point. The simulated mouse cursor movement and maximum deviation box were not visible to participants. This content is only provided to help the reader understand how the mouse-cursor trajectory is realized.

Measures

COVID-19 Preventative Behaviors

Due to the presumed differences in agreement surrounding the COVID-19 pandemic, we were interested in how these differences may be expressed with reference to protective and non-protective COVID-19 behaviors.

Explicit Decision–Categorical Response Choice

The novelty of COVID-19 has necessitated information regarding best practices to change over time. Combined with differences in communication (e.g., politicians vs. scientists) about the virus, the public appears to be split on their beliefs about what constitutes a protective COVID-19 behavior (Pennycook et al., 2020). A protective behavioral endorsement was created to provide a quantitative understanding of how likely individuals were to endorse protective and/or reject non-protective behaviors (based on Pennycook et al., 2020) to measure how participants adapt their behavior to the ongoing pandemic. Endorsement of protective behaviors (*agree* = 1; *disagree* = 0) and rejection of non-protective behaviors (*agree* = 0; *disagree* = 1) were used to create a preventative behavior endorsement measure.

Cognitive Conflict–Maximum Deviation

Though reaction time has traditionally been used to measure cognitive conflict (Shtulman & Valcarcel, 2012), recent work suggests mouse-tracking provides a more sensitive measure of *ongoing* conflict than reaction time (Yamauchi et al., 2019). This study used maximum deviation as a measure of implicit processing. Maximum deviation (MD) is the maximal perpendicular deviation of the participant's mouse cursor trajectory from the direct, straight-line trajectory (Freeman & Ambady, 2010). This measure provides information about the implicit conflict in the cognitive system, such that greater MD indicates greater cognitive pull/conflict toward the unselected response (Figure 1). Implicitly, if a participant is *absolutely sure* of a response, their cursor trajectory would reflect an ideal straight-line trajectory, with no deviation or *pull* toward a competing response option.

Health-Specific Knowledge

The decision to assess health-specific knowledge was explicitly tied to the understanding of COVID-19 (e.g., germ theory; Shtulman & Valcarcel, 2012) based on the deficit model (i.e., knowledge is a determining factor in scientific beliefs), such that individuals may be "antiscience" because they lack the requisite knowledge to understand the findings (Allum et al., 2008; Sturgis, & Allum, 2004).

Mask Knowledge. Accuracy of mask knowledge was important to assess because understanding how masks may protect others and oneself from COVID-19 may promote protective health behaviors. To assess mask knowledge, each statement was evaluated for correctness, such that participants indicated if a given statement was True or False, permitting us to calculate a measure of mask-knowledge accuracy. True statements were based on CDC guidelines and empirical work (Cheng et al., 2020) at the time of experiment deployment. False statements were based on previously stated information about masks that was subsequently rejected or revised by experts in light of new information.

Germ Theory. Both scientific and naïve germ theories serve a deductive function. Their primary difference is their ability to accurately explain the natural world, with naïve theories possibly serving an adaptive function (e.g., water kills germs) but nonetheless being ill-aligned with scientific evidence (e.g., heat kills germs; see Shtulman & Valcarcel, 2012). Understanding the theories individuals use to rationalize their health behaviors is important during a public-health crisis. When individuals make health decisions based on naïve theories, those decisions can be ineffective or counterproductive (e.g., quickly rinsing hands under cold water without soap, thinking it will kill germs as effectively as hot water with soap; Sigelman, 2012; Shtulman & Valcarcel, 2012). We hypothesized the greater knowledge of scientific germ theory, the more likely individuals are to endorse preventative health behaviors. To assess germ theory, participants indicated whether the statement was True/False, resulting in a germ-theory accuracy score (*correct* = 1; *incorrect* = 0).

General Knowledge

General knowledge refers to constructs or skills that may influence individuals' understanding of COVID-19 but are not directly tied to the virus (Lipkus & Peters, 2009; Peters et al., 2006).

Science Change. Interpreting information from experts may require some level of precision related to the broad understanding of science. Because science is continuously updated as evidence accumulates, some naïve consumers of health guidelines may begin to distrust expert advice. However, someone with a salient understanding of science as change should be better able to assess risk (Sturgis & Allum, 2004). We assessed general knowledge of science change (True/False), resulting in a science-change accuracy score (*correct* = 1; *incorrect* = 0).

