

Trust in News on Social Media

Hendrik Heuer, Andreas Breiter

Institute for Information Management Bremen GmbH (ifib)
Centre for Media, Communication and Information Research (ZeMKI)
University of Bremen, Germany
hheuer@ifib.de, abreiter@ifib.de

ABSTRACT

This paper investigates trust in news on a social media platform. The paper is motivated by the finding that social media is the primary news source for a large group of people, especially young adults. Considering the challenges posed by online misinformation and fake news, an understanding of how users quantify trust in news and what factors influence this trust is needed. In a study with 108 participants, German high-school students provided trust ratings for online news including quality media and fake news. The study shows that users can quantify their trust in news items and that these trust ratings correspond to rankings of the sources by experts. The paper finds that psychometric scales that measure interpersonal trust are predictive of a user's mean trust rating across different news items. We show how this can be used to provide interventions for those prone to false trust and false distrust.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous;

Author Keywords

Trust Rating; False Trust; False Distrust; Social Media; Facebook; Fake News; Online News; Social Navigation; Trusting Beliefs.

INTRODUCTION

News is increasingly consumed through social media [32, 12, 40, 4, 14]. A representative 2017 survey by the Pew Research Center (N=4,971) showed that two-thirds (67%) of U.S. adults get at least some of their news on social media. For almost half (47%), reading news on social media happens sometimes (27%) or often (20%) [40]. Worldwide, social media is becoming an important source of news, especially for young adults. 33% of the 18-24 year-olds in the Reuters Digital News Report 2017 (N=70,000 from 36 markets) named social media as their primary source of news [32]. While the reliance on

social media decreases with age, it is still high for 25-34 year-olds (21%), 35-44 year-olds (15%), 45-54 year-olds (10%) and 55+ year-olds (7%). Media consumption practices also differ per country [32]. In Germany (N=2,062), the most frequently named news source in 2017 was television (77%), followed by online sources (incl. social media, 60%) and print (34%). Social media (excl. other online sources) was named by 29% of the German participants. In the United States (N=2,269), online is the most frequently named news source (77%), followed by TV (66%) and print (26%). Social media was named by 51% of the U.S. participants. The popularity of social media is noteworthy since social networks like Facebook and Twitter are different from news outlets like TV stations and newspapers. While traditional news outlets produce the majority of content themselves, social media platforms aggregate and curate content from a variety of news sources with different levels of trustworthiness. Sources like family members, close friends, or quality media are juxtaposed with advertisements and fake news blogs. This makes the decision which news items to trust increasingly complex and motivates us to understand the role of trust in news on social media. From a human-computer interaction point of view, we want to understand what influence social navigation features like the display of likes, shares, and comments have and whether trust ratings can be used to identify users prone to false trust and false distrust. This is important considering the challenges posed by online misinformation and fake news. Lazer et al. defined fake news as fabricated information that mimics news media content in form but not in organizational process or intent [22]. Allcott and Gentzkow defined fake news as news articles that are intentionally and verifiably false and could mislead readers. The common definition of fake news, however, is much fuzzier [2]. A mail survey found that 28% of U.S. adults (N=19,000) consider accurate news stories that cast a politician or political group in a negative light to always be fake news (42% of all Republicans, 17% of all Democrats) [12]. Considering the prevalence of fake news, Flintham et al. report that one-third of their survey respondents experienced being exposed to fake news they initially believed to be true [11]. Guess et al. investigated the selective exposure to fake news and misinformation in the context of the 2016 U.S. presidential campaign [15]. They estimate that approximately 25% of U.S. adults (N=2,525) visited a fake news website between October 7 and November 14, 2016. Since research showed that information environments affect people's perception and behaviors [18], this paper investigates

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NordiCHI'18, September 29-October 3, 2018, Oslo, Norway

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DOI: <https://doi.org/10.1145/3240167.3240172>

trust in the specific context of news on a social media platform. The majority of U.S. adults considers fake news to be a very serious (56%) or somewhat serious threat (32%) to democracy [12]. At the same time, 72% of Americans were very confident that they can tell when a news source is reporting factual news versus commentary or opinion. Research on the consumption of fake news also showed that it is heavily concentrated among a small group of people: 60% of visits came from the 10% of people with the most conservative online information diets [15]. Motivated by this, we investigate ways to identify those prone to false trust and false distrust. For this, we use generalized beliefs as measured by psychometric scales on interpersonal trust as a proxy. We also investigate whether users can distinguish different news sources by their trustworthiness. For our investigation of news in social media, we focus on Facebook, which is currently (2018) the social media site with the largest user base and the key vector of fake news distribution [2]. As a complex socio-technical system, Facebook provides a variety of social navigation features that guide users in the information space by showing them the activity of others and allowing them to make decisions based on the decisions of others [8].

