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What Are They Thinking? Exploring College Students' Mental Processing and Decision-Making About COVID-19 (Mis)Information on Social Media

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Abstract

More and more, people are abandoning the active pursuit of news, assuming instead that important information will be pushed to them via their social media networks. This approach to news makes people susceptible to the vast amounts of misinformation online, yet research on the effects of this kind of engagement is mixed. More research is needed on technology incidental learning effects, defined as changes in knowledge, attitudes, beliefs, and behaviors as a result of being exposed to information while pursuing goals other than learning (e.g., entertainment). In this study, we examined how 51 college students responded to incidental exposure to accurate and inaccurate COVID-19 information delivered via a simulated social media environment. Participants' verbalizations during think-aloud protocols indicated numerous mental processes including cognition, metacognition, epistemic cognition, motivation, and emotions. Positively valenced mental processing was more often expressed with accurate COVID-19 information and negatively valenced mental processing was more often verbalized with misinformation. Negatively valenced evaluations of knowledge claims and sources predicted less engagement with COVID-19 misinformation posts. However, in many cases the relations among verbalized mental processing and behavioral responses were complex or non-obvious. For example, participants' positive metacognition and epistemic cognition verbalizations decreased their likelihood of engaging with accurate COVID-19 information, whereas positive interest was associated with an increased likelihood of engaging with misinformation. Our findings have implications for how to accurately infer people's beliefs and intentions from their social media behaviors and how to design interventions to help people be more active and thoughtful consumers of online information.

Keywords

Incidental learning; cognition; misinformation; social media; socioscientific issues

Avery stands in line at their college bookstore, waiting to buy a new sweatshirt. Bored, they open their mobile phone and begin casually scrolling through their social media feed. At

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one point, they come across a post claiming “Experts concerned new COVID-19 booster causes cancer.” Avery glances at the post and quickly moves on, looking at almost one hundred other unrelated posts before getting to the front of the line and paying for their clothing. Avery spent less than two seconds reading that COVID-19 post, nonetheless, did it affect them and if so, how? Will it affect their attitudes toward vaccines, or their vaccination behavior, in the future? Would Avery be aware of such a change? And what happens when someone like Avery encounters such content many times, every day, over weeks or months? Answers to these questions require investigations of technology incidental learning effects (TILE; Greene et al., 2021b), defined as exposure to information when the person was using the technology for a goal other than learning (i.e., incidental exposure) and where that exposure led to a change in thinking, behavior, attitudes, or values (i.e., learning). Intentional learning in technology environments has received a great deal of attention (e.g., Azevedo et al., 2022; Greenhow et al., 2022), but much more research is needed regarding how people respond to incidental exposure to content and ideas.

Decreasing interest in, and use of, traditional news sources (Kümpel, 2022; Newman et al., 2018), alongside increasing use of social media (Pew Research Center, 2020), have greatly increased people’s likelihood of being incidentally exposed to news and information in technology environments, particularly among young people (Masip et al., 2018). In the United States, social media is becoming young people’s primary source of news (Gaultney et al., 2022), yet such platforms do not enhance their political knowledge (Amsalem & Zoizner, 2022) and are associated with misinformation (e.g., about COVID-19; Borah, Austin, et al., 2022; Borah, Su, et al., 2022). In fact, many young adults have adopted a “news-finds-me” mentality, decreasing their active pursuit of news information with the assumption that anything important will be “pushed” to their social media feed (Gil de Zúñiga et al., 2017). This mentality risks people incidentally encountering, and being swayed by, the vast amount of misinformation online (Marwick & Lewis, 2017; Scheufele & Krause, 2019).

However, the empirical research on the effects of incidental exposure to news is mixed. Some scholars have found incidental exposure is positively related to knowledge gain (Tewksbury et al., 2001) whereas others have found evidence of a negative relationship (Lee & Xenos, 2019), and some have found no evidence of a relationship (Cacciatore et al., 2018; Edgerly et al., 2018). In some studies, prior knowledge has played an important moderating role in incidental learning effects (e.g., Baum, 2003), whereas in other studies, beliefs and a desire to resolve cognitive dissonance seemed to be the most influential factors (Cappella et al., 2015; Zimmer et al., 2019). Some researchers have pointed to the negative effects of echo chambers (Hills, 2019) or motivated reasoning (Sinatra et al., 2014) as proximal causes of incidental and intentional learning effects, whereas others have argued users’ ability to recognize misinformation, and their willingness to devote sufficient effort to scrutinize it, are stronger predictors of such effects (Gil de Zúñiga et al., 2021; Pennycook & Rand, 2019). Given the unsettled state of the literature, we argue for the need for more basic, foundational research into people’s mental processing after incidental exposure, whether individual differences in knowledge and dispositions predict such processing, whether these effects vary based upon the type of information presented, and what effects, if any, individual differences and mental processing have on how people respond to incidental exposure. Like

Avery, many people are not actively pursuing news content, instead expecting it to be pushed to them. Therefore, research is needed on what incidental exposure effects occur and how they happen, so educational interventions can be developed to inoculate people from being swayed by misinformation in technology environments (Lewandosky & van der Linden, 2021; Roozenbeek et al., 2022).

Literature Review

Incidental Exposure Scholarship

Researchers began investigating incidental exposure in the 1950's by studying what happened when people saw the end of a news program that preceded an entertainment show they were tuning in to watch. (Downs, 1957). Researchers found these people did retain some knowledge of the incidentally exposed news content, sparking changes to television programming (e.g., putting less-watched but important content before popular shows) and new lines of scholarship into a variety of effects including but extending beyond learning (Makri & Blandford, 2012; Yadamsuren & Erdelez, 2017). For example, some researchers have found a positive relationship between incidental exposure to news and subsequent civic action (e.g., political participation; Kim et al., 2013; Weeks et al., 2017) but attempts to capture such effects experimentally have been unsuccessful (Theocharis & Quintelier, 2016). With time, research has expanded from questions about what knowledge is retained after incidental exposure to what users think and do in response to incidental exposure (e.g., moving on from content, reading content; Yadamsuren & Erdelez, 2017), as well as what factors might moderate relations among exposure, response behaviors, and changes in knowledge and action (Jiang et al., 2015). Further complicating matters, many modern technology platforms use algorithms to push content to users based upon their inferred interests and the platform's goals (Ruggiero, 2000; Thorson & Wells, 2016), illustrating a dynamic relationship between user factors and technology environment factors. Such dynamic interactions among users, platforms, content, and the environment beg for a model of incidental learning effects that can accommodate multiple factors and the relations among them.

Technology Incidental Learning Effects Model

Greene et al. (2021b) created the TILE model to integrate models of incidental exposure with models of intentional learning. Researchers in both areas of scholarship have acknowledged the roles of individual and contextual factors as moderators of the relationship between perception and learning, albeit with intentional learning researchers typically incorporating a wider variety of cognitive, motivational, and affective phenomena (e.g., epistemic cognition, Greene et al., 2016; expectancy-value theory, Wigfield & Eccles, 2020; control value theory, Pekrun, 2006). However, a critical difference is the majority of intentional learning theories and models have assumed active pursuit of a learning goal (e.g., the model of domain learning, Alexander et al., 2009; reading comprehension; McMaster & Kendeou, 2023; self-regulated learning theory, Zimmerman, 2013) whereas learning can result from incidental exposure even when the person is not actively pursuing a learning goal or engaging in intentional learning behaviors. It may be the case that theories developed for intentional learning are largely applicable to situations where people are incidentally exposed to information, but such transferability should not be assumed (Greene, 2022). As such, the TILE model was created to better describe whether and how people respond to incidentally exposed information when they were pursuing goals other than learning.

With the TILE model (see Figure 1), Greene et al. (2021b) posited a cyclical incidental learning process spanning people's interests and motivations driving their technology use (Thorson & Wells, 2016), through whether and why they notice incidentally exposed content (Bago et al., 2020; Pennycook & Rand, 2019), the types of mental processing that can result (Evans, 2019; Richter et al., 2009), how their response behaviors drive subsequent learning processes (Pennycook & Rand, 2021), and how the results of those processes in turn affect their interests and motivations for future engagement with technology. In this study, we focused on those aspects of the TILE model occurring after someone notices content to which they were incidentally exposed and subsequently processes it deliberatively. Deliberative mental processing can include a variety of phenomena studied by educational psychologists, including *metacognition, emotions, interest, evaluations of the content's intentions, evaluations of the content's sources, epistemic cognition*, and *cognitive operations*. This deliberative processing predicts people's choice of *response behavior*, which can include returning (i.e., making a conscious choice to stop processing and return to prior activities; Yadamsuren & Erdelez, 2017), responding (e.g., liking, sharing the incidentally exposed content; Lee & Ma, 2012), or selecting and reading the content. Importantly, *user and content factors* can affect the types of deliberative processing people enact, the choice of response behaviors, and the effects of those choices on subsequent learning outcomes (Jiang et al., 2015).

Deliberative Mental Processing—As shown in Figure 1, how people respond to incidentally exposed content (e.g., skipping a post versus liking, sharing, or reading content linked in the post) can be predicted by how they deliberatively process it. However, this processing is complex and nuanced. For example, decisions to share content are not reliably associated with people's assessment of the veracity of that content (Pennycook & Rand, 2021). People sometimes share content they do not believe, and researchers remain divided on why this is so. Proposed reasons include ideological factors (Hopp et al., 2020), psychological factors (Sinatra & Hofer, 2021), or how effortfully people attend to the material (Pennycook & Rand, 2017). Thus, more research is needed into the relationship between how people think about incidentally exposed content (i.e., cognitive operations, metacognition, emotions, motivation, interest, evaluations, source evaluations, epistemic cognition) and how they respond to that content. Here, we present necessarily brief overviews of each area of scholarship, given most are vast. In each overview, we discuss plausible potential relations between the factors and incidental learning effects, each of which requires further empirical research, which our study initiates.

Cognitive Operations.: Models of self-regulated learning (e.g., Winne & Hadwin, 1998) detail many ways people cognitively engage with content when learning, and how that engagement predicts learning (e.g., Dent & Koenka, 2016; Dunlosky et al., 2013). For example, empirical evidence suggests prior knowledge activation can predict learning (McCarthy & McNamara, 2022) but circumstances can drive whether the relationship is positive, negative, or negligible (Simonsmeier et al., 2022). As such, more research is needed on how cognitive operations during deliberative processing predict how people respond to incidentally exposed content.

Metacognition.: Meta-analytic research has shown both immediate and long-term positive effects of metacognitive strategy interventions (de Boer et al., 2018), indicating metacognition's importance in learning. Scholarship by Efklides (2011) and others has delineated three types of metacognition: metacognitive knowledge (i.e., knowledge about one's own cognition, other's cognition, and the person, task, and strategy factors influencing cognition), metacognitive skills (i.e., planning, monitoring, controlling, and evaluating one's cognition), and metacognitive experiences (i.e., cognitive or affective phenomena that arise from or affect thinking). Much of the research on the processing of information in technology environments has focused on whether and how people enact metacognition during noticing, for example showing metacognition is less likely to be enacted when information is congruent with prior knowledge (Richter et al., 2009). However, metacognitive knowledge, skills, and experiences may influence not only whether and how well incidentally exposed information is deliberatively processed, but also how effective that processing is. For example, often people are miscalibrated regarding how susceptible they are to misinformation, leading to ineffective behavioral responses to it (Salovich & Rapp, 2021). As such, the role of metacognition in deliberative processing is worth investigating.

Emotions.: Emotions can be categorized both by their valence (i.e., positive or negative) but also by the kind of arousal they invoke (i.e., activating and deactivating emotions; Pekrun, 2006), with subsequent nuanced and complex effects upon engagement and learning (Muis et al., 2018). Research findings regarding emotions and incidental exposure are complex. Yadamsuren and Erdelez (2017) found incidentally encountered headings that elicited strong positive or negative emotions were more likely to be noticed. Yet, negative emotions are also associated with less engagement with content (Yadamsuren & Erdelez, 2017) whereas positive emotions have the opposite effect (Jiang et al., 2015).

Engagement with incidentally exposed content may activate epistemic emotions (i.e., emotions resulting from appraisals of information; Muis et al., 2018). For example, when incidentally exposed information is inconsistent with prior knowledge, surprise can result, which can increase engagement. On the other hand, experiencing confusion or curiosity when new information does not align with prior knowledge may deepen engagement (e.g., selecting and reading; Muis et al., 2018), also. Finally, as an example of how emotions can vary based on content, Martel and colleagues (2020) found both positive and negative emotional responses were associated with greater belief in fake news headlines, but not actual news headlines. Overall, the connections between emotions and mental processing, coupled with the complex nature of emotions (e.g., valence, arousal) and mixed findings regarding how they predict noticing and engagement, illustrate the importance of studying emotions after incidental exposure.

Motivation.: Motivation, involving processes that both initiate and sustain behavior (Schunk et al., 2014), is a user factor that can predict noticing as well as the likelihood of deliberative processing (Greene et al., 2021b). Among the many models of motivation, expectancy-value theory (Eccles & Wigfield, 2020) may be particularly applicable to incidental learning, given evidence that relevance and utility perceptions positively predict engagement during incidental learning (Masip et al., 2018). Also, the desire to avoid missing out on critical information (Kümpel, 2019) and a person's values (McCay-Peet & Toms, 2015) both positively predict social media behaviors such as selecting and reading incidentally exposed content.

Interest.: Interest (i.e., people's cognitive and motivational energy for seeking out and engaging in particular content; Renninger & Hidi, 2020), positively predicts whether people notice and deliberatively engage with incidentally exposed content (Lee & Ma, 2012). These positive relations can be moderated by a person's moment-to-moment goals and inclinations (Ruggiero, 2000), suggesting the need for considering both situational and individual interest as drivers of engagement (Renninger & Hidi, 2020). More research is needed to determine whether each kind of interest has unique effects upon processing after incidental exposure.

