Interaction of source credibility and readers' prior beliefs in the sourcing and validation of social media posts

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Prior research has shown that readers' prior beliefs can influence how they process and use source information during reading (sourcing), and that source credibility and readers' prior beliefs can be jointly considered in routine evaluations of the plausibility of incoming information (validation). These effects have been observed especially when readers' prior beliefs are incongruent with the information in the text. However, most prior research on the topic has not used precise eye tracking methods, and no prior studies have investigated the interaction of source credibility and prior beliefs in sourcing behaviour. This study examined the effects of source credibility and prior beliefs on sourcing and validation in a social media context.

Eighty-three Finnish participants' (primarily university students) beliefs on eight societally relevant topics were measured with an online questionnaire, after which they took part in an eye tracking experiment. During the experiment, participants were shown 76 mock-up Twitter posts from either credible or noncredible sources. The tweets consisted of a target sentence (pro- or contra-claim), followed by a more neutral spillover sentence. Separate interest areas were defined for sources (authors of the tweets) and both sentences. Source reading times (summed fixation duration after reading the target sentence) and look-back probabilities (1/0) were calculated for source areas. First-pass and look-back reading times, along with look-back probabilities, were calculated for target and spillover sentences. The eye movement measures were analysed using linear mixed-effects models.

The results showed that source reading times and source look-back probabilities increased when participants saw disagreeable claims from credible sources. Source look-back probabilities also increased when participants saw agreeable claims from noncredible sources. Similarly, look-back probabilities for both target and spillover sentences and look-back reading times for target sentences increased when participants saw either disagreeable claims from credible sources or agreeable claims from noncredible sources. No effects were observed in first-pass reading times, indicating that the effects on reading occur with a slight delay. With neutral beliefs, source credibility had little influence. These results suggest that an incongruence between source credibility and prior beliefs directs readers' attention to source information and increases the cognitive resources needed for validation. Thus, in addition to text–belief inconsistencies, further research should investigate other situations of incongruence, such as an inconsistency between the reader's beliefs and the perceived credibility of the source. Future studies should also utilize a variety of reading contexts and both on-line and off-line measures of cognitive processing.

Key words: reading, eye tracking, text comprehension, validation, source credibility, sourcing, social media

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Aiemmissa tutkimuksissa on havaittu, että lukijoiden mielipiteet voivat vaikuttaa lähdetiedon käsittelyyn lukemisen aikana, ja että lähteen uskottavuus ja lukijoiden mielipiteet saattavat yhdessä vaikuttaa tekstitiedon uskottavuuden rutiinimomaiseen arviointiin (validaatioon). Vaikutuksia on havaittu etenkin silloin, kun lukijan mielipiteet ovat ristiriidassa tekstin sisältämän tiedon kanssa. Suurin osa aiemmista tutkimuksista ei kuitenkaan hyödynnä tarkkoja katseenseurantamenetelmiä, ja lähteen uskottavuuden ja aiempien mielipiteiden yhdysvaikutuksia lähdetiedon käsittelyyn ei ole vielä tarkasteltu yhdessäkään tutkimuksessa. Tässä tutkimuksessa tarkasteltiin lähteen uskottavuuden ja lukijan mielipiteiden vaikutusta lähdetiedon huomioimiseen ja tekstin validaatioon sosiaalisen median kontekstissa.

Tutkimuksessa suomenkielisten osallistujien (n = 83, pääosin yliopisto-opiskelijoita) mielipiteitä kahdeksasta yhteiskunnallisesti ajankohtaisesta aiheesta mitattiin nettikyselyllä. Tämän jälkeen he osallistuivat laboratoriossa silmänliikekokeeseen, jonka aikana heille näytettiin yhteensä 76 uskottavien ja epäuskottavien lähteiden kirjoittamaa tekaistua Twitter-postausta. Jokainen twiitti koostui kohdelauseesta (varsinainen pro- tai kontra-väite), jota seurasi neutraalimpi spillover-lause. Analyyseja varten twiitteihin luotiin alueet lähteille (twiitin kirjoittaja) sekä kummallekin lauseelle erikseen. Lähdealueilla tarkasteltiin lähdelukuaikaa (yhteenlaskettu lähteeseen kohdistuneiden fiksaatioiden kesto kohdelauseen lukemisen jälkeen) ja kohde- ja spillover-lauseilla ensimmäisen lukukerran kestoa, jälkimmäisten lukukertojen kestoa sekä takaisinpaluun todennäköisyyttä (1/0). Silmänliikkemuuttujat analysoitiin lineaarisia sekamalleja käyttäen.

Tulokset osoittivat, että lähdelukuajat ja lähteeseen kohdistuneiden takaisinpaluiden todennäköisyydet olivat korkeimmillaan, kun osallistujat olivat eri mieltä uskottavien lähteiden kirjoittamien twiittien kanssa. Lähteeseen kohdistuneiden takaisinpaluiden todennäköisyydet kasvoivat myös silloin, kun osallistujat olivat samaa mieltä epäuskottavien lähteiden kirjoittamien twiittien kanssa. Vastaavasti kohde- ja spillover-lauseisiin kohdistuneiden takaisinpaluiden todennäköisyydet sekä kohdelauseiden jälkimmäisten lukukertojen kesto kasvoivat, kun osallistujat olivat eri mieltä uskottavien lähteiden kirjoittamien ja samaa mieltä epäuskottavien lähteiden kirjoittamien twiittien kanssa. Ensimmäisillä lukukerroilla ei havaittu yhdysvaikutuksia, mikä viittaa siihen, että mielipiteet ja lähteen uskottavuus vaikuttavat lukemiseen pienellä viiveellä. Lähteen uskottavuudella ei myöskään ollut vaikutusta silloin, kun osallistujien mielipiteet olivat neutraaleja. Tutkimuksen tulokset viittaavat siihen, että ristiriita lukijoiden mielipiteiden ja lähteen uskottavuuden välillä ohjaa tarkkaavaisuutta lähdetietoon ja lisää validaation vaatimia kognitiivisia resursseja. Jatkotutkimusten pitäisi siis teksti–mielipide-ristiriitojen ohella tarkastella muunkinlaisia ristiriitatilanteita, kuten epäyhdenmukaisuutta lukijan mielipiteiden ja lähteen koetun uskottavuuden välillä. Tulevaisuudessa olisi myös tärkeää hyödyntää monenlaisia lukemisympäristöjä ja erilaisia kognitiivisen prosessoinnin mittareita.

Avainsanat: lukeminen, silmänliiketutkimus, tekstin ymmärtäminen, validaatio, lähdekriittisyys, sosiaalinen media

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1. Introduction

In today's hectic and fast-changing media environment, readers face a constant stream of societally and personally significant claims. However, not all information is created equal – readers may purposefully or unknowingly believe and share erroneous or misleading content. The dissemination of mis- and disinformation has become a serious global problem: online fake news appear to spread much faster than authentic news (Vosoughi et al., 2018), while debunking and countering their effects can be difficult (Chan et al., 2017; Lewandowsky et al., 2012). The influence of misleading information is not cornered to the confines of social media: for example, it has been connected to pandemic prevention efforts (Barua et al., 2020; Greene & Murphy, 2021), voting behaviour (Bovet & Makse, 2019; Cantarella et al., 2023), and climate change denial (Boussalis & Coan, 2016; Lewandowsky et al., 2015). The ability to critically evaluate sources has thus become a vital skill for navigating social media and online news outlets (Bråten et al., 2017; Sinatra & Lombardi, 2020).

Despite the increasing importance of source evaluation skills, little research exists on how factors outside the text, such as source credibility and readers' prior beliefs, affect the processing of written information. Knowing when readers pay attention to sources, and how source information affects reading – or fails to do so – is crucial for understanding and hindering the spread of harmful false information online. The purpose of this eye-tracking study was to investigate the effects of source credibility and readers' prior beliefs on the reading of social media posts. More specifically, the study focused on validation; a routine process of reading comprehension whereby readers evaluate text information against long-term memory, resulting in updated mental representations (O'Brien & Cook, 2016; Richter & Maier, 2017; Singer, 2013). The results further the theoretical and practical understanding of the processes involved in reading comprehension and help fill a gap in the existing literature.

1.1 Processing Source Information

1.1.1 Sourcing and Source Credibility

Sourcing can be defined as readers' ability to pay heed to and critically evaluate information about a text's source – that is, who wrote the text, what kind of a text it is, and what kinds of judgements should one make based on these factors (Bråten et al., 2017). The ability to critically engage with source information has sometimes also been conceptualized as an important subcomponent of digital media literacy, which refers to a more general capability to comprehend messages in online media (Cheever & Rokkum, 2015). Good sourcing skills have been linked to better critical thinking skills (Ku et al., 2019), argumentation skills (Anmarkrud et al., 2014; Barzilai et al., 2015), and reading comprehension (Strømsø et al., 2010). One relatively consistent finding in the literature is that unskilled readers and laypeople are generally poor at sourcing unless they are explicitly instructed to do so, while skilled readers and subject experts use source information more effectively (Anmarkrud et al., 2022). Unfortunately, even with adequate proficiency, sourcing has become increasingly difficult in the 21st century, as online information sources are often diffuse, copious, contradictory, and varying in credibility (Goldman & Scardamalia, 2013). In addition, relevant information about a text's source is not always easily accessible on webpages and social media platforms (Bråten et al., 2017). Merely finding and paying attention to a source does not necessarily lead to better outcomes either, as readers might fail to critically engage with the source information or ignore it when evaluating the text (Barzilai et al., 2015; Brante & Strømsø, 2018; Kim & Hannafin, 2016; Sparks & Rapp, 2011).

An important aspect of source information in evaluating texts is the credibility of the source. Traditionally, source credibility has been defined as having two main dimensions: *trustworthiness* and *expertise* (Hovland et al., 1953; Pornpitakpan, 2004). In their seminal work, Hovland et al. (1953) conceptualize expertise as referring to a source's competence (e.g. knowledge, credentials, or skills) to provide information on a given topic, whereas trustworthiness refers more to a source's perceived honesty, integrity, or possible biases. A source could be perceived as high in one dimension and low in the other at the same time: for example, a doctor might have a medical degree (high expertise), and still have profit-driven personal biases to recommend a given treatment (low trustworthiness). Other dimensions of source credibility, such as dynamism and objectiveness have been proposed, but the two-factor model has remained the most widely used definition (Pornpitakpan, 2004). In this study, source credibility refers to trustworthiness and expertise, unless stated otherwise.

It is important to note that trustworthiness and expertise do not necessarily reflect a source's actual expertise or trustworthiness – instead, they are readers' subjective evaluations that can rely on possibly irrelevant attributes of both the reader and the source. For example, the source's physical attractiveness, ideological proximity to the evaluator, stereotypes regarding the source's ingroup, and the source's age and gender can all affect perceived credibility (Pornpitakpan, 2004; Sbaffi & Rowley, 2017; Wathen & Burkell, 2002). Another essential clarification is that source credibility refers only to the source itself, and not the content of the message, although source credibility can affect evaluations of message credibility as well (Kuutila et al., 2024). Source attributes can also affect how readers resolve conflicts in what they read: variation in trustworthiness between sources may lead to readers assigning conflicts to motivational differences, while variation in expertise may provoke more explanations related to differences in competence (Gottschling et al., 2020).