In this paper, users quantify their trust in news items. We explore the influence that social navigation features like the number of Facebook likes, comments and shares have on the trustworthiness ratings of news. To better understand trust in news on social media, we operationalized trust and conducted a study with 108 German high-school students who provided trust ratings for online news including quality media and fake news. This paper contributes to our understanding of trust in social media and investigates the human-computer interaction needs of social network users by answering the following research questions:

- How do users rate the trustworthiness of online news items? Do they differentiate news sources by their trust ratings and can they distinguish fake news and quality media?
- What influence do generalized beliefs as measured by psychometric scales have on user's trust ratings? How can these beliefs be utilized in the design of social networks?
- What influence do a platform's social navigation features like the number of Facebook likes, comments and shares have on user's trust ratings?

RELATED WORK

Definitions of Trust

Trust is a multidimensional and multidisciplinary construct: trust can be placed in oneself [27], other people [35], organisations [28], automation [30, 31, 23], intelligent systems [44, 17] and abstract things like money or political power [25]. Definitions of trust focus on a willingness to be vulnerable, a confident, positive expectation, and a willingness to rely [36] as well as integrity, benevolence, and a capacity to fulfill a promise [28]. In automation, Muir et al. focus on an expectation of behavior and relate trust to reliability [30]. In Luhmann's definition of trust, which was adopted by Muir et al. for trust in automation, trust allows people to manage complexity and cope with risk [30, 25]. For Luhmann, trust

compensates for mastery and full understanding. This connects to the task the participants of the experiment in this paper had to fulfill. To rate their trust in news items, complexity had to be reduced, since verifying every detail of a news item, both in the experiment and in practice, would be an overextension for a person. Luhmann also emphasizes that trust helps manage risk. This is crucial since risk cannot be avoided when making decisions. In the context of online news, the risk can be trivial, e.g. by wasting some time. The risk can also be severe, e.g. by believing a fake news story that leads to becoming misinformed and voting for a political candidate with negative consequences for oneself, others, or the environment.

McKnight and Chervany describe prior definitions of trust in the literature as diverse, incomplete and inconsistent [29]. In the context of e-commerce, they distinguish a disposition to trust (i.e. the propensity to trust others), an institution-based trust, trusting beliefs (like competence, benevolence, and integrity), trusting intentions (i.e. an intention to engage in trust-related behavior), and trust-related behaviors. Like Rousseau et al., their definition focuses on making oneself vulnerable to a vendor. Like Luhmann, they connect trust to risk. For our operationalization, the notion of trusting beliefs is especially relevant. Their model motivated us to measure trust via psychometric scales on interpersonal trust. In the context of a spam filter, Lee and See define trust as an attitude of an agent with a goal in a situation that is characterized by some level of uncertainty and vulnerability [23]. They state that trust guides reliance when the complexity of an automation makes a complete understanding impractical. This connects to our use case since the decision to trust has to be made on a news item on Facebook based only on what is visible, i.e. without reading the entire article and without further research on the source or the article. This connects to common news consumption practices. In an investigation by Flintham et al., 39% of survey respondents (N=309) did not read the full story and said sufficient information was given in the headline [11]. Of those that did read both, the full article and the headline, only 55% believed that the headline accurately matched the content. This suggests that dealing with uncertainty, reducing complexity, and coping with risk play an important role when interacting with news on social media.

Research on Trust

In the context of a process control simulation, Muir and Moray showed that operators' subjective ratings of trust provide simple nonintrusive insights into their use of automation [31]. Muir showed that operators can meaningfully rate their trust in a machine and that this trust can be operationalized as interpersonal trust [30]. Informed by this, we explore trust ratings in the context of news on social media and how this can be used to predict users' propensity for false trust and false distrust. Similar to Muir et al., MacLeod et al. explore how users quantify their trust. For this, they studied how blind and visually impaired users self-report their trust in automatically-generated captions [26]. Their results show that users are trusting automatically-generated captions, even when they are incorrect. They also found that technical proficiency and education level were not predictive of trust in the captions and that trust correlates with how useful participants found

a caption. This informed the decision to disregard technical proficiency and focus on a specific education level for a more homogeneous sample with a similar age.

