Who Does Not Benefit from Fact-checking Websites?

A Psychological Characteristic Predicts the Selective Avoidance of Clicking Uncongenial Facts

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ABSTRACT

Fact-checking messages are shared or ignored subjectively. Users tend to seek like-minded information and ignore information that conflicts with their preexisting beliefs, leaving like-minded misinformation uncontrolled on the Internet. To understand the factors that distract fact-checking engagement, we investigated the psychological characteristics associated with users' selective avoidance of clicking uncongenial facts. In a pre-registered experiment, we measured participants' ($N = 506$) preexisting beliefs about COVID-19-related news stimuli. We then examined whether they clicked on fact-checking links to false news that they believed to be accurate. We proposed an index that divided participants into fact-avoidance and fact-exposure groups using a mathematical baseline. The results indicated that 43% of participants selectively avoided clicking on uncongenial facts, keeping 93% of their false beliefs intact. Reflexiveness is the psychological characteristic that predicts selective avoidance. We discuss susceptibility to click bias that prevents users from utilizing fact-checking websites and the implications for future design.

CCS CONCEPTS

• **Human-centered computing**; • **Human computer interaction (HCI)**; • **Empirical studies in HCI**;

KEYWORDS

Fact-checking, Misinformation, Click bias, Psychological factor

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1 INTRODUCTION

Misinformation is a significant concern in emergency situations such as pandemics because it can adversely affect human behavior [5, 20, 35, 50]. Misinformation differs from dis-information: Misinformation is defined as false information, which is shared with no intention to harm, whereas dis-information is false information shared to cause harm [73]. People tend to share misinformation because they believe it to be true [51]. Correcting people's false beliefs, for example, through fact-checking initiatives, is one way to debunk misinformation, including algorithmic and legislative solutions [70]. An advantage of visiting fact-checking websites is that they aggregate false information and share corresponding corrections. Porter and Wood [61] demonstrated that fact-checking was effective in mitigating misinformation and that its effects lasted more than two weeks in multiple countries. Fact-checking procedure entails extracting claims, assessing the accuracy of these claims, and providing results to users [9]. Since the 1990s, several fact-checking websites have emerged in the U.S.; these include factcheck.org, Snopes.com, and politifact.com. Approximately 350 fact-checking websites are now active worldwide [14]. During the recent COVID-19 pandemic, fact-checkers from more than 70 countries entered an international alliance to fight against misinformation [10]. For example, one website was established to debunk misinformation and provide FAQs and the latest stories about the COVID-19 pandemic [1]. Despite the increasing availability of fact-checking websites, users still face challenges.

The question that arises is how users can benefit from fact-checking websites. Numerous studies in the social sciences field have repeatedly demonstrated that people seek like-minded information and ignore or discount information that conflicts with their preexisting beliefs [22, 25, 28, 29, 32, 67]. This information-seeking tendency, called *selective exposure*, potentially prompts fact-checking website visitors to click on only a few fact-checking stories with which they are already familiar, simply to confirm their preexisting beliefs, while neglecting other stories that are contrary to their beliefs. This psychological bias could detract significantly from the benefits of fact-checking websites. In reality, during the 2012 U.S. presidential election, social media users shared congenial fact-checking messages while discounting fact-checking messages that opposed their own partisanship [63]. Even if fact-checking websites can cover a wide range of misinformation by automating some parts of their process through recent advances in technology

[33, 72] and objectively explaining how false each piece of misinformation is, fact-checking messages can be shared or ignored subjectively, thereby allowing some false beliefs to pass through despite the corrections.

There is a growing need for human-computer interaction (HCI) research that furthers our understanding of human factors and design technology to support users' deliberative decision-making [6, 60]. As misinformation spreads online, often exploiting both users' psychological vulnerabilities and the usability of communication technologies, harnessing misinformation is an interdisciplinary challenge [46, 47]. A key question in HCI in terms of mitigating misinformation is how to design interfaces that help users engage in better information processing, rather than simply displaying information [12]. In line with this consideration, one pressing need for a fact-checking technological environment is to develop designs that encourage users to check facts that are uncongenial to their preexisting beliefs and to think critically about false beliefs. Considering the rapidly increasing availability of fact-checking websites, HCI research that aims to improve interface design, based on the empirical study of user understanding, could contribute to debunking misinformation.

Ideally, fact-checking websites should incorporate designs that support users' effortful cognitive processing because uncongenial information, which tends to induce selective exposure, requires more cognitive effort to process than like-minded information [44]. To develop such a design, we are interested in understanding users who are vulnerable to this type of cognitive processing. If we can empirically determine what prevents users from benefiting from fact-checking websites and how they behave when using them, this understanding will bring us one step closer to developing designs that reduce cognitive vulnerability. Eventually, these steps will lead to an increase in the minimum level of users' fact-checking engagement and increase the utility of fact-checking websites.

The process users undergo from when they visit a fact-checking website to when they make decisions can be divided into at least three phases: clicking a link to open a story page, reading a fact-checking story and examining a preexisting belief related to the facts presented, and making decisions about whether to reject or keep the belief. Different design interventions depend on the user's focused processes in each phase. This study focuses on the first phase of clicking links because it is an essential step leading to the subsequent phases. In particular, we consider users clicking on links related to facts that contradict their preexisting false beliefs rather than on links related to congenial facts, and on selective avoidance rather than selective exposure. These focuses are discussed in detail in the following section. This study examined the following research questions:

***RQ1*:** Do some users selectively avoid clicking fact-checking messages when they are uncongenial to their preexisting beliefs?

***RQ2*:** Do the psychological characteristics of users that are related to their effortful thinking style predict selective avoidance of clicking facts that are uncongenial to their preexisting beliefs?

After the literature review, we present hypotheses that describe our predictions regarding these research questions, and report on the human-participant online experiment we conducted to examine these hypotheses. This study's major contributions are as follows: (i) To understand fact-checking engagement more precisely, we propose a new index that specifically measures selective avoidance separately from selective exposure; (ii) through a human-participant online experiment, we examine the psychological characteristics that predict the selective avoidance of clicking on links related to uncongenial facts; and finally, (iii) based on empirical evidence, we discuss who does not benefit from fact-checking websites and how to incorporate user understanding into future designs that facilitate these users to click on links that reveal uncongenial facts in order to check the veracity of their preexisting false beliefs.

2 RELATED WORK

Several biases exist on the Internet, including both algorithmic bias and users' selection bias. Click bias, which is one type of selection bias, refers to the tendency for users to click on what they easily see but not to click what they do not [2]. While HCI research has focused on the effects of the position and ranking of stimuli presented online on click behavior [13, 18, 34], there is a lack of research on how the psychological characteristic of avoiding uncongenial information can affect click behavior. In this section, by reviewing the extant literature, we explain the importance of understanding users' information-avoiding tendencies in the context of fact-checking engagement.

2.1 Selective Exposure and Avoidance

Past research on selective exposure has demonstrated that people tend to seek like-minded information and avoid information that conflicts with their preexisting beliefs [22, 25]. However, one question that has not yet been fully answered is whether selective avoidance is the flip side of selective exposure [67]. Garrett [28, 29] demonstrated an asymmetric relationship between these two phenomena. Emphasizing the importance of distinguishing between these phenomena, Garett claimed that selective avoidance of conflicting information can have more harmful consequences in deliberation than selective exposure [29]. In the fact-checking context, selective avoidance is important because it is an avoidance of facts that can correct users' false beliefs: Users' false beliefs will not be updated if they avoid uncongenial facts, potentially leading to like-minded misinformation being perpetuated on the Internet. Therefore, the present study focuses on selective avoidance rather than selective exposure. Notably, there is greater emphasis on understanding individuals who tend to selectively avoid uncongenial facts and supporting these users from the HCI perspective.

Despite previous studies indicating that these two are two asymmetric phenomena, the available methods to measure them separately are inadequate. Hence, we propose an index to measure selective avoidance separately from selective exposure in this study, as discussed in detail in the Methods section. Furthermore, since previous studies in this field have focused heavily on political topics [28–30, 38, 44, 75], in which avoidance of uncongenial information does not necessarily mean retaining false beliefs, it is unclear to what extent we can predict users' fact avoidance based on these studies. Thus, it is necessary to examine whether the selective avoidance phenomenon is observed in the fact-checking context.

Fact-checking websites that share corrections of misinformation represent a debunking strategy. Lewandowsky et al. [48] summarized recommendations for making debunking more effective based on abundant empirical findings; for example, they suggested that refraining from correcting misinformation for fear of a backfire effect is unnecessary. They also provided a guideline for an effective format for correction messages, including starting and ending such messages by stating a fact. One empirical study, upon which their recommendations were based, examined the design of fact-checks and demonstrated that the effect of a short format that corrected misinformation only by using a "false" label was lower after one week than a long-format that refuted misinformation by explaining why it is false in addition to using a "false" label [16]. However, as Ecker et al. [16] pointed out, the short-format is most commonly used by fact-checking websites. For visibility and space saving, it might be necessary to adopt the short format on the landing page of fact-checking websites in order to display a list of misinformation. Accordingly, this layout entails a strategy to facilitate users to proceed from short-format to long-format fact-checks. Nevertheless, the kind of obstacles present are yet to be clarified.