1.1.2 Source Information in Text Comprehension

Multiple models of discourse processes consider source information an important part of comprehension (Braasch & Bråten, 2017; List & Alexander, 2019; Rouet & Britt, 2011; Stadtler & Bromme, 2014). For the purposes of this study, however, the most relevant ones are the Discrepancy-Induced Source Comprehension model (D-ISC; Braasch & Bråten, 2017) and the Content–Source Integration model (CSI; Stadtler & Bromme, 2014), because they make explicit predictions about how sourcing relates to reading conflicting information.

Even though readers sometimes fail to engage in sourcing, the Discrepancy-Induced Source Comprehension model predicts that certain situations are more likely to attract attention to source information (Braasch & Bråten, 2017). According to the D-ISC, sourcing is particularly important when a text conflicts with the reader's general world knowledge, prior beliefs, or with previously read text. The D-ISC holds the common assumption within text comprehension research that a basic goal of reading is to form a coherent representation of what is being read, resulting in a memory representation that satisfactorily captures the meaning of the text (Braasch & Bråten, 2017; Kintsch, 1988; McNamara & Magliano, 2009). These representations are often broadly divided into at least two levels: the *text base* and the *situation model* (van Dijk & Kintsch, 1983). The text base refers to a locally and globally organized network of propositions forming the structure and meaning of the text itself, whereas the situation model is a more general representation of what the text is about, integrating the reader's prior knowledge with the text's content (van Dijk & Kintsch, 1983). Discrepant information can pose a challenge for creating a coherent situation model, as it creates conflicts that need to be resolved somehow. The D-ISC assumes that if readers encounter such information, they will allocate more attention to source information, because connecting conflicting claims to different sources might be more efficient than trying to reconcile the conflict with semantic text features alone (Braasch & Bråten, 2017). This, in turn, leads to a situation model in which information is organized via more pronounced source–content links, compared to merely text content and the information activated in working memory (Braasch & Bråten, 2017; Braasch & Kessler, 2021). In contrast, when there are no discrepancies or the reader fails to detect them, source information is not needed to form a coherent representation, and attention to sources should be diminished (Braasch et al., 2016).

There exists a growing literature supporting this assumption of sourcing having a prominent role in conflict resolution during reading. For example, discrepancies between or within texts increase the amount of attention readers allocate to sources, which can be observed as longer and more frequent fixations in source areas (Braasch et al., 2012; Kammerer et al., 2016; Saux et al., 2021), more mentions of sources in verbal summaries (Braasch et al., 2012; Kammerer et al., 2016; Rouet et al., 2016), and enhanced memory for source information (Braasch et al., 2012, 2016; Kammerer et al., 2016; Saux et al., 2017, 2018, 2021; Stang Lund et al., 2017). Similar effects have also been observed in the presence of a text–belief inconsistency, that is, when readers encounter information that contradicts their prior beliefs (Bråten et al., 2016; Maier & Richter, 2013). Not all studies, however, have found evidence for text–belief consistency effects in sourcing (van Strien et al., 2016).

The Content–Source Integration model (CSI) makes partly similar assumptions regarding conflict resolution (Stadtler & Bromme, 2014). The CSI predicts that when readers encounter conflicts, they can resolve them either by referring to their general world knowledge or by assigning the conflicting positions to differing sources – of these two, the latter option ("whom to believe") is thought to be applied especially when general world knowledge is insufficient to resolve the conflict (Stadtler & Bromme, 2014). However, the CSI primarily focuses on conflicts between multiple texts or multiple sources within one text and makes no strong predictions about text–reader discrepancies, as is the case in the current study.

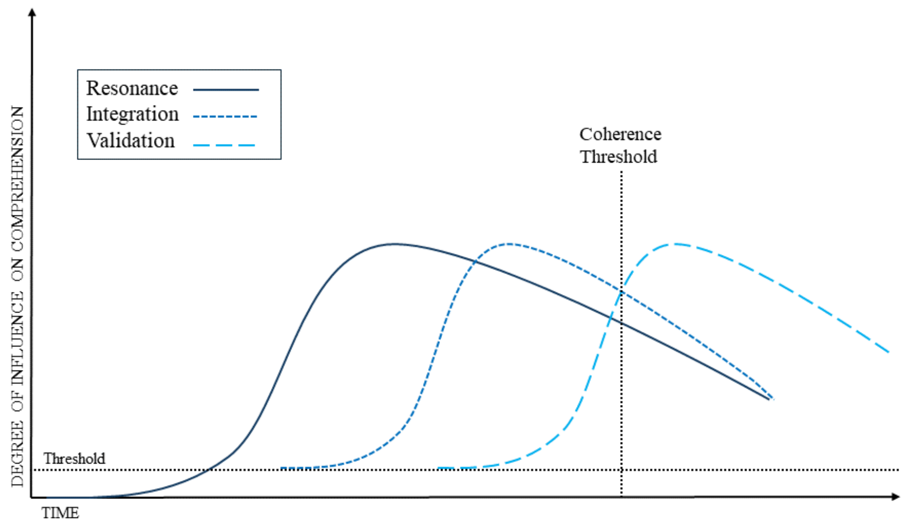
1.2 Validation of Text Information During Reading

1.2.1 The RI-Val Model of Comprehension

As stated earlier, an important goal of reading comprehension is to form a coherent mental representation of the text being read (McNamara & Magliano, 2009). The RI-Val model of reading comprehension (*Resonance-Integration-Validation*; Cook & O'Brien, 2014) formulates a sequence of three processes that occur during reading, visualized in Figure 1. The model assumes that as the reader proceeds in the text, long-term memory (LTM) representations are automatically and indiscriminately activated by the text. This happens via a passive and "dumb" process called resonance (*R*), in which overlapping features in the text cause any related information, be it earlier text content or general world knowledge, to be activated in an associative network of LTM representations (Myers & O'Brien, 1998). In a second stage, integration (*I*), this information is linked to the contents currently active in working memory. The initial strength and number of these links is supposedly based only on the extent of featural overlap, or "goodness-of-fit" between working memory content and the activated concepts (O'Brien & Cook, 2016). These two processes, resonance (sometimes called activation) and integration, are largely similar to earlier major bottom-up models of text comprehension, such as the Construction-Integration model (Kintsch, 1988) and Myers and O'Brien's resonance-based model (1998). What the RI-Val model adds to the picture, then, is a third stage called validation (*Val*), during which the links formed in the integration stage are evaluated against the reader's broader understanding of the text and the world. The purpose of validation is to make sure that all of the pieces fit together, and the information makes sense in the corpus of the reader's world knowledge, beliefs, and previously read text content (Cook & O'Brien, 2014). As such, validation could be considered a sort of general "plausibility check" for all incoming text information (Richter, 2015).

Figure 1

The RI-Val Model of Comprehension



Note. Recreated from Figure 1 in O'Brien and Cook (2016) with publisher's permission.

According to the RI-Val, validation is completed after the reader reaches their *coherence threshold* (O'Brien & Cook, 2016). The coherence threshold varies based on the reader's *standards of coherence* – that is, their general understanding of what an adequate level of comprehension is in a given reading situation (van den Broek et al., 1995). Although validation itself is thought to be a bottom-up process, standards of coherence can be influenced by specific reading tasks, goals, and perspectives (e.g. Kaakinen et al., 2015; Kaakinen & Hyönä, 2008; van den Broek et al., 2011)

All three processes; resonance, integration, and validation, are assumed to run to completion even if the reader moves on in the text, and even though they are asynchronous, there can be partial temporal overlap (Cook & O'Brien, 2014). This results in the possibility of so-called "spillover" effects, where the processing of a later sentence is slowed down because an earlier sentence is still being validated in the background. There exists ample evidence for a routine process of assessing the plausibility of incoming information, and that it can sometimes lead to spillover effects (O'Brien & Cook, 2016; Richter, 2015; Singer, 2019). However, multiple open questions remain, such as how to reliably differentiate between validation and other processes (notably integration), and how exactly top-down processes affect validation (Singer, 2019).

1.2.2 Plausibility, Prior Beliefs, and Source Credibility in Validation

In general, reading implausible information seems to increase the cognitive resources needed for validation compared to plausible information (Isberner & Richter, 2013; Patson & Warren, 2010; Rayner et al., 2004; Staub et al., 2007; Wertgen & Richter, 2020). Most of this research has focused on sentences that were quickly and easily recognizable as implausible based on common knowledge. Some evidence also exists that processing is slower when readers encounter information that they find implausible based on their prior topic beliefs or opinions (Abendroth & Richter, 2023; Edwards & Smith, 1996; Gilead et al., 2019; Maier et al., 2018; Wertgen & Richter, 2023), but the effects may be dependent on the specific reading task or presentation format (Abendroth & Richter, 2023; Maier & Richter, 2016).

Few studies have focused specifically on the interaction of plausibility and source credibility in validation. Foy et al. (2017) presented participants with fictional narratives containing plausible and implausible events witnessed by credible and noncredible sources. For example, in the narratives, either sober or intoxicated partygoers claimed to have seen a pack of wolves in the backyard. These assertions were then followed by a sentence confirming or disconfirming the claim (e.g., there actually were wolves in the backyard). Foy and colleagues found that when implausible claims coming from credible sources were confirmed, reading times were faster compared to situations in which they were disconfirmed. In contrast, when implausible claims from noncredible sources were confirmed, reading times were longer. These results suggest that both source credibility and plausibility are considered in validation, and that a credible source might make the validation of implausible claims easier. Building on this work, Wertgen and Richter (2020) used fictional narratives with credible and noncredible sources making claims that were plausible or implausible based on general world knowledge, and found a differing pattern. Reading times for implausible claims coming from credible sources were longer for both target and spillover sentences, but no significant effects were found for plausible claims. Wertgen and Richter (2020) suggest that the difference in their results compared to Foy et al.'s study was due to the difference in the materials used – they used sentences that the participants could disconfirm based on their own knowledge, whereas Foy and colleagues used assertions that only the narrative itself could resolve.

To investigate whether the type of implausibility could have affected the previous results (Foy et al., 2017; Wertgen & Richter, 2020), Wertgen, Richter, and Rouet (2021) continued this line of work by manipulating the degree of the claims' implausibility. Again, participants were presented with short narratives containing plausible and implausible factual claims coming from sources of varying credibility. This time, in addition to highly implausible claims, an intermediate level of somewhat implausible claims was added. No interaction of source credibility and plausibility was found for target sentences. For spillover sentences, however, reading times varied as a function of source credibility and the degree of implausibility – somewhat implausible claims from credible sources were read faster compared to noncredible sources, whereas highly implausible claims from credible sources were read slower compared to noncredible sources. No difference was observed for plausible claims. Wertgen and colleagues (2021) hypothesize that these results could be explained by the role of source information in reading comprehension: A high-credibility source increases the discrepancy of a highly implausible claim. On the other hand, if it is harder to determine the truth value of an implausible claim, a high-credibility source might ease reaching a conclusion.