Evaluation.: Incidental exposure to content often invokes an evaluation of the intent of the author as well as the plausibility or feasibility of the post's content (Greene et al., 2021b). Such evaluations can be based solely on the post itself (e.g., the quality or plausibility of the information; Jiang et al., 2015; Karnowski et al., 2017; Lombardi, Danielson, et al., 2016) as well as more person-specific factors such as a general level of distrust in content encountered online (Mayo, 2019). These evaluations, in turn, can predict people's type of engagement with incidentally exposed content (Yadamsuren & Erdelez, 2017), with positive evaluations predicting more substantive forms of engagement (e.g., selecting and reading).

Source Evaluation.: The proliferation of information sources in the modern world, particularly those hosted on the Internet, has increased interest in whether and how people evaluate those sources (Braasch, 2020; Braasch et al., 2018; Barzilai et al., 2020). Such evaluations can focus on the nature of the content in the incidentally exposed information as well as perceptions of the content's source (e.g., information on Facebook might be evaluated differently than information on Twitter) and perception of the content's author, which may or may not be the same as the source (Barzilai et al., 2020). On social media, the source of content is multifaceted and includes the original creator of the content as well as numerous pathways by which the information may have been shared, liked, or amplified before it is seen (Macedo-Rouet et al., 2019; Metzger et al., 2003). When engaging with social media, there is evidence that incidentally exposed information shared by a person's contacts can be perceived as more credible and thus more likely to be read or deliberatively considered than information shared by others (Boczkowski et al., 2018). Thus, understanding whether and how people evaluate the many possible sources of incidentally exposed content (e.g., author, publication source, contact who shared the content), is important to predicting how they engage with it.

Epistemic Cognition.: Evaluations of whether or to what degree a claim is an accurate representation of the world requires individuals to enact epistemic cognition (i.e., how people think about, create, and evaluate knowledge and other cognitive achievements such as justified beliefs and understanding; Barzilai & Chinn, 2018). Chinn and colleagues (2011, 2014) have argued for a conceptualization of epistemic cognition with three main components: epistemic aims, epistemic ideals, and reliable processes. Epistemic aims, or people's knowledge goals (e.g., knowledge, understanding), drive people's thinking. People use epistemic ideals to determine whether epistemic aims have been reached (e.g., whether a knowledge claim or evaluation meets the person's criteria for knowledge), and these ideals are pursued via reliable processes (e.g., strategies for achieving knowledge such as replicating findings; Greene et al., 2021a). Meta-analyses have shown positive relations between epistemic cognition and academic achievement (Greene et al., 2018a) and positive effects from interventions to develop epistemic cognition (Cartiff et al., 2021). Despite no known empirical work directly connecting epistemic cognition to incidental exposure, it is plausible that people's determination of the veracity of a social media post as well as their processes and criteria for making that determination would affect the nature and likelihood of deliberation and subsequent choice of response. However, per the scholarship on metacognition (e.g., Richter et al., 2009) positive evaluations of knowledge claims, and the arguments for them, might predict responses indicative of less engagement (e.g., liking, moving on) rather than more engagement (e.g., reading), which might be pursued when claims contradict prior knowledge.

Response Behaviors—In the TILE model, Greene et al. (2021b) posited that behaviors in technology environments (e.g., returning, responding, or selecting and reading; see Figure 1) mediate relations between deliberative processing and learning effects. For example, users' motivations and interest influence their response behaviors: when users engage with social media for entertainment purposes, they are less likely to share content (Lee & Ma, 2012). Information may spread more quickly in technology environments in response to these behaviors, leading to either vicious cycles of misinformation or virtuous cycles of accurate information (Cinelli et al., 2020). However, much of the research on the effects of interventions and other design choices to affect people's interactions with misinformation online have used intended behavior surveys or accuracy evaluations to measure effects, rather than capturing actual user behaviors in technology environments. Compared to self-reported outcomes like accuracy judgments, user behaviors, as captured via keyclick software installed on participants' devices or via digital trace data in a simulated social media feed, are more ecologically valid indicators of both the effects of interventions (e.g., McPhedran et al., 2023) on processing after incidental exposure as well as the effects of such processing itself, as was the focus in this study.

User Factors—Both deliberative processing and response behaviors are affected by user factors. Greene et al. (2021b) posited a wide range of user factors that could potentially play a role in processing after incidental exposure (e.g., interests, prior knowledge, tolerance for cognitive dissonance; Baum, 2003; Cappella et al., 2015; Lee & Xenos, 2019; Zimmer et al., 2019), also acknowledging that much more research is needed to establish and understand these factors' effects. We drew from both the incidental exposure and educational psychology literatures to identify what user factors might manifest in our study. We focused on prior knowledge (McCarthy & McNamara, 2021) and need for cognition (Cacioppo et al., 1996).

Prior knowledge.: Greene et al. (2021b) review of the literature on incidental exposure and learning revealed that prior knowledge predicts what is noticed (Karnowski et al., 2017; McCay-Peet & Toms, 2017) as well as what kind of processing follows (i.e., information that is aligned with prior knowledge is more likely to be automatically processed; Evans, 2019; Richter et al., 2009). Information discrepant with prior knowledge is more likely to be deliberatively processed, although such processing can be quick when the discrepancy is great (e.g., dismissing it; Richter et al., 2009). Such findings are aligned with research in educational psychology showing prior knowledge plays an important role in directing mental processing such as metacognition and cognitive operations (Efklides, 2011; Moos & Azevedo, 2008) and positively predicting learning performance (Simonsmeier et al., 2022). Prior knowledge can certainly change in nature and quantity over the course of a learning task (McCarthy & McNamara, 2021), but tends to be treated as an individual difference variable in studies focused on between-person effects.

Need for cognition.: Another individual difference variable that researchers have focused upon in both incidental exposure and educational psychology research is need for cognition (i.e., “people’s tendency to engage in and enjoy effortful cognitive activity”; Cacioppo et al., 1996, p. 197). For example, Müller et al. (2016) found the negative relationship between the news-finds-me perception (Gil de Zúñiga et al., 2017) and news-seeking behaviors on social media was stronger for participants with low need for cognition. Likewise, need for cognition can predict motivation, engagement, and academic achievement (e.g., Luong et al., 2017). As such, in the TILE model, need for cognition is another individual difference variable posited to affect both noticing and deliberative processing during incidental learning (Greene et al., 2021b). Given the TILE model is in its early stages of development, hypotheses were not warranted but it seemed plausible need for cognition would relate to people’s social media behavior choices.

Content Factors—Research on the effect of content factors on mental processing after incidental exposure includes studies of the characteristics of the content itself (e.g., salience and salaciousness of the information; Yadamsuren & Erdelez, 2017), as well as characteristics of the technology environment (e.g., user interface quality; content pushed to users; Jiang et al., 2015). With the rise in prominence of social media and misinformation, there has been a tremendous increase in research on how people process and respond to misinformation across health (Wang et al., 2019), marketing (Di Domenico et al., 2021), communications (Chen et al., 2021), politics (Allcott et al., 2019), and psychology disciplines (Pennycook & Rand, 2019, 2021; Richter et al., 2009). Much of this work has focused on understanding how people process misinformation and then how to intervene so they identify and reject misinformation more reliably (e.g., Lewandowsky et al., 2022). There is little research directly comparing how people’s mental processing differs when they encounter different types of information and misinformation in technology environments like social media (cf. Pennycook, 2023), and to our knowledge no such research when people are incidentally exposed to such content. Thus, in this study, we aimed to study people's mental processing and responses to both accurate information and misinformation.

TILE Model Summary—In sum, the TILE model includes a variety of mental processing, user, and context factors that, together, determine whether and how people respond to incidentally exposed content. This model affords many plausible hypotheses about how and why these phenomena manifest and lead to various outcomes, including learning, attitude change, and technology environment behaviors such as liking or sharing. More empirical research is needed to iteratively refine the descriptive aspects of this model (Greene, 2022) and to better understand and predict how people respond to and learn from incidental exposure (e.g., Valeriana & Vaccari, 2016).

Purpose of this Study

With modern society's increasing move away from active pursuit and engagement with news and information to more non-goal-directed engagement in technology environments, there is a growing need to understand how incidental exposure to information affects people's behaviors, which in turn can affect what, if anything, they learn. Given mixed findings in the incidental exposure literature (Yadamsuren & Erdelez, 2017) and the need for more research and theory-building regarding the psychological mechanisms that occur during incidental exposure (Greene et al., 2021b), we conducted a non-experimental, laboratory-based study to substantiate, revise, and expand the descriptive aspects of the TILE model (see Figure 1; Greene, 2022). Specifically, we captured participants' verbalizations of their deliberative mental processing after noticing social media content, via think-aloud protocol data. We allowed participants to choose one of three responses to content, skipping to the next post (i.e., returning), liking the post, or selecting and reading the content. Further, we examined whether user factors (i.e., prior knowledge and need for cognition; Cacioppo et al., 1996) related to participants' responses. Finally, we examined whether participants' mental processing and subsequent response behaviors, as well as the relations between those phenomena, varied by the nature of the content, specifically whether it was COVID-19 information or misinformation. Thus, to explore these phenomena, we focused on four research questions:

> Research Question 1: What mental processes do college students verbalize when they are incidentally exposed to posts about COVID-19 in a simulated social media environment?
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> Research Question 2: How do college students' verbalized mental processes differ when simulated social media posts contain information versus misinformation about COVID-19?
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> Research Question 3: How does college students' prior knowledge about COVID-19 prevention and treatment and their need for cognition relate to their verbalized mental processing when they are exposed to posts containing COVID-19 information and misinformation in a simulated social media environment?
>
> Research Question 4: How do college students' prior knowledge, need for cognition, and verbalized mental processing predict their behaviors in response

to incidental exposure to COVID-19 information and misinformation in a simulated social media environment?

Research Question 5 (post hoc): How do college students' verbalizations of mental processing and behaviors in response to incidental exposure to COVID-19 information and misinformation posts in a simulated social media environment relate to the content of these posts?

Our findings can lead to more informed investigations of subsequent TILE phenomena, such as how non-goal-directed versus purposeful engagement with incidentally exposed misinformation affects users' knowledge, attitudes, and future engagement. Such investigations have implications for how to help people be more thoughtful, critical, and effective users of technology in the modern world (Greene et al., 2018b).

Methods

Transparency and Openness

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study, and we follow JARS (Kazak, 2018). All data and analysis code are available at https://osf.io/fv69a/?view_only=09cc0c030d1e40e1a896bff2a63aaf8c. Due to the low percentage of total missing data, they were treated as missing completely at random. Data were analyzed using Mplus version 8.8. This study's design and analyses were not pre-registered.

Participants

This study was approved by the institution's review board. Participants were 51 undergraduate students who attended classes in the spring of 2022 in the school of education of a large, selective public university located in the southeastern United States. We began with 52 participants, but one participant did not complete the prior knowledge and need for cognition measures and was excluded from analysis. Participants had an average age of 19 (SD = 2.1) and an average GPA of 3.6 (SD = 0.4; See Table 1) out of 4. We chose this particular sample for both convenience as well as the evidence that college students in the United States are increasingly using social media to obtain their news and thus are more likely to experience incidental exposure to such information and also at an age where such exposure could have societal effects in terms of whether and how they choose to vote in local, state, and national elections (Borah, Austin, et al., 2022; Borah, Su, et al., 2022; Gil de Zúñiga et al., 2017; Masip et al., 2018; Newman et al., 2018; Pew Research Center, 2020).

All participants completed informed consent, were debriefed after their participation was complete, and were given the option to withdraw consent after debriefing; none chose to do so. To our knowledge, there are no prior studies with the same or similar phenomena (e.g., mental processing while engaging with social media captured via TAPs; behavioral responses) therefore no formal power analysis could be conducted. We sought a sample size that seemed sufficient to investigate our phenomena of interest while also accounting for the high human resource demands involved with collecting, coding, and analyzing TAP data

(Greene et al., 2013), including the development of a new codebook for mental processing during social media use (DeCuir-Gunby et al., 2011).

Context

Data collection occurred between February and April of 2022, which was during a time when the pandemic was still prominent but also changing. We describe that context here, briefly, given its relevance to participants' responses. To generate a summary of COVID-19 news from the five days prior to running our first participant (i.e., January 28-February 2, 2022), we used the Wayback Machine internet archive (https://archive.org) to access the main news pages for four of the most visited news media websites in the US (Reuters Institute for the Study of Journalism, 2022). The headlines on COVID-19 were recorded and we reviewed them for common themes and ideas. In this time frame, COVID-19 was becoming a less prominent news item than it had been in the months prior. Many international communities were lifting restrictions and, though the US was still enforcing mask mandates and many organizations had vaccine requirements, many news outlets were reporting that an end to restrictions in the US was forthcoming. The Omicron BA.2 variant began spreading in this timeframe, but most news media discussed how it was milder compared to other variants, despite the Centers for Disease Control reporting that it was leading to severe spikes in COVID-19 infections and deaths. Vaccines for school-age children had been authorized in December 2021 and the New York Times and CNN had articles promoting vaccination in this age group. In January of 2022, the FDA revised guidance on multiple monoclonal antibody treatments for COVID-19, due to evidence that they were not effective treatments, the Moderna vaccine moved from an emergency-use authorization to full FDA approval, and booster vaccine guidance changed from six months to five months of time between the primary dose and the booster (CDC, 2023).