Seckler et al. investigated what website characteristics enhance trust or cause distrust [37]. They found that distrust is mostly an effect of graphical and structural design issues of a website, while trust is based on social factors such as reviews or recommendations by friends. They discuss how to design interventions that can be used to enhance trust or to prevent distrust. This motivated the research questions whether users differentiate news sources by their trust ratings and whether social navigation features like Facebook likes, comments, and shares influence trust ratings. Sillence et al. investigated trust and mistrust in online health sites [41]. In their study, they interviewed participants who researched a topic online for four weeks in the face of a risky health decision. Their research showed that design appeal of a website predicts how credible the information on a website is perceived. This informed us to control for the visual design of the website by adopting the well-known and fairly generic Facebook design. Eslami et al. showed that users can detect algorithmic bias during their regular usage of a system and that this affects trust in the platform [9]. Their usage context is online hotel rating platforms, where one platform was biased towards low-to-medium quality hotels. They found that while bias breaks trust, transparency can help rebuild it. This bias connects to the different news sources we presented to our participants and motivates the research question whether the bias of different sources also affects trust in news on social media. Our paper is also similar to Pennycook and Rand's work on crowdsourcing judgments of news source quality [33]. They found that laypeople across the political spectrum rate mainstream media outlets as far more trustworthy than either hyper-partisan or fake news sources. Their ratings are based on a heterogeneous sample of US residents (N=1,011) sourced via Amazon Mechanical Turk. We add to their core contribution by providing an in-situ investigation with a homogenous sample of young adults from Germany. In addition to that, we investigate the influence of social navigation features and generalized beliefs as measured by psychometric scales on interpersonal trust. Our work is also complementary to Flintham et al.'s investigation of the consumption of news on social media [11]. Their qualitative research examined the role of a news source's reliability, the content, and a user's interest in a story. We extend on this by focusing on trust. This includes whether trust can be measured, how generalized beliefs on interpersonal trust interact with trust and how such generalized beliefs can be used to address those prone to false trust and false distrust.

METHOD

Operationalization

For our operationalization, we regard trust as a social phenomenon with the following characteristics: Facing uncertainty [23, 36, 29] and managing complexity [25, 30], e.g. when assessing the quality of a news item in a short time with limited information. We further include taking a risk [25, 30] and making oneself vulnerable [23, 36, 29], e.g. by becoming misinformed. Following Muir, we adopt a model of



Figure 1. The experiment was conducted in a German school using a web application. Participants rated their trust in different news items on a scale from 0 (exercise caution) to 10 (can trust) for one item at a time. The interface resembled the look and feel of Facebook, which was the source of the news items.

trust between people and extend it to a human-machine relationship [30]. This enables us to use Rotter's scale for the measurement of interpersonal trust as an instrument [35]. Rotter's definition of trust regarding interpersonal trust focuses on the expectancy that a verbal or written statement can be relied upon, which makes it well suited for an application in the context of news on social media. We adopt the two errors in trust, namely false trust and false distrust, from Muir [30].

Study Design

The experiment was conducted in a German school with 108 high-school students. It took approximately 30 minutes and consisted of three parts: answering the German version of the Rotter Interpersonal Trust Scale (RITS) [35, 3], answering the Social Trust Scale (STS) from the European Social Survey (ESS) [34], and rating news items from different news sources including quality media and fake news. The psychometric scales and news items were presented to the participants in a web application with the rating interfaces shown in Figure 1. The different parts were conducted individually in direct succession. The experimenter was not in the room. The experiment was supervised by the teachers of the students. To prevent a language barrier from adding bias, the experiment was conducted in German. Before the experiment, each student attended a 30-minute lecture that served two purposes: 1. to show the experimental stimulus and explain the study, and 2. to teach them how machine learning works and how it is applied (the latter was meant to provide something in return for participating in the experiment). In the lecture, the phenomenon Fake News was illustrated using three examples:

one international (Pope Francis backing Trump), two German (the Green party banning meat and an alleged scientist urging people not to put up a Christmas tree out of consideration for refugees with non-Christian religious backgrounds). The different news sources present in the experiment were not named and there was no debriefing after the experiment.

We performed an external validation of our participant's trust ratings of news items. For this, we ranked the news sources by their mean trust rating and compared this to a ranking of the news source's trustworthiness by independent media experts. The experts were recruited from two German research institutes with a focus on media research on public communication and other cultural and social domains. For this, all members of the two research institutes were contacted through internal newsletters. In a self-selection sample, nine media researchers (three male, six female) provided their rankings via e-mail: three from the Hans-Bredow-Institute in Hamburg, Germany, six from the Centre for Media, Communication and Information Research (ZeMKI) in Bremen, Germany.