Past research on selective avoidance indicates that this strategy is complex. If users tend to avoid uncongenial facts, they might stop at the point where they can only see a list of headlines with labels. To access full stories in a long format, users must click on a link. This raises the following questions: Do users decide to avoid clicking links even before the facts are displayed? Moreover, do they selectively avoid only links that *will* display uncongenial facts among many links labeled "false"? These questions pertain to whether users foresee congeniality/uncongeniality only through a list of labeled headlines. Answering these questions can help us understand the effect of the current interface design adopted by several fact-checking websites on updating false beliefs. In this study, we investigate these questions based on the cognitive process when engaging in fact-checking.

2.2 Cognitive Model for Processing Misinformation

When misinformation spreads rapidly and broadly, people need to evaluate which information is likely to be true and decide whether to accept or reject it. In an emergent situation such as a pandemic, in particular, it is not uncommon for initial information to later turn out to be false. Consequently, people need to examine and update their beliefs. Based on dual-process theories, we can assume that two cognitive processes are involved when people engage in misinformation processing. Dual-process theories have been developed in psychology to explain how the human mind works, distinguishing two types of cognitive processes named System 1 and System 2: System 1 refers to intuitive, effortless, fast, automatic, unconscious, and evolutionarily old processing, whereas System 2 refers to reflective (deliberative), effortful, slow, controlled, conscious, and evolutionarily recent processing [21, 23, 43, 64]. Recent research on misinformation has adopted these two types of cognitive processes to explain why people accept and spread misinformation without a deliberative process, and how the negative impact of communication technology on users' beliefs can be moderated by such a deliberative process [3, 17, 58, 59, 66, 68].

A recent discussion in HCI concerns how technologies promote users' deliberative thinking, calling for technological solutions to alleviate the negative impact of misinformation [12]. One idea for such technological solutions is a design that facilitates users' *conflict detection.* Past research in cognitive psychology has assumed that conflict detection is key to triggering deliberative thinking [54, 57] and facilitating the updating of preexisting beliefs [15, 42]. Conflict detection involves a phase in which conflicting information is displayed; in the fact-checking context, this corresponds to the phase in which a user is already reading a fact-checking story. Thus, while reading the story, a user detects conflict between the story and their beliefs. For convenience, we call this "*active* conflict detection." On fact-checking websites, there is another phase in which the user can detect conflicts: the "click link" phase. If a user believed a headline to be accurate, and the headline was labeled "false," it would be easy for them to detect a conflict between a fact-checking story and what they believe. As this type of conflict detection is not actively performed by users but something that they are forced to detect by the fact-checking interface design, we call it "*passive* conflict detection." The fact-checking design that lists headlines with "false" labels can tell users, "Hey, there is a conflict between the fact-checking results and what you believe. Click this link to see the conflict in detail." While this click link phase is essential to move users forward to the next reading-story phase, there is a lack of research that has explained whether passive conflict detection facilitates click behavior toward updating preexisting beliefs in the same way as active conflict detection does. However, passive conflict detection may have a different influence from active conflict detection; that is, passive conflict detection may trigger off the avoidance of the opportunity of deliberative thinking.

Furthermore, previous research on misinformation has demonstrated the relationship between the perception of misinformation and individual differences in effortful thinking styles [3, 59]. Especially in relation to correcting false preexisting beliefs, individuals who were not good at effortful thinking, for example, analytical thinking and open-minded thinking, did not utilize correction to update false beliefs [41, 52]. These findings raise the following questions: Are these individual differences also associated with progressing from the phase of clicking links toward reading the fact-checking story? Moreover, are there individual differences in the responses to passive conflict detection? For example, are some users facilitated to click uncongenial fact-related links when they detect conflict based on the headline and its label while other users are not? Addressing these questions can help us understand who does not benefit from the current design of fact-checking websites and why. This study investigates the possibility that users with a less effortful thinking style avoid clicking links that will display uncongenial fact-checking stories because it requires effortful thinking, which they are not good at.

3 HYPOTHESES

This study aimed to predict fact-checking engagement based on users' psychological characteristics, specifically focusing on psychological tendencies toward an effortful thinking style. This thinking style was measured using the Bullshit Receptivity Scale (BSR) [55], Generic Conspiracist Belief Scale (GCB) [7], Actively Open-Minded Thinking Scale (AOT) [65], Need for Cognition Scale (NFC) [8], and Cognitive Reflection Test (CRT) [24, 69]. Prior research has demonstrated that these scales measured the human properties of

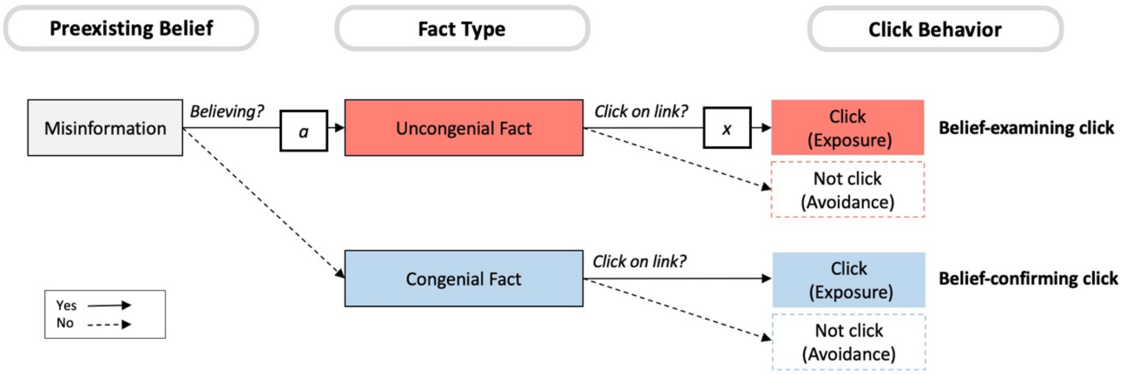


Figure 1: The relationship between preexisting beliefs, fact type, and click behavior. See Equations 1 and 2 for a and x: a is the number of false messages (misinformation) that a participant believes to be true and x represents the targeted click behavior of a participants, which is the observed number of links clicked that display facts that are uncongenial to the user's preexisting false beliefs.

misinformation: the BSR and the CRT were negatively and positively correlated with the perceived accuracy of misinformation, respectively [59]; the GCB was a predictor of conspiratorial beliefs about COVID-19 [31]; and the AOT predicted the acceptance of corrections [52]. We also employed the NFC, a scale that measures the preference for cognitively challenging activities [8], to evaluate users' effortful thinking style. We expected that users' effortful thinking style would also contribute to seeking for fact-checking information, as well as processing misinformation and correction. Thus, this study investigated the following hypotheses:

H1: Individuals who are more receptive to *bullshit* are less likely to engage in fact-checking.

H2: The tendency to engage in conspiracy theories makes individuals less likely to engage in fact-checking.

H3: Open-mindedness makes individuals more likely to engage in fact-checking.

H4: The need for cognition makes individuals more likely to engage in fact-checking.

H5: Analytic thinking makes individuals more likely to engage in fact-checking.

To describe the fact-checking engagement mentioned in these hypotheses more clearly, we divide click behavior associated with fact-checking engagement into two types. Figure 1 represents the relationship between preexisting beliefs, fact type, and click behavior. For users who visit fact-checking websites that display a list of links to fact-checking stories, two types of click behavior prevail: (1) When users believe the misinformation, corresponding facts are uncongenial for them. If they click on links related to the uncongenial facts, the click will lead them to update their false beliefs (belief-updating click). (2) When users do not believe in misinformation, corresponding facts are congenial for them. If they click on links related to congenial facts, the click will lead them to confirm their beliefs (belief-confirming click). As discussed earlier, this study focuses on belief-updating clicks, rather than belief-confirming clicks. In particular, we place greater importance on understanding the avoidance of belief-updating clicks. We propose an index to measure the avoidance of belief-updating clicks in the Methods section. In addition to examining these hypotheses, we conducted an explanatory investigation to determine whether verbal intelligence and experiences of COVID-19 were potential moderators of the hypothesized relationships.

4 METHODS

4.1 Open Practices and Ethical Statement

This study corresponds to a pre-registered plan (AsPredicted File #98968; aspredicted.org/qw54m.pdf). The Institutional Review Board of Nagoya Institute of Technology exempted our research protocol. To avoid overloading participants, we conducted the experiment over two sessions. Informed consent was collected from each participant in every session. No personal information was obtained from the participants; they were debriefed and provided with monetary compensation after completing of each session.