At least one study has investigated these effects using a social media context as opposed to fictional narratives. In Wertgen and Richer (2023), participants saw mock-up Twitter posts in which the trustworthiness of the source was manipulated between two tweet versions. In Experiment 1, the tweets were either consistent or inconsistent with the posters' supposed positions (e.g. an oil company advocating for climate-based market restrictions), and plausibility was measured as how likely the participants thought the claims were. Participants read implausible tweets faster when the claim and source were consistent compared to claim-source inconsistent tweets. Interestingly, participants also read plausible tweets faster in claim-source consistent situations compared to inconsistent ones. In Experiment 2 (Wertgen & Richter, 2023), trustworthiness was operationalized by varying the perceived reputation of journalistic news outlets, and plausibility varied as the world knowledge consistency of the claims (e.g. conspiracy theories vs. well-known news events). The analyses revealed a significant interaction of plausibility and source trustworthiness in reading times. Plausible tweets from trustworthy sources were read faster compared to untrustworthy sources, but, contrary to the authors' hypotheses and earlier research, no significant differences were found for implausible tweets. Overall, based on the studies outlined above (Foy et al., 2017; Wertgen et al., 2021; Wertgen & Richter, 2020, 2023), source credibility and different kinds of plausibility are jointly considered in validation, but the direction of the effects seems to vary considerably across different situations.

1.3 Aims and Hypotheses

The aim of the current study was to add to this nascent area of research by investigating the effects of source credibility and readers' prior beliefs on how people process social media posts and source information. Most of the studies on the topic thus far have used fictional narratives as materials, and it is unclear how these findings generalize to a more naturalistic social media context. To this end, the current study utilized mock-up Twitter posts or "tweets" (of the foregone social media platform currently known as X). Twitter's feed displays sources (authors of the tweets) prominently with little additional context, and readers must make decisions based on short messages. Misinformation has been shown to be commonplace on Twitter (Suarez-Lledo & Alvarez-Galvez, 2021; Vosoughi et al., 2018), which is why it is important to know how people process the content they encounter on the platform. In addition, prior research has measured reading times using a self-paced paradigm, where readers proceed to the next sentence or tweet by pressing a button on the keyboard. Eye tracking, however, provides more detailed data about the processes occurring during reading – for example, analysis of first-pass and look-back reading times for different sentences, look-back probabilities, and precise moment-to-moment information about where participants direct their attention (Hyönä et al., 2003). Proceeding sentence-by-sentence also forbids readers the opportunity to make look-backs during reading, which is known to be an essential part of reading comprehension (e.g. Hyönä, 1995). The cognitive load elicited by validation has been measured using first-pass and look-back reading times (Richter, 2015; Singer, 2013) and look-back probabilities (Maier et al., 2018; Rayner et al., 2004). In this study, eye movements measures were examined separately for target sentences, spillover sentences, and source areas.

The following hypotheses were formulated:

1. When participants disagree with a claim, they make more look-backs and read source areas longer compared to agreement, reflecting heightened attention to sources.
2. Source credibility influences first-pass and look-back reading times and look-back probabilities of target and spillover sentences depending on the certainty of participants' disagreement:
   2a. When participants strongly disagree with a claim, a credible source results in longer reading times and increased look-back probabilities compared to more uncertain disagreement.
   2b. The more uncertain (closer to neutrality) participants are of their disagreement, a credible source leads to decreasing reading times and look-back probabilities compared to strong disagreement.
3. When readers agree with a claim, source credibility does not affect reading times or look-backs.

2. Methods

2.1 Participants

A total of eighty-six participants were recruited for the study, three of whom had to be excluded due to poor data quality, leaving the final sample size at eighty-three (N = 83). The participants were aged 18–59 (M = 26.1, SD = 6.1). Sixty-four (77.1%) participants reported their gender as female, 17 (20.5%) as male, and 2 (2.4%) participants preferred not to state their gender. When asked for the highest level of education the participants either had completed or were currently enrolled in, 52 (62.7%) responded bachelor's degree or equivalent, 22 (26.5%) master's degree or equivalent, 7 (8.4%) upper secondary education, 1 (1.2%) Finnish basic education (grades 1–9), and 1 (1.2%) none of the above or no formal education. All spoke Finnish as their first language. All participants gave informed consent. Appropriate sample size was determined by conducting a power simulation (Kumle et al., 2021) with 80% power and α = .05, based on data from Wertgen and Richter (2023). The simulation is described in detail under section 2.5.3.

The data was collected in Spring 2023, and the majority of participants were students at the University of Turku. Participants were recruited by advertising the study face-to-face, by email, and by flyers across the university campus. To be included in the study, the participants had to speak Finnish as their first language, be at least 18 years old, and have adequate vision (or corrected via glasses or contact lenses) to be able to read small text from a computer screen at a close distance. By completing the study, the participants could receive either a €10 gift card or course credit for introductory courses in psychology.

2.2 Apparatus

Eye movements were recorded monocularly using the EyeLink Portable Duo (SR Research Ltd., 2016) at a 1000 Hz sampling frequency. Stimuli were presented on a BenQ XL2411 screen with a 100 Hz refresh rate and a resolution of 1920 x 1080 px. The screen was positioned at a 70 cm distance from the participants, whose heads were stabilized with a chin-and-forehead rest.

2.3 Materials

2.3.1 Claims, Sources, and Mock-Up Twitter Posts

A total of 152 mock-up Twitter posts or tweets were used in the experiment, consisting of 76 tweets in Finnish with two versions of each. The pairs were otherwise identical, but the credibility of the source was altered between versions (see Figure 1 for translated examples). The pairs were divided into two counterbalanced lists: each participant only saw 76 tweets, one of the two versions.

The mock-up tweets contained pro- and contra-positions about eight different societally relevant topics: veganism, health, national defence, immigration, gender, climate change, economic policies, and nuclear power. The tweets consisted of two sentences: the target sentence, containing an actual claim about the topic, and a shorter, more neutral spillover sentence. The target sentences included both factual and normative claims with and without supportive reasons or evidence for the claim. If reasons or evidence were included in the target sentence, they always followed the claim.

Each tweet had a low- and a high credibility source version. High credibility sources included government officials, research organizations, trusted third-party organizations, and individuals with a degree in a relevant field. For example, if the tweet was about health, credibility might be signalled by “MD” next to the name and a profile picture depicting a doctor. Low credibility sources included known conspiracy websites, marginal political parties, and individuals with either no signals of expertise or signals of strong personal bias. Some of the profiles were real and some of them were made up for the experiment. If the profile was real, the username, name, profile picture and “verified” sign were matched with the real-world counterpart. The number of likes, retweets and comments for each tweet was randomly generated, likes ranging from 10 to 60, retweets from 1 to 25, and comments from 0 to 10, with the numbers of retweets and comments always kept smaller than the number of likes. The tweets were dated between 2018 and 2023 in a manner that matched the publishing date with the relevance of the topic: for example, online conversation about Finland’s NATO membership spiked after February 2022.

Figure 2

Example Materials with High Credibility (Above) and Low Credibility Versions

Note. High credibility sources: *THL*, a trusted Finnish health official and *Lääkärilehti*, The Finnish Medical Association's peer-reviewed journal that also publishes articles for the popular audience. Low credibility sources: *Antti*, an anonymous account with no visible credentials and *Corona Truths*, an anonymous account displaying possibly conspiratorial tendencies. Translated from Finnish originals.

The materials were piloted with participants recruited from Prolific ($N = 21$), using a questionnaire hosted on the Webropol online survey platform (Webropol, 2024) where participants were presented with 80 target sentences and 160 screenshots of Twitter profiles separately. The participants were told to evaluate on a Likert scale ranging from -5 to 5 how strongly they agree or disagree with the target sentences, with 5 indicating extreme agreement and -5 extreme disagreement. In addition, participants were told to evaluate the credibility of the profiles on a similar scale, with -5 indicating minimal credibility and 5 maximal credibility. The profiles were presented in connection with the topics they would be tweeting about in the actual experiment ("If the topic was X, how credible a source would you find the following account to be?"). The distribution of mean agreement ratings across items was fairly uniform, with an overall mean of around zero ($M = 0.17$) and mean minimum and maximum ratings ranging from -3.71 to 3.81 across items. Overall, the claims elicited an approximately equal amount of certain and uncertain negative and positive beliefs as well as neutral beliefs. Uniformity in source credibility ratings was determined as a low credibility source receiving a mean rating lower than -2.5, and a high credibility source receiving a mean rating higher than 2.5, with a standard deviation no greater than 2. Four sources (and thus four pairs of tweets) had to be removed, because they did not receive uniform ratings of credibility, dropping the final number of items from 160 to 152 (low credibility item means: $M = -3.34$, $SD = 0.46$, $Min = -4.38$, $Max = -2.52$; high credibility item means: $M = 2.86$, $SD = 0.46$, $Min = 2.33$, $Max = 4.14$).

The length of each tweet was calculated to control for it in statistical analyses, defined as the total number of characters in the sentence for target and spillover sentences, and as the summed number of characters in the profile name and username for the source areas. The mean number of characters in target sentences was 121.4 ($SD = 21.10$) and in spillover 36.24 ($SD = 5.17$). The mean number of characters in source areas was 27.95 ($SD = 9.60$), with a slight difference between the means of credible and noncredible sources (credible: $M = 31.03$, $SD = 10.71$; noncredible: $M = 24.88$, $SD = 7.20$).

2.3.2 Prior Beliefs Questionnaire

Prior beliefs were measured with an online questionnaire hosted on the open source formr platform (Arslan et al., 2020), to which the participants were sent a link prior to the eye tracking experiment. Beliefs were measured prior to the eye tracking experiment to minimize the possible biasing influence of source credibility on participants' responses. The questionnaire contained the same 76 target sentences as the tweets, presented in randomized order, and participants were asked to rate how much they agreed or disagreed with the claims on a Likert scale ranging from -5 to 5. Participants were instructed to answer based on how certain they were of their beliefs, with -5 indicating extreme disagreement and 5 extreme agreement, whereas values closer to 0 would indicate a higher degree of uncertainty and 0 neutrality. In addition, the questionnaire was used to collect the participants' age, gender, education, and first language. The questionnaire also contained a simple control question to gauge engagement ("Please indicate that you agree strongly with this statement"), to which all participants answered correctly.

2.3.3 Tweet Credibility Ratings

In between reading each individual tweet during the eye tracking experiment, participants were asked to rate the credibility of each Twitter post on a Likert scale ranging from 1–5, where 5 indicated the highest degree of credibility, 1 the lowest degree, and 3 neutrality. The main purpose of this task was to keep the participants critically engaged in reading without revealing the purpose of the study, which is why the instructions were left unspecific. Analyses for the tweet credibility ratings were exploratory and therefore not preregistered.

2.3.4 Source Credibility Ratings

At the end of the experiment, each participant was asked to rate the credibility of the sources they saw during the eye tracking part. These evaluations were collected to ensure that the source credibility manipulation worked. Credibility was defined as expertise and trustworthiness, and it was evaluated on a Likert scale ranging from 1 to 9, where 9 indicated maximal credibility, 1 minimal credibility, and values closer to 5 neutrality or uncertainty. The questions were posed such that the sources were linked to the topics they commented on in the tweets: ("If the topic was X, how credible sources would you find the following accounts to be?"). The participants were instructed to ignore any tweets they remembered from the experiment and try to not let it affect their evaluations of credibility. Topics were presented in randomized order.

2.4 Procedure

Participants were invited to take part in a study where they would be reading social media posts while their eye movements would be recorded. They then read the study description on the university's participant recruitment website, and picked a laboratory time that suited them. Participants gave informed consent either through the recruitment website while making a lab reservation, or, if they did not have a university account to log in to the website, they could make a reservation by emailing the experimenter (in which case consent was collected by signing a consent form).