Procedures

Research assistants virtually attended two sections of an undergraduate course in human development to recruit participants. While attending these courses, research assistants explained what was involved in participation and allowed students to ask questions. These recruitment efforts masked the purpose of the study and characterized the researcher's goals as being about "studying how people think when they use social media." Recruitment efforts did not mention misinformation or the COVID-19 pandemic. Participants were provided with a weblink to sign up for the study and encouraged to email the researchers if they had further questions.

One week before their scheduled participation time, participants were sent an email with a link to review and sign the consent form and then complete a prior knowledge and a need for cognition measure. Our goal was to capture these data prior to participants' actual engagement with our simulated social media environment, to decrease the likelihood that the data collection would affect the nature of participants' engagement. If participants did not complete their pre-participation activities within two days of their participation, a research assistant emailed them a prompt to do so. Any participant who had not completed their survey by the morning of their participation was rescheduled. On the day of participation, participants were seated in front of a single computer screen that showed both a copy of the consent form and the Qualtrics survey interface used for social media engagement and data collection. The researcher offered the participant an opportunity to ask any questions about the consent form and then began data collection.

Simulated Social Media Environment—Participants engaged with a Qualtrics survey designed to replicate the experience of a social media platform. The survey was not designed to fully replicate any existing social media platform and included a fictious logo and name created for the research project. The survey presented "posts" one at a time and allowed participants to respond in three ways: liking, reading, or skipping (see Figure 2). We aimed to capture participants' typical engagement with social media, therefore we told them: "We are interested in understanding how you typically respond to social media posts." Participants were required to choose a response and the survey automatically advanced to the next post when a response was selected. Even when participants responded they would like to select and read the post, they were automatically advanced to the next post, because allowing participants to choose to read posts would make total participation time highly variable, potentially confounding our phenomena of interest (e.g., relationship between mental processing and responses). The posts were formatted uniformly using a researcher-created template that included a "user" with a profile image, an image related to the post, and the text of the post.

There were 30 posts in all, and every participant was presented with all 30 posts, in a randomized order. The 30 posts included 10 posts containing accurate COVID-19 information, 10 posts containing COVID-19 misinformation, and 10 posts with current popular culture information that served as distractors (e.g., "Ridley Scott is plotting a TV series based on his #BladeRunner franchise. Tap the link in our bio for more."). The accurate COVID-19 information posts included real social media posts made by the Centers for Disease Control (CDC) and researcher-generated posts adapted from COVID-19 information taken from the CDC, Johns Hopkins University, the National Institutes of Health, the Federal Drug Administration, and the US Department of Health and Human Services (e.g., "Remember: Mild side effects after getting a #COVID19 vaccine are normal signs that the body is building protection."). The COVID-19 misinformation posts were taken from social media and blog posts published on Politifact's "Pants on Fire" section for COVID-19 information, which included the most inaccurate information Politifact had found (e.g., "NIH COVID Treatment Guidelines Approve Ivermectin.'"). We invented fictional sources for the misinformation posts.

The researcher introduced participants to this environment by using a filler post that did not appear in the main survey. The researcher explained that participants would need to read the post aloud, decide how to respond, and then click that response. Participants were told they would not actually complete the action they chose (i.e., they would not actually get to read articles for posts they chose to "Read") and would instead be auto-advanced to the next post. Participants' responses to posts were recorded through Qualtrics and their verbalizations were recorded through a screen capture software that also records external audio.

Think-Aloud Protocol—Participants were trained to think-aloud using procedures adapted from previous think-aloud studies (Greene et al., 2018c, 2022; Ericsson, 2006;

Latini & Bråten, 2021). Participants were presented with the same post that was used to introduce them to the learning environment and researchers explained that participants should read all posts aloud and say what they were "thinking, doing, and feeling" before, during, and after encountering each post. Initial development of the think-aloud protocol (TAP) methodology raised concerns that explanations may change the nature of cognition (Ericsson, 2006). Fox and colleagues (2011) conducted a meta-analysis of verbal reporting procedures that included data from almost 3,500 participants from 94 independent data sets. They found that think-aloud verbalizations that did not include explaining had no effect on other cognitive processes, whereas verbalizations with explanations did lead to changes in cognition. Thus, in studies focused upon participants' authentic cognition, such as ours, participants should be coached to verbalize but not explain their thinking, which we did. Participants were told that the researcher would not be able to help them or answer questions during the actual reading time, but they would be prompted if they were silent for more than two seconds.

Measurement

Prior Knowledge—The prior knowledge measure included 21 questions that were generated based on the content of the 30 posts. The questions were meant to measure specific knowledge claims made by the posts (i.e., "How long should a person who has tested positive for COVID-19 Quarantine?"). The questions also included distractor items based on the distractor posts used in the study, but those items were not scored and did not contribute to the overall prior knowledge score calculated for each participant. Responses were scored as 0 or 1 based on accuracy and then analyzed for construct validity and optimal data reduction. Only two out of 1,071 datapoints were missing; given their infrequency, they were treated as missing completely at random (Enders, 2022). Descriptive statistics indicated that one item had a mean of one and three other items had means of .96, suggesting only 1 participant per item incorrectly answered it (see Supplemental Materials, Table S1). Further, the correlation between items 1 and 2 was 1.000. Thus, our confirmatory factor analysis, treating each item as dichotomous using Mplus 8.8's WSLMV estimator, could not include item 8 due to no variance and could not include both item 1 and item 2 due to collinearity. We chose to drop item 1 from the analysis. The initial CFA did not converge, due to item 12 having a solution R^2 value greater than one, therefore we dropped this item, also. This CFA did converge with a statistically non-significant model chi-square value $\chi^2(135) = 156.617$, $p = .0983$. Marginal reliability of the saved factor scores, which is an appropriate reliability index when measured indicators are binary, was calculated as .915 (Thissen & Wainer, 2001). Therefore, we accepted this as our final model and saved factor scores from it for inclusion as measured variables in analyses for our research questions. Final model estimates are shown in Supplemental Materials, Table S2.

Need for Cognition—Participants completed the 18-item Need for Cognition Scale by Cacioppo and Petty (1984). The scale requires participants to rate themselves on a series of statements (i.e., "I would prefer complex to simple problems"). Rankings were on a scale of 1 to 5 where 1 was "Extremely Uncharacteristic" and 5 was "Extremely Characteristic." Some items were designed to be reverse scored (i.e., "Learning new ways to think doesn't excite me very much."; Cacioppo & Petty, 1982). Two out of 918 datapoints were missing, thus they were treated as missing completely at random (Enders, 2023). Descriptive statistics indicated relatively low scores, on average, for each item (see Supplemental Materials, Table S3).

Initial confirmatory factor analyses, using Mplus 8.8 with maximum likelihood estimation, did not converge due to non-positive definite matrices, with errors indicated for items 13 and 18. These items were dropped. In addition, two error covariances, between items 1 and 2 and items 8 and 9, were statistically significant per modification indices. The model with these changes had a statistically non-significant model chi-square value $\chi^2(102) = 123.867$, $p = .0695$ and served as our final measurement model (see Supplemental Materials, Table S4 for factor loadings). Construct reliability (i.e., Coefficient *H*) for this measure was .847 (Weiss, 2011). Factor scores were saved as measured variables for the main research question analyses.

Response Behaviors—We provided participants with three response options for each post: skip the post, like the post, or select and read the linked article. The use of behavioral responses as our outcome measure, as opposed to stated intention or attitudinal questions, served a threefold role in this research. First, such outcomes are more ecologically valid than self-report alternatives: engaging with content in a realistic simulated interface more closely resembles actual use of social media. Second, such outcomes arguably reduce the likelihood of researcher demand effects: we provided an authentic set of potential interactions with each post, allowing for low-inference data on this important outcome variable. Likewise, by nesting misinformation posts in a simulated ‘feed’ alongside legitimate posts, our research design and questions were better concealed. Third, this approach is largely novel in the extant literature, and therefore provides unique information about social media behavior that complements the results of previous research (McPhedran et al., 2023).

Mental Processing Codebook Development

We developed a codebook to capture key mental processes verbalized by students when they were incidentally exposed to information and misinformation (see Appendix A for the codebook and a flowchart of the coding process). Codebook development was an iterative process, with several rounds of revision before reaching the final codebook used in this study. To begin the coding process, we selected transcripts for open coding (Corbin & Strauss, 2008). During these early sessions, we focused on identifying mental processes that seemed related to participants’ understanding of, and responses to, the simulated social media posts. When transcripts were unclear, we watched the participant’s video. Following these independent sessions, we reconvened to share codes and themes that emerged across the data, and we began considering bodies of literature that could help refine our understandings of those themes. Then we identified another set of transcripts to review, and the process was repeated until we reached saturation. This led to the final draft of the codebook for this study, which features both theory-driven and data-driven codes (DeCuir-Gunby et al., 2011). This codebook included nine categories of codes related to cognitive operations, metacognition, emotions, motivation, interest, evaluation, source evaluations, knowledge claims, and epistemic cognition.

Cognitive Operations—We created a category for mental processing needed to accomplish the task based on Winne and Hadwin’s (1998) model of self-regulated learning. These operations result in cognitive products or information that allow the participant to continue engaging with a task. Examples of these processes include activating prior knowledge (e.g., “My whole family got Moderna.”) and forming new conclusions beyond what is presented in the environment (e.g., “I feel like if we would’ve done it in the beginning, then this probably wouldn’t have been as big of a deal.”).

Metacognition—Within the metacognition category, two subcategories were created based on the work by Efklides (2011): metacognitive knowledge and metacognitive experiences. Metacognitive knowledge codes captured beliefs and knowledge about how different factors may shape the cognition of oneself or others (e.g., “I prefer to look at pictures.”, “I feel like everyone knows that.”, “I’m tired of reading about COVID.”). Metacognitive experiences about the posts and their content were also coded. These codes were applied to utterances that were referring to a participants’ specific mental experience such as expressions articulating levels of understanding (e.g., “I’m not sure I get what they are trying to say.”), or feelings of recognition (e.g., “This sounds familiar.”).

Emotions—Pekrun’s (2006) work, based in part in Posner and colleagues’ (2005) Circumplex Model of Affect, was used as a basis for codes designed to capture participants’ affective responses to their interactions with various posts (e.g., “I’m excited!”). In this model, affect can be classified along two dimensions. The first dimension, valence, captures whether a participant verbalized experiencing a positive (e.g., happy) or negative (e.g., frustrated) emotion. The second dimension captures whether an emotional state involves a high (e.g., excited) or low (e.g., calm) level of arousal. Surprise was also coded, given its prominence in research on epistemic emotions (Muis et al., 2018). “Emotion monitoring” was used to capture instances where students verbalized actively reflecting on how a post was making them feel, rather than simply articulating a feeling (e.g., “Thinking about this is making me feel anxious.”). Although this does qualify as a metacognitive experience, we felt the focus on emotion was different enough from other kinds of metacognitive experiences to constitute its own category.

Motivation—We created a block of data-driven codes based on motivation-related utterances articulated by students. For example, we observed that students verbalized evaluating the relevance of posts to their daily lives (e.g., “That really doesn’t apply to me.”) and how useful the content of a post was (e.g., “That’s really important, everyone should know that.”) when considering how to interact with the post. Also, we found that students would at times verbalize considering whether the message of the post aligned with their existing values (e.g., “I support vaccination so I like this post.”). In these ways, the participants’ verbalizations seemed indicative of the literature on expectancy value theory (Eccles & Wigfield, 2020).

Interest—We also noticed participants expressed various interest-related reasons for engaging in specific actions. Instances where participants commented on the aesthetic appeal of posts (e.g., “That picture really catches my eye.”) and where students expressed levels of interest (e.g., "That doesn't really interest me.") were coded in this category. These expressions seemed to span both situational and individual interest (Renninger & Hidi, 2020), but there were not a sufficient number of verbalizations to differentiate these types, thus we combined them into positive and negative general interest variables.

Evaluation—The *Evaluation* category included codes that involved judgements about the participants' general impressions of the post. These judgments included attitudes towards the post (e.g., "I think that this seems like a bad/good idea"), the intentions behind the post (e.g., "This post is just trying to scare people"), and whether complying with a claim would be feasible (e.g., "I think we could definitely do that"). Plausibility judgements (i.e., tentative appraisals of the potential truthfulness of the claim; Lombardi, Danielson, et al., 2016; Lombardi, Nussbaum, et al., 2016) were also included in this category.

Source Evaluation—A set of codes related specifically to participants' source evaluation (e.g., Abet & Barzilai, in press; Barzilai et al., 2020; Macedo-Rouet et al., 2019) was developed. These codes explicitly addressed the strategies participants verbalized using to identify and evaluate the sources of knowledge claims presented in each post. Source evaluations were differentiated by the factor used to make the judgment (e.g., whether the source was *balanced, benevolent, familiar*, etc.).

Epistemic Cognition—Epistemic cognition codes included the quality of the knowledge claims made by the post (i.e., *knowledge claim evaluation*) as well as the criteria for evaluating those claims (e.g., *coherence, corroboration across other sources*). In addition, we coded strategies and other behaviors participants verbalized as likely to lead to knowledge (i.e., reliable processes). Also, we coded the goals students articulated that motivated them to pursue additional information (i.e., *epistemic aims*).

Actions—Participants verbalized engaging in actions that leveraged social media features to extend or limit the reach of the information being presented to them. For example, some participants stated they would "like" a post as a way of amplifying the message (e.g., "Other people should know about this, so I'll like it."). Conversely, some participants also expressed the desire to report false information to limit its impact (e.g., "If there was a report button, I'd report this."). Therefore, we coded these verbalizations as social media actions (Yadamsuren & Erdelez, 2017).