4.2 Experimental Design

We used a within-subjects experimental design to predict the selective avoidance of clicking uncongenial facts based on psychological characteristics measured using the five scales. Participants' preexisting beliefs were also measured to determine which stimuli were uncongenial. The details of the stimuli, scales, and the measurement of click behavior are described in sections 4.4 and 4.5.

4.3 Participants

The sample size and data exclusion criteria were set prior to the experiment (see aspredicted.org/qw54m.pdf). The participants were aged from 20–69 years old (evenly distributed by gender and ages) and were recruited from Cross Marketing, Inc. Panels. In Session 1, among the 2,767 participants who provided informed consent, 1,738 participants were excluded because they (a) did not complete a series of questions; (b) spent less than 3 min or more than 45 min; (c) did not pass all the attention check questions; or (d) selected an excessive amount (> 27 of 30 items) of answers in the same position on the BSR. The remaining 1,029 participants received an invitation to participate in Session 2. Among the 702 participants

Table 1: Examples of the stimuli A fact message corresponds to a false message by correcting falseness. Filler messages are independent from false and fact messages. When a participant believed a false message to be accurate, the corresponding fact message was categorized as an uncongenial fact for the participant.

Stimuli	Text
False message	Owing to the COVID-19 pandemic, foreigners have abused Japanese health insurance. The cause of this was the Cabinet's decision made by the Democratic Party of Japan in 2010 to strengthen medical tourism.
Fact message	It is true that medical tourism has been strengthened under the Democratic Party of Japan, but the "medical visa" treatment that was introduced in 2011 is not covered by the national health insurance system and is fully self-paid. Therefore, it is incorrect to say that "it causes foreigners to abuse Japanese health insurance."
Filler message	Analysis by the National Center for Global Health and Medical Research has confirmed a relationship between the risk of becoming more severely infected with the new coronavirus and smoking history. The risk of becoming severely ill requiring a ventilator or oxygenator (ECMO) was 1.5 times higher in men who had smoked and 1.9 times higher in women who had smoked than in those who had never smoked.

who gave informed consent in the second session, 196 participants were excluded as they believed no false message to be accurate, in addition to criteria (a)–(c), thus leaving 506 participants (250 women, $M_{\text{age}} = 45.1$, $SD_{\text{age}} = 13.6$). Of the participants, 54% held a bachelor's degree or higher. Participants received approximately 25 Japanese yen in Session 1 and 100 Japanese yen in Session 2 as compensation.

4.4 Materials

4.4.1 Stimuli. Following the procedures used to select and operationally define "true/false" stimuli messages in previous studies [48, 53, 56], we collected fact-checking stories related to COVID-19 from third-party fact-checkers (mainichi.jp, buzzfeed.com, and infact.press). We then extracted 44 false claims and 44 fact messages that corrected the corresponding false claims from the stories. Each claim and its correction were summarized in a short message. Additionally, 26 real news stories related to COVID-19 were collected from a major news website (nhk.co.jp) and summarized into short messages as filler stimuli. We conducted a preliminary online survey to select the optimal stimuli that would not induce polarized responses. For each of the 114 messages, we asked a different set of participants (n =180, 84 women, $M_{\text{age}} = 51.9$, $SD_{\text{age}} = 10.6$) the following two questions, displaying one message at a time in a random order: "Have you ever heard about this news story?" (Yes/No); and "How accurate do you think this news story is?" (1: *not at all accurate*; 7: *very accurate*). Twenty-four false messages were evaluated as suboptimal because only a few participants had heard about the story (< 10%), indicating that most participants did not have preexisting beliefs, that most participants did or did not think the claim was accurate (skewness of the distribution of perceived accuracy > .05, or < -0.5), or both. Three filler messages were also evaluated as suboptimal because most participants did or did not think the story was accurate (skewness of the distribution of perceived accuracy > .05, or < -0.5), leaving 20 false messages, their corresponding 20 fact messages, and 23 filler messages as stimuli for the experiment. The approximate length of each message was 130 Japanese characters (SD = 36.9).

Table 1 shows examples of the stimuli used in the experiment (see the full set of stimuli in the Supplementary Material). Participants were asked the following two questions for each message: "Have you ever heard about this news story?" (Yes/No) (Familiarity); and "How accurate do you think this news story is?" (1: *not at all accurate*; 6: *very accurate*) (preexisting belief). Responses for false messages were scored as 1 when options 4, 5, or 6 were chosen and 0 when options 1, 2, or 3 were chosen.

4.4.2 Scales. The BSR, GCB, AOT, NFC, and CRT were used to measure individual differences in psychological characteristics of an effortful thinking style. In addition, we measured verbal intelligence as a potential moderator using a subscale of the Wechsler Adult Intelligent Scale (WAIS).

The BSR, developed by Pennycook et al. [55], comprises 10 pseudo-profound bullshit sentences that included random patches of abstract buzzwords (e.g., hidden meaning transforms unparalleled abstract beauty). Following the procedure of Pennycook et al. [55], bullshit sentences were presented randomly mixed with 10 prototypically profound sentences and 10 mundane sentences. Participants rated the items on a 5-point Likert scale (1 = *not at all profound*; 5 = *very profound*). The GCB obtained from Brotherton et al. [7] consisted of 15 items (e.g., the spread of certain viruses and/or diseases is the result of the deliberate, concealed efforts of some organizations). Participants rated the items on a 5-point Likert scale (1 = *definitely not true*; 5 = *definitely true*). A total of 10 items from the flexible thinking scale of the AOT developed by Stanovich and West [65] were used. Participants rated the items (e.g., a person should always consider new possibilities) using a 6-point Likert scale (1 = *strongly disagree*, 6 = *strongly agree*). The NFC was originally developed by Cacioppo and Petty [8] and later shortened by Kouyama and Fujihara [45], consisting of 15 items (e.g., I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought). Participants rated the items on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). The item order of the BSR, GCB, AOT, and NFC was randomized within each scale. The CRT was originally developed by Frederick [24] to evaluate analytical cognitive style using three items (e.g., A bat and a ball cost $1.10 in total. The bat costs one dollar more than the ball. How much does the ball cost? [Correct answer: 5 cents; intuitive answer: 10 cents]). We adapted a 7-item CRT, including an additional four items from Toplak et al. [69]. To measure verbal intelligence, we used the vocabulary part of the Verbal Comprehension Index subscale of the WAIS-IV [74]. Participants were asked to choose the most appropriate meaning for each of the 20 words (e.g., breakfast and evolution) from among the five options that were shown in random order.

4.4.3 Demographics and Experiences of COVID-19. Demographic questions included age, gender, and educational background. Participants' experiences of COVID-19 were also assessed using the following four items: (1) have you ever tested positive for COVID-19? (Yes/No); (2) has someone in your family, relatives, or friends ever tested positive for COVID-19? (Yes/No); (3) have you been vaccinated against COVID-19? (Yes, more than twice/Yes, once/No, but I intend to be vaccinated/No, and I do not intend to be vaccinated); (4) Which media sources have you primarily used to obtain COVID-19 related information in the past two years (select all that apply)? (TV/newspaper articles/weekly magazines/Internet news sites/other internet sites/social media/Ministry of Health, Labor, and Welfare website/CDC website/friends and family/other).

4.5 Measurement of Click Behavior

As abovementioned, understanding click bias has been a significant concern in the HCI research [2, 13, 18, 34]. Consequently, several methods have been developed to measure click behaviors in relation to preexisting beliefs [26, 27, 62]. For example, Gao et al. [26] developed an index to measure click behavior by dividing the proportion of targeted click behavior by the total number of click behaviors. Another method uses the proportion of targeted click behavior divided by the total number of displayed links [62]. Although these methods contribute to understanding users' click behavior, there were some problems in adopting these methods in the current study.

First, these methods focus on what users clicked on and not on what they avoided. Assume an example case in which a user clicked on some uncongenial links (e.g., two links), but also avoided clicking on other uncongenial links (e.g., eight links). How can we determine whether this user has selective exposure or selective avoidance tendency? Figure 2 shows several example cases of click behavior among 20 links (each link is represented as a block). When observing only what was clicked, Users A and B are identical: Both users clicked three congenial links and one uncongenial link. However, when observing what was not clicked, they are different. User A avoided clicking nine uncongenial links, whereas User B avoided only one uncongenial link. This is because of the different preexisting beliefs among the users. Even if the same set of links is given, a fact-related link is congenial for some users and uncongenial for others. Not counting what was avoided could lead to a distorted understanding of the users. In addition, User C clicked twice as many as User B. Paying attention only to the number of clicked uncongenial links, User C will be overrated as having a higher fact-exposure tendency than User B, although User C avoided more uncongenial facts than User B in terms of proportion. To understand click behavior more precisely, we need to count what is avoided as well as clicked. Specifically, we need a criterion to distinguish selective avoidance from selective exposure by considering several parameters that vary among users.