The link to the online questionnaire measuring prior beliefs and demographics was sent to the participants via email 48 hours before their lab time, and they were instructed to fill the questionnaire at least 24 hours before coming to the laboratory. In the email, each participant received a randomly generated four-number code to later combine the questionnaire data with the eye tracking data. These codes were deleted after the data was combined.

Upon arriving at the lab, the participants were asked whether they had filled out the questionnaire, and what their four-number code was. As the items were divided into two counterbalanced lists, every other participant was assigned to list A, and every other to list B. The participants were then asked to read the instructions for the eye-tracking experiment on the computer screen, after which an initial five-point calibration of the camera was performed. Calibration was deemed successful if the mean calibration error was less than 0.5°, and all individual calibration points had a maximum error of less than 1°. After the calibration, three practice trials were performed, so that the participants would get used to the process. If the participants had no further questions and the calibration was successful, both visually and based on the calibration error, the actual experiment was launched.

During the experiment, participants were presented with 76 mock-up tweets. The tweets were presented in randomized order with an experiment designed with Experiment Builder v2.4.1 (SR Research Ltd, 2023a). The tweets were positioned in the middle of the screen. Each tweet was preceded by a drift check point (black dot) positioned on the left side of where the upcoming tweet's profile picture would land; when the participant looked at the dot, the experimenter presented them with the tweet. Participants were instructed to read the tweet at their own pace, and when they were ready, to continue by pressing the space bar on the keyboard. After each individual item, the participants were asked to evaluate the credibility of the tweet using the number keys on the keyboard. After the participant had answered, the experiment automatically proceeded with a short reminder for the participant to blink, and then to the drift check point for the next item. The eye tracking data was monitored throughout the experiment, and recalibrations were performed when necessary. The eye tracking part of the experiment lasted for approximately 20–45 minutes.

After the eye tracking part had ended, the source credibility evaluation was started, in which the participants were shown screenshots of the profiles they had seen during the experiment. The participants were told to carefully read the instructions on the screen and proceed at their own pace. The participants used number keys to rate the credibility of each profile as a source connected to the topic they had commented on. The profiles were presented one at a time, and the topic order was randomized.

After rating the credibility of the sources, the participants were asked what they thought the study was about, and if they had any thoughts on the tweets they saw. If the participant said nothing about the authenticity of the tweets, they were asked whether they thought there was anything weird about them. If they still did not indicate that they thought at least some of the tweets were fake, they were asked directly whether they thought the tweets were real. This process was completed to see how authentic the tweets seemed to the participants. Before the participants left, the purpose of the study was explained, and everyone was explicitly told that all tweets were fake. Completing the whole session took the participants approximately 45–60 minutes. The gift cards or course credits were given to the participants afterwards.

2.5 Statistical analyses

2.5.1 Data Preparation

Preprocessing of the eye movement data was performed with EyeLink Data Viewer v4.3.210 (SR Research Ltd, 2023b). If the fixations landed outside the interest areas due to calibration error, but it was possible to infer which text row they belonged to, they were manually corrected to the right position. In addition to three participants that had to be completely excluded, 93 trials (approximately 1.5% of all trials) were removed from the analyses due to poor data quality.

To calculate sentence-level eye movement measures (Hyönä et al., 2003), separate interest areas were created for the target sentences, spillover sentences, source areas and profile pictures. The profile pictures were excluded from analyses because they were not necessarily indicative of credibility, and possible confounders (such as interestingness) were not controlled for between source credibility conditions, which means that differences in gaze durations could have been caused by irrelevant features within the profile pictures.

First-pass reading times (ms), defined as the summed duration of fixations directed at the interest area during initial reading, were computed based on the eye tracking data for target- and spillover sentences separately. As the study focuses on source credibility, first-pass reading times for any individual trials where the participants did not look at the source area before reading the target or spillover sentence were coded as missing.

Look-back reading times (ms), defined as the conditional summed duration of fixations directed at the interest area during revisits, were computed for target and spillover sentences separately. Again, any individual trials where the participants did not look at the source area before the second-pass reading were coded as missing for the target and spillover sentences.

S*ource reading times* (ms) were computed for the source areas. The study's hypotheses concerning sources focus on prior beliefs (and thus require that the participants' beliefs are activated), which is why reading times were computed only for the fixations directed at the source after reading the target sentence; trials where participants only looked at the source before reading the target sentence, or did not look at the source at all, were coded as missing. If multiple passes were made at the source, but the first one occurred before reading the target sentence, first-pass reading times were subtracted from the total reading time.

Look-back probabilities (1/0), defined as the probability of revisiting the interest area after it has been exited, were computed for the target sentences, spillover sentences and source areas. Any individual trials where the participants never looked at the source area were coded as missing.

2.5.2 Statistical Analyses

The statistical analyses were conducted using R Statistical Software (v4.3.2; R Core Team, 2023) in RStudio (RStudio Team, 2024) for Windows. Separate analyses were conducted for each dependent variable and for the three interest areas: sources, target sentences, and spillover sentences. Analyses were conducted with linear mixed-effect models (LMMs) for continuous variables and generalized linear mixed-effect models (GLLMs) for binary variables with the *lme4* package (Bates et al., 2015). Tweet credibility ratings were analysed with a cumulative link mixed-effects model (CLMM) using the *ordinal* package (Christensen, 2023). Plots were generated using the *sjPlot* package (Lüdecke, 2023).

Source type (credible vs. noncredible) was fitted into the models as contrast-sum coded [-0.5, 0.5]. Item length was grand mean centered before adding it to the models; source type and prior beliefs were left uncentered due to their naturally symmetrical scales. To improve model fit (Nicklin & Plonsky, 2020), non-normally distributed continuous dependent variables were either logarithm– or square root–transformed based on histograms, Q-Q plots, and skewness measures. Model residuals were inspected using the *ggResidpanel* package (Goode & Rey, 2022) for LMMs and *DHARMa* (Hartig, 2022) for GLMMs. If the residual diagnostics indicated issues, the models were trimmed by removing any individual observations with scaled Pearson residuals larger than 3 standard deviations and rerunning the model using the trimmed dataset.

As per Barr et al. (2013), a maximal random effects structure was initially fitted to the data, including random intercepts for participants and items, and by-participant random slopes for source type and prior beliefs. Formulas for the full initial models can be found in Table 1. Final models for each dependent variable are specified under the results section. Whenever convergence issues emerged, the first step was to try and adjust the model optimizers as outlined in Brown (2021). If this failed, the models were trimmed by removing the random slope with the smallest variance in ascending order, or in case of a singular fit, by removing the random slope with the highest correlation. Calculating degrees of freedom for the t-statistics produced by linear mixed-effect models is difficult, making it hard to determine p-values (Baayen et al., 2008), which is why a *t* or *z* value greater than |1.96| was interpreted as an indicator of statistical significance at an alpha level of .05. If a significant interaction between prior beliefs and source credibility was found, the predicted trends were further tested for significance at different levels of source credibility using the *emmeans* package (Lenth et al., 2024).

Table 1

Full Initial Models

Dependent variable	Initial model	Type
Target/spillover area reading times or look-back probabilities	Dependent v. ~ source type + belief + item length + source type * belief + (source type + belief | participant) + (1 | item)	LMM/ GLMM
Source area reading times or look-back probabilities	Dependent v. ~ belief + item length + (belief | participant) + (1 | item)	LMM/ GLMM
Source credibility ratings	Dependent v. ~ source type + (source type | participant) + (1 | item)	LMM
Tweet credibility ratings	Dependent v. ~ source type + (source type | participant) + (1 | item)	CLMM

Note. LMM = linear mixed-effects model, GLMM = generalized linear mixed-effects model, CLMM = cumulative link mixed-effects model.

2.5.3 Power Simulation

Appropriate sample size was determined with a power simulation using data from Experiment 2 in Wertgen and Richter (2023), which examined the effects of information plausibility and source credibility on the validation of social media posts. In their within-subjects design, participants (n = 50) were asked to read mock-up tweets while their reading times were recorded. Source credibility and plausibility varied between tweets, with the items divided into counterbalanced lists. Reading times were recorded by participants pressing a button on a keyboard to proceed to the next tweet. The final LMM for the reading times used in the power simulations was identical to the one in the original article: main effects for plausibility, credibility, sentence length and trial order, an interaction for plausibility and credibility, and random intercepts for participants and items. For the simulations, item number was fixed at 76 (current study), while participant number was varied in steps of 10 with 1000 successful runs for each step. The critical value for a statistically significant effect was set at |1.96| (α = .05). For the smallest effect in the model (source credibility) a power level of 80% was reached at 80 participants. To account for possible data loss, the sample size goal for the current study was thus set at 85. The LMM was built using the *lme4* package, and simulations were conducted using the *mixedpower* package (Kumle et al., 2021).

2.6 Ethics

The study plan was reviewed and approved by the University of Turku Ethics Committee for Human Sciences. All participants gave written consent. The study protocol and hypotheses were preregistered and can be found on Open Science Framework, along with the analysis code, power simulation code, and data file (osf.io/qh2bg).

3. Results

3.1 Descriptive Statistics

Means and standard deviations of the reading times and look-back probabilities for all interest areas can be found in Table 2.

Table 2
Descriptive Statistics for Reading Times and Look-Back Probabilities

Interest area	First-pass reading time (ms) *M* (*SD*)	Look-back reading time (ms) *M* (*SD*)	Look-back probability *M* (*SD*)
Target sentence	2875 (1232)	1984 (1982)	.69 (.46)
Spillover sentence	1131 (614)	950 (809)	.43 (.50)
Source (total)		862 (684)	.61 (.49)
Credible		907 (691)	.64 (.48)
Noncredible		827 (673)	.58 (.49)

Note. All means and standard deviations are based on untrimmed and untransformed data.

3.2 Evaluations of Source Credibility and Tweet Credibility

3.2.1 Source Credibility Ratings

Source credibility ratings were examined to assess the successfulness of the source credibility manipulation. On average, high credibility sources (M = 7.00, SD = 2.02) were rated as more credible than low credibility sources (M = 2.05, SD = 1.64; scale range: 1–9). Source credibility ratings were analysed using a linear mixed effects model with source type (credible vs. noncredible) as a fixed effect, a by-participant random slope for source type, and random intercepts for participants and items. To improve model fit, individual observations with large residuals were removed (> 3 SD, n = 82). The final model is detailed in Table 3. The source credibility condition had a significant effect (β = -5.14, t = -35.86, d = 3.11) on source credibility ratings, suggesting that the manipulation was successful.

Table 3

Final Model for Source Credibility Ratings

Fixed effects	β	SE	95% CI[a]	t[b]
(Intercept)	4.52	0.12	4.30 – 4.75	**39.09**
Source type	-5.14	0.14	-5.43 – -4.86	**-35.86**
Random effects		**Variance**	**SD**	**Correlation**
Participant (intercept)		0.51	0.71	
Source type | Participant (slope)		1.62	1.27	-.11
Item (intercept)		0.53	0.73	
Residual		1.66	1.29	
Model fit		**Marginal R^2**	**Conditional R^2**	
		.68	.83	
Model equation: Source credibility rating ~ Source type + (Source type | Participant) + (1 | Item)				

Note. SE = standard error, CI = confidence interval. N = 5956 (84 participants, 75 items).
[a] Confidence intervals were calculated using the Wald method.
[b] Statistically significant values (t > |1.96|; α = 0.05) in bold.