Participants

Our sampling controlled for differences in age and education level. We carefully weighed potential limitations regarding the generalisability of our findings against the necessity of having a homogeneous group of participants. A homogeneous group is desirable to limit biasing factors and control for experience with online news without facing the challenging problem of measuring media literacy [6]. A sample of high-school students has the advantage of being comparable in age and educational background. While the relatively low age limits generalisability, it allows us to focus on those who rely on social media the most. Research showed that every third 18-24-year-old and every fifth 25-34-year-old reported social media as their primary source of news [32].

The experiment was conducted in a German school with six different classes finishing their secondary education (equivalent to U.S. high schools). Two school classes in the sample are studying towards their general higher education entrance qualification. Four classes are part of a programme that combines a vocational training with a subject-linked university entrance qualification. Note that the German vocational training is demanding and can be regarded as equivalent to Bachelor's degrees in areas like IT, mechatronics, and banking. Since the vocational training requires a school-leaving qualification, the mean age in the sample is higher than that of U.S. high school students. The 108 participants have a mean age of 21.50 (SD=4.11). Our experiment has a strong gender bias: 95 participants are male, ten female, two chose not to disclose their gender and one identified as a non-binary gender.

Instruments

Rotter Interpersonal Trust Scale

The Rotter Interpersonal Trust Scale (RITS) measures generalized expectations that one can trust somebody's words and promises in verbal or written form [35]. The scale includes 25 items and was initially reported with 547 participants. We selected RITS as the most cited questionnaire available. On the RITS, there are two groups of items: One group is aimed at trust in friends, teachers, and politicians. The other group of

items measures "general optimism" towards society. To prevent a potential language barrier from adding bias, we used the German version of the RITS, which is not simply a translation of the original RITS. The German version (N=135) includes 27 items: 20 from the original Rotter Scale and seven newly added [3]. The German scale has a Cronbach's Alpha (N=135) of .85. A retest performed one and a half years after the original experiment (N=27) had a retest correlation of $r = .74$ [3].

Social Trust Scale

The Social Trust Scale (STS) is part of the European Social Survey (ESS), which has been conducted every two years since 2001 with a large sample of 29 European countries [34]. The STS has three items, which are available in 27 European languages. The items focus on three generalized statements about whether most people 1. can be trusted, 2. would try to take advantage of the respondent, and 3. try to be helpful. The STS was selected as the questionnaire with the largest available sample (N=54,673). The internal consistency of the scale as measured by Cronbach's Alpha is .69 for Germany (N=2,958) and .78 across all E.U. countries (N=54,637) [34].

Experiment

Dataset

The dataset of the news items was sourced from Facebook which was selected as the social media site with the largest user base and the key vector of fake news distribution [2]. Articles were collected from 13 Facebook pages, which can be grouped as quality media (7), fake news blogs (3) and tabloid media (3). Quality media was included based on their reach as measured by Facebook likes. Since no peer-reviewed research on German fake news outlets was available, we had to rely on a convenience sample based on news articles on German fake news [5]. In addition to that, we included three tabloid news sources, which are both, popular based on their number of likes and known to occasionally publish biased or fake news [1]. They are more similar to quality media in style and more similar to fake news in terms of their content. For the experiment, we used a random sample of news items taken from two days of publicly available Facebook posts of the sources (retrieved on the 28th of April 2017). The dataset covers a broad range of topics, ranging from sports like soccer over social issues like homelessness and refugees to individual politicians from Germany (Frauke Petry), France (Marie Le Pen) and the USA (Donald Trump).

Rating Interface

News items appeared in the same visual format as if they had been posted or shared by a regular Facebook user as shown in Figure 1. Participants were shown the headline, lead paragraph, lead image, name of the source, source logo, source URL, date and time, as well as the number of likes, comments, and shares of a Facebook post. Participants were not able to follow any links or read the entire article. The design was identical to the official design of the Facebook News Feed at the time of the experiment (April 2017). In addition to the experimental stimulus, we presented a rating interface. Each participant rated 20 news items. The news items come from a weighted sample, consisting of eight quality media news items, eight fake news items, and four items from other