The second problem concerns measurement validity. The methods using simple proportions of targeted click behavior divided by the total number of click behaviors [26, 27] or the total number of displayed links [62] return values that exhibit limited patterns, as each parameter is usually one or at most two-digit integers in an experiment. More seriously, regardless of the denominator values, these indices always return to zero when the targeted click behavior does not occur (e.g., Users D and E in Figure 2). This potentially causes a *floor effect* in which a large proportion of participants perform extremely poorly [49], making it impossible to differentiate individual differences in click behavior.

These problems emphasize the need to develop a different method to measure click behavior specific to a fact-checking environment. In this study, we propose a new index that satisfies the following properties: (1) it focuses on the avoidance of facts that are uncongenial to false preexisting beliefs (i.e., the avoidance of belief-updating clicks); (2) it operationally defines selective avoidance and selective exposure by using a mathematical baseline that distinguishes users who have fact-avoidance tendency from those who have fact-exposure tendency; and (3) it differentiates individual differences in belief-updating click behavior using parameters that vary considerably among users in fact-checking engagement, thereby preventing a floor effect.

To measure the selective avoidance of belief-updating clicks specifically, we developed a new index that we called the Fact Avoidance/Exposure Index (FAEI). The FAEI is calculated using the following formula, where x represents the targeted click behavior of a participant, which is the observed number of clicked links that display facts that are uncongenial to their preexisting false beliefs, and EV represents the expected value for the number of uncongenial facts that can be clicked if any links were randomly clicked under a specific condition:

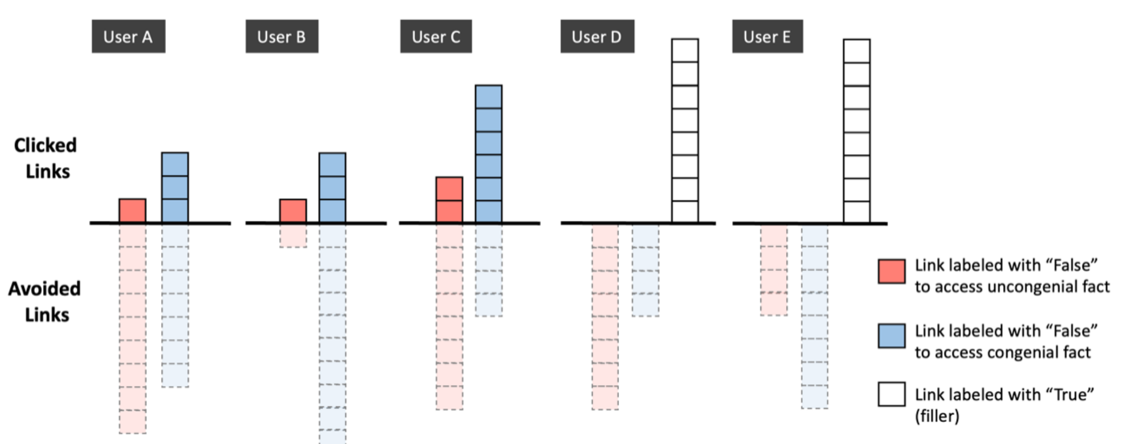
$$FAEI = x - EV \tag{1}$$

EV is calculated using the following formula, where n is the total number of links shown, a is the number of false messages that the participant believes to be true, and b is the total number of links clicked by the participant.

$$EV = \sum_{i=0}^{k} \frac{C(a, i) \times C(n-a, b-i)}{C(n, b)} \times i \tag{2}$$

Here, i represents the possible number of uncongenial facts clicked when the participant randomly clicks any links b times. It goes from 0 to k. k takes on the smaller number of a or b because the number of uncongenial facts clicked cannot be larger than the smaller of a or b. The FEAI is calculated per participant as the parameters x, a, b, and EV vary among participants. The FAEI value becomes negative when a participant is less engaged in checking uncongenial facts than expected (fact avoidance), whereas it becomes positive when a participant is more engaged in checking uncongenial facts than expected (fact exposure).

The FAEI has several advantages in examining click behavior. First, this index measures fact avoidance separately from fact exposure using EV as a baseline. Based on the value of the index, we can divide participants into two groups: one that tends to avoid uncongenial facts (fact-avoidance group) and another that tends to click on uncongenial facts (fact-exposure group). This index is essential in extracting individuals who have fact-avoidance tendency among all individuals. Our focus is on the fact-avoidance group.



Indices	User A	User B	User C	User D	User E
FAEI	-1.0	0.6	-2.0	-3.2	-1.6
x/n	0.05	0.05	0.1	0.0	0.0
x/b	0.25	0.25	0.25	NA	NA

* see Equations 1 and 2 for FAEI, x, n, and b.

Figure 2: Example cases of clicking and avoiding behaviors for 20 links. Users A–C) Each block represents a link that displays either an uncongenial or congenial fact. Among the 20 links per user, the blocks above the horizontal line represent clicked links, whereas those below the line represent links that the users avoided clicking on. Users A and B appear to have identical click behavior, despite the difference in their avoiding behaviors. Based solely on click behavior, User C clicked on twice as many uncongenial facts as User B, even though User C avoided more uncongenial facts than User B in terms of proportion. The table on the bottom right shows the scores of the users' tendencies to click on uncongenial facts (x) measured by the three different indices used in this study. n and b represent the total number of links shown and the total number of links clicked, respectively. See Equations 1 and 2 for the FAEI. Although x/n [62] and x/b [26] do not distinguish between Users A and B, or any other users, the FAEI differentiates these users compared with the mathematical baseline, indicating that Users A and C have a fact-avoidance tendency, whereas User B has a fact-exposure tendency. Users D–E) The 20 links include filler links. Although Users D and C are identical in terms of the number of links clicked and the patterns of links they avoided, the FAEI distinguishes between them by returning a larger negative value for Users D than User C. User E is identical to User D, except for the patterns of the links they avoided. The FAEI differentiates between these two users, returning a smaller negative value for Users E than User D. The index x/n returns the lowest possible value of 0 for both Users D and E, regardless of how many uncongenial facts they avoided. The index x/b is not applicable to these cases because both parameters are 0.

As random clicking can include some clicks on links to uncongenial facts, observing only belief-updating clicks (x) does not tell us whether the number is higher or lower than the chance level. The exposure tendency of some users, who generally tend to click links much more than others, might be overrated (e.g., User C in the comparison with Users A and B in Figure 2). As a countermeasure to this issue, the FAEI compares x with a baseline, EV, and then estimates the selective tendency of each participant. This allowed us to identify the participant group that engaged less in belief-updating click behavior than expected. Second, the FAEI differentiates individual differences in belief-updating click behavior by entering important parameters (i.e., x, a, and b in Equations 1 and 2) that vary considerably among individuals. Existing methods that used simple proportions of their targeted click behavior divided by the total number of displayed links (x/n) [62] or the total number of click behaviors (x/b) [26, 27] potentially cause a floor effect. In contrast, FAEI differentiates participants who have no or the same number of targeted clicks by returning different values in accordance with the combination of other parameters (e.g., Users D and E in Figure 2). Third, the FAEI appropriately addresses the following case: Some participants click all the links (i.e., $x = a$ and $n = b$). Clicking on everything is not selective, and analyzing unselective clicking combined with selective clicking leads to data distortion. In this case, the FAEI returns to zero and enables us to exclude the value from the analysis.

It is important to note that the FAEI is not a diagnostic assessment for use at the individual level because the smaller the difference between x and EV, the less meaningful each value might be. Thus, we define the FAEI as an index that measures targeted click behavior at the group level by distinguishing the fact-avoidance group from the fact-exposure group using EV as a cut-off value.

Although the values of the FAEI are returned in the form of continuous quantities, the meaning of quantitative values changes starting from 0, which is equal to EV. Although users' effortful thinking style might predict both negative and positive quantities, there is also a possibility that it might predict only one of them: Users with a less effortful thinking style might avoid uncongenial facts as much as possible, resulting in higher negative scores. Meanwhile, users with a more effortful thinking style might not click as much as possible. Instead, they might try to read a few fact-checking stories deliberately, limiting the possibility to receive more positive scores. Furthermore, people's tendency to click approximately 25% of all links [13, 62] might also limit the quantity of click behavior by the fact-exposure group. Therefore, we predicted belief-updating click behavior by psychological characteristics for the fact-avoidance and the fact-exposure groups separately.

4.6 Procedure

The participants accessed the experiment through the internet using a computer, smartphone, or tablet. The experiment was conducted from June 9–17, 2022, over two sessions with an interval of three days to avoid overloading the participants. In each session, participants were instructed to answer all the questions within 45 min.

4.6.1 Session 1: Administering the Scales. The participants answered demographic questions. After providing informed consent, they proceeded to the questionnaire phase that presented the BSR, COVID-19 experience questions, NFC, CRT, AOT, WAIS, and GCB one by one. Three attention check questions were inserted into the NFC, AOT, and GCB, with one in each questionnaire. Participants who satisfied the data exclusion criteria mentioned in section 4.2 received the invitation link for Session 2.