3.2.2 Tweet Credibility Ratings

Analyses for the tweet credibility ratings were exploratory. On average, participants gave similar ratings of credibility for tweets from high credibility sources (M = 2.95, SD = 1.34) and low credibility sources (M = 2.94, SD = 1.34; scale range: 1–5). Tweet credibility ratings were analysed using a cumulative link mixed model with source credibility as a fixed effect. The model included random intercepts for participants and items, but the by-participant random slope for source credibility resulted in a singular fit and was removed. The proportional odds assumption was tested with a likelihood ratio test, on a model without random effects, as tools for mixed models are currently not available. However, the trimmed model produced results close to the original model (random effects only explained a small proportion of the variance), and the assumption was met ($\chi^2(3) = 3.51$, $p = .320$). The final model is detailed in Table 12. The results showed that the source credibility condition had no significant effect on tweet credibility ratings (*OR* = 0.98, $z = -0.42$).

Table 4

Final Model for Tweet Credibility Ratings

Fixed effects	*OR*	*SE*	95% CI[a]	z[b]
Source credibility	0.98	0.04	0.90 – 1.07	-0.42
Threshold coefficients	*OR*	*SE*	95% CI	z
1|2	0.22	0.01	0.20 – 0.24	**-33.07**
2|3	0.72	0.03	0.67 – 0.78	**-8.02**
3|4	1.44	0.06	1.33 – 1.56	**8.95**
4|5	6.43	0.31	5.84 – 7.07	**38.16**
Random effects		Variance	*SD*	
Participant (intercept)		0.08	0.28	
Item (intercept)		0.06	0.24	
Model fit		Nagelkerke R^2		
		< .00		
Model equation: Tweet credibility rating ~ Source credibility + (1 | Participant) + (1 | Item)				

Note. *OR* = odds ratio, *SE* = standard error, CI = confidence interval. $N = 6120$ (83 participants, 76 items).
[a] Confidence intervals were calculated using the Wald method.
[b] Statistically significant values ($z > |1.96|$; $\alpha = 0.05$) in bold.

3.3 Prior Beliefs and Attention Directed at the Source

3.3.1 Source Reading Times

To test whether the subjects' prior beliefs (their degree of agreement) affected how much attention they directed at the source (Hypothesis 1), source reading times were initially analysed using a linear mixed-effects model with prior beliefs and item length as fixed effects.

Due to convergence issues, the by-participant random slope for prior beliefs was removed from the model, leaving random intercepts for participants and items. In addition, residual fit was poor, and the model was rerun after removing individual observations with large residuals (> 3 *SD; n* = 45). In this model, item length was the only factor with a significant effect on reading times (β = 0.02, t = 13.54) while no significant effect was found for prior beliefs (β = -0.00; t = -0.20). These results were surprising given the existing literature, which is why exploratory analyses were conducted by adding the source type into the model.

The final exploratory model included prior beliefs, source type, their interaction, and item length as fixed effects. The by-participant random slope for prior beliefs was removed due to convergence issues, leaving the by-participant random slope for source type, and random intercepts for participants and items. Again, observations with large residuals were removed (> 3 *SD; n* = 48). The final model is detailed in Table 5.

Table 5

Final Model for Source Reading Times

Fixed effects	β	*SE*	95% CI[a]	t[b]
(Intercept)	6.45	0.04	6.37 – 6.53	**156.82**
Belief	-0.00	0.00	-0.01 – 0.01	-0.13
Source type	-0.02	0.03	-0.07 – 0.03	-0.78
Item length	0.02	0.00	0.01 – 0.02	**11.83**
Belief * Source type	0.04	0.01	0.03 – 0.05	**7.12**

Random effects	Variance	*SD*	Correlation
Participant (intercept)	0.11	0.34	
Source type | Participant (slope)	0.02	0.15	.10
Item (intercept)	0.02	0.12	
Residual	0.37	0.61	

Model fit	Marginal R^2	Conditional R^2
	.05	.31

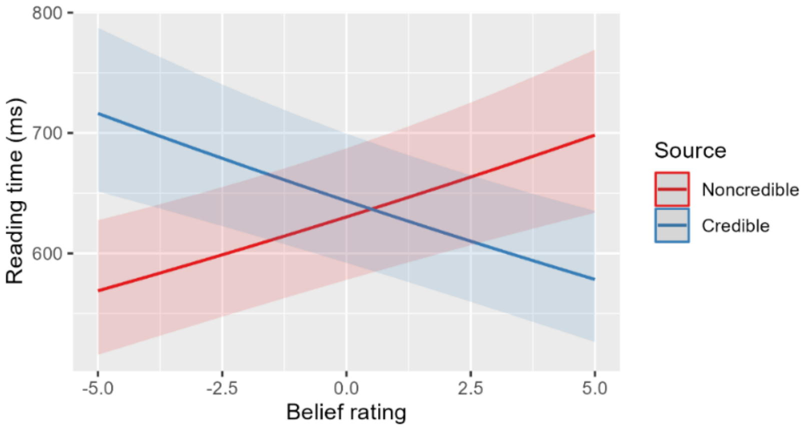
Model equation: Reading time (log) ~ Belief + Source type + Item length + Belief * Source type + (1 + Source type | Participant) + (1 | Item)

Note. SE = standard error, CI = confidence interval. N = 4446 (83 participants, 76 items). Source reading times were logarithmically transformed.
[a] Confidence intervals were calculated using the Wald method.
[b] Statistically significant values (t > |1.96|; α = 0.05) in bold.

A significant effect on source reading times was found for item length (β = 0.02, t = 11.83) and there was an interaction of source type and prior beliefs (β = 0.04, t = 7.12), whereas prior beliefs (β = -0.00, t = -0.13) and source type (β = -0.02, t = -0.78) had no significant main effects. These results are visualized in Figure 3, which suggests that reading times for credible sources decreased the more participants agreed with the claims presented in the tweets, whereas reading times for noncredible sources increased the more participants agreed with the claims. This interpretation was supported by the simple slope analyses, which showed that prior beliefs had a significant effect both for noncredible (β = 0.02, t = 4.479) and credible sources (β = -0.02, t = -4.721)

Figure 3

Effects of Source Credibility and Prior Beliefs on Source Reading Times



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

3.3.2 Source Look-Back Probabilities

Similarly to source reading times, the preregistered analyses of look-back probabilities were conducted using a generalized linear mixed effects model with prior beliefs and item length as fixed effects. The by-participant random slope for prior beliefs was removed due to convergence issues, leaving random intercepts for participants and items. Observations with large residuals were also removed (> 3 SD; n = 28). Again, item length was the only factor with a significant effect on source area look-back probabilities (OR = 0.01, t = 3.02) while prior beliefs had no significant effect (OR = 0.01; z = 0.750).

Exploratory analyses were conducted by adding the source type into the model. The final exploratory model for source look-back probabilities included prior beliefs, source type, their interaction, and item length as fixed effects. Convergence issues lead to the removal of the by-participant slope for source type, leaving a by-participant random slope for prior beliefs and random intercepts for participants and items. To improve model fit, individual observations with large residuals were removed (> 3 *SD*; $n = 30$). The final model is detailed in Table 6.

There was an interaction of source type and prior beliefs in source look-back probabilities ($OR = 1.11$, $z = 4.96$). Source type also had a significant main effect ($OR = 0.71$, $z = -4.87$), whereas the effects of prior beliefs ($OR = 1.01$, $z = 0.44$) and item length ($OR = 1.00$, $z = 1.14$) were not significant. These results are visualized in Figure 4, which suggests that participants were the more likely to make look-backs to credible sources and the less likely to make look-backs to noncredible sources the more they disagreed with the claims presented in the tweets. However, the difference in look-back probabilities between source credibility conditions diminished the more participants agreed with the claims. Simple slope analyses showed that the increase in look-backs to noncredible sources ($\beta = 0.05$, $z = 3.68$) and the decrease to credible sources ($\beta = -0.04$, $t = -2.63$) the more participants agreed with the claims was significant.

Table 6

Final Model for Source Look-Back Probabilities

Fixed effects	*OR*	*SE*	95% CI[a]	z[b]
(Intercept)	1.59	0.29	1.11 – 2.27	**2.56**
Belief	1.01	0.01	0.98 – 1.03	0.44
Source type	0.71	0.05	0.62 – 0.82	**-4.87**
Item length	1.00	0.00	1.00 – 1.01	1.14
Belief * Source type	1.11	0.02	1.06 – 1.15	**4.96**

Random effects	Variance	*SD*	Correlation
Participant (intercept)	2.55	1.60	
Belief | Participant (slope)	0.00	0.02	-.50
Item (intercept)	0.03	0.17	

Model fit	Marginal R^2	Conditional R^2
	.01	.45

Model equation: Look-back probability ~ Belief + Source type + Item length + Belief * Source type + (1 + Belief | Participant) + (1 | Item)

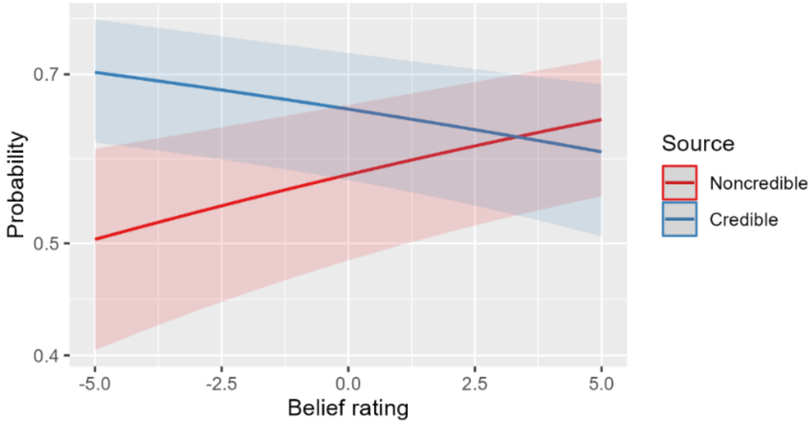
Note. OR = odds ratio, *SE* = standard error, CI = confidence interval. $N = 5444$ (83 participants, 76 items).

[a] Confidence intervals were calculated using the Wald method.

[b] Statistically significant values ($z > |1.96|$; $\alpha = 0.05$) in bold.

Figure 4

Effects of Source Credibility and Prior Beliefs on Source Look-Back Probabilities



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

3.4 Prior Beliefs, Source Credibility, and Validation

3.4.1 First-Pass Reading Times

3.4.1.1 Target sentences. To test whether source credibility and participants' prior beliefs influenced the validation of the tweets (Hypotheses 2 and 3), the different eye movement measures for target and spillover sentences were analysed separately. First-pass reading times for target sentences were analysed using a linear mixed-effects model with prior beliefs, the source type, their interaction, and item length as fixed effects. The by-participant random slope for source type was removed due to a singular fit, leaving a by-participant slope for prior beliefs, and random intercepts for participants and items. To improve model fit, individual observations with large residuals were removed (> 3 *SD*, $n = 76$). The final model is detailed in Table 7.

Significant effects were found for prior beliefs ($\beta = 0.13$, $t = 2.09$) and item length ($\beta = 0.23$, $t = 17.62$), but the effects of source type ($\beta = 0.43$, $t = 1.83$) and the source type–prior beliefs interaction ($\beta = 0.01$, $t = 0.07$) were not significant. These results are visualized in Figure 5. Interestingly, prior beliefs' effect was in an unexpected direction, with disagreeable sentences being read slightly faster than agreeable ones.