Quantitative Reasoning. Quantitative information (e.g., incidence rates) is given by experts to communicate risk (Lipkus & Peters, 2009). Understanding this information has salient effects, as it indicates how information is understood, encoded, and used in the decision-making process (Nelson et al., 2008). Less numerate individuals are less likely to use numerical data in decision-making and more likely to be influenced by opposing or less-relevant information (Peters et al., 2006). Quantitative reasoning may also be predictive of how careful individuals are when making decisions about COVID-19. We calculated a quantitative reasoning accuracy measure based on the proportion of participants' correct responses (*correct* = 1; *incorrect* = 0) when asked to solve word problems and interpret graphs.

Contextual Factors

Contextual factors, not just knowledge, should be considered in relation to how the public understands science (Sturgis & Allum, 2004). The following two factors are considered *contextual factors* because they have the ability to shape

incoming information. For instance, failure to trust medical experts should influence not only the information that individuals obtain but also how that information is used to make decisions (e.g., deciding to wear a mask because it is a recommendation put forth by the CDC relative to media). Due to the novelty of COVID-19, two contextual factors are important to consider: incidence rate and trust in scientific and medical experts.

Incidence Rate. Case fatality rate (CFR; deaths per 100,000) and incidence rate (IR; positive cases per 100,000) were both considered. Because numerical magnitude is processed automatically based on the integers shown (Lipkus & Peters, 2009), we chose to only include IR in the present analysis. The magnitude of IR trends is greater than CFR trends, so IR is likely to have a greater effect on behavior endorsement (Lipkus & Peters, 2009). Understanding how local IR trends affect COVID-19 behaviors is important, as states use IR to determine phased openings and closings. As IR increases, citizens are likely more aware of the potential risk of infection—potentially increasing protective health behaviors.

Participants provided their zip codes to allow us to capture local IR. Geographic centroids for each zip code were created and overlaid against county polygons (Figure 2). Zip code centroids were used instead of exact locations to preserve participant anonymity. County-level IR trends were calculated over a 3-week period (October 12–November 1, 2020) using Johns Hopkins University's COVID-19 Data Repository (Dong et al., 2020). This three-week period was chosen because it expands the typical 14-day quarantine period for COVID-19 contagion (CDC, 2020). IR data was then appended to county polygons, allowing for a point-in-polygon data merge in R (Pebesma, 2018). Once IR by county was identified, slopes (x = day; y = IR) were calculated within the resident county for each participant for the three-week period. IR slope is believed to be indicative of the county COVID-19 environment and public-health system. In line with the availability-by-recall heuristic, we hypothesized the steeper the slope, the greater likelihood of engagement in protective behaviors, as increased local incidence rate trends should act as a cue to elicit more protective behaviors.

Trust in Scientific/Medical Experts. Experts are the primary source of information about science (e.g., COVID-19) available to the public. Expert trust is mediated by their affiliations, meaning information disseminated from a politician is likely to be evaluated differently than a CDC scientist (Sturgis & Allum, 2004). Individuals must make rapid trust assessments, and this influences the extent to which information experts provide is trusted (Cairney & Wellstead, 2021). A dichotomous, forced-choice question asked participants to indicate agreement that health experts had the public's best interest in mind when making COVID-19 policy decisions (Pennycook et al., 2020).

Results

Analytic Approach

Logit and linear mixed random effects models (non-aggregated data) and a logit generalized linear model (aggregated for analysis) evaluated how knowledge and contextual factors affected protective COVID-19 behavior endorsement in R (R Development Core Team, 2012). Predictors were mean centered prior to entry into each model, with maximal random-effect structures implemented, permitting model convergence. Participants and items were set as random intercepts (See OSF for all data and analyses).