4.6.2 Session 2: Measuring Preexisting Beliefs and Click Behavior. Session 2 consisted of two phases. In Phase 1, after providing informed consent, participants were given the following instruction: "We will display one message at a time, taken from websites on the internet. Please read each message carefully." They then answered the following two questions about each of the 20 false messages and 23 filler messages: (1) have you heard this information? (Yes/No); (2) how accurate do you think this information is? (1: *Not at all*, 6: *Highly accurate*). The messages were displayed one at a time in a random order, including an attention check question.

In Phase 2, participants were instructed as follows: "The fact-checking the messages that we have shown so far can be divided into correct information and misinformation. You can read an explanation of each correct and misinformation piece by clicking on the links. Click on at least five links that interest you. Note that a button to proceed to the next page will appear after 3 min." They then proceeded to the next page, which displayed a list of 43 links in random order (Figure 3a). A link displayed the first 40 characters of each message presented in Phase 1. Each link was labeled with either "false" for the false messages or "true" for the filler messages. By clicking the link labeled with "misinformation," a corresponding fact message was shown below the misinformation (Figure 3b). Conversely, a filler message was shown that read, "There is no indication that this information is false" if the participant clicked the links labeled "true" (Figure 3c). Clicking the "return to the list" button brought the participants back to the list page.

After completing the minimum requirements (i.e., 3 min, five clicks) in Phase 2, the participants were allowed to proceed to the next page at their own pace. Finally, they were debriefed about the main purpose of the experiment and provided with all the false messages again with a warning.

5 RESULTS

5.1 Descriptive Statistics

Of the 20 false messages, participants believed 7.07 messages (SD = 4.72) to be accurate on average. In Phase 2 of Session 2, participants clicked the links 10.92 times (SD = 5.63), spending 4.1 min on the task (SD = 4.5). On average, 9.69 (SD = 4.40) of the 43 links were clicked at least once. Of the 20 fact-related links, the number of links clicked was 5.14 (SD = 3.08) including 1.97 links (SD = 1.98) related to uncongenial fact messages and 3.17 links (SD = 2.60) related to congenial fact messages. Regarding experiences of COVID-19, 2% of the participants had tested positive, 25% had someone in their family, relatives, or friends who had tested positive, and 85% had been vaccinated at least once. The participants had used 3.01 (SD = 1.56) different information sources to obtain information related to COVID-19 over the previous two years. Furthermore, 54% had graduate or undergraduate degrees.

5.1.1 Evaluating the Effectiveness of the FAEI.. Based on the data collected in Session 2, the FAEI was calculated for each participant. To examine whether the FAEI was an appropriate index for differentiating click behavior among many participants, we compared its measurement properties with those of other measurements used in previous studies [26, 62]. A considerably large proportion (more than 15%) of the participants obtaining the worst (best) possible score in any of the measurements would indicate that the distribution of scores was skewed, which would make it impossible to discriminate between individual differences at the lower (higher) level. This is known as the floor (ceiling) effect [49].

Figure 4 shows the relationships between the FAEI evaluation values versus that of previous measurements. Overall, the FAEI values were positively correlated with both previous measurements (x/n: $r = .77$, $p < .001$, x/b: $r = .53$, $p < .001$). However, these indices differed in terms of the degree of capturing individual differences in click behavior. Table 2 shows the top five highest frequencies of values and cumulative percentages for the same sample ($n = 506$) from the three measurements. In both previous measurements (x/n, x/b), the highest frequency value was the lowest possible score, and it dominated by 26.3% and 23.6%, indicating a floor effect in each. In addition, each measurement constringed approximately 50% of the participants into only two or four patterns of values. In contrast, the highest proportion of the FAEI was 1.6%, which is much lower than the criteria for floor and ceiling effects. When we measured the sample using the FAEI, the values had 268 patterns, whereas the previous measurements (x/n and x/b) had 12 and 40 patterns, respectively.

Based on the FAEI values, we grouped the participants as follows: one of the 506 participants scored zero on the FAEI because that person clicked all the links unselectively; and the individual was, thus, removed from the following grouping and analyses; the other 505 participants were divided into either the fact-avoidance group (FAEI < 0; $n = 217$) or the fact-exposure group (FAEI > 0; $n = 288$). The following complementary analyses were conducted with more

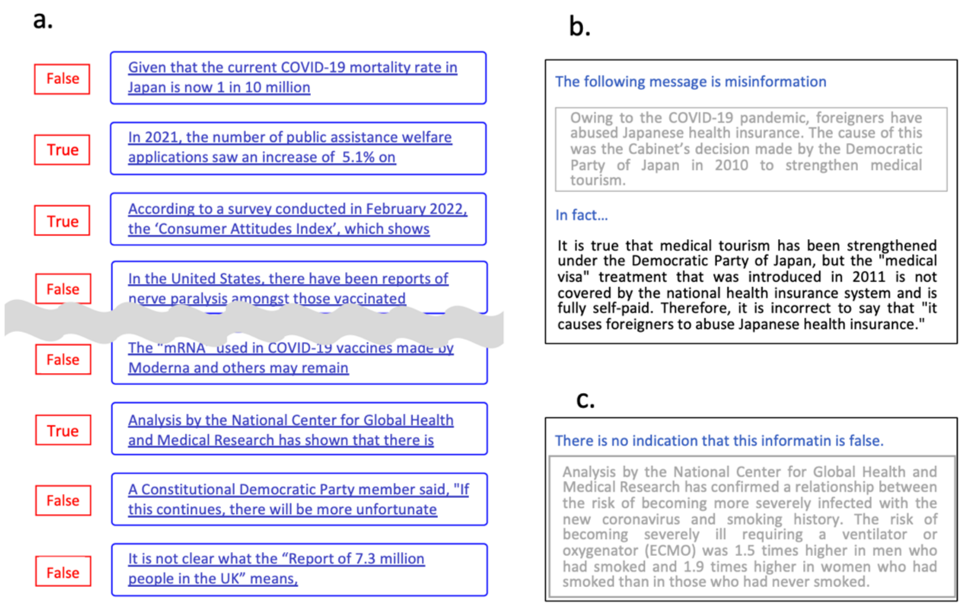


Figure 3: Interfaces for measuring click behavior (Phase 2 in Session 2, see Appendix for the original Japanese version). a) The main page displaying the list of the 43 links in random order. On the right, a link displayed the first 40 characters of each message presented in Phase 1. On the left, each link is labeled "false" for false messages or "true" for filler messages. b) A fact-checking story page that was displayed after clicking on a corresponding link labeled "false," in which the false message, "The following message is misinformation," was displayed first, followed by a corresponding fact message "In fact. . ." (see Table 1 for translations of the false and fact messages). c) A page that was displayed after clicking on a corresponding link labeled "true," with the filler message "There is no indication that this information is false" (see Table 1 for the translation of the filler message).

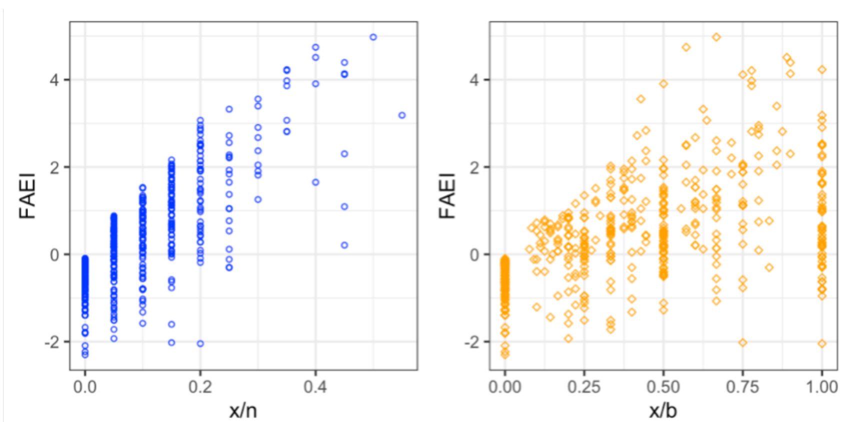


Figure 4: Relationships between the FAEI values versus the two previous measurements, x/n [62] (left panel) and x/b [26] (right panel).

stringent grouping criteria, avoiding the near zero scores (-0.25~0.25 and -0.5~0.5) with the same patterns of results.