Table 7

Final Model for Target Sentence First-Pass Reading Times

Fixed effects	β	*SE*	95% CI[a]	t[b]
(Intercept)	52.83	0.81	51.25 – 54.41	**65.52**
Belief	0.13	0.06	0.01 – 0.24	**2.09**
Source type	0.43	0.23	-0.03 – 0.88	1.83
Item length	0.23	0.01	0.21 – 0.26	**17.62**
Belief * Source type	0.01	0.07	-0.14 – 0.15	0.07

Random effects	Variance	*SD*	Correlation
Participant (intercept)	45.06	1.60	
Belief | Participant (slope)	0.09	0.30	.32
Item (intercept)	4.73	2.17	
Residual	46.92	6.85	

Model fit	Marginal R^2	Conditional R^2
	.20	.61

Model equation: Reading time (sqrt) ~ Belief + Source type + Item length + Belief * Source type + (1 + Belief | Participant) + (1 | Item)

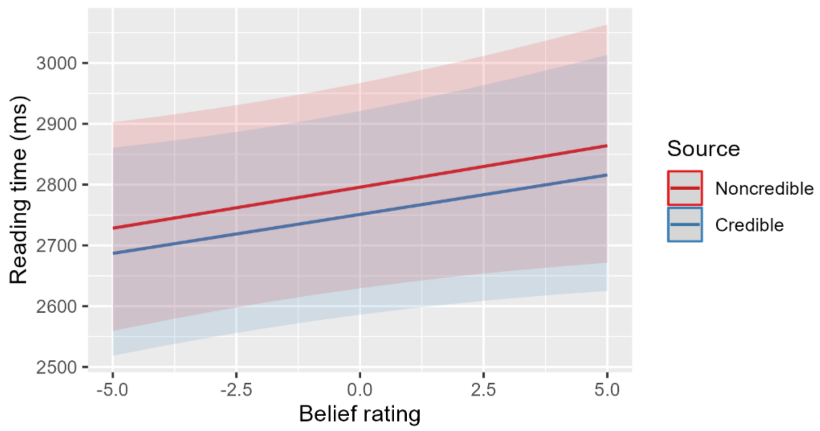
Note. *SE* = standard error, CI = confidence interval. N = 3554 (82 participants, 76 items). Reading times were square-root-transformed.

[a] Confidence intervals were calculated using the Wald method.

[b] Statistically significant values ($t > |1.96|$; $\alpha = 0.05$) in bold.

Figure 5

Effects of Source Credibility and Prior Beliefs on Target Sentence First-Pass Reading Times



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

3.4.1.2 **Spillover Sentences.** First-pass reading times for spillover sentences were analysed using an LMM with prior beliefs, source type, their interaction, and item length as fixed effects. The by-participant random slope for source type was removed due to a singular fit and convergence issues, leaving a by-participant random slope for prior beliefs, and random intercepts for participants and items. To improve model fit, individual observations with large residuals were removed (> 3 *SD*, $n = 54$). The final model is detailed in Table 8.

The only significant effect on reading times was found for item length ($\beta = 0.31$, $t = 5.87$), whereas the effects of source type ($\beta = -0.13$, $t = -0.58$), prior beliefs ($\beta = 0.05$, $t = 1.13$), and their interaction ($\beta = -0.03$, $t = -0.38$) were not significant. These results are visualized in Figure 6.

Table 8

Final Model for Spillover Sentence First-Pass Reading Times

Fixed effects	β	*SE*	95% CI[a]	t[b]
(Intercept)	32.17	0.54	31.12 – 33.22	**60.01**
Belief	0.05	0.05	-0.04 – 0.14	1.13
Source type	-0.13	0.23	-0.58 – 0.31	-0.58
Item length	0.31	0.05	0.20 – 0.41	**5.87**
Belief * Source type	-0.03	0.07	-0.17 – 0.12	-0.38
Random effects		Variance	*SD*	Correlation
Participant (intercept)		16.36	4.04	
Belief | Participant (slope)		0.00	0.07	.40
Item (intercept)		4.47	2.11	
Residual		45.52	6.75	
Model fit		Marginal R^2	Conditional R^2	
		.04	.34	

Model equation: Reading time (sqrt) ~ Belief + Source type + Item length + Belief * Source type + (1 + Belief | Participant) + (1 | Item)

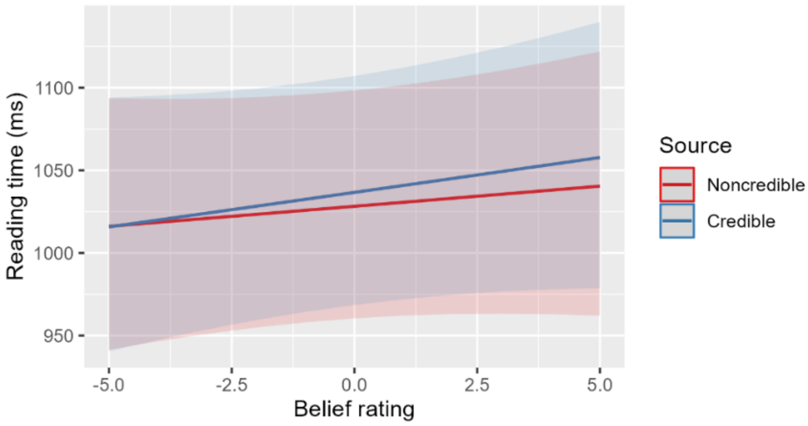
Note. *SE* = standard error, CI = confidence interval. $N = 3575$ (82 participants, 76 items). Reading times were square-root-transformed.

[a] Confidence intervals were calculated using the Wald method.

[b] Statistically significant values ($t > |1.96|$; $\alpha = 0.05$) in bold.

Figure 6

Effects of Source Credibility and Prior Beliefs on Spillover Sentence First-Pass Reading Times



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

3.4.2 Look-Back Probabilities

3.4.2.1 **Target Sentences.** Look-back probabilities for target sentences were analysed using a GLMM with prior beliefs, source type, their interaction, and item length as fixed effects. The by-participant random slope for source type was removed due to a singular fit, leaving a by-participant random slope for prior beliefs, and random intercepts for participants and items. To improve model fit, individual observations with large residuals were removed (> 3 *SD, n* = 45). The final model is detailed in Table 9.

There was an interaction of source type and prior beliefs in look-back probabilities (*OR* = 1.08, $z = 3.56$). No significant main effects were found (prior beliefs: *OR* = 1.01, $z = 0.43$; source type: *OR* = 0.89, $z = -1.66$; item length: *OR* = 1.00, $z = -0.55$). These results are visualized in Figure 7, which suggests that participants were the less likely to make look-backs to target sentences from noncredible sources the more they disagreed with the claims, and the more likely the more they agreed with the claims. This trend was reversed for credible sources, although the effect was less pronounced. Simple slope analyses supported this interpretation: the effect of prior beliefs was significant for noncredible ($\beta = 0.04$, $z = 2.42$), but not for credible sources ($\beta = -0.03$, $z = -1.66$).

Table 9

Final Model for Target Sentence Look-Back Probabilities

Fixed effects	*OR*	*SE*	95% CI[a]	z^b
(Intercept)	3.61	0.71	2.46 – 5.31	**6.53**
Belief	1.01	0.02	0.98 – 1.04	0.43
Source type	0.89	0.06	0.78 – 1.02	-1.66
Item length	1.00	0.00	0.99 – 1.00	-0.55
Belief * Source type	1.08	0.02	1.03 – 1.12	**3.56**

Random effects	Variance	*SD*	Correlation
Participant (intercept)	2.85	1.69	
Belief | Participant (slope)	0.00	0.03	-.19
Item (intercept)	0.08	0.29	

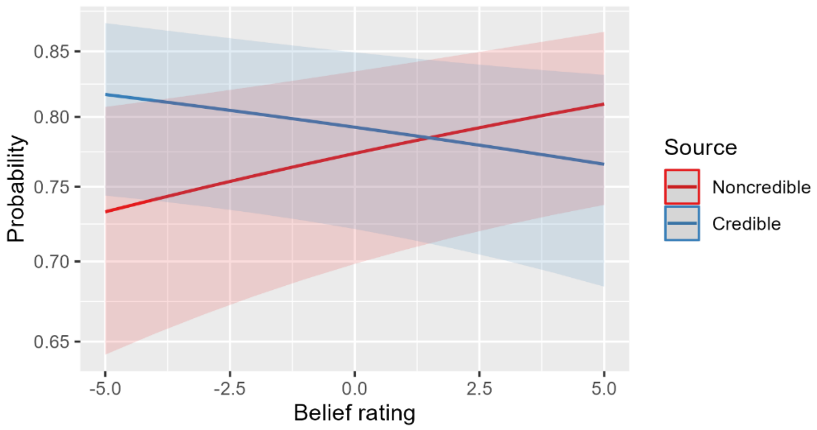
Model fit	Marginal R^2	Conditional R^2
	.00	.47

Model equation: Look-back probability ~ Belief + Source type + Item length + Belief * Source type + (1 + Belief | Participant) + (1 | Item)

Note. *OR* = odds ratio, *SE* = standard error, CI = confidence interval. *N* = 5426 (83 participants, 76 items).
[a] Confidence intervals were calculated using the Wald method. [b] Statistically significant values ($z > |1.96|$; $\alpha = 0.05$) in bold.

Figure 7

Effects of Source Credibility and Prior Beliefs on Target Sentence Look-Back Probabilities



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

3.4.2.2 **Spillover Sentences**. Look-back probabilities for spillover sentences were analysed using a GLMM with prior beliefs, source type, their interaction, and item length as fixed effects. The by-participant random slopes for both prior beliefs and source type were removed due to singularity, leaving random intercepts for participants and items. The final model is detailed in Table 10.

There was a significant interaction of source type and prior beliefs (*OR* = 1.09, z = 4.62), and an effect of source type (*OR* = 0.87, z = -2.22) on look-back probabilities. No significant main effects were found for prior beliefs (*OR* = 1.00, z = -0.31) or item length (*OR* = 1.00, z = -0.32). These results are visualized in Figure 8, which suggests that participants were the more likely to make look-backs to spillover sentences from credible sources the more they disagreed with the claims presented in the tweets, and the less likely the more they agreed.

Table 10

Final Model for Spillover Sentence Look-Back Probabilities

Fixed effects	*OR*	*SE*	95% CI[a]	z[b]
(Intercept)	0.68	0.09	0.53 – 0.88	**-2.97**
Belief	1.00	0.01	0.98 – 1.02	-0.31
Source type	0.87	0.05	0.77 – 0.98	**-2.22**
Item length	1.00	0.01	0.98 – 1.01	-0.32
Belief * Source type	1.09	0.02	1.05 – 1.14	**4.62**
Random effects		Variance	*SD*	
Participant (intercept)		1.21	1.10	
Item (intercept)		0.06	0.24	
Model fit		Marginal R^2	Conditional R^2	
		.01	.28	

Model equation: Look-back probability ~ Belief + Source type + Item length + Belief * Source type + (1 | Participant) + (1 | Item)

Note. *OR* = odds ratio, *SE* = standard error, CI = confidence interval. N = 5465 (83 participants, 76 items).