Data Cleaning

Mouse-tracking data were cleaned prior to analysis and subsetted to include only participants who began moving their
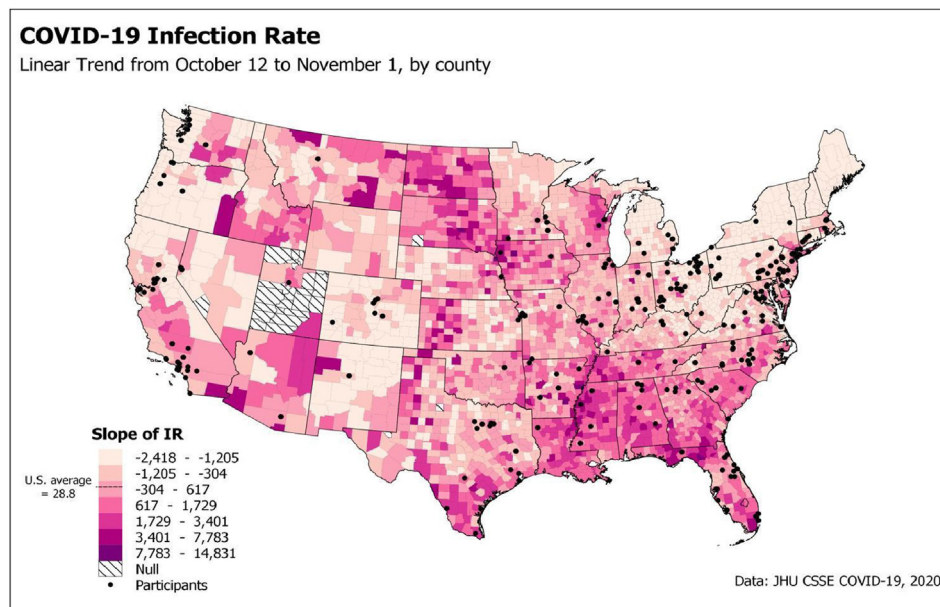
Figure 2. Zip codes provided by participants were mapped onto incidence rate (IR) using their geographic centroids over the three-week period for the data collection period. Darker colors represent steeper IR slopes by county for the given time period.

computer mouse on mouse-tracking trials in under 2,000 ms (cf. MouseTracker default 1,000 ms; Freeman & Ambady, 2010), resulting in 21% data loss. Response options were not presented until 1,000 ms into the trial to allow participants to finish reading the statement. Typically, if the initiation time exceeds 1,000 ms, participants are prompted with a reminder to move the cursor more quickly—a feature not currently available in FindingFive. Evaluation of both the full and reduced datasets indicated that results did not differ. Only the reduced dataset is reported, as it is more conservative.

Descriptive Statistics

First, we attempt to provide a descriptive profile of the data, in which we show how individuals responded to the different question types (i.e., questions related to COVID-19 behaviors, masks, germs, science as change, and quantitative reasoning). Each question category was assessed using probit glms for binary outcomes. In reference to the COVID-19 behaviors and mask usage questions, participants chose responses that reflected more careful or protective behaviors than risky behaviors in response to COVID-19 ($\beta = 0.38$, $SE = 0.05$, $t = 7.88$, $p < .001$, protective-behavior endorsers: $n = 250$; non-protective-behavior endorsers: $n = 44$) and tended to be more aware of mask facts than myths (i.e., mask knowledge questions: $\beta = 0.63$, $SE = 0.05$, $t = 13.25$, $p < .001$). Regarding knowledge-based questions (i.e., germ theory, science as change, and quantitative reasoning), participants were more likely to endorse scientific than naïve (i.e., incorrect) ideas about germ theory ($\beta = 0.60$, $SE = 0.04$, $t = 13.52$, $p < .001$). Participants were also more knowledgeable about science-change facts than myths ($\beta = 0.80$, $SE = 0.04$, $t = 18.35$, $p < .001$), but they exhibited more difficulty answering quantitative reasoning questions (Table 2) with no differences between question types, all ps < 0.05. As a general profile, the participants in this study tended to endorse safe health behaviors and were more knowledgeable about science and how germs spread. However, we were interested in how context impacted cognitive conflict during the decision-making process.