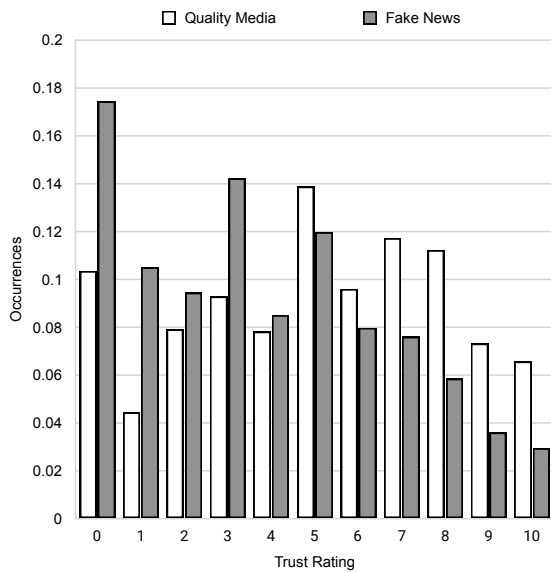


Figure 2. The normalized histograms of trust ratings for quality media (white, N=1,120) and fake news (grey, N=799). For fake news, the five highest trust ratings are the least frequently assigned (in descending order). For quality media, the strongest peak can be observed for the neutral condition (5).

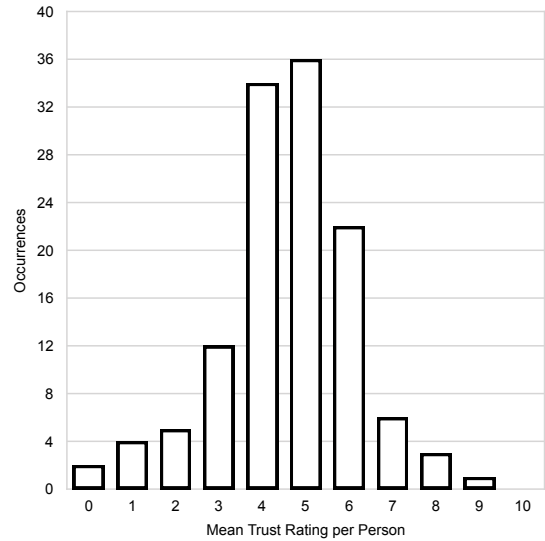


Figure 3. The histogram of the participant's mean trust rating approximates a normal distribution. The outliers on both sides are participants that almost exclusively gave a low trust rating or a high trust rating. These two extremes could be supported by training and tools that help these users improve their media literacy.

sources (tabloids). The weighting accounted for the focus on fake news and online misinformation.

For each news item, a participant provided a trust rating on an 11-point rating scale ranging from 0 to 10, which is modeled after the first question of the Social Trust Scale (STS) of the European Social Survey (ESS): “Generally speaking, would you say that this news item can be trusted or that you can’t be too careful? Please tell me on a scale of 0 to 10, where 0 means you can’t be too careful and 10 means that this news item can be trusted” [34]. In the German translation of the Social Trust Scale, the word “vorsichtig” is used, which translates to “careful”, “cautious” and “wary”.

To investigate the influence of generalized beliefs on trust ratings, we performed a regression analysis. Since missing data is problematic for a regression analysis, all samples with missing data, e.g. unanswered items in the Rotter Interpersonal Trust Scale (RITS) or Social Trust Scale (STS), were excluded, which yields 1,919 valid trust ratings with corresponding RITS and STS.

RESULTS

In total, the participants provided 1,120 trust ratings for news items from the seven quality media sources and 799 trust ratings for news items from the three fake news blogs in the sample. Figure 2 compares the normalized histogram of trust ratings for quality media (white) and fake news (grey). The histograms were normalized due to the different number of valid ratings for quality media and fake news. The histograms show that users clearly distinguish the two different groups by their trust rating. The reason for the lower number of fake news items is that more of these items were skipped. For quality media (white), the strongest peak can be observed for

the neutral condition (188 occurrences of 5) on the 11-point rating scale. The distribution is shifted towards high trust ratings. 7 is the second most frequent (159) rating, followed by 8 (152). Surprisingly, the lowest possible rating of 0 is assigned 140 times as well. The second lowest trust rating of 1 is the least frequently assigned (60). If you were to disregard the peak at 0 (140 occurrences), the trust ratings for quality media would approximate a normal distribution. For fake news (grey), the lowest possible trust rating of 0 is the most frequently assigned (131), followed by 3 (107) and the neutral condition of 5 (90). The five highest trust ratings are the least frequently assigned. Their frequency follows a descending order: 6 (60), 7 (57), 8 (44), 9 (27), and 10 (22).