Coding and Reliability

Participants' audio-recorded verbalizations were transcribed by a commercial service. Transcripts were imported into MAXQDA for analysis (VERBI Software, 2022). First, Author 2 coded all sections where the participant was reading text from the screen or was responding to filler posts (i.e., posts that did not present information related to COVID-19). This coding was considered objective, therefore interrater reliability was not calculated. Next, we turned our focus to verbalizations related to COVID-19 information and misinformation posts. To establish reliability, Authors 2 and 3 began by coding the first five participants independently. Cohen's Kappa was calculated at 0.74, indicating substantial agreement (Landis & Koch, 1977). Discrepancies were discussed and resolved. Instances where Authors 2 and 3 were uncertain of which code was more appropriate were brought to Author 1. If Author 1 felt the stanza was too ambiguous to code, a “no code” was applied to that segment. All disagreements were resolved in this manner, ultimately resulting in 100% agreement.

The substantial level of agreement in the initial round of coding indicated that this codebook could be reliably applied to our data. We proceeded to code the remainder of the data, meeting after every 8–10 participants to calculate reliability and resolve disagreements as described above. Authors 2 and 3 both coded every participant. Ultimately, the overall level of agreement before resolving discrepancies was substantial (Cohen’s Kappa: 0.74)

Data Analysis

Our analyses for Research Question 1 were descriptive, involving frequencies of participants’ mental processing as coded according to our codebook. Our examination of differences in mental processing by post type (i.e., COVID-19 information versus misinformation), for Research Question 2, were exploratory and required first determining the best-fitting distribution for each macro-level mental processing count variable (i.e., normal, Poisson, negative-binomial; Greene et al., 2011). We used information criteria values to determine the optimal distribution, with lower AIC and BIC values indicating a better-fitting distribution. Once the optimal distribution for each mental processing variable was determined, then, for each variable, we conducted the equivalent of a t-test, with a count distribution for the outcome variable when warranted, between posts containing COVID-19 information and those containing COVID-19 misinformation. Research Question 3, which was also descriptive and exploratory in nature, required an examination of correlations among individual-level variables (i.e., prior knowledge and need for cognition) and post-level variables (i.e., mental processing counts), split across COVID-19 information and misinformation posts. These correlations were calculated using a maximum likelihood cluster-robust estimator to account for clustering of posts within individuals (i.e., to correct the standard errors for nesting effects; Stapleton et al., 2016).

Research Question 4 (i.e., “How do college students’ prior knowledge, need for cognition, and verbalized mental processing predict their behaviors in response to incidental exposure to COVID-19 information and misinformation in a simulated social media environment?”) was the main focus of our study. This research question was exploratory given the TILE model (Greene et al., 2021b) is relatively new with insufficient empirical research to warrant strict hypothesis testing. Exploratory research is a necessary step of epistemic iteration from phenomena to strict theory that describes and explains those phenomena (Greene, 2022; Borsboom et al., 2021; Szollosi & Donkin, 2021). Therefore, we conducted a comprehensive analysis, reporting both overall as well as Type-I-error-controlled findings. First, we conducted multilevel, multinomial logistic regressions to investigate whether and how individual characteristics (i.e., prior knowledge and need for cognition) and mental processing predicted participants’ behavioral decisions about how to respond to each post (i.e., choice of liking, selecting the link to read, or skipping the post). These analyses were conducted separately for COVID-19 information and misinformation posts. In this analysis, mental processing and behaviors in response to posts were nested within individuals.

Decision behaviors (i.e., liking, reading, or skipping a post) comprised the nominal outcome variable, mental processes were level-1 predictors, and individual characteristics were level-2 predictors. In some analyses for Research Question 4, particular types of verbalized mental processing occurred so infrequently that they could not be included in the analysis. For the COVID-19 information post analyses, the following mental processes could not be included due to convergence errors likely due to low variance in the macro-level variable: Motivation Negative, Emotions, Interest Negative, Action, Source Evaluation Negative, Knowledge Claim Unvalenced, Operations, and Epistemic Aims. For the COVID-19 misinformation post analyses, the following macro-level variables could not be included: Metacognition about Others, Metacognition about the Post Positive, Motivation Negative, Motivation Positive, Interest Negative, Action, Source Evaluation Positive, Knowledge Claim Positive, and Operations. After reporting the results of those analyses with statistical significance set at the typical $p < .05$ level, we applied the False Discovery Rate adjustment (Benjamini & Hochberg, 2000) to p-values across both multilevel, multinominal logistic regressions, combined, and reported adjusted statistical significance as well. Thus, reporting both unadjusted and adjusted p-values adheres to the exploratory nature of Research Question 4, while also providing readers with more conservative estimates regarding which findings are most likely to replicate in the future.

Research Question 5 (“How do college students’ verbalizations of mental processing and behaviors in response to incidental exposure to COVID-19 information and misinformation posts in a simulated social media environment relate to the content of these posts?”) was prompted by reviewer feedback requesting a deeper qualitative look at the relationship between post content and participant responses. Mental processing and response behavior data for each post was compared. Two researchers looked for the most common codes in each post and considered the ways those codes related to the most common responses. For this analysis, posts were organized into information and misinformation categories and then further classified into categories based on the type of content (i.e., topic) being discussed.

Results

Research Question 1: What mental processes do college students verbalize when they are incidentally exposed to posts about COVID-19 in a simulated social media environment?

Having developed a codebook to characterize participants’ verbalizations while reviewing simulated social media posts, we were able to examine what kinds of verbalizations occurred and how often (see Table 2). There were 1,359 coded verbalizations across the 1,020 instances (i.e., 20 posts, each viewed by 51 participants), for an average of 1.33 coded verbalizations per instance. Most participants verbalized two to three sentences after reading a post and before choosing a response.

Participants most frequently verbalized mental processes related to operations (e.g., “COVID must be highly communicable, given these statistics.”), but did so more frequently for information compared to misinformation posts. The same was true for the next most frequently verbalized mental process, positive metacognition about the post (e.g., “I recognize this study.”). The opposite was true for the next most frequently verbalized mental process, negative metacognition about the post, where participants’ statements were coded as such much more often for misinformation compared to information posts. On the other hand, Action verbalizations (e.g., "I would report this post.") were least frequently verbalized and roughly equally coded across both types of posts. Source evaluations were also infrequently coded, with positive ones more common for information posts and negative ones more common for misinformation posts.

Research Question 2: How do college students' verbalized mental processes differ when simulated social media posts contain information versus misinformation about COVID-19?

The listing of verbalized mental processes derived for Research Question 1 and the notable differences in means across COVID-19 information and misinformation posts (see Table 2) begged the question of whether the frequency of coded mental processes differed by post type. The count nature of our mental process data, and examination of the skewness and kurtosis of the mental process variables (see Table 2), suggested we should investigate whether some of those variables should be modeled using count distributions (e.g., Poisson, negative-binomial; Greene et al., 2011). Data-model fit comparing count distributions to a normal, Gaussian distribution, are shown in Supplemental Materials, Table S5.

Next, we regressed each macro-level variable, using the optimal distribution, on a dummy-coded variable where zero was the COVID misinformation posts and one was COVID information posts (see Table 3). When participants viewed COVID-19 information posts, on average, they verbalized more metacognition about themselves, positive metacognition about the post, positive motivation, positive evaluations, positive source evaluations, positive views of the knowledge claim, and operations. On the other hand, for the COVID-19 misinformation posts, participants, on average, verbalized more emotional content, positive interest, negative evaluations of the source, negative views of the knowledge claim, and unvalenced views of the knowledge claim.

Research Question 3: How does college students' prior knowledge about COVID-19 prevention and treatment and their need for cognition relate to their verbalized mental processing when they are exposed to posts containing COVID-19 information and misinformation in a simulated social media environment?

For Research Question 3, we separated the data by COVID-19 information and misinformation posts (see Table 4). Participants' prior knowledge was not statistically significantly related to their need for cognition ($r = .078$, ns). Many correlations among prior knowledge, need for cognition, and verbalized mental processing were statistically non-significant. Notable statistically significant correlations included prior knowledge positively correlated with Action for COVID-19 information posts. This suggests the more participants knew about COVID-19 information, the more likely they were to express a desire to share it. Similarly, prior knowledge was positively related with Negative Evaluation verbalizations among the COVID-19 misinformation posts. Prior knowledge was negatively related to the frequency of Negative Interest statements for the COVID-19 misinformation posts, suggesting the more participants knew about the virus, the less likely they were to express negative interest in posts about COVID-19 misinformation. Prior knowledge was positively related to verbalized negative judgments of the knowledge claim for misinformation posts. Need for Cognition had fewer statistically and practically significant relations with verbalized mental processing, although for COVID-19 misinformation posts, it was positively related to Negative Motivation and Positive Evaluation verbalizations.

Research Question 4: How do college students' prior knowledge, need for cognition, and verbalized mental processing predict their behaviors in response to incidental exposure to COVID-19 information and misinformation in a simulated social media environment?

First, we examined the raw data regarding participants' responses to COVID-19 information and misinformation posts (see Supplemental Materials, Table S4). Skipping was the most frequent behavioral response choice for both COVID-19 information and misinformation posts. However, there were large differences in the frequency of the other two responses, with participants more frequently liking than reading COVID-19 information posts but much more frequently reading than liking COVID-19 misinformation posts.

Next, we used multilevel, multinomial logistic regression models with no level-1 or level-2 predictors to evaluate whether participants differed in their likelihood of selecting to like, skip, or read a post, separately for COVID-19 information and misinformation posts. Participants were more likely to like (Odds Ratio = 1.413, $p < .05$) or skip (Odds Ratio = 1.802, $p < .001$) information posts, than to read them. However, there was no statistically significant difference in the likelihood of selecting like versus skip for COVID-19 information posts (Odds Ratio = .784, $p = .171$). For the COVID-19 misinformation posts, participants were far more likely to select to read (Odd Ratio = 11.531, $p < .001$) or skip (Odd Ratio = 14.311, $p < .001$) them than to like them. There was no statistically significant difference in their likelihood of selecting to skip or read misinformation posts (Odds Ratio = 1.242, $p = .100$).

Then we ran multilevel, multinomial logistic regression models with only the level-2 predictors (i.e., prior knowledge, and need for cognition), predicting the level-1 means (i.e., odds ratios for each behavioral response decision compared to the others). We found neither prior knowledge nor need for cognition statistically significantly related to participants' odds of liking, reading, or skipping information posts (all *p*s > .117). The same was true for COVID-19 misinformation posts (all *p*s > .172), except in the case of prior knowledge predicting the likelihood of skipping versus reading the post, in which case prior knowledge was positively related to an increased likelihood of skipping (Odds Ratio of coefficient = 1.723, $p = .047$). Given these findings, we included prior knowledge as a level-2 predictor in our subsequent analyses of mental processing and COVID-19 misinformation posts, but in every analysis prior knowledge was statistically non-significant.

Next, we investigated how the level-1, verbalized macro-level mental process variables predicted the likelihood of the three response behaviors, separately for COVID-19 information and misinformation posts, again using multilevel, multinomial, logistic regression. For each kind of post, we attempted to use all the macro-level mental process variables as predictors, but several had so little variance for a particular kind of post that including them resulted in non-positive definite matrices. Therefore, when necessary, we removed these macro-level variables from the analyses. We report here final models with all listed predictors successfully included in the model, without any estimation errors.

For the COVID-19 information posts (see Table 5), controlling for mental processing, participants were more likely to skip than read these posts, but there were no differences in their likelihood of skipping versus liking or liking versus reading. After controlling for potential Type I error using the False Discovery Rate procedure (Benjamini & Hochberg, 2000), the likelihood of reading versus liking accurate COVID-19 information posts increased when participants expressed positive interest in the content (e.g., "That seems interesting") or they verbalized cognitive operations such as activating prior knowledge (e.g., "My, my mom was literally sick with a high fever for a day"). On the other hand, the likelihood of liking the content versus reading it increased when the participants verbalized evaluating the intentions of the content positively (e.g., "And I'm also vaccinated, so I, um, I do like this post, and, as it is, um, encouraging people to get vaccinated.") or verbalized thinking the content was true (e.g., "It seems like it's pretty accurate"). The likelihood of skipping versus reading the content increased when they verbalized thinking the content was true (e.g., "I definitely agree"). On the other hand, verbalized interest (e.g., "I'm definitely interested in it") increased the likelihood of participants reading versus skipping the post. Participants' likelihood of skipping rather than liking the post increased when their verbalizations were coded for metacognition about themselves (e.g., "I honestly would not take the time to read through this") or negative evaluation of the intention of the post (e.g., "I don't think I would need to come back to that"). The likelihood of liking versus skipping the post increased when they expressed positive motivation (e.g., "I feel like this is topical"), positive evaluation of the post's intention (e.g., "I'm glad that's being explained"), or verbalized thinking the post content was true (e.g., "I also agree with that").

For a concrete example of how to interpret the statistical findings, it is instructive to examine how mental processing related to the likelihood of participants skipping versus reading COVID-19 information posts. The baseline odds ratio for skip versus read was 1.895 ($p < .01$), meaning that for participants with no verbalizations, the skip behavioral response was nearly 1.9 times more likely than read (see Table 5). However, if a participant verbalized one coded instance of positive interest, then the odds ratio between skipping and reading would change to .354 (i.e., $1.895 \times .187 = .354$), meaning that for this participant who verbalized positive interest, reading would be more likely than skipping, because their odds ratio was less than one.