Explicit Behavior (RQ.1)

A logit linear model evaluated how knowledge and contextual factors affected the selection and activation of explicit processes (i.e., endorsement of protective behaviors and rejection of non-protective behaviors). Due to model convergence issues, the final model used an intercept-only structure, with subject and item set as intercepts, with no random slopes. Results indicate mask knowledge ($\beta = 0.11$, $SE = 0.05$, $z = 2.34$, $p < .05$), germ theory accuracy ($\beta = 0.12$, $SE = 0.05$, $z = 2.68$, $p < .01$), incidence rate ($\beta = 0.16$, $SE = 0.08$, $z = 2.01$, $p < .05$), and expert trust ($\beta = 0.38$, $SE = 0.08$, $z = 4.97$, $p < .001$) were all predictive of endorsement of preventative COVID-19 behaviors (Supplemental Table 2), accounting for 34% of the variance. Higher levels of mask and germ-theory knowledge, as well as greater local incidence rate and trust in experts, predicted a greater likelihood of endorsing preventative COVID-19 behaviors relative to non-preventative behaviors, providing support for our hypotheses informed by the contextualized deficit model (CDM). When context supports knowledge, explicit behavioral responses may be driven by heuristics that promote easier support from cognition (i.e., availability-by-recall heuristic)—we test this in the next model.

Implicit Behavior (RQ.2)

The second analysis evaluates cognitive conflict and if knowledge type and contextual factors also affect cognition

Table 2
Means and Standard Deviations Associated with Each of the Question Category Types

Category	Variable type	Responses	Mean (SD)
Explicit decision	Dependent variable	Non-protective	0.73(0.45)
		Protective	0.84(0.37)
		Preventative behavior endorsement	0.78(0.41)
Cognitive conflict	Dependent variable	Non-protective	0.08(0.13)
		Protective	0.07(0.12)
Mask knowledge	Predictor variable	Fact	0.85(0.35)
		Myth	0.66(0.47)
		Accurate understanding of mask usage	0.77(0.43)
Germ theory	Predictor variable	Scientific	0.77(0.42)
		Naïve	0.56(0.50)
		Accurate understanding of germ theory	0.67(0.47)
Scientific change	Predictor variable	Fact	0.68(0.47)
		Myth	0.36(0.48)
		Accurate understanding of scientific change	0.52(0.50)
Quantitative reasoning	Predictor variable	COVID-19 word problems	0.59(0.49)
		COVID-19 graphs	0.56(0.50)
		Generic Word Problems	0.62(0.49)
		Generic Graphs	0.61(0.49)
		Quantitative reasoning across items	0.60(0.49)

Note. Each variable is labeled as a dependent or predictor variable.
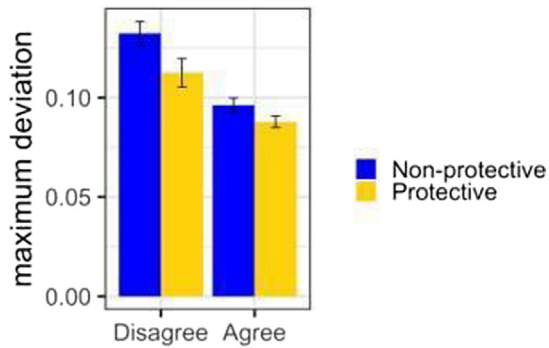
Figure 3. Means and standard errors associated with cognitive pull (maximum deviation) as a function of protective or non-protective COVID-19 health behaviors (see Supplementary Materials for specific items). The greater the maximum deviation, the greater the cognitive conflict.

during the decision-making process. A linear mixed random effects model was used to evaluate maximum deviation (McKinstry et al., 2008) as a function of COVID-19 decisions and the relative effect on knowledge type and contextual factors.

Mask knowledge ($\beta = -0.006$, $SE = 0.002$, $t = -3.46$, $p < .001$), quantitative reasoning ($\beta = -0.005$, $SE = 0.002$, $t = -2.71$, $p < .01$), and an interaction between behavioral statement type by behavioral endorsement ($\beta = -0.019$, $SE = 0.008$, $t = -2.27$, $p < .05$) predicted differences in cognition outcomes (see Supplemental Table 3), accounting for 40.44% of the variance in maximum deviation. A numerical difference in cognitive conflict (i.e., maximum deviation) existed between protective and non-protective questions (Figure 3; $\beta = 0.01$, $SE = 0.005$, $t = 2.46$, $p = .07$), such that, numerically, non-protective behavioral decisions predicted more cognitive conflict. Moreover, indicating disagreement with both protective ($\beta = -0.02$, $SE = 0.006$, $t = -2.88$, $p = .02$) and non-protective COVID-19 behaviors ($\beta = -0.01$, $SE = 0.004$, $t = -3.60$, $p = .002$) predicted significantly more cognitive conflict (see Figure 3) with the least amount of cognitive conflict occurring for endorsed protective behaviors. Critically, the greater quantitative reasoning and mask knowledge individuals had, the less cognitive effort was needed to predict explicit COVID-19 preventative decisions. It is somewhat unsurprising that participants exhibited less cognitive conflict when endorsing statements because of the *yes* bias (i.e., it is easier to say yes or to endorse something than to reject it; Duran et al., 2010; McKinstry et al., 2008). In fact, individuals are even more likely to display the *yes* bias when they are less knowledgeable about the information in question (Krosnick & Fabrigar, 2011). The tendency to endorse may also have aided cognition, as the cognitive conflict was reduced significantly when participants had more knowledge about masks but also better quantitative reasoning skills.