5.1.2 Scoring. Cronbach's alpha was used to assess the internal reliability of the scales for psychological characteristics [11]. The BSR, GCB, and NFC were reliable (α = .86, .92, and .90, respectively); however, the AOT exhibited low reliability (α = .34). As measures of psychological characteristics, an average rating score among the 10 items of the BSR and the total rating scores among the items of the GCB, AOT, NFC, and WAIS were used. Descriptive statistics of the FAEI values and scales measuring the psychological characteristics of the two groups are presented in Table 3. The correlations among

Table 2: Top five highest frequencies of values and the cumulative percentages by the FAEI versus previous measurements In both the previous measurements, x/n [62] and x/b [26], the highest frequency value was the lowest possible score, and it dominated by 26.3% or 23.6%, respectively, indicating a floor effect. In contrast, the highest proportion of the FAEI was 1.6%, which is less than the criteria for floor and ceiling effects.

	FAEI			x/n			x/b		
	Value	Frequency	Cumulative (%)	Value	Frequency	Cumulative (%)	Value	Frequency	Cumulative (%)
1	0.55	8	1.6	0.00	133	26.3	0.00	115	23.6
2	-0.49	7	3.0	0.05	125	51.0	0.50	60	35.9
3	-0.19	7	4.3	0.10	79	66.6	1.00	52	46.5
4	-0.05	7	5.7	0.15	77	81.8	0.33	34	53.5
5	-0.56	6	6.9	0.20	46	90.9	0.25	30	59.6
	Total	506			506			488*	

* 18 participants who clicked only filler links were excluded because this resulted in a denominator of zero, making it impossible to return a value.

Table 3: Means and standard deviations for psychological scales

Group	BSR	GCB	AOT	NFC	CRT	WAIS
Fact Avoidance (FAEI < 0, n = 217)	2.95 (0.69)	39.6 (10.8)	39.4 (4.26)	61.2 (14.6)	3.49 (2.02)	24.1 (4.72)
Fact Exposure (FAEI > 0, n = 288)	3.00 (0.72)	40.1 (11.3)	39.4 (4.07)	60.8 (14.4)	3.45 (2.14)	24.8 (4.60)

* One participant who scored zero on the FAEI was excluded from the grouping.

Table 4: Pearson's r correlations among the psychological scales

	BSR	GCB	AOT	NFC	CRT	WAIS
Bullshit receptivity (BSR)	–					
Generic Conspiracist Belief (GCB)	0.11*	–				
Actively Open-Minded Thinking (AOT)	-0.09	-0.26***	–			
Need for Cognition (NFC)	0.05	-0.10*	0.26***	–		
Cognitive Reflection Test (CRT)	-0.13**	-0.20***	0.25***	0.22***	-	
Wechsler Adult Intelligence Scale (WAIS)	-0.14**	-0.16***	0.10*	0.13**	0.28***	–

Note. N = 506. ***p < .001; **p < .01; *p < .05.

the five scales are presented in Table 4. Experiences of COVID-19 were also scored to put into the regression model: In questions (1) and (2), we coded them into 1 (Yes) or 0 (No); the responses to question (3) were dichotomized into 1 (Yes, more than twice/Yes, once) or 0 (No, but I intend to be vaccinated/No, and I do not intend to be vaccinated); and in question (4), the number of media sources each participant selected was used.

5.2 Predicting the FAEI by Psychological Characteristics

We predicted that individuals who are receptive to *bullshit* are less likely to engage in belief-updating clicks (*H1*). We also predicted that the tendency to engage in conspiracy theories makes individuals less likely to engage in belief-updating clicks (*H2*). Meanwhile, we posited that open-mindedness (*H3*), the need for cognition (*H4*), and analytic thinking (*H5*) make individuals more likely to engage in belief-updating clicks. To examine these hypotheses, the FAEI was used as the dependent variable in the following regression models. The explanatory expectation suggested that users' verbal intelligence and experiences of COVID-19 were potential moderators. However, contrary to explanatory expectations, the results of the simple regression analyses of the WAIS scores revealed that it was not significantly associated with the FAEI in either of the two groups (ps > .10). Similarly, none of the four questions about experiences of COVID-19 was significantly associated with the FAEI in either of the two groups (p = .095 for question 1 in the fact-avoidance group, ps > .10 for the others). Consequently, the WAIS scores and experiences of COVID-19 were not included in the following regression analyses as moderators. To examine the hypotheses, we conducted a simple regression analysis to predict the FAEI for each group separately by entering the BSR [50], GCB

Table 5: Simple regression coefficients of bullshit receptivity on fact avoidance and fact exposure groups

	Model (Fact-Avoidance Group, n = 217)					Model (Fact-Exposure Group, n = 288)				
	B	SE	t	p	95% CI	B	SE	t	p	95% CI
BSR	-0.110	0.047	-2.315	0.022*	[-0.203, -0.016]	-0.132	0.083	-1.584	0.114	[-0.295, 0.032]
F	5.359					2.511				
R^2	0.024					0.009				

Note. BSR: bullshit receptivity; CI: confidence interval. $^{*}p < .05$.

[7], AOT [61], NFC [8], and CRT [23, 65] scores, corresponding to *H1–H5*, respectively.

Simple regression analysis revealed that the BSR was a significant predictor of FAEI in the fact-avoidance group, R^2 = .024, $F(1, 215)$ = 5.359, p < .05, 95% CI [-0.203, -0.016], supporting *H1*. In contrast, BSR did not significantly predict FAEI in the fact-exposure group, R^2 = .009, $F(1, 288)$ = 2.511, p =.114, 95% CI [-0.295, 0.032]. Table 5 presents the coefficient estimates, standard errors, and t values. A simple regression analysis of GCB scores revealed that they were related to the FAEI in the fact-avoidance group, but the association was not statistically significant, R^2 = .001, F(1, 215 = 2.983, p =.086, 95% CI [-0.011, 0.001]. GCB scores did not significantly predict fact-exposure behaviorR^2 = .003, $F(1, 288)$ = 0.926, p =.337, 95% CI [-0.005, 0.015], which did not support *H2*. NFC, AOT, and CRT scores did not significantly predict either fact-avoidance or fact-exposure behaviors (all ps > .10), thus not supporting *H3–H5*.

As a complementary analysis for comparisons of the FAEI with the two measurements of click behavior (x/n, x/b), we conducted the same regression analysis of BSR scores to determine whether this psychological characteristic predicted the targeted click behaviors calculated using each measurement. Neither of the measurements extracted the relationship between the BSR and targeted click behaviors (ps > .10). As an additional complementary analysis, we conducted a one-way analysis of variance (ANOVA) using groups as independent variables. The results revealed no significant difference in BSR scores between the fact-avoidance group (M = 2.95, SD = 0.69) and the fact-exposure group (M = 3.00, SD = 0.72).

5.3 Click Behaviors on Uncongenial Facts

In addition to pre-registered analyses, we examined whether the fact-avoidance group avoided clicking on only links related to uncongenial facts or any links labeled as "false." As the number of links related to uncongenial and congenial facts differed among the participants, it was not appropriate to compare the number of links clicked. We calculated the percentage of uncongenial facts, congenial facts, and filler links clicked per participant (corresponding to belief-updating clicks, belief-confirming clicks, and unrelated clicks, respectively). The responses of three participants in the fact-avoidance group and two participants in the fact-exposure group, who believed all 20 false messages to be accurate, were excluded from the analyses because the proportions could not be calculated when the number of congenial facts was zero.

Using the type of stimulus (uncongenial fact/congenial fact/filler) as an independent variable, a one-way ANOVA was performed to compare the proportions of links clicked in the fact-avoidance group. The results revealed a significant difference in the proportion of links clicked among the three stimulus types, $F(2,426)$ = 134.0, p < .001, η^2 = .25. Post hoc pairwise comparisons revealed that uncongenial facts were clicked less (M = 0.07, SD = 0.10) than congenial facts (M = 0.232, SD = 0.17, p < .001) and fillers (M = 0.232, SD = 0.12, p < .001). There was no significant difference between the congenial facts and fillers (p = .99) (Figure 5, middle panel). For the fact-exposure group, the result of the one-way ANOVA also revealed that the main effect of stimulus type was significant, $F(2,570)$ = 178.6, p < .001, η^2 = .26; however, post hoc pairwise comparisons revealed different patterns: Uncongenial facts were clicked more (M = 0.42, SD = 0.21) than congenial facts (M = 0.26, SD = 0.19, p < .001) and fillers (M = 0.17, SD = 0.12, p < .001). Congenial facts were clicked more than fillers (p < .001) (Figure 5, left panel).

When we conducted a one-way ANOVA for all participants without FAEI grouping, the main effect of stimulus type was significant, $F(2,998)$ = 22.42, p < .001, η^2 = .03. However, post hoc pairwise comparisons revealed a similar pattern to the fact-exposure group, but not to the fact-avoidance group: uncongenial facts were clicked (M = 0.27, SD = 0.25) more than congenial facts (M = 0.25, SD = 0.19, p = .03) and fillers (M = 0.17, SD = 0.12, p < .001). Congenial facts were clicked more than fillers (p < .001) (Figure 5, right panel).