As another way to understand the results, all the statistically significant findings for the COVID-19 information posts are visualized in Figure 3. The three response options are ordered from most to least frequent from left to right and connected by arrows, which point to the more frequent response. The number shown above the arrow is the odds ratio of the more frequent response to the less frequent response. Statistically significant predictors of the mental processes related to the skip versus read odds ratio are shown above the responses and the mental processes related to the skip versus like and like versus read odds ratios are shown below them. The arrows pointing away from mental processes indicate how a verbalization of that mental process shifts the odds ratio. As another concrete example, as shown in Figure 3, the baseline odds ratio that a participant with no verbalizations would like versus read a COVID-19 information post was 1.392, p = ns, indicating they would be more likely to like than read that post (i.e., the odds ratio is above one) but that this value is not statistically significantly different than even odds (i.e., odds ratio is one). However, a participant who verbalized positive interest once when reviewing a COVID-19 information post would be statistically significantly more likely to read than like that post (i.e., 1.392 × .269 = .374). Two verbalizations of positive interest would even more strongly shift the likelihood to reading rather than liking (i.e., 1.392 × .269 × .269 = .101). Thus, Figure 3 and Figure 4, which is described below, visualize how the baseline odds ratios change when participants verbalize specific mental processes that were statistically significantly related to participants' responses.

For the COVID-19 misinformation posts, controlling for mental processing, participants were more likely to skip or read these posts, rather than like them (see Table 6 and Figure 4). After applying the False Discovery Rate adjustment, skipping the content, rather than reading it, was more likely when participants verbalized a negative evaluation of the post's source (e.g., "Seems like a fake news article on Facebook") or knowledge claim (e.g., "I don't believe that there has not been a single COVID death in two months. I don't think that's true"). On the other hand, both verbalized positive interest (e.g., "That actually is pretty interesting") and positive evaluations of the post's intent (e.g., "Um, *I think that this seems like a good idea*. I'm not sure if it's true, but *it seems like it couldn't hurt.*") decreased the likelihood of skipping the post and, thus, increased the likelihood of either reading or liking it.

Research Question 5 (post hoc): How do college students' verbalizations of mental processing and behaviors in response to incidental exposure to COVID-19 information and misinformation posts in a simulated social media environment relate to the content of these posts?

We grouped posts into three main topics: vaccination, masking, and treatments. A single information post did not fit well into these categories and was included in its own category on quarantining. Participants often seemed familiar with the content in the information posts (e.g., "[responding to a post about quarantining time] Um, I already knew this as well, so I'm gonna do next post") or they verbalized trust in the source and then immediately skipped the content (e.g., "[responding to a post from the CDC] Um, yes, that is true that vaccines can reduce that risk. It's from the CDC again, credible source, um, so I'm going to like this post"). This pattern was consistent across the masking and vaccination posts, but participant responses were different for the two information posts that discussed treatment options, with participants rarely liking them and primarily reading or skipping. These posts were also more likely to prompt statements suggesting the participants did not recognize the content. Thus, information post responses seemed related to novelty, with familiar content eliciting liking and skipping and unfamiliar content prompting reading or skipping.

Misinformation posts with masking and vaccination content co-occurred with mental processing that suggested participants had concerns about the post's accuracy, but also, they felt compelled to investigate further due to personal interest (e.g., "[after reading a post about vaccines causing strokes in pilots] So it doesn't seem like this would be true, but I'm interested in reading more"). At the time of the study, masking and vaccination were being covered in the media in a highly politicized manner, which may explain why participants were more likely to engage with content about them. Participants may have felt that, despite knowing something was likely untrue, they needed to understand both sides of the argument (e.g., “Hmm, okay, interesting. I’m not sure this is true or not. This seems kind of ... It doesn’t make sense to me. …Um, I will press Read More just to learn more about what they’re saying.”). When misinformation post content contained overt errors (i.e., a post with a typo that researchers chose to retain from the source material) or fell into the treatment category (i.e., a post suggesting that silver solution could cure COVID), participants were more likely to question the post’s accuracy and choose to skip it (e.g., “[after reading a post about silver solution killing COVID] That sounds bogus. We’ll, I, I don’t even know how you can believe that. I don’t even know what that is honestly”). Given that COVID-19 did not have a known cure and treatment options were limited at the time of this study, participants may have been more skeptical of misinformation posts discussing treatments.

Discussion

As people continue to move away from traditional news sources (Newman et al., 2019) and rely more and more on social media to “push” important news to them (Gil de Zúñiga et al., 2017; Masip et al., 2018), more research is needed to understand how and why people engage, or not, with content (Greene et al., 2021b). Such research will require ways to capture not only what users do in such environments, but also what they are thinking when they engage with content, as well as what user and content factors moderate that engagement. Through this study, we have produced what we believe is the first codebook (DeCuir-Gunby et al., 2011) for categorizing think-aloud protocol data reflecting college students’ mental processing after being incidentally exposed to science-related content, in this case COVID-19 information and misinformation, via social media (Greene et al., 2021b). The macro-level categories of mental processing in this codebook spanned literature on metacognition (Efklides, 2011), emotions (Posner et al., 2005), motivation (Eccles & Wigfield, 2020), epistemic cognition (Chinn et al., 2014), and source evaluation (Barzilai & Zohar, 2012; Breakstone et al., 2021; McGrew, 2021). As shown in Supplemental Materials, Table S4, codes from each literature were verbalized for both COVID-19 information and misinformation, providing evidence to support Greene et al.’s (2021b) argument that models of incidental exposure (e.g., Yadamsuren & Erdelez, 2017) would benefit from integration of theory and research on these topics, including work in educational psychology and intentional learning. Evidence for a variety of verbalized mental processing types suggests several viable targets for intervention and necessitates research into which aspects of mental processing, alone or in combination, prove to be the more malleable factors (Greene, 2015) for inoculating people from misinformation (Lewandowsky & van der Linden, 2021; Roozenbeek et al., 2022). Existing models of incidental learning and media exposure have captured how users’ interests and motivations affect what appears in their feed (Thorson & Wells, 2016), but given our findings regarding how these phenomena related to participants’ responses to posts (e.g., positive motivation and interest increased the likelihood of liking or reading, rather than skipping, COVID-19 information posts, the same was true of positive interest for misinformation posts), there is a need for more research on how motivation and interest affect how users engage with what appears in their feed, also. Findings regarding whether, how, and why users’ interests and motivations change their engagement with social media can inform interventions to make users more thoughtful and intentional regulators of these phenomena (Miele & Scholer, 2018; Miele et al., 2020).

As we suspected, participants verbalized different mental processes depending upon the nature of the content they saw in our simulation (i.e., COVID-19 information vs. misinformation), substantiating another aspect of the TILE model (Greene et al., 2021b). On average, participants produced positively valenced verbalizations more often for the COVID-19 information posts and negatively valenced verbalizations more often for the misinformation posts (see Supplemental Materials, Table S5). This suggests these participants were, on average, able to discern accurate and inaccurate COVID-19 information, contrary to other findings suggesting students often find such discernment challenging (Bräten et al., 2018). Given our sample of participants came from a university with competitive admissions standards, it was unsurprising their source evaluations and perceptions of the truth of the knowledge claims therein aligned with the veracity of the posts. There was a notable exception, however. Participants verbalized more positive interest for the COVID-19 misinformation than the information posts (e.g., “I’m very intrigued”), perhaps to better understand positions they did not hold. This finding provides context for a related finding that participants more often chose to read COVID-19 misinformation than information posts. At least in this sample, many participants were intrigued by misinformation and actually chose to engage more with this content, perhaps out of curiosity or surprise, aligned with research on epistemic emotions (Muis et al., 2018).

Overall, participants far less frequently liked COVID-19 misinformation posts compared to information posts, but fairly evenly distributed their responses between skipping and reading the misinformation. Individual difference variables (i.e., prior knowledge, need for cognition) did not reliably predict whether participants chose to like, skip, or read posts. Further, relations among these individual differences and various verbalized mental processes were scarce, suggesting, for this particular sample, individual differences were not useful predictors. Thus, our findings added to the existing “mixed” state of the literature on the relationship between individual differences and technology engagement and effects (Cacciatore et al., 2018; Edgerly et al., 2018; Lee & Xenos, 2019; Tewksbury et al., 2001). More research is needed to understand what individual difference factors, for which people, affect whether and how people engage with information in a social media technology context.

Our qualitative analysis further nuanced these findings, revealing information about why some people may respond to misinformation in apparently maladaptive ways (i.e., by engaging with it). Many participants were inclined to seek a better understanding of the false content. We saw a few reasons for this engagement, but the most important seemed to stem from unfamiliarity with the post content and from posts whose content was related to something widely debated in political spaces (e.g., treatment options). False posts that participants skipped were often poorly edited or seen as ridiculous and obviously untrue. Notably, participants rarely chose to like false posts, possibly because they understood that liking posts elevated them. Further, true content seemed to lead to disengagement due to familiarity, but participants were still much more willing to like true posts, possibly to help disseminate information they perceived as helpful or important. True posts that participants were unfamiliar with were far more likely to prompt further engagement through reading, a result that aligns with prior research showing that novelty promotes engagement with social media (Cappella et al., 2015).

Many of the relationships between mental processing and choice of response were complex, but trends can be found in Figures 3 and 4. For the accurate COVID-19 information posts, verbalized positive interest and motivation were associated with more engagement with the content (i.e., liking and reading). These findings are not surprising given the interest and motivation literatures (Eccles & Wigfield, 2020; Renninger & Hidi, 2020), but they are notable in how they differ from the kinds of mental processing associated with increased skipping: negative evaluations of the content but also positive metacognition cued by the post and positive judgments of the knowledge claim. These findings suggest that skipping behaviors are not reliable indicators of either negative or positive evaluations of the content. Thus, it is difficult to infer why a person skips a social media post from the behavior alone. In essence, positive cognition and metacognition can lead to behaviors that, if not investigated via think-aloud protocols or other in-depth methods, might be mistaken for disinterest or disagreement.

In addition, for COVID-19 information posts, verbalized negative evaluations about the post's intent increased the likelihood of both skipping and reading behaviors, compared to liking, suggesting mental processing can be associated with more than one kind of response. More research is needed to understand this variability. Verbalized self-focused metacognition and operations had the same effect of pushing people away from liking toward responses indicating both more (i.e., reading) and less (i.e., skipping) engagement with the content. On the other hand, verbalized positive evaluations of the post and the knowledge claim therein increased our participants' likelihood of liking the post, suggesting people's epistemic cognition (Chinn et al., 2014) may drive liking responses more than other behaviors. More research is needed to understand what "liking" means to participants, so that its relationship to epistemic cognition can be better understood. Confirmation of that relationship might help researchers use liking behaviors as an indicator of aspects of epistemic cognition, which would provide a new method for tracking that kind of cognition in social media contexts.

Our COVID-19 misinformation posts were rarely "liked" but verbalized positive interest and evaluations of those posts' intent were strong predictors of this behavioral response. Interest also drove participants to select to read the content in these posts, rather than skip them. A question for future research is the nature of this positive interest, specifically whether it is situational, individual, or perhaps for some users, both (Renninger & Hidi, 2020). Understanding the aspects of the misinformation posts that cue participants' positive interest and evaluations would inform interventions to help participants monitor when posts were designed to cue such responses, and inhibit them accordingly (Miele & Scholer, 2018; Roozenbeek et al., 2022). Somewhat surprisingly, participants' emotions were not verbalized enough to include in analyses of responses to COVID-19 information posts. Verbalized emotions could be included in analyses regarding COVID-19 misinformation, but they were not statistically significant predictors of behavioral responses despite having medium-sized odds ratio effects. A larger sample, coupled with physiological sensors, might allow for more powerful differentiation regarding which emotions coincided with participants' behavioral responses (Posner et al., 2005), which in turn could expand the scholarship on epistemic emotions (Muis et al., 2018) via behavioral data.

Finally, given skipping and reading were the two most common response behaviors to misinformation posts, it is informative to examine what predicted these responses. Interest greatly enhanced the likelihood of reading versus skipping this content, an unsurprising result. Negative evaluations of the post's intentions, knowledge claim, or source increased the likelihood participants would skip rather than read the post. Emotions and motivation were noticeably absent from among the mental processes differentiating skipping and reading responses. Thus, when it comes to COVID-19 misinformation, at least for our sample, participants' interests and thoughts were stronger predictors of responses than their motivations or emotional responses. These findings suggest misinformation inoculation efforts might be best targeted toward helping people recognize when their situational interest is being manipulated and encouraging them to self-regulate toward invoking their epistemic cognition instead.

In sum, despite a relatively small sample, we were able to detect many relations among a variety of verbalized mental processes (i.e., metacognition, motivation, emotion, epistemic cognition) and behavioral outcomes, for accurate and inaccurate posts about COVID-19. Some of these relations were intuitive, such as how verbalized positive interest relates to participants' choice to engage with content, be it accurate or inaccurate. However, other relations were not intuitive, such as how participants' choice to read content can signal both endorsement as well as skepticism and curiosity. In general, verbalized interest and motivation was predictive of more effortful engagement, whereas verbalized cognition and metacognition predicted less effortful engagement (i.e., skipping). These findings suggest the need for more studies like ours, to better understand what social media response behaviors mean, and further how to shape education and interventions to help people more thoughtfully and consciously monitor and control how they respond to these posts (Greene, 2018).