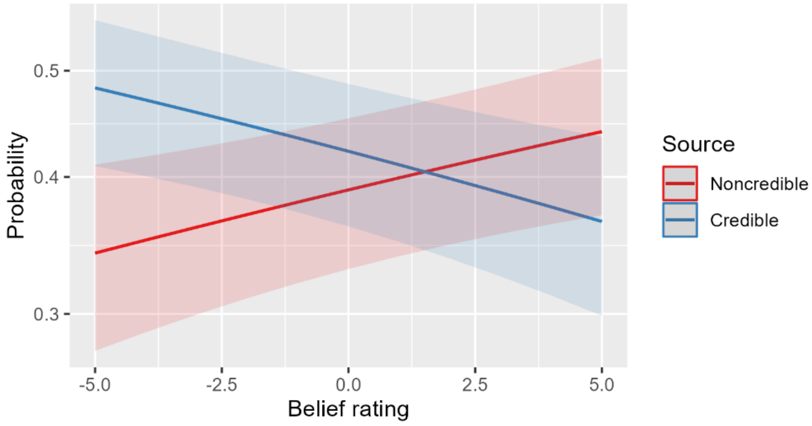
[a] Confidence intervals were calculated using the Wald method.

[b] Statistically significant values ($z > |1.96|$; $\alpha = 0.05$) in bold.

This pattern was reversed for spillover sentences from noncredible sources, with participants being the less likely to make look-backs the more they disagreed, and the more likely the more they agreed. However, the predicted difference in reading times between source credibility conditions was smaller when participants agreed with the claims. The results of the simple slope analyses were in line with these observations: the effect of prior beliefs was significant for both credible (β = 0.05, z = -3.30) and noncredible sources (β = 0.04, z = 2.85).

Figure 8

Effects of Source Credibility and Prior Beliefs on Spillover Sentence Look-Back Probabilities



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

3.4.3 Look-Back Reading Times

3.4.3.1 **Target Sentences.** Look-back reading times for target sentences were analysed using an LMM with prior beliefs, source type, their interaction, and item length as fixed effects. The by-participant random slope for source type was removed due to a singular fit, leaving a by-participant random slope for prior beliefs, and random intercepts for participants and items. To improve model fit, individual observations with large residuals were removed (> 3 *SD*, n = 25). The final model is detailed in Table 11.

Table 11

Final Model for Target Sentence Look-Back Reading Times

Fixed effects	*β*	*SE*	95% CI[a]	t^{b}
(Intercept)	7.03	0.06	6.90 – 7.15	**110.79**
Belief	-0.003	0.01	-0.02 – 0.01	-0.47
Source type	-0.04	0.03	-0.11 – 0.02	-1.26
Item length	0.004	0.00	0.00 – 0.01	**3.40**
Belief * Source type	0.04	0.01	0.02 – 0.06	**3.60**

Random effects	Variance	*SD*	Correlation
Participant (intercept)	0.26	0.51	
Belief | Participant (slope)	0.00	0.03	.04
Item (intercept)	0.03	0.18	
Residual	0.88	0.94	

Model fit	Marginal R^2	Conditional R^2
	.01	.27

Model equation: Reading time (log) ~ Belief + Source type + Item length + Belief * Source type + (1 + Belief | Participant) + (1 | Item)

Note. *SE* = standard error, CI = confidence interval. *N* = 3401 (82 participants, 76 items). Reading times were logarithmically transformed.

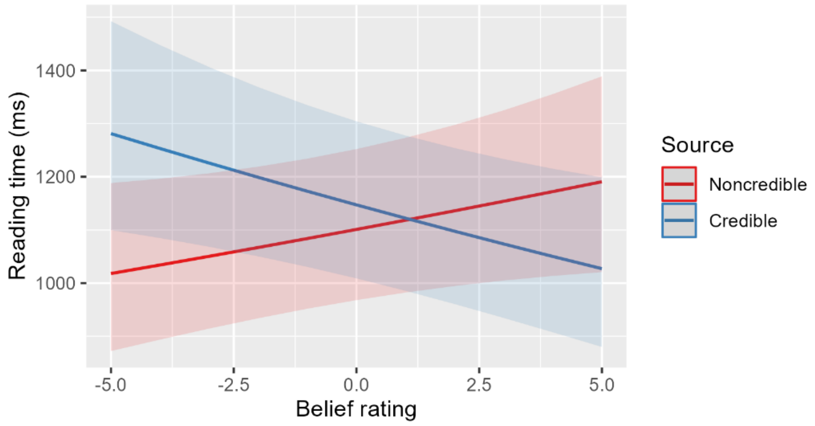
[a] Confidence intervals were calculated using the Wald method.

[b] Statistically significant values ($t > |1.96|$; $\alpha = 0.05$) in bold.

Significant effects on reading times were found for item length ($\beta = 0.004$, $t = 3.40$) and the interaction of source type and prior beliefs ($\beta = 0.04$, $t = 3.60$). The main effects for source type ($\beta = -0.04$, $t = -1.26$) and prior beliefs ($\beta = -0.003$, $t = -0.47$) were not significant. These results are visualized in Figure 9, which suggests that reading times for claims from credible sources increased the more participants disagreed with the claims, whereas reading times for claims from noncredible sources decreased the more participants disagreed. A difference between source credibility conditions was observed also when participants agreed with the claims, but it was less pronounced compared to disagreement. Simple slope analyses showed that the effect of prior beliefs was significant for credible ($\beta = -0.02$, $t = -2.55$), but not for noncredible sources ($\beta = 0.02$, $t = 1.79$). This supports the interpretation that an incongruence between source credibility and prior beliefs had less of an effect on reading times when participants agreed with the claims.

Figure 9

Effects of Source Credibility and Prior Beliefs on Target Sentence Look-Back Reading Times



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

3.4.3.2 Spillover Sentences. Look-back reading times for spillover sentences were analysed using an LMM with prior beliefs, source type, their interaction, and item length as fixed effects. By-participant random slopes for both prior beliefs and source type were removed due to singularity, leaving random intercepts for participants and items. The final model is detailed in Table 12.

There was a significant interaction of source credibility and prior beliefs (β = 0.03, t = 2.82) in look-back reading times for spillover sentences, along with main effects for prior beliefs (β = -0.01, t = -2.04) and item length (β = 0.01, t = 3.15). The main effect for source credibility was not significant (β = -0.01, t = -0.44). These results are visualized in Figure 10, which suggests that reading times for claims from credible sources increased the more participants disagreed with the claims and decreased the more they agreed. This trend was not observed for claims from noncredible sources. Simple slope analyses supported this interpretation: the effect of prior beliefs was significant for credible (β = -0.03, t = -3.42), but not for noncredible sources (β = 0.00, t = 0.45).

Table 12

Final Model for Spillover Sentence Look-Back Reading Times

Fixed effects	*β*	*SE*	95% CI[a]	*t*[b]
(Intercept)	6.45	0.04	6.37 – 6.53	**154.55**
Belief	-0.01	0.01	-0.02 – -0.00	**-2.04**
Source type	-0.01	0.03	-0.08 – 0.05	-0.44
Item length	0.01	0.00	0.00 – 0.02	**3.15**
Belief * Source type	0.03	0.01	0.01 – 0.05	**2.82**
Random effects		Variance	*SD*	
Participant (intercept)		0.11	0.32	
Item (intercept)		0.01	0.08	
Residual		0.59	0.77	
Model fit		Marginal R^2	Conditional R^2	
		.01	.17	

Model equation: Reading time (log) ~ Belief + Source type + Item length + Belief * Source type + (1 | Participant) + (1 | Item)

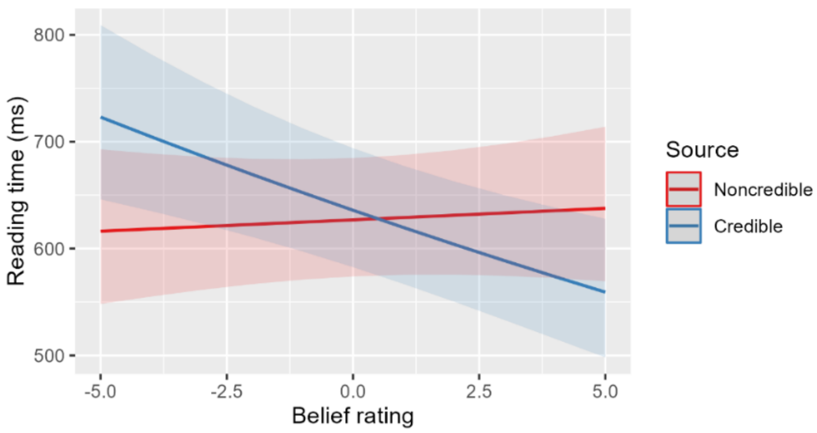
Note. *SE* = standard error, CI = confidence interval. *N* = 2349 (82 participants, 76 items). Reading times were logarithmically transformed.

[a] Confidence intervals were calculated using the Wald method.

[b] Statistically significant values ($t > |1.96|$; $\alpha = 0.05$) in bold.

Figure 10

Effects of Source Credibility and Prior Beliefs on Spillover Sentence Look-Back Reading Times



Note. Belief rating scale: -5 = extreme disagreement, 0 = neutrality, 5 = extreme agreement. Shaded areas represent 95% confidence intervals.

4. Discussion

The aims of this study were to investigate how readers process source information in social media posts, and how source credibility and readers' prior beliefs interact in validation. To this end, the study produced multiple interesting findings.

Attention to source information during reading was not predicted solely by the participants' prior negative beliefs (Hypothesis 1). Instead, an interaction of prior beliefs and source credibility emerged – source area look-back reading times and look-back probabilities were the highest when participants saw credible sources make highly disagreeable claims, and lowest when the claims came from noncredible sources. Surprisingly, source reading times were longer also when participants saw agreeable claims from noncredible sources.

Hypotheses about validation received mixed support. Both source credibility and prior beliefs were, as expected, considered in validation. These effects were observed in look-back probabilities and look-back reading times, but not in first-pass reading times. The results for each eye movement measure were largely similar between target sentences and spillover sentences. An interaction was expected to occur when participants saw claims they disagreed with (Hypothesis 2), reading times and look-back probabilities being the highest when credible sources made claims participants strongly disagreed with (2a), as opposed to situations where the participants' disagreement was more uncertain (2b). Accordingly, target sentence and spillover sentence look-back reading times and probabilities increased for credible sources and decreased for noncredible sources the more participants disagreed with the claims. However, contradicting Hypothesis 3, effects (although smaller) were observed also when participants agreed with the claims: look-back probabilities for target and spillover sentences and look-back reading times for target sentences increased for noncredible sources and decreased for credible sources the more participants agreed with the claims. No differences between source credibility conditions were observed when participants held neutral beliefs. Lastly, exploratory analyses indicated that source credibility did not affect evaluations of message credibility. Possible explanations and implications for these results are discussed below, along with the strengths and limitations of the study and avenues for future research.

4.1 Discrepant Information and Attention to Sources

As stated in Hypothesis 1, source reading times and source look-back probabilities were expected to vary as a function of participants' prior beliefs, in that attention to sources was expected to be heightened when participants disagreed with the claims. These predictions were based on the D-ISC model (Braasch & Bråten, 2017) and associated research, in which source information plays a role in conflict resolution during reading. Discrepant information, such as belief-inconsistent text, is thought to create a rift in constructing a coherent representation of the text and source information may help resolve the conflict, whereas belief-consistent text should not require any additional information, as there is no conflict. This study, however, did not find such a straightforward text–belief consistency effect in sourcing that for example Maier and Richer (2013) and Bråten et al. (2016) have reported. Instead, prior beliefs alone had no significant effects on either source reading times or look-back probabilities: participants paid a similar amount of attention to sources regardless of whether they agreed or disagreed with the claims.