6 DISCUSSION

This study investigated whether users' psychological characteristics predicted their selective avoidance of clicking facts. We proposed a new index, the FAEI, to measure belief-updating click behavior. Regarding *RQ1*, our results indicated that 43% of the participants avoided clicking uncongenial facts with their preexisting beliefs. Regarding *RQ2*, a psychological characteristic predicted selective avoidance of facts. In this section, we discuss who does not benefit from fact-checking websites and how to incorporate user understanding into future designs that encourage such users to click on uncongenial facts.

6.1 Selective Avoidance of Clicking Uncongenial Facts

The results revealed that the fact-avoidance group clicked only 7% of the facts that were uncongenial to their preexisting false beliefs. This finding indicates that they were unlikely to benefit from fact-checking websites because they missed most opportunities to update their false beliefs. Did they do this selectively or did they avoid any links labeled "false"? The answer to this question uncovers what they used to avoid clicking facts. If the former question were true, the results would show the difference in two types of clicks: belief-updating clicks that opens links to uncongenial facts and

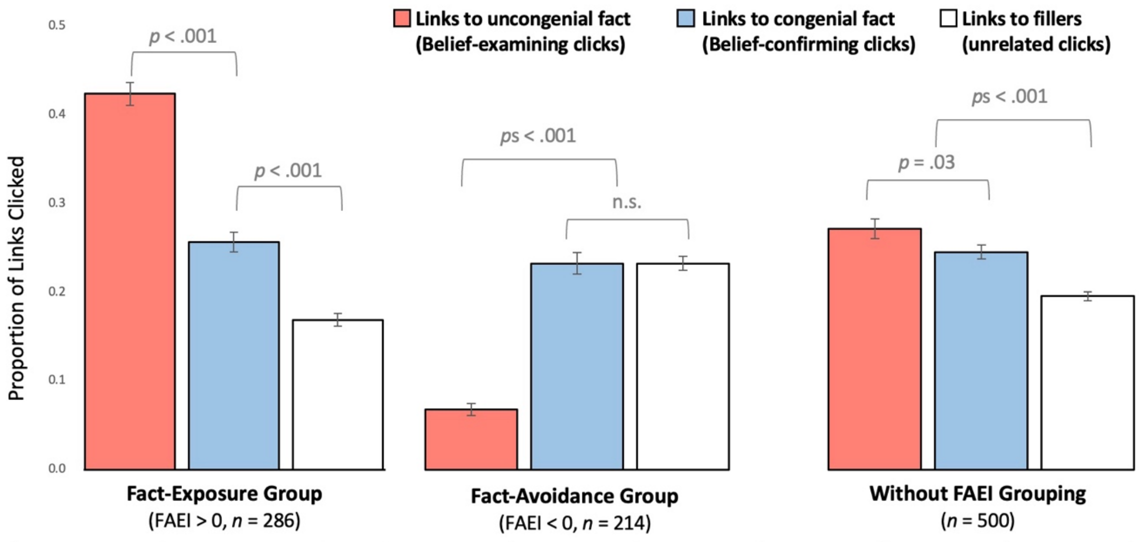


Figure 5: Proportions of uncongenial facts, congenial facts, and filler-related links clicked. Left and middle panels) In comparisons of stimulus types (uncongenial fact/congenial fact/filler), the fact-exposure group clicked on uncongenial facts the most, whereas the fact-avoidance group clicked on uncongenial facts the least. The fact-avoidance group clicked on congenial facts as much as fillers, selectively avoiding only uncongenial facts. Right panel) Without categorizing the participants according to the FAEI, the distinctive features of the fact-avoidance group were hidden. The error bars indicate standard errors. Five participants who believed all false messages to be accurate were excluded from these analyses because the proportion could not be calculated when the number of congenial facts was zero.

belief-confirming clicks that opens links to congenial facts. If the latter question were true, this group would avoid any fact-related links, regardless of their inconsistency with their beliefs. Our results support the former, demonstrating that the fact-avoidance group clicked 23% of the congenial facts, which was significantly larger than the 7% of the uncongenial facts that they clicked (Figure 5, middle panel). Moreover, the clicked proportion of congenial facts labeled "false" was as high as that of filler messages labeled "true." Taken together, these results indicate that the fact-avoidance group selectively avoided uncongenial facts, not according to the label "false" itself, but rather according to the conflicting relationship between the label and their preexisting beliefs. In other words, the fact-avoidance group tended to selectively avoid links that implied "Hey, what you believe is false."

Meanwhile, the fact-exposed group exhibited the opposite pattern of clicking uncongenial facts; they clicked uncongenial facts the most, accounting for 42%, whereas the congenial facts they clicked accounted for 26%. Owing to the grouping associated with the clicking of uncongenial facts, it is unsurprising that the fact-exposure group clicked on uncongenial facts more than the fact-avoidance group. However, in the comparisons of uncongenial facts with congenial facts, our results demonstrated that two different types of user groups had opposite selectivity in belief-updating clicks in comparison to belief-confirming clicks. These results indicate the individual differences in the effect of the current predominant fact-checking interface design that facilitates passive conflict detection by displaying a list of headlines with "true/false" labels: This design is effective for the fact-exposure group in moving forward to the next reading-story phase whereas it is ineffective for the fact-avoidance group, thereby triggering their avoidance of uncongenial facts.

6.2 Who Avoided Clicking Uncongenial Facts and Why?

To understand users who avoid clicking on uncongenial facts, we examined the psychological characteristics that predict selective avoidance. The psychological characteristics were measured using five scales, the BSR [55], GCB [7], AOT [65], NFC [8], and CRT [24, 69], which were associated with an effortful thinking style.

The results revealed that the BSR predicted selective avoidance, supporting hypothesis *H1*, which posited that participants who misperceived bullshit sentences as profound avoided clicking uncongenial facts more than expected. Demonstrating that bullshit receptivity was positively correlated with perceptions of fake news accuracy, Pennycook and Rand [59] assumed that the BSR measured the tendency to accept claims uncritically, which is known as *reflexive* open-mindedness. Contrastingly, *reflective* open-mindedness is a deliberative tendency to critically examine one's own intuitions [55]. Our results were consistent with previous studies, indicating that participants who had high reflexive open-mindedness to bullshit tended to close their minds against links that potentially display uncongenial facts that challenge their preexisting beliefs. This may be referred to as *reflexive close-mindedness.*

Notably, a psychological characteristic related to an effortful thinking style predicted behavior in the click phase, which occurs before phase in which a user reads a fact-checking story. Although previous research has demonstrated that an effortful thinking style is associated with the phase of reading corrections [41, 52], our results indicated that it has a double impact on fact-checking engagement in the current predominant web design, consisting of two phases: 1) the click phase (the focus of this study) and 2) the reading phase.

However, the BSR did not predict the fact-exposure group, with a 95% confidence interval slightly straddling zero. This may be due to the characteristics of general click behavior. On average, the participants clicked approximately 25% of all links, which was similar to the results of previous research [13, 62]. This suggests that the volume of click behavior generally reaches an upper limit around this proportion, thereby limiting the higher-level layer in the fact-exposure group, which had high FAEI scores. The substantially low R^2 value of the model for the fact-exposure group also supports this suggestion (Table 5). Compared with the model for the fact-avoidance group, belief-updating click behavior in the fact-exposure group was affected by factors other than bullshit receptivity. In reality, users need not check all false beliefs simultaneously; as long as they do not avoid examining false beliefs, these beliefs will be updated sooner or later.

Furthermore, the mean bullshit receptivity scores between the fact-avoidance and fact-exposure groups were not significantly different (Table 3). Therefore, it is not possible to infer from these results that improving reflexiveness would encourage users who already check uncongenial facts more than expected to check them even more. Rather, the significance of these results lies in fundamentally understanding what prevented users from checking uncongenial facts and discovering how the minimum level of belief-updating click behavior can be raised. This understanding is particularly important because it contributes to explaining why misinformation has been perpetuated on the Internet despite a variety of debunking efforts. Fact-checking websites expect users to think critically and update their beliefs based on these facts. However, our results demonstrate that 43% of users selectively tended to abandon this opportunity and retain their false beliefs. To raise the minimum level of belief-updating click behavior, we must focus on this type of user.