The mean trust rating for quality media is 5.26 (SD=3.00), the mean trust rating for fake news blogs is 3.73 (SD=2.86) on the 11-point rating scale. An unpaired, two-tailed t-test shows that the difference between the trust ratings of quality media and fake news blogs is considered to be statistically significant ($p < 0.0001$, $t = 11.21$, $DF = 1,917$). This shows that trust in quality media and fake news is distinguished by users. Since the trust rating question was modeled after the first question of the STS, we can also compare the mean trust rating for quality media and fake news to the STS. The mean trust rating for quality media at 5.26 (SD=3.00) is higher than the first question of the Social Trust Scale (STS) as answered by our participants at 4.41 (SD=2.76) and the larger STS sample at 4.94 (SD=2.48). The mean trust rating for fake news blogs is lower at 3.73 (SD=2.86).

Distinguishing different sources

In this section, we show that participants differentiated news sources by their trust rating. The highest mean trust rating for a source is 6.00 (SD=2.67), the lowest is 2.25 (SD=2.48). The

mean of means is 4.56 (SD=1.09). Table 1 shows that the seven sources with the highest mean trust rating are the seven quality media sources. The three sources with the lowest mean trust rating are the three fake news sources. The most trustworthy news source, Source 1, is a conservative newspaper of record. Source 13, the least trustworthy source in the sample, is a blog accused of publishing fake news.

External Validation

To validate our trust ratings, we compared participant’s trust ratings per source to expert rankings of the sources. For this, we ranked the sources by the mean trust rating by the participants. This is compared to an independent ranking of the news sources by nine media research experts (three male, six female). The experts are from two German research institutes with a focus on media research on public communication and other cultural and social domains. In both rankings, two clusters emerge that distinguish quality media and fake news. Note that in the cluster of quality media, the ranking of news sources within the cluster varies a lot. Also note that of the three tabloid sources, none was ranked higher than any quality media news source. The biggest surprise is that participants rated source 7, the Facebook page of the television news service of the German public-service television relatively low compared to the experts. However, this rank is only based on one news story with 24 trust ratings. Overall, the comparison of rankings shows that the trust ratings reflect the quality of the news source.

Likes, Shares, and Comments

We further investigated the influence of social navigation, i.e. features that guide users in the information space by showing them the activity of others. Social networking platforms like Facebook provide a variety of such features. Facebook indicates how many other users “liked”, i.e. virtually endorsed, or shared a certain posting with their “friends”. The interface also indicates how many comments a posting has. In our investigation, we presented the number of Facebook likes, shares, and comments that each article had at the time of the download. We found no significant pattern that explains the relationship

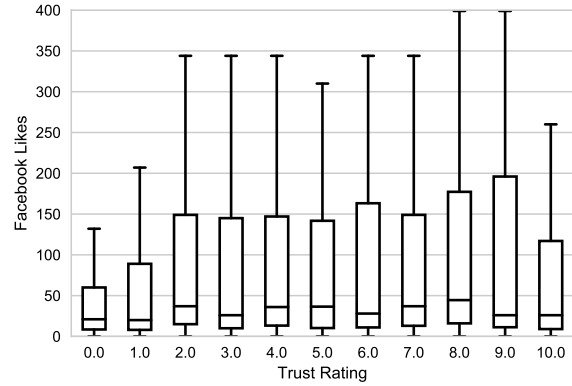


Figure 4. Box plot of the relationship between the number of Facebook likes of a news item and its trust rating.

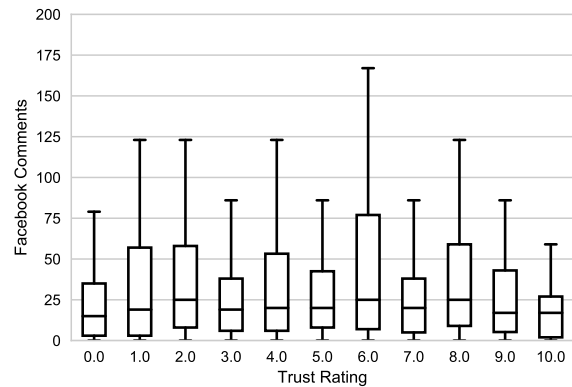


Figure 5. Box plot of the relationship between the number of Facebook comments a news item received and its trust rating.