Limitations

Our findings are novel and specific to our choice of sample (i.e., college students at a highly selective public university in the United States). Therefore, these findings must be replicated with a similar sample, and tested with other samples, before confident inferences and generalizations can be made about the relations in the TILE model and how our findings support them. Despite the concerns about statistical power that arise from a sample of 51 participants, it seems plausible that homogeneity in our college student sample resulted in a restriction of range that may have made it difficult to detect statistically significant relations among need for cognition, prior knowledge, and participants' behavioral decisions in response to posts. The COVID-19 prior knowledge and need for cognition means were relatively high, with small standard errors. Such homogeneity in scores is not surprising given our sample. Likewise, we were unable to investigate several positively valenced verbalized mental processing variables' relationship with behavioral decisions in response to COVID-19 misinformation, because they were so infrequent with this sample. The opposite was also true: for COVID-19 information, negatively valenced verbalizations of source evaluations or knowledge claims were sufficiently rare that those variables could not be included in the analysis. Finally, out of 510 responses to the COVID-19 misinformation posts, only 19 times did a participant indicate they would like the post. Again, this indicates a homogeneity of viewpoint that likely limited our ability to fully investigate all the posited relations in our dataset.

Our focus on a single topic (i.e., COVID-19) likely also limited our ability to investigate relations among individual differences, verbalized mental processing, and participants' behavioral responses to posts. This singular focus allowed for a deep investigation of this particular topic, but provided no insight on other topics or how people's verbalized mental processing or responses might vary across topics. We kept our behavioral response choices limited to avoid confusing participants, but a more authentic social media experience would include both additional types of responses (e.g., sharing) as well as the option to choose more than one response option (e.g., liking and then reading a post). It may be the relationships between verbalized mental processing and behavioral choices will change when participants have more and multiple response options.

Further, given this is the first study of relations posited in the TILE model and given the need to capture mental processing via think-aloud protocols, we elected to create a highly-controlled laboratory study. The affordances of such a laboratory study (e.g., ability to capture think-aloud protocol data, elimination of potentially confounding contextual factors) necessarily come with a commensurate set of constraints (e.g., lack of external validity to more authentic contexts). Also, our findings are based on a simulation of social media platforms and their features, which limits their external validity in two ways. First, given evidence that the prevalence of misinformation varies across social media platforms (Suarez-Lledo & Alvarez-Galvez, 2021), which may or may not play a role in differences in people's responses to content across platforms (Pennycook & Rand, 2021), it will be important to conduct conceptual replications of this study using simulations that mimic a wider variety of platforms. The mental processes predicting types of responses may differ by platform. The simulated nature of this study's platform is the second limiting factor, given we necessarily constrained how participants could use it (i.e., they could not actually click on and read an article, lest participant time on task vary greatly). If our findings prove replicable across simulated social media platforms, the next set of studies would necessarily need to investigate incidental learning in authentic contexts, such as via web browser plug-ins or other tools to collect engagement behavior.

Finally, during the review process, the associate editor mentioned another limitation of our study: the high proportion of participants identifying as women in our sample. This limits generalizability to people identifying as men, but may have also affected the analyses given there is evidence of gender differences in COVID-19 perceptions (e.g., severity), reactions (e.g., emotional responses), actions (e.g., intention to get vaccine), and conspiracy theory beliefs (Alsharawy et al., 2021; Cassese et al., 2020; Galasso et al., 2020; Head et al., 2020; Sallam, 2021). We conducted a post-hoc, exploratory analysis of whether gender, a level-2 variable in our multilevel, multinomial logistic regression, predicted response behaviors for either information or misinformation posts, but relations were not statistically or practically significant. Even with those exploratory findings, concerns about bias in the sample and their responses remain, suggesting the need for studying TILE model phenomena in larger and more balanced samples.

Future Directions for Research

The necessary limitations of our study also suggest a number of promising directions for future research. For example, having investigated people's verbalized mental processing and responses to COVID-19 information and misinformation, it seems reasonable to study next how participants respond to a variety of socioscientific topics (e.g., climate change, nuclear power). Such an investigation could reveal the ways people do and do not vary in how they react to different types of social media content, as well as how content interacts with individual difference variables (Greene et al., 2021b). Similarly, a larger and more diverse sample, including people outside of the postsecondary context, would likely result in more variance in both individual difference and verbalized mental processing variables, allowing for stronger tests of relations posited in the TILE model. Likewise, a larger sample might result in sufficient variance to investigate the predictive validity of not just the macro- but also the micro-level mental processing variables. In particular, people's specific type of source evaluation (e.g., evaluating the author of the content versus evaluating the source of the post) may be an important factor in their response decision. More data, from more participants, might allow for investigations of whether situational interest relates differently to incidental learning processing than individual interest (Renninger & Hidi, 2020). In terms of social media behaviors, most platforms allow users to select more than one response to a post (e.g., reading a linked article in the post, then liking the post). Future research should allow participants to select multiple responses, if they wish. Social media and other technology environments are increasing their use of video and multimedia, therefore future research should include examinations of how incidental learning in these environments does and does not differ from more text-based environments (Abed & Barzilai, 2023). Finally, within-subjects designs with think-aloud protocols could be used to address questions of whether and how deliberative processing after noticing incidentally exposed content differs from the kinds of processing people enact after selecting and reading that content (e.g., reading comprehension processes, self-regulated learning processes).

Conclusion

Social media and other technology environments are prominent contexts in which people learn about a variety of topics (Pew Research Center, 2020). However, often people do not actively seek out news or other information in these online environments and are instead incidentally exposed to information; more research is needed to understand how such exposure happens and what is learned from it (Greene et al., 2021b). Our findings suggest users activate a variety of cognitive, metacognitive, motivational, and affective mental processes when incidentally encountering both accurate and inaccurate information. These processes are related to their behavioral responses to this information, many of which are not intuitive and require more research to understand. We found some evidence that inoculation efforts might be augmented by reminding people to inhibit responses invoked by situational interest, replacing it with more epistemic cognition. Ultimately, education and interventions designed to make people more informed, active, and critical consumers of online information (e.g., Lewandosky & van der Linden, 2021; Roozenbeek et al., 2022) will be enhanced by a better understanding of the many ways people process the information they do not expect to encounter, but nonetheless have grown to depend upon for their news.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Authors' note:

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Appendix A: Verbalized Mental Processing Codebook

Macro- and Microlevel Mental Process Codes	Description	*M*	*SD*
Cognitive Operations	Participant uses a tactic, strategy, or an unintentional response to a post that is not metacognitive in nature.	4.57	5.42
Forming New Conclusion	Participant integrates 2 or more pieces of information to generate a novel conclusion that extends beyond the provided information.	1.04	1.71
Prior Knowledge Activation (Personal)	Participant recalls prior knowledge that relates to them personally.	1.94	2.34
Prior Knowledge Activation (Impersonal)	Participant recalls prior knowledge that does not personally relate to them.	1.59	2.40
Metacognitive Knowledge About the Self	Participant comments on something related to their own thinking.	1.86	.19
Metacognitive Knowledge of Self	Participant comments on how they would typically respond to content or in a social media environment more generally.	1.25	1.43
COVID Fatigue	Participant mentions feeling negatively towards COVID-19 content due to overexposure.	0.61	1.40
Metacognitive Knowledge About Others	Participant comments on another person's thinking.	0.82	1.77
Metacognitive Knowledge of Others	Participant comments on another person's thinking.	0.82	1.77
Metacognition About Posts/Content (+/−)	Participant comments on their own thinking as it relates to a post or the content of that post.	3.10/2.96	3.18/2.71
Feeling of Recognition +/−	Participant mentions that content is/or is not familiar to them.	2.61/1.55	2.71/1.60
Judgement of Understanding +/−	Participant mentions that content does/does not make sense to them.	0.27/0.92	0.53/1.44
Monitoring Information Coherence +/−	Participant notices that content is/is not consistent with their prior knowledge.	0.06/0.10	0.24/0.30
Judgement of Additional Information +/−	Participant mentions believing that the decision to read more about a post will/will not lead them to information they value.	0.16/0.39	0.64/0.85
Emotions	Participant mentions experiencing an emotion.	1.02	1.70
Emotion Monitoring	Participant notices that they are experiencing an emotion in response to content.	0.29	0.73

Macro- and Microlevel Mental Process Codes	Description	*M*	*SD*
Arousal +/−	Participant mentions an emotional state that has high or low arousal.	0.24/0.06	0.62/0.24
Valence +/−	Participant mentions an emotional state that has high or low valence.	0.06/0.24	0.24/0.62
Surprise+/−	Participant indicates that they either are or are not surprised by content.	0.30/0.06	0.34/0.42
Motivation (+/−)	Participant comments on their desire to engage or not engage with a post and/or the reasons for having that desire.	0.76/0.49	1.16/1.12
Relevance to Self +/−	Participant mentions that a post is/is not relevant to them personally.	0.12/0.14	0.38/0.49
Relevance to General +/−	Participant mentions that a post is/is not relevant to people generally.	0.18/0.04	0.56/0.20
Relevance to Others +/−	Participant mentions that a post is/is not relevant to someone that they know.	0.06/0.00	0.24/0.00
Importance +/−	Participant mentions that content is/is not important to know.	0.24/0.14	0.55/0.50
Interest (+/−)	Participant comments on a quality of a post that does/does not interest them.	2.45/0.98	2.09/1.46
Aesthetics +/−	Participant comments on the appearance of a post being appealing or unappealing.	0.31/0.08	0.91/0.27
Interest +/−	Participant notes that a post's content is/is not interesting to them.	2.14/0.90	1.83/1.46
Values Alignment +/−	Participant comments on how a post does/does not align with their personal values.	0.18/0.l8	0.43/0.62
Evaluation +/−	Participant makes a judgement about a post's content after engaging with that content.	2.37/2.29	2.51/2.81
Attitude +/−	Participant expresses positive or negative feelings towards a post.	1.84/0.84	1.98/1.86
Intention of Post	Participant expresses belief about the intentions of a post's author(s). Included in both valences of the Evaluation macro.	0.37	1.06
Length of Post +/−	Participant mentions that a post's length is/is not appropriate.	0.04/0.12	0.20/0.38
Plausibility +/−	Participant mentions that a post's claim is/is not plausible.	0.12/0.80	0.38/1.86
Judgement of Feasibility +/−	Participant mentions that following a post's recommendation or guidance is/is not feasible.	0.00/0.16	0.l0/0.42
Source Evaluation (+/−)	Participant weighs merits and qualifications of a source of a knowledge claim.	0.39/0.75	0.92/1.32
No subcode +/−	Participant evaluates a source's quality without using any specific qualifications.	0.22/0.16	0.67/0.54
Balanced +/−	The source is evaluated as credible/uncredible because it does/does not present information on both sides of the argument.	0.00/0.04	0.00/0.28
Benevolence +/−	The source is evaluated as credible /uncredible because they are/are not acting in the interest of the reader.	0/0.02	0/0.14
Design of website +/−	The source is evaluated as credible/uncredible because of the aesthetics and/or navigability of the website	0/0	0/0
Expertise +/−	The source is evaluated as credible/uncredible because they have/do not have experience, credentials knowledge, and competence in a relevant domain	0.10/0	0.30/0
Genre +/−	The source is evaluated as credible/uncredible because it is of a particular genre.	0/0.18	0/0.65
Familiarity +/−	The source is evaluated as credible/uncredible because the reader is personally familiar with the source.	0.02/0	0.14/0
Recency +/−	The source is evaluated as credible/uncredible because it was published recently.	0/0	0/0

Macro- and Microlevel Mental Process Codes	**Description**	***M***	***SD***
Popularity +/−	The source is evaluated as credible/uncredible because it is a well-known source.	0/0	0/0
Scientific evidence or research +/−	The source is evaluated as credible/uncredible because they include/do not include scientific research, evidence, or citations.	0.04/0	0.20/0
Quality +/−	The source is evaluated as credible/uncredible due to a surface-level quality feature (i.e., correct grammar, useful or clear visuals).	0/0.27	0/0.60
Other +/−	This code is a placeholder for other source evaluation criteria that may emerge in the data.	0/0.08	0/0.27
Knowledge Claim Codes(+/−)	Participant evaluates the accuracy of a claim.	1.18/2.59	1.60/2.50
Evaluating Knowledge Claim +/−	Participant verbalizes whether a claim made by a post is true or not.	0.90/1.71	1.17/1.75
Evaluating Knowledge Claim: Tentative	Participant is unsure whether a claim made by a post is true or not	0.80	1.20
Criteria for Evaluating Knowledge Claims	Standards used by participant to evaluate whether epistemic ends have been achieved. These are included in the full Knowledge Claim Codes macro.		
Coherence +/−	Participant establishes a warrant for or against a claim based upon the claim aligning with/not aligning with other claim/ claims that they believe are sufficiently warranted.	0.12/0.33	0.33/0.62
Corroboration across multiple sources +/−	Participant establishes a warrant for or against a claim based on multiple sources stating/not stating the same claim.	0/0.04	0/0.20
Personal perception +/−	Participant uses one of their five senses as warrant for a claim, or as reason to disregard a claim as knowledge.	0.02/0	0.14/0
Memory +/−	Participant establishes warrant for or against a claim based upon recalling it/not recalling it from their memory.	0.06/0.06	0.24/0.24
Testimony +/−	Participant establishes a warrant for or against a claim based upon the views/arguments/beliefs of someone that they believe is an authority on the matter.	0/0.02	0/0.14
Rationality/logic +/−	Participant establishes warrant for or against claim based upon thinking, logic, or reasoning.	0.06/0.31	0.31/0.62
Normative disciplinary methods +/−	Participant justifies a claim based on the use of reliable epistemic processes that were used to produce that claim or rejects a claim based on reliable epistemic processes not being used to produce that claim.	0.02/0.04	0.14/0.20
Religion +/−	Participant establishes the warrant for or against a claim based upon the claim of a religious source.	0/0	0/0
Other +/−	As a holding place for epistemic ideals that show up that do not fit into the above categories.	0/0.08	0/0.27
Reliable Epistemic Processes	Processes identified by participant by which knowledge and other epistemic processes are reliably produced.	0.10	0.30
Construct argument claim	When a participant constructs a claim to address the learning task/prompt.	0	0
Corroborating sources	Comparing information from two separate sources to find similar information and verify the accuracy of a claim.	0.10	0.30
Seeking an alternative position	After reading information from one source, the participant actively seeks or states that they would actively seek another information source that presents a different perspective to verify/ refute the accuracy of a knowledge claim or to build their own understanding.	0	0
Epistemic Aims	Goals that motivate participants to seek or evaluate information.	1.45	1.96
Action	Participant indicates the desire to take some action in response to a post.	0.31	0.73

Macro- and Microlevel Mental Process Codes	Description	*M*	*SD*
Intent to Amplify	Participant expresses the desire to ensure other people are exposed to a post.	0.22	0.61
Reporting	Participant expresses the desire to take some sort of negative action towards a post, such as reporting or "thumbs downing" a post.	0.10	0.41

Note: Macro-level mental process code in italics, micro-level mental process code in plain text.