We also predicted that the tendency to engage in conspiracy theories makes individuals less likely to engage in belief-updating clicks (*H2*) whereas open-mindedness (*H3*), the need for cognition (*H4*), and analytic thinking (*H5*) make individuals tend to engage in belief-updating clicks. These hypotheses were not supported: Conspiracist tendency, measured by the GCB, was associated with the selective avoidance of uncongenial facts but not significantly. The AOT, NFC, and CRT scales did not predict click behavior toward examining false preexisting beliefs. One interpretation of the failure to reject the null hypothesis regarding open-mindedness (H3) relates to the methodology used. The low reliability of the AOT ($\alpha = .34$) indicates that open-mindedness was not appropriately measured. However, the high reliabilities of the GCB and NFC ($\alpha = .92$ and $.90$) suggest a different interpretation: The effortful thinking style measured by the GCB, NFC, and CRT might not be associated with belief-updating click behavior. Unlike the reading-story phase in the fact-checking context, the click-link phase did not yet require users to read corrections or update their preexisting beliefs. The CRT and GCB, which are correlated with perceiving misinformation [59] and predict conspiratorial beliefs [31], might be associated with the reading-story phase but not with the click-link phase. Although the NFC, that is, the preference to enjoy cognitive challenging activities [8], was postulated to predict belief-updating click behavior, this preference might, in fact, dissociate from actual click behavior. The low correlation coefficients of the BSR with other scales (Table 4) are also consistent with this interpretation. As for explanatory investigation, contrary to our expectations, verbal intelligence and experiences of COVID-19 did not moderate the association between psychological characteristics and selective avoidance.

6.3 Contributions of the FAEI to Understanding Users

The evaluation of the effectiveness of the FAEI revealed that it was an appropriate index for determining individual differences in click behavior. Compared to previous measurements [26, 62] that induced the floor effect, the distribution of FAEI values was less skewed, and neither the floor effect nor the ceiling effect was observed. The FAEI, which includes several important parameters, differentiated between individuals' belief-updating click behaviors, assigning 268 different values to the participants, which is 6.7 times more value patterns than that of the previous measurements for the same sample. The FAEI also effectively separated selective avoidance of belief-updating clicks from selective exposure, making it possible to categorize the participants into two groups. Furthermore, the results revealed that the FAEI identified the association between psychological characteristics and the selective avoidance of belief-updating clicks, whereas other measurements did not. This indicates the advantage of the FAEI in differentiating individual differences in belief-updating click behavior.

Moreover, the FAEI prevented spurious understandings of click behavior. If we analyzed click behavior without grouping participants according to the FAEI, the result would have shown that users clicked on uncongenial facts the most (Figure 5, right panel), creating an incorrect impression, as if there was no need to improve belief-updating click behavior. However, this is just an apparent result because the characteristic of the fact-exposure group masked those of the fact-avoidance group. By distinguishing between these two user groups, which have opposite selectivity in their belief-updating click behaviors, the FAEI contributed to a precise understanding of user click behavior.

6.4 Implications For Future Designs

The results demonstrated that the commonly used fact-checking interface design, which displays a list of headlines with "true/false" labels, was effective in encouraging 57% of participants to move forward to the next reading-story phase; however, it was not effective for the other participants by leading the avoidance of uncongenial facts. In light of this, we emphasize the need to devise future designs for fact-checking websites that are more effective for users who tend to avoid clicking on facts that are uncongenial to their false beliefs.

A promising research question could be, "Which design interventions mitigate reflexive closed-mindedness and encourage users to reflect on their false beliefs based on facts?" This question can be approached from different perspectives, including explaining the social importance of debunking misinformation on the landing page of a website, nudging users toward deliberativeness [4, 37, 56, 60], considering the display order of fact-checking stories by taking advantage of click behavior that is affected by ranking bias [2, 18, 19], and using the effects of labeling and warning [27, 40].

For example, ranking bias, which is the human tendency to click more on top-ranked links [2], can be caused by users' reflexiveness. If ranking bias is used ethically, then it is potentially effective for users who have reflexive closed-mindedness in reaching uncongenial facts by displaying links in positions where users tend to click. In this case, it is not necessary to personalize the order of links; it is implausible for information providers to collect users' preexisting beliefs in advance. Instead, the point here is to share facts with people for whom these facts are uncongenial. One way is to display links at the top of the page based on the algorithmically calculated ratio of retweeted misinformation over corrections, as the higher the ratio, the more uncongenial the fact is for more people. However, it is unclear yet how stubborn the fact-avoidance tendency is. If the fact-avoidance tendency were stronger than ranking bias, a different design intervention or mixed design interventions would be required. Further empirical research is needed to examine the interaction between design interventions and human factors in correction-sharing.

Moreover, our findings have implications for the future development of design as well as for studies that have examined design in the past and those that will examine them in the future. The result showing that the same interface design has opposite effects when interacting with users' characteristics highlights new considerations regarding the past design research. The issues faced by current fact-checking website designs cannot be revealed only by observing users as a whole since one type of user masks the characteristics of others. This indicates that some design research that has failed to confirm their effectiveness of a design has potentially found different results by separating users who have opposite characteristics. Similarly, considering these user factors will expand the perspective of examining effective future fact-checking website designs that support users' deliberative decision-making.

From a positive viewpoint, the result that 43% of participants tended to avoid clicking uncongenial facts allows us to expect that there is significant room for increasing the effectiveness of fact-checking websites through design interventions.

7 LIMITATIONS

Our study has several limitations. First, the study focused on a specific phase after users access a fact-checking website and before they read fact-checking stories. This is one phase in a series of processes that use fact-checking websites for deliberative decision-making. One challenge related to fact-checking websites is how to invite users to such websites. Another challenge is that reading a fact-checking story does not necessarily lead to deliberative decision-making owing to a different psychological obstacle known as *the continued influence effect* [36, 39, 48]. While this study sheds light on the impact of selective-avoidant click behavior and demonstrates that a considerable proportion of false beliefs failed to be debunked during this phase, further research is needed to comprehensively understand various user factors and how their interactions with design factors that reduce the utility of fact-checking websites.

The second limitation concerns the methodology used to conduct online empirical research on users' psychological characteristics. The low Cronbach's alpha coefficient of the AOT suggests that open-mindedness was not appropriately assessed in this study. This explains why selective avoidance was predicted by the BSR but not by AOT, despite the similar constructs behind these two scales. The low coefficient of AOT could be attributed to the order of the scale disposed of in the timing when participants got slack among several scales, including approximately 100 question items. Although we conducted the experiment over two sessions to avoid overloading participants, the volume of question items might have been too heavy for them. For both participant-friendly and methodologically reliable experiments, fewer items would be appropriate when using psychological scales in future online experiments.

The third limitation was related to the ratio of participants who started Session 1 but did not participate in Session 2 owing to failure to meet the participation criteria (63%). While it was not easy to determine whether this proportion was particularly high because research that has used identical procedures is lacking, it was relatively higher compared with a previous study that conducted an online survey including various psychological scales and questions about misinformation (46%) [56]. Thus, the volume of questions in Session 1 may have played the role of screening for participants who were both curious about the stimuli and could cope with the questions, which was an effortful task. The lower drop-off ratio in Session 2 (28%) was also consistent with this possibility, indicating that if only Session 2 was conducted, the sample would have included more participants with reflexive tendencies.

The fourth limitation relates to the limited elements of the stimuli used. For experimental purposes, we mimicked a short-format design commonly used by fact-checking websites [16]. However, fact-checking websites, in reality, also include other elements that could affect click behavior when users encounter links to fact-checking stories. For instance, the website factcheck.org displays an image for each link that includes a face of a politician and a screenshot of social media related to misinformation. Thereafter, the false label is stamped in red on an image when the information is false. In addition, the responses of other users would be another element that could influence user behavior. Wang and Fussell [71] emphasized that people employ the cognitive process of paying attention to others to decide whether to check facts. For example, when PolitiFact.com uses Twitter to share fact-checking stories, each tweet includes the number of retweets, replies, and likes from other users in addition to a link and a label. These elements might affect click behavior. To predict belief-updating click behavior in the real world, further experiments are needed that consider multiple elements.

It is also important to note that participants were required to click on at least five links. This requirement is not present for users in reality but was adopted for experimental purposes to capture individual differences in belief-updating click behavior. The scores of the FAEI tend to distribute wider as the number of clicks increases when other parameters are fixed. Although the minimum requirement does not induce click behavior to either avoidance or exposure, the kurtosis of the FAEI distribution will vary depending on the minimum requirement of links to click on. Similarly, it should be emphasized that the FAEI is used to measure click behavior under a specific condition (e.g., the number of links given and the minimum requirement of links to click on) but is not a diagnostic assessment for general use at the individual level. In addition, FAEI scores measured under a specific condition should not be directly compared with those measured under a different condition.

8 CONCLUSION

Proposing a new index for measuring belief-updating click behavior, this study demonstrated that more than 40% of users did not benefit from fact-checking websites. They selectively avoided clicking on links related to facts that were uncongenial to their preexisting beliefs, leaving 93% of their false beliefs unexamined. These findings explain why misinformation has prevailed online despite the increasing availability of fact-checking websites. However, our finding regarding the psychological characteristics that predict selective avoidance paves the way for future fact-checking website designs. Design interventions that counteract users’ reflexive close-mindedness are key to raising the minimum level of belief-updating click behavior. In conclusion, we emphasize the need to devise a design for fact-checking websites based on further empirical studies on the user factors that interact with design, thereby facilitating the development of websites that are more effective at debunking misinformation.

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APPENDIX

The original Japanese version of Figure 3.