Prospective Behavior (RQ.3)

While the preventative endorsement and cognitive conflict models are helpful in understanding the processes underlying active health decisions, they do little to explain how knowledge

and contextual factors could affect prospective health behaviors. Explanatory coexistence suggests that previously established theories may maintain status in cognition. Therefore, differential vaccine-endorsement decisions should be observed based on whether participants lean on context, such as relying on expert-communicated information about masks because COVID-19 vaccines were still undergoing testing at the time of the current study, or scientific knowledge (i.e., understanding that vaccines protect against infectious disease).

This model investigated which factors predicted prospective COVID-19 vaccine decisions. Results from a logit generalized linear model suggest contextual factors (e.g., expert trust, incidence rate) and endorsement of preventative behaviors predict willingness to get the COVID-19 vaccine, explaining 18.5% of the variance (see Supplemental Table 4). Specifically, as preventative behavioral endorsement ($\beta = 0.53$, $SE = 0.18$, $t = 2.92$, $p < .01$) and expert trust ($\beta = 0.65$, $SE = 0.16$, $t = 4.03$, $p < .001$) increase, participants indicated more willingness to get the COVID-19 vaccine. Higher levels of mask knowledge ($\beta = -0.43$, $SE = 0.21$, $t = -2.04$, $p < .05$) predicted less willingness to get the COVID-19 vaccine as soon as it is available, potentially because, at the time of testing, masks were the predominant protective mechanism with COVID-19 vaccine information in flux.

Discussion

The present study explored whether explicit (RQs.1, 3) and implicit (RQ.2) decisions could be predicted by knowledge and context, potentially adding to the field's understanding of how best to communicate updated information when it contradicts previously shared information (i.e., explanatory coexistence, cognitive conflict). Our results supported the hypothesis that the more knowledge individuals had and the more that knowledge was supported by local context, the more likely they would make active, prospective decisions in line with updated CDC guidelines.

Participants endorsed scientific facts (i.e., science as change, germ theory) and protective COVID-19 decisions in alignment with CDC guidelines at the time of testing. Competition between implicit and explicit processes *still* affected their cognition. If participants preferred heuristic-based processing, we would expect to see less cognitive conflict and more endorsement of health misconceptions (e.g., masks do not prevent COVID-19 spread). Results from this study supported the opposite—participants were more likely to reject health misconceptions explicitly (RQ.1) *and* exhibited greater cognitive conflict when disagreeing with a non-protective COVID-19 behavior (i.e., health misconceptions–RQ.2, Figure 3); however, they were less likely to endorse the COVID-19 vaccine (RQ.3). These results support predictions made by DPM during decision-making because it is clear that previously held beliefs compete for activation with updated knowledge (i.e., explanatory coexistence, cognitive conflict).

Findings suggest the more contextualized (i.e., supported by health experts and local incidence rates), health-specific knowledge individuals had, the more they endorsed protective health behaviors (RQ.1). Moreover, individuals experienced *less* cog-

nitive conflict when they were more knowledgeable (e.g., quantitative reasoning, mask knowledge) but differentially experienced cognitive conflict depending on the statement type and their endorsement (RQ.2; Figure 3). These findings support the CDM and the availability-by-recall heuristic in which individual circumstances influence outcome variables, potentially because they are more accessible within cognition (i.e., alignment between knowledge and context makes accurate recall easier). Our participants largely endorsed protective behaviors; when they agreed with these protective behaviors, they exhibited the least amount of cognitive conflict. This is in direct support of the CDM, suggesting that greater knowledge (in context) allows for easier cognitive processing. In line with our hypotheses, a greater cognitive conflict existed when participants indicated disagreement relative to endorsement. The most cognitive conflict existed when participants disagreed with non-protective behaviors (i.e., information shared at the outset of the pandemic), showing evidence of active inhibition of prior COVID-19 knowledge in favor of up-to-date, scientific findings (providing support for RQ.2).