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Educational Impact and Implications Statement

When people use technology like social media for entertainment, and they encounter accurate or inaccurate information, does it affect them and, if so, what can we infer about those effects from how they respond to the information? We found when people encountered information while using social media they described many different kinds of thoughts, with these thoughts often having non-intuitive relationships with people's subsequent responses such as liking or choosing to click on a link. Our findings suggest researchers, educators, and parents should be cautious when inferring why students choose, or choose not, to engage with content in a social media post, and that inoculation efforts might be enhanced by encouraging self-regulation of situational interest about the post in favor of critical thinking about its intentions and veracity.

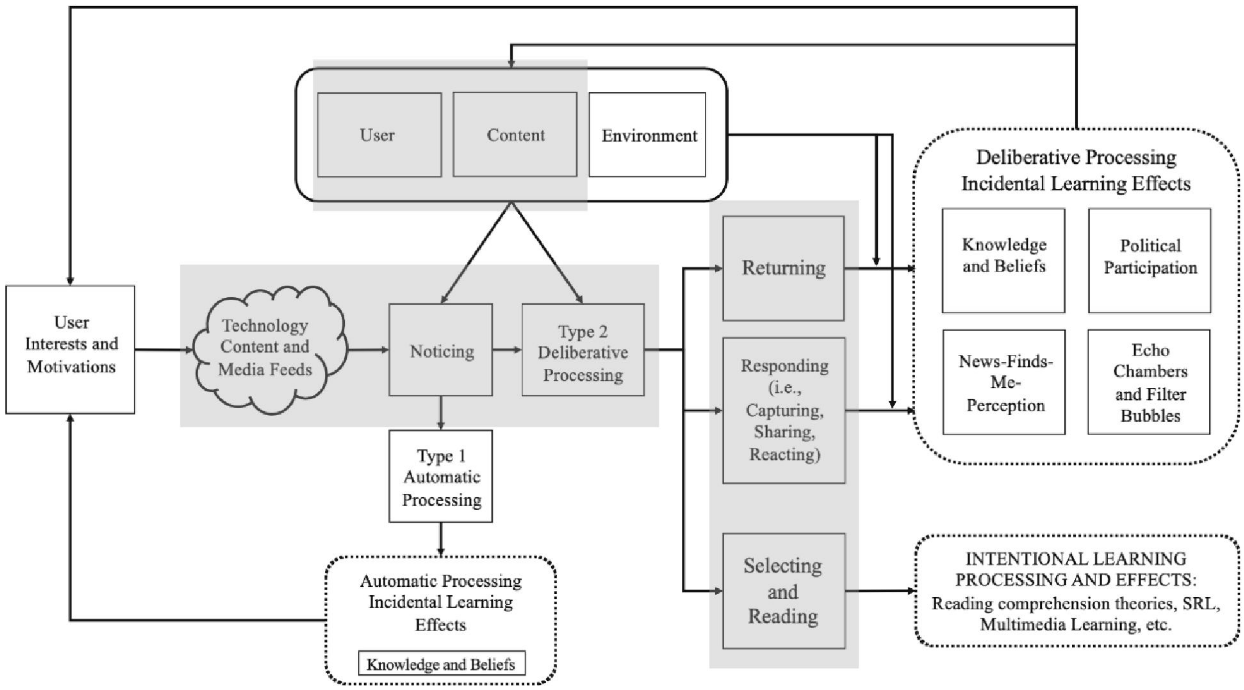

Figure 1. The Technology Incidental Learning Effects Model

Note. From “A model of technology incidental learning effects” Greene et al. (2021b), Source information anonymized for peer review. Shaded areas indicate foci for this study.

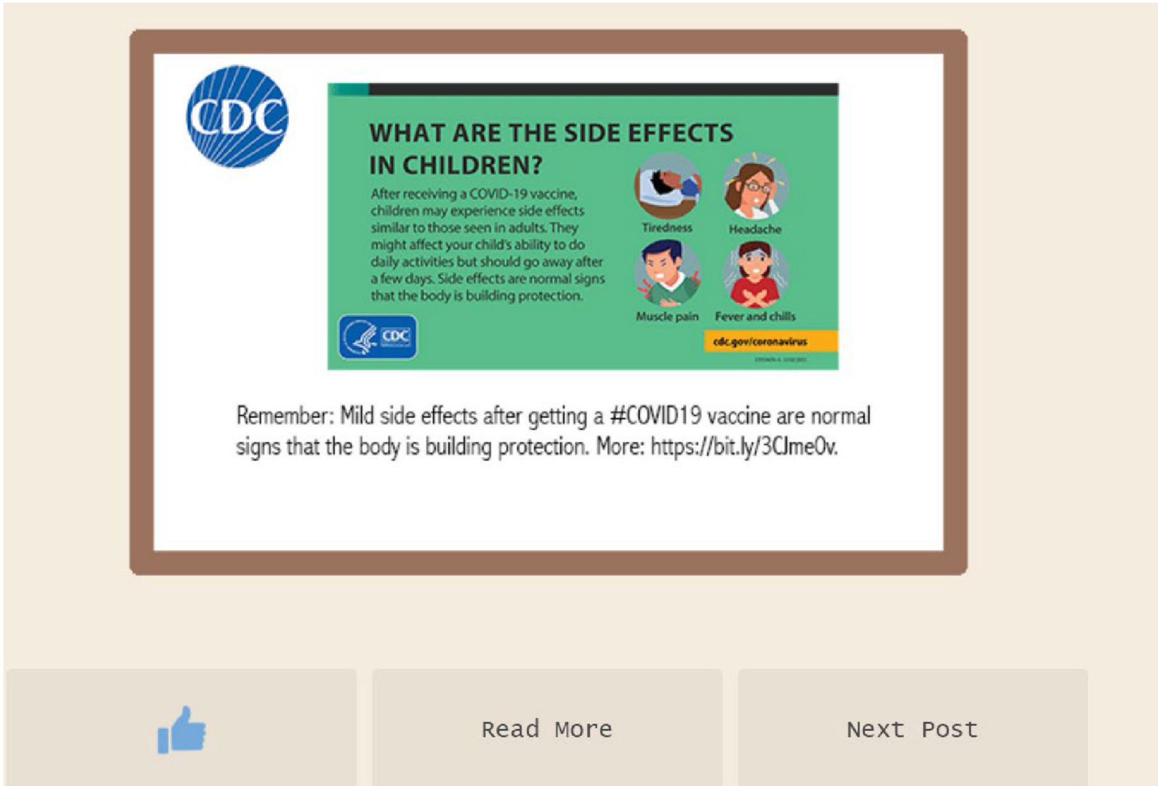

Figure 2. Screenshot of Simulated Social Media Environment Post

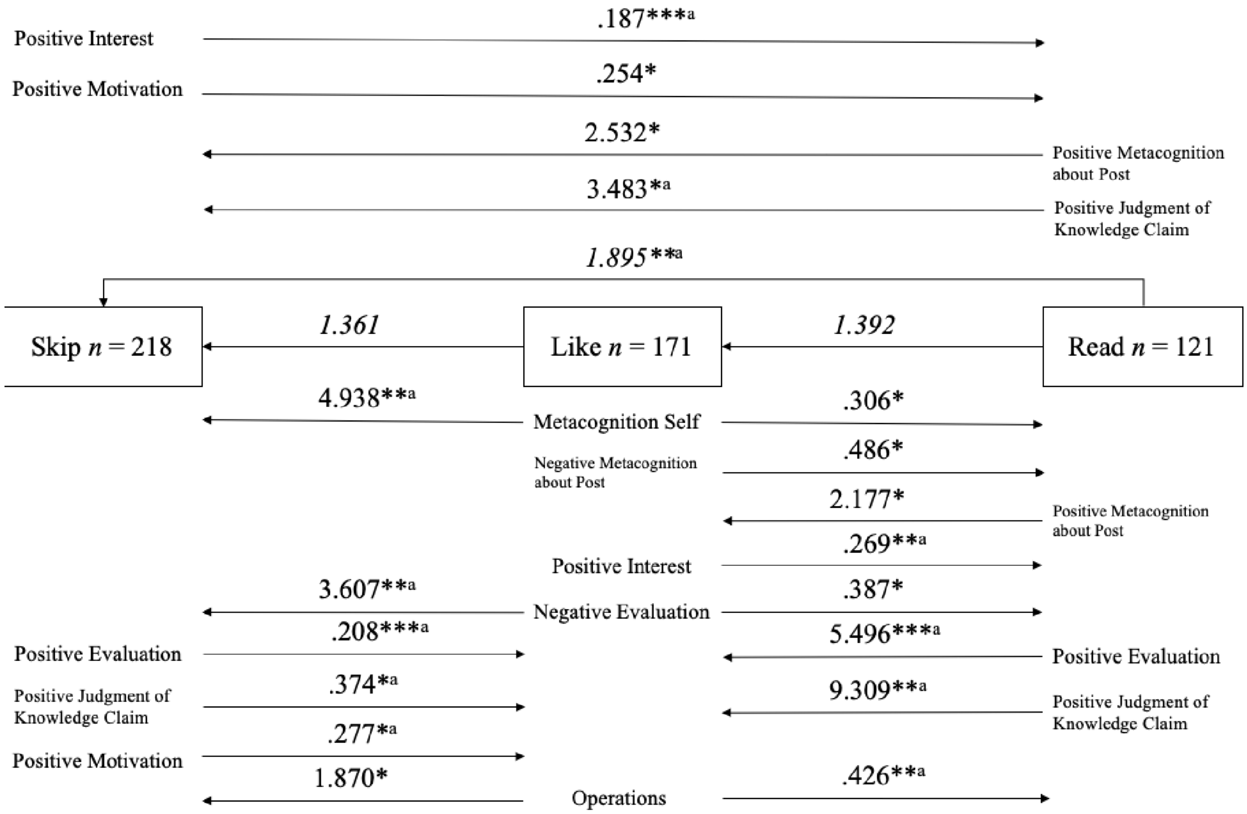

Figure 3. Multilevel Multinomial Logistic Regression Results for COVID-19 Information Posts

* $p < .05$, ** $p < .01$, *** $p < .001$, [a] statistically significant after False Discovery Rate adjustment

Note. All numeric values are odds ratios. Italicized numeric values indicate baseline odds ratios between response options, controlling for mental processing. Plain text numeric values indicate the multiplicative change in baseline odds ratio for the two behaviors connected by the accompanying arrow, with the arrow pointing toward the response option that would become more likely.

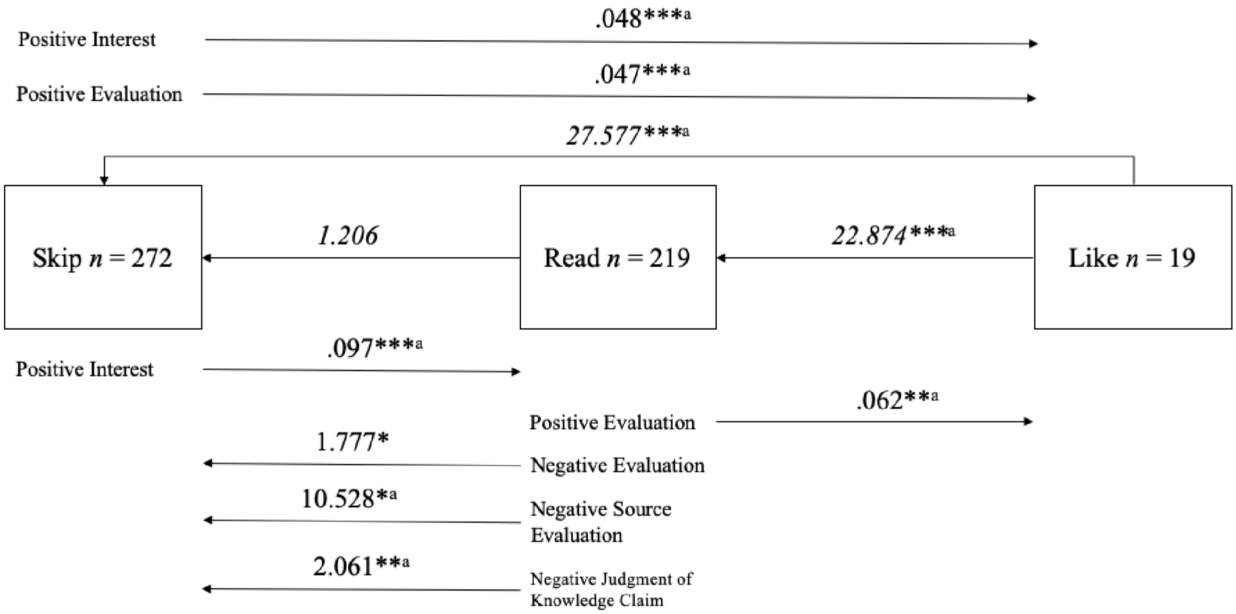

Figure 4. Multilevel Multinomial Logistic Regression Results for COVID-19 Misinformation Posts

* $p < .05$, ** $p < .01$, *** $p < .001$, [a] statistically significant after False Discovery Rate adjustment

Note: All numeric values are odds ratios. Italicized numeric values indicate baseline odds ratios between response options, controlling for mental processing. Plain text numeric values indicate the multiplicative change in baseline odds ratio for the two behaviors connected by the accompanying arrow, with the arrow pointing toward the response option that would become more likely.