#	Trust Rating		Source Ranking per Expert								
	Mean	N	I	II	III	IV	V	VI	VII	VIII	IX
1	6.00	256	7	3	3	3	4	4	3	7	7
2	5.73	215	4	7	4	2	2	7	7	3	3
3	4.97	138	3	4	2	7	7	2	4	2	4
4	4.87	134	2	2	7	4	3	3	5	4	2
5	4.85	265	1	5	1	1	5	1	2	1	1
6	4.78	148	5	6	5	5	1	6	1	6	5
7	4.54	24	6	1	6	6	6	5	6	9	6
8	4.22	262	8	8	8	8	8	8	8	5	9
9	3.39	257	9	9	9	9	9	10	9	8	10
10	2.25	129	10	10	10	10	10	9	10	10	8

Table 1. The table ranks news sources by their mean trust rating (column 1). This is compared to an independent ranking of the sources by nine media researchers from two German research institutes: three from Hans-Bredow-Institute (I-III), six from ZeMKI (IV-IX). Fake news sources are marked in bold. The clusters that emerge show that quality media (Source 1-7) and fake news blogs (Sources 8-10) are clearly distinguished by both participants and experts.

between trust ratings and the number of Facebook likes, shares, and comments. Figure 4 shows a box plot of trust ratings and the number of Facebook likes, Figure 5 shows a box plot of trust ratings and the number of Facebook comments. Both box plots do not show a noticeable relationship between likes and comments on the trust rating. The same is true for the box plot of the shares, which is omitted.

Participant’s false trust and false distrust

Figure 3 shows the histogram of the mean trust rating of each participant, which approximates a normal distribution. Outliers on both sides are participants that almost exclusively gave a low trust rating or a high trust rating. These two extremes of the normal distribution should be addressed, since both, false distrust, i.e. those 11 participants with a mean trust rating of 0 (2), 1 (4), or 2 (5), and false trust, i.e. those four participants with a mean rating of 8 (3), 9 (1), or 10 (0), might indicate media competency issues that will be further addressed in the Discussion.

Item	B	SE B	β
STS 1	0.12	0.02	0.08
STS 2	0.39	0.02	0.11
STS 3	0.32	0.02	0.26
RITS 1	0.10	0.02	0.10
RITS 2	0.05	0.01	0.08
RITS 3	-0.01	0.01	-0.01
RITS 4	0.06	0.02	0.08
RITS 5	0.16	0.02	0.23
RITS 6	0.22	0.02	0.27
RITS 7	0.06	0.01	0.06
RITS 8	0.08	0.02	0.07
RITS 9	-0.06	0.02	-0.09
RITS 10	-0.09	0.02	-0.14
RITS 11	0.18	0.02	0.17
RITS 12	-0.09	0.02	-0.13
RITS 13	-0.06	0.02	-0.06
RITS 14	0.11	0.02	0.11
RITS 15	-0.10	0.02	-0.13
RITS 16	0.09	0.02	0.10
RITS 17	0.09	0.02	0.11
RITS 18	0.03	0.02	0.02
RITS 19	0.20	0.02	0.26
RITS 20	0.06	0.02	0.10
RITS 21	0.15	0.02	0.15
RITS 22	-0.11	0.02	-0.17
RITS 23	-0.12	0.02	-0.14
RITS 24	0.06	0.02	0.08
RITS 25	-0.14	0.02	-0.19
RITS 26	0.12	0.02	0.17
RITS 27	-0.22	0.02	-0.27

Table 2. The response of the participants (N=108) on the Social Trust Scale (STS) and the German version of the Rotter Interpersonal Trust Scale (RITS) can be used to predict their mean trust rating. The three items of the STS have an R^2 of .137, the 27 items of the RITS .374. We report the raw or unstandardized coefficients (B), the standard error of the raw or unstandardized coefficients and the standardized coefficients (β) for the STS (top) and the RITS (bottom).

Predicting mean trust from generalized beliefs

We also investigated the relationship between the mean trust rating of an individual participant and his or her generalized beliefs as measured by the German version of the Rotter Interpersonal Trust Scale (RITS) and the Social Trust Scale (STS). Cronbach's Alpha, which estimates the reliability of psychometric tests, is similar for our sample for the RITS and the STS. Cronbach's Alpha of the RITS in our sample (N=108) is .83, which is close to the German RITS (N=135) at .85 [3]. For the STS, Cronbach's Alpha is .72 for our sample (N=108). This is slightly higher than Cronbach's Alpha for the STS in Germany at .69 (N=2,958) and lower than Cronbach's Alpha of the three items across all E.U. countries (N=54,637) at .78 [34]. We applied the psychometric tests to measure trusting beliefs, which McKnight and Chervany regard as a solid conviction that a trustee has favorable attributes to induce trusting intentions [29]. For McKnight and Chervany, trusting beliefs are aimed at competence, benevolence, and integrity. Competence,