Individuals' active behavior endorsement also affected prospective-vaccine endorsement (RQ.3). Individuals who consistently endorsed preventive behaviors were more likely to endorse getting a COVID-19 vaccine as soon as it is available. Greater trust in experts (Sturgis & Allum, 2004) also contributed to prospective health decisions. However, mask knowledge decreased vaccine endorsement, possibly because, at the time of testing, it was unclear when a vaccine would be available, and mask usage was the predominantly communicated protective measure. The dissemination of conflicting information throughout the pandemic created an "infodemic" (Adhanom Ghebreyesus, 2020) in which individuals needed to reconcile the effects of explanatory coexistence. Intuitive theories (e.g., masks are safer than novel vaccines) may need to be replaced with scientific theories (updated empirical evidence), but because participants may have believed wearing masks was sufficient, they could then believe getting a "novel" vaccine was not completely necessary (i.e., because masks are effective; Reiner et al., 2020). This may have contributed to the health officials' struggles to get the general public vaccinated. Nevertheless, now that the COVID-19 vaccines are widely available in the U.S., this effect should be tested again to determine whether the change in context (i.e., expert dissemination of vaccine information) would alter this finding.

This work employs a novel approach to broaden the understanding of how context shapes behavior and cognition. Using geographic data, we investigated how variation in participant residence location affected individual decision-making. No work has combined geographic and psychological data to evaluate cognitive conflict and deficit models, particularly in the context of a novel coronavirus. This study is not without limitations. Due to the higher rate of protective-behavior endorsers, we were unable to address cognition among non-protective-behavior endorsers. However, data from these participants were consistent with predictions under the deficit model (Section E2, Supplemental Analysis OSF). We also did not include all potential contributing factors (e.g., political affiliation) that may impact health-related decisions. Future work should address these limitations.

Most participants endorsed preventative COVID-19 health behaviors, but conflict still occurred within the cognitive system, meaning individuals needed to proactively engage limited cognitive resources to make accurate decisions. Thus, understanding how experts and media outlets can help ease this decision-making process is important. When individuals have difficulty grasping relevant scientific findings, they may have a tendency to turn to media outlets to help them interpret knowledge (Holmes et al., 2009). This has important health implications. When information communicated to the general public is unclear, confusing, or limited, it may lead individuals to prefer easier implicit processing, even when the information is inaccurate (e.g., availability-by-recall heuristic; Pachur et al., 2012). This may lead to risky health-related behaviors, having a negative impact on global public health. Using context to inform the distribution of knowledge to the general public may help mitigate risk to the global community. This is important to consider because *how* public-health policies are communicated has the potential to affect autonomy and adherence to guidelines and mandates. Therefore, the results of this study provide knowledge gained from basic research in an applied context, communicating how cognitive processes affect decision-making when laypersons are faced with choosing health-related behaviors when health information is constantly changing.

Author Contributions

All authors contributed to the study design. T.A. helped identify instruments. G.M. and J.R. programmed the study in FindingFive. G.M. organized data collection and participant payment across Mechanical Turk and FindingFive platforms. C.W. provided geographical expertise in addition to programming the R code for the integration and analysis of geographical information. J.R. performed the statistical analysis for the psychological constructs with G.M. G.M. drafted the manuscript with B.M. and J.R. (theoretical framing), J.R. (method and results), and C.W. (geographical analysis, theory). T.A. provided critical revisions. All authors approved the final version of the manuscript.

Data Availability Statement

Data from this study is openly available on Open Science Framework at osf.io/46w9z/?view_only=25c43a252e9749338 2c2692029d0aec7. The COVID-19 incidence rate data was derived from the COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University, which is a resource available in the public domain: https:// github.com/CSSEGISandData/COVID-19.

Conflict of Interest

The authors declare they have no conflict of interest.

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Online Supplement

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jarmac.2021.07.007.

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