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Table 1

Participant Demographic Information

Characteristic	***n***	**%**
Gender		
Male	8	16
Female	43	84
Race		
White	29	57
Black or African American	9	18
Asian	8	16
Other	2	4
Prefer to Self-Describe	1	2
Multiple Racial Identities	2	4
Ethnicity		
Not of Hispanic, Latino/a/x, or Spanish origin	43	84
Mexican, Mexican American, Chicano/a/x	4	8
Puerto Rican	1	2
Another Hispanic, Latino/a/x or Spanish origin	2	4
Multiple Ethnicities	1	2
Year In School		
1st	27	53
2nd	10	20
3rd	4	8
4 or more	10	20
Major		
Social Science	27	53
STEM	17	33
Business	5	10
Undecided	2	4

Note. $N = 51$.

Table 2

Descriptive Statistics, with Mental Processing and Behavior Response Count Variables Split By COVID-19 Information and Misinformation Posts

Variable	Overall Mean (SD)	COVID-19 Information Posts Mean (SD/Skewness/Kurtosis)	COVID-19 Misinformation Posts Mean (SD/Skewness/Kurtosis)
Prior Knowledge[a]	−.054 (.429)		
Need for Cognition[a]	−.000 (.918)		
Metacognition Self	.095 (.307)	.120 (.337/2.657/6.161)	.071 (.271/3.941/15.924)
Metacognition Other	.041 (.218)	.045 (.217/4.965/25.745)	.037 (.218/7.616/76.228)
Negative Metacognition about Post	.148 (.423)	.127 (.393/4.014/23.253)	.169 (.451/2.994/9.966)
Positive Metacognition about Post	.155 (.403)	.229 (.474/2.048/4.189)	.080 (.300/3.937/16.198)
Negative Motivation	.025 (.155)	.018 (.132/7.349/52.207)	.031 (.174/5.392/27.185)
Positive Motivation	.038 (.211)	.053 (.257/6.008/46.113)	.024 (.152/6.305/37.906)
Emotions	.051 (.283)	.027 (.206/8.161/69.652)	.075 (.341/4.806/22.762)
Negative Interest	.049 (.216)	.049 (.216/4.190/15.616)	.049 (.216/4.190/15.616)
Positive Interest	.123 (.348)	.092 (.296/3.054/8.301)	.153 (.392/2.507/5.775)
Negative Evaluation	.116 (.366)	.067 (.279/5.055/32.875)	.165 (.430/2.806/8.467)
Positive Evaluation	.119 (.361)	.169 (.424/2.672/7.830)	.069 (.275/4.240/18.961)
Action	.016 (.124)	.018 (.132/7.349/52.207)	.014 (.116/8.384/68.553)
Negative Source Evaluation	.037 (.195)	.004 (.063/15.921/252.484)	.071 (.264/3.681/13.056)
Positive Source Evaluation	.020 (.146)	.037 (.200/5.626/33.813)	.002 (.044/22.583/510.000)
Negative Judgment of Knowledge Claim	.129 (.385)	.006 (.077/12.961/166.647)	.253 (.510/1.997/3.690)
Positive Judgment of Knowledge Claim	.059 (.274)	.114 (.375/3.937/18.868)	.004 (.063/15.921/252.484)
Unvalenced Judgement of Knowledge Claim	.040 (.206)	.008 (.108/15.314/252.711)	.073 (.267/3.612/12.490)
Epistemic Aim	.073 (.271)	.057 (.240/4.259/18.280)	.088 (.297/3.353/10.973)
Operations	.228 (.554)	.265 (.623/3.081/12.077)	.129 (.450/2.440/6.257)
Response		**Count for COVID-19 Information Posts**	**Count for COVID-19 Misinformation Posts**
Like		171	19
Read		121	219
Skip		218	272

Note: Standard error of skewness was .108, standard error of kurtosis was .216.

[a]Prior knowledge and Need for Cognition scores were saved from confirmatory factor analyses, thus their means were approximately zero.

Table 3

Mean Comparisons of Mental Processing Frequency on COVID-19 Information and Misinformation Posts

Mental Processing Variable	Distribution of Variable	Intercept	Regression Coefficient Unstandardized Estimate (Standard Error)	Regression Coefficient Standardized Estimate
Metacognition Self	Normal	.071***	.049(.018)**	.080
Metacognition Other	Normal	.037*	.008(.016)	.018
Negative Metacognition about Post	Negative-Binomial	−1.780***	−.280(.227)	−.140
Positive Metacognition about Post	Poisson	−2.521***	1.049(.257)***	.524
Negative Motivation	Normal	.031**	−.014(.009)	−.044
Positive Motivation	Normal	.024**	.029(.014)*	.070
Emotions	Normal	.075***	−.047(.019)*	−.083
Negative Interest	Normal	.049***	.000(.014)	.000
Positive Interest	Normal	.0153***	−.061(.028)*	−.087
Negative Evaluation	Poisson	−1.804***	−.904(.234)***	−.452
Positive Evaluation	Negative-Binomial	−2.679***	.899(.276)**	.449
Action	Normal	.014*	.004(.009)	.016
Negative Source Evaluation	Normal	.071***	−.067(.016)***	−.171
Positive Source Evaluation	Normal	.002	.0356(.013)**	.121
Negative Knowledge Claim	Poisson	−1.375***	−3.761(.546)***	−1.881
Positive Knowledge Claim	Normal	.004	.110(.022)***	.201
Knowledge Claim Unvalenced	Normal	.073***	−.065(.017)***	−.157
Epistemic Aim	Normal	.088***	−.031(.021)	−.058
Operations	Negative Binomial	−1.595***	.007(.003)*	.156

* $p < .05$

** $p < .01$

*** $p < .001$

Note. Binary predictor variable coded as 0 = COVID-19 misinformation, 1 = COVID-19 information

Table 4

Correlations Among Prior Knowledge, Need for Cognition, and Mental Processes, Split By COVID-19 Information / Misinformation

	COVID-19 Information		COVID-19 Misinformation	
Mental Process	**Prior Knowledge**	**Need for Cognition**	**Prior Knowledge**	**Need for Cognition**
Metacognition Self	.078	.060	.012	.084
Metacognition Other	.058	−.031	.056	.042
Negative Metacognition about Post	.036	−.061	.036	.061
Positive Metacognition about Post	.051	−.024	.091	.070
Negative Motivation	−.009	.323	.204	.253*
Positive Motivation	.238	.064	.010	.078
Emotions	.062	.099	.048	−.031
Negative Interest	.048	.078	−.192*	.063
Positive Interest	.026	.025	−.061	.006
Negative Evaluation	.034	.049	.109*	.017
Positive Evaluation	.139	−.018	.040	.138*
Action	.498***	.004	.462	.260
Negative Source Evaluation	.044	.021	.027	−.032
Positive Source Evaluation	.044	−.004	.065	−.011
Negative Judgment of Knowledge Claim	.051	−.065	.221*	−.022
Positive Judgment of Knowledge Claim	.085	−.027	.021	.072
Unvalenced Judgement of Knowledge Claim	.045	−.048	.072	.042
Epistemic Aim	.045	−.019	.049	.021
Operations	.134	.067	.156*	.067

* $p < .05$

** $p < .01$

*** $p < .001$

Note: All correlations calculated with adjustment to standard errors for clustering, accounting for participant-level status of prior knowledge and need for cognition.

Table 5

Multilevel, Multinomial Logistic Regression for COVID-19 Information Posts

Level	Response Comparison	Mental Processing Variable	Logit (*SE*)	Odds Ratio
Within	Like versus Read	Metacognition Self	−1.184(.589) *	0.306
		Metacognition Other	.792(.739)	2.208
		Negative Metacognition about Post	−.721(.363) *	0.486
		Positive Metacognition about Post	.778(.372) *	2.177
		Positive Motivation	−.088(.471)	1.092
		Positive Interest	−1.313(.418) **a	0.269
		Negative Evaluation	−.950(.439) *	0.387
		Positive Evaluation	1.704(.387) ***a	5.496
		Positive Source Evaluation	−.773(.744)	0.462
		Negative Judgment of Knowledge Claim	−1.075(1.402)	0.341
		Positive Judgment of Knowledge Claim	2.231(.638) ***a	9.309
		Operations	−.854(.296) **a	0.426
	Skip versus Read	Metacognition Self	.413(.383)	1.511
		Metacognition Other	.944(.678)	2.570
		Negative Metacognition about Post	−.529(.296)	0.589
		Positive Metacognition about Post	.929(.380) *	2.532
		Positive Motivation	−1.371(.587) *	0.254
		Positive Interest	−1.678(.473) ***a	0.187
		Negative Evaluation	.333(.488)	1.395
		Positive Evaluation	.134(.526)	1.143
		Positive Source Evaluation	−.821(.646)	0.440
		Negative Judgment of Knowledge Claim	−1.214(1.375)	0.297
		Positive Judgment of Knowledge Claim	1.248(.502) *a	3.483
		Operations	−.228(.185)	0.796
	Skip versus Like	Metacognition Self	1.597(.585) **a	4.938
		Metacognition Other	.152(.609)	1.164
		Negative Metacognition about Post	.192(.312)	1.212
		Positive Metacognition about Post	−.151(.363)	0.860
		Positive Motivation	−1.283(.506) *a	0.277
		Positive Interest	.365(.576)	1.441
		Negative Evaluation	1.283(.469) **a	3.607
		Positive Evaluation	1.571(.393) ***a	0.208
		Positive Source Evaluation	−.047(.798)	0.954
		Negative Judgment of Knowledge Claim	−.139(.852)	0.870
		Positive Judgment of Knowledge Claim	−.984(.378) **a	0.374
		Operations	.626(.269) *	1.870

Level	Response Comparison	Mental Processing Variable	Logit (*SE*)	Odds Ratio
Between				
	Like versus Read Mean		.331(.227)	1.392
	Skip versus Read Mean		.639(.229) **a	1.895
	Skip versus Like Mean		.308(.225)	1.361

* $p < .05$

** $p < .01$

*** $p < .001$

[a] statistically significant after False Discovery Rate adjustment

Note: For COVID-19 information posts, the following macro-level variables could not be included as predictors due to errors in model estimation likely due to low variance in the predictor: Motivation Negative, Emotions, Interest Negative, Action, Source Evaluation Negative, Knowledge Claim Unvalenced, Epistemic Aims

Table 6

Multilevel, Multinomial Logistic Regression for COVID-19 Misinformation Posts

Level	Response Comparison	Mental Processing Variable	Logit (*SE*)	Odds Ratio
Within	Read versus Like	Metacognition Self	−1.253(.946)	0.286
		Metacognition Other	−1.136(1.279)	0.321
		Negative Metacognition about Post	2.082(1.886)	8.020
		Emotions	2.359(1.335)	10.580
		Positive Interest	−.712(.644)	0.491
		Negative Evaluation	1.159(1.359)	3.187
		Positive Evaluation	−2.779(.548) ***a	0.062
		Negative Source Evaluation	−1.655(1.631)	0.191
		Negative Judgment of Knowledge Claim	−.118(1.027)	0.889
		Unvalenced Judgment of Knowledge Claim	.538(1.036)	1.713
		Operations	−.283(.620)	0.754
	Skip versus Read	Metacognition Self	1.366(.886)	3.920
		Metacognition Other	−.316(.509)	0.729
		Negative Metacognition about Post	−.001(.221)	0.999
		Emotions	−.240(.335)	0.787
		Positive Interest	−2.332(.503) ***a	0.097
		Negative Evaluation	.575(.265) *	1.777
		Positive Evaluation	−.280(.416)	0.756
		Negative Source Evaluation	2.354(.774) **a	10.528
		Negative Judgment of Knowledge Claim	.723(.250) **a	2.061
		Unvalenced Judgment of Knowledge Claim	−.735(.431)	0.480
		Operations	−.133(.266)	0.875
	Skip versus Like	Metacognition Self	.114(1.130)	1.121
		Metacognition Other	−1.452(1.206)	0.234
		Negative Metacognition about Post	2.080(1.849)	8.004
		Emotions	2.118(1.428)	8.314
		Positive Interest	−3.044(.788) ***a	0.048
		Negative Evaluation	1.733(1.361)	5.658
		Positive Evaluation	−3.059(.617) ***a	0.047
		Negative Source Evaluation	.699(1.527)	2.012
		Negative Judgment of Knowledge Claim	.606(1.029)	1.833
		Unvalenced Judgment of Knowledge Claim	−.198(1.211)	0.820
		Operations	−.417(.605)	0.659
Between				
	Read versus Like Mean		3.130(.571) ***a	22.874
	Skip versus Read Mean		.187(.203)	1.206
	Skip versus Like Mean		3.317(.600) ***a	27.577

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* $p < .05$

** $p < .01$

*** $p < .001$

[a] statistically significant after False Discovery Rate adjustment

Note: For COVID-19 misinformation posts, the following macro-level variables could not be included as predictors due to errors in model estimation likely due to low variance in the predictor: Metacognition about Others, Metacognition about the Post Positive, Motivation Negative, Motivation Positive, Interest Negative, Action, Source Evaluation Positive, Knowledge Claim Positive.