Because these results were unexpected, exploratory analyses were conducted by including the source credibility condition in the models. This revealed that the lack of effects observed in the original models was due to a cross-over interaction between source credibility and prior beliefs: source look-back probabilities and reading times increased for credible sources and decreased for noncredible sources the more participants disagreed with the claims. Also unexpectedly, the more participants agreed with the claims, the more source reading times increased for noncredible and decreased for credible sources. Look-back probabilities, however, did not exhibit this difference between source types with agreeable claims.

What these results might mean, then, is that text–belief inconsistencies were not the only thing responsible for steering participants' attention to source information in this study. One possible explanation is that some other type of inconsistency is a more powerful elicitor of sourcing compared to a conflict between the reader and the text. Because the current study observed an interaction in agreeable as well as disagreeable claims, increased attention to sources could have been caused by a conflict between prior beliefs and the perceived credibility of the source, or, alternatively, a perceived conflict between the text and the source.

Source–belief inconsistencies could trigger discrepancies where source information is relevant regardless of the direction of the reader's beliefs – for example, "I completely disagree with this claim, but the source seems credible; something must be wrong" vs. "I think this is a terrible source, yet I seem to agree with them; something must be wrong". Another possibility is that participants allocated more attention to sources because they saw something they perceived as a *text–source* inconsistency. For example, participants might have found it unlikely or unexpected that a source would be serious in claiming whatever it was they were tweeting about. This, again, could trigger attention to sources regardless of the direction of the participants' beliefs, because the conflict is outside of the participant. It is also possible that both types of discrepancies affect reading. Regardless, one should note that a fully crossed interaction was observed only in source reading times, while look-back probabilities were higher only when participants disagreed with claims from credible sources.

It might be that text–belief consistency still had an effect, but it was undetectable in source reading times due to another effect, or it could occur earlier than the other effects and thus be present in both eye movement measures. For example, what the results might indicate is that participants did make look-backs to sources even when they agreed with the claims, but they kept reading the source information only if the credibility was in contradiction with their beliefs or the text. This kind of discrepancy becomes salient only after making the look-back. Belief-inconsistent information, on the other hand, already on its own signals a discrepancy to the reader. In addition, participants consistently allocated the least attention to noncredible sources making highly disagreeable claims, which could indicate that they made use of source information in conflict resolution by promptly assigning a discrepancy to an untrustworthy or incompetent source.

An obvious explanation for the different findings between this study and the studies of Maier & Richter (2013) and Bråten et al. (2016) is that the sources included in their studies were all relatively credible. Ergo, there was no discrepancy when participants agreed with the texts. There are also several other differences between the studies that could account for the results. Firstly, this study measured on-line processing via eye tracking, whereas their studies focused on an off-line measure of source memory. It is not self-evident that these two measures should correlate, because increased attention to sources might not always lead to stronger source–content links in long-term memory representations. Secondly, the materials used in the studies were different: Maier and Richer used eight 900-word texts about climate change and vaccinations with sources embedded within them. Bråten et al. used two 400-word texts about the connection between cell phones and cancer alongside information about the source. The current study, however, utilized very short tweets with the sources featured more prominently right next to the tweet content. This could attract attention in a different manner. Thirdly, prior beliefs were measured differently between the studies: Maier and Richter used an index of ten questions gauging participants' beliefs about each topic, while Bråten et al. used two questions about the one topic. The current study directly measured participants' beliefs about each of the specific claims featured in the tweets. These differences in measurement could lead to variance in results.

Taken together, these results are not explicitly predicted by the D-ISC, but they can be considered to extend the model There is still a discrepancy that induces readers' sourcing behaviour, it just isn't necessarily always a discrepancy between the text and the reader's beliefs. Braasch & Bråten (2017) have previously discussed the unexplored differences and similarities between different types of discrepancies: for example, text–belief, within-text, and across-text contradictions, in addition to contradictions between layers of sources, such as when a writer of an article contradicts with an embedded source. Source–belief and text–source inconsistencies could very plausibly be added to this list.

4.2 Prior Beliefs and Source Credibility in Validation

Hypotheses 2 and 3 were concerned with how readers' prior beliefs and source credibility affect validation. An interaction of these two factors was expected to occur when participants disagreed with the claims (Hypothesis 2), but not when they agreed (Hypothesis 3). In addition, when disagreeing with the claims, the effects of source credibility were expected to vary based on the degree of strength of the participants' beliefs – a credible source was expected to hinder validation with strong disagreement (2a) but make it easier with more uncertain disagreement (2b). This was expected to be reflected in increased first-pass and look-back reading times and look-back probabilities for both target and spillover sentences.

Other than item length, the only significant effect observed in first-pass reading times was a main effect of prior beliefs for target sentences. First-pass reading times for target sentences were slightly faster the more participants disagreed with the claims, which was unexpected in light of earlier research, but the effect was rather small. However, an interaction of source credibility and prior beliefs was observed in look-back reading times and look-back probabilities for both sentences. These results indicate that readers do consider both factors in validation, but that the effects on processing occur with a slight delay. This time course is partly in concordance with the results from Wertgen et al. (2021), in which reading times for spillover sentences, but not target sentences, were affected. In this study, however, the time course was reflected only between first-pass and look-back measures, while the results between target sentences and spillover sentences were largely similar for each eye movement measure. This could be due to methodological differences. In a sentence-by-sentence paradigm such as in the earlier studies on the topic, reading is essentially divided into different stages by necessity based on pressing a key, whereas in the current study, participants could see both sentences simultaneously. Thus, the increased spillover reading times in a sentence-by-sentence setup might be comparable to the look-back measures in an eye-tracking experiment with short texts.

What the look-back reading times and probabilities showed, was that processing claims coming from credible sources was more effortful the more participants disagreed with the claims. Processing claims coming from noncredible sources, however, was easier the more participants disagreed with the claims. Source credibility's effects decreased the closer to neutrality participants' beliefs were. These results are in line with Hypotheses 2a and 2b. Contrary to Hypothesis 3 but similarly to participants' sourcing behaviour, the credibility condition also showed effects when participants agreed with the claims, although the differences between source types were smaller compared to disagreement. With a noncredible source, target sentence look-back probabilities and look-back reading times as well as spillover sentence look-back probabilities increased the more participants agreed with the claims. No observable effect was found in spillover sentence look-back reading times for agreeable claims.

So far, the only study to report an effect of source credibility with belief-consistent claims is Wertgen and Richter's (2023), in which untrustworthy sources increased the reading times for plausible tweets. Wertgen and Richter speculate that these findings could have occurred because source information is more saliently displayed on Twitter compared to earlier studies using other kinds of materials. As such, the current study's results could also be explained by the type of materials used. A further interpretation to consider is that (at least in situations of high source salience), readers consider not just text–belief consistencies in validation, but also source–belief or text–source consistencies, as already discussed at length with regards to the differences in readers' attention to sources. General world knowledge might dominate the validation process when source information is not easily available, but it is possible that readers are sensitive to all kinds of discrepancies during reading if these discrepancies can be detected effortlessly enough.

4.3 Tweet credibility

Analyses of the source credibility condition's effect on evaluations of tweet credibility were exploratory, which is why no hypotheses were formed beforehand. Source credibility has been shown to affect perceived message credibility (e.g. Kuutila et al., 2024), and it was thought interesting to see whether this was the case in the current study as well. However, the tweet credibility did not significantly differ between credible and noncredible sources. It is unclear why no effect was observed. One thing to note is that the tweet credibility evaluations were initially intended only as a task to keep the participants engaged in reading during the experiment without revealing the purpose of the study. This is why the instructions for participants were left unelaborated and the Likert scale was cruder than the other measures in this study. It is possible that different participants interpreted the task differently, and the question did not consistently measure message credibility. An interesting alternative is that even though participants processed credible and noncredible source information differently based on their prior beliefs, evaluations of message credibility are largely determined by prior beliefs alone, with contextual factors such as source credibility exerting a much smaller influence. However, these explanations are mere speculation at this point.

4.4 Strengths and Limitations

To the best of the author's knowledge, this was the first study to use eye tracking to investigate the effects of source credibility and readers' prior beliefs on validation and sourcing behaviour. Precise on-line measures such as the reported eye-movement variables provide previously unexplored information about the time course of these phenomena. In addition, no prior studies have manipulated the credibility of the source when investigating text–belief consistency effects in sourcing. Source credibility might explain why some studies have observed no increases in sourcing even when readers have disagreed with the text (e.g. van Strien et al., 2016). Eye tracking also enables the researcher to make sure that participants actually look at the sources – it is not possible to investigate how source credibility affects validation if a participant has never seen the source, which is not an unlikely scenario given the literature about an average student's sourcing skills (Anmarkrud et al., 2022). Using eye tracking could thus decrease the probability of both type I and II errors. What this study does lack is an additional off-line measure of sourcing such as source memory, which could have provided richer information.

This study utilized a social media context as opposed to the fictional narratives in most previous research about validation. Even though this may increase the generalizability of the effects in a real-world setting, an eye tracking laboratory experiment is still not an ecologically valid reading environment. For example, participants might have had different reading strategies or standards of coherence than when they normally scroll through social media. Another important aspect to consider is the task given during the experiment, in which participants were asked to rate the credibility of each tweet. This could have influenced their reading. Furthermore, the sample of the study was biased towards young university students, who might read differently relative to the general population. Lastly, the observed effects are not large, which should be taken into consideration while interpreting the results of this study.

Perceived source credibility can sometimes be a very subjective characteristic to measure. In the current study, the source credibility manipulation appears to have worked consistently based on the participants' evaluations. Similar ratings were also acquired when the materials were piloted. However, it cannot be completely ruled out that socially desirable answering affected the participants' evaluations. An additional consideration in designing the experiment was the timing and format of the questionnaire used to measure participants' prior beliefs. Asking participants to rate the exact claims presented in the materials effectively removes the error in representing their beliefs about the specific issues featured in the tweets, but it also means that participants had already read the target sentences before coming to the laboratory. With such a large sample of items and at least 24 hours in between, it is unlikely that participants consciously remembered every claim, but it is still possible that familiarity influenced the results.

4.5 Conclusions and Future Directions

In conclusion, these results comprise an interesting addition to the existing literature about the interaction of source credibility and readers' prior beliefs in sourcing and validation. The results show that readers consider both factors while processing social media posts, and that they can be sensitive to multiple kinds of discrepancies within or peripheral to the text. Future studies should further explore the role of different types of discrepancies in sourcing and validation, as this study suggests that text–belief consistency is not the only important text–

reader factor involved in these processes. Whenever the influence of source information is investigated, the credibility of the source (or lack thereof) should also be considered to account for multiple kinds of conflicts. It is also possible that the kind of source credibility (expertise vs. trustworthiness), the salience of source information, and the length of the text moderate the results observed in this study, and future endeavours would benefit from a range of differently structured materials. A major advantage of this study compared to earlier studies is the use of eye tracking measures, which provide precise information about the time course of events and the direction of participants' attention. However, future studies should include both on-line and off-line measure to get a fuller picture of these phenomena. Finally, source credibility and prior beliefs should be studied in all kinds of different reading contexts and involve more representative populations (and not just university students) to fully reflect the complexity of today's media ecosystem.

4.6 Acknowledgements

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5. References

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