and integrity are also central to the statements in the RITS, which measures generalized expectations that one can trust somebody's words and promises in verbal or written form [35]. We found that such generalized statements on interpersonal trust can be used to predict the mean trust rating of an individual. For this, a regression analysis was performed between the mean trust rating of a participant and his or her answers to the 27 items of the German RITS and the three items of the STS. Table 2 reports both, the raw or unstandardized coefficients (B) and the standardized coefficients (β). B is used to estimate the impact of an item on the mean trust rating, β can be utilized for a relative comparison of items. The coefficients of the regression model show how statements correlate with a user's mean trust rating and how strong this effect is. The items of the psychometric scales explain a great amount of the variance of the mean personal trust as measured by the coefficient of determination R^2 . The three items of the STS have an R^2 of .137, the RITS has .374. In combination, the generalized statements on interpersonal trust measured by the RITS and the STS have an R^2 of .438. This can be used to predict the mean trust rating of a user shown in Figure 3 and to cluster users based on their propensity to trust.

DISCUSSION

The goal of this paper is to motivate the importance of trust in the context of a social media platform like Facebook that aggregates and presents news. Our findings are relevant to three groups of people: those who conduct research on these systems, e.g. by analyzing social media postings, those who design and develop these systems, and those who use these systems. Designers and developers can use these findings to identify and address users who are prone to false trust and false distrust, e.g. by providing additional information or visualizations.

The experiment shows that participants can give meaningful trust ratings that differentiate quality media from fake news. The results also show that participants differentiate news sources by their trust and that this corresponds to expert rankings of the trustworthiness of the different news sources. This connects to the challenging of established hierarchies of trustworthiness and the issues exacerbated by the indiscriminate mixing of a multitude of pieces of information in social media feeds [11]. Our results show that the trust assessment of a news source can be nuanced and fine-grained. In this investigation, we presented the news items individually. Usually, the news items are embedded in a specific context, e.g. the Facebook News Feed. Further research is needed to understand whether untrustworthy outliers influence the trust rating of an algorithmic news curation system as a whole.

We faced the challenging problem of defining and operationalizing a complex construct like trust. We are aware that a variety of factors can potentially influence the trust of a user. In our context of online news, factors like the wording of the headline, the quality and aesthetic appeal of the lead image, the writing style of the leading paragraph, prior experience with a news source, and prior beliefs of the participants can influence the trustworthiness of a news item. By combining trust ratings with an external validation by experts, we show

that the trust ratings are meaningful in differentiating between quality media and fake news blogs. In addition to that, we show that the number of Facebook likes, shares, and comments has no influence on trust ratings. In the context of German news on social media, our sample of young adults from Germany gave meaningful trust ratings that differentiate between quality media and fake news blog. The distribution of trust ratings for quality media and fake news blogs provides a distinct fingerprint for both groups. We saw that the trust ratings for quality media approximate a normal distribution (with the lowest trust rating at 0 as an outlier), while the ratings for fake news blogs have a strong peak at the lowest possible trust rating with all those trust ratings above 5, i.e. those that indicate a trust higher than neutral, in descending order. Audience ethnographies could start with this to better understand the individual factors that shape and influence trust.

One of the primary motivations for this paper is the dissemination of fake news through social networks. Our research on trust is embedded in an effort to provide the necessary theoretical and practical means to prevent fake news from spreading. So far, there is little consensus on how to effectively tackle fake news and online misinformation. Facebook's strategy to address fake news focuses on making it easier to report a hoax, disrupting financial incentives for spammers, analyzing user behavior, e.g. by detecting articles that people are significantly less likely to share after reading them, and including information from third-party fact-checking organizations [10]. Fact-checking operations are also what the ARD, the Consortium of public broadcasters in Germany, focusses on to counteract fake news [43]. While good in theory, research suggests that fact-checking services that correct fake news stories are not effective in tackling exposure to misinformation in practice [15, 39]. None of the participants in Guess et al.'s investigation of the U.S. 2016 presidential election who read one or more fake news articles visited any of the fact-checking websites that debunked the claims of the fake news [15]. Shao et al. further showed that the sharing of fact-checking content typically lags behind the sharing of misinformation by 10–20 hours [39]. This, combined with the high cost of operating a fact-checking service and the low cost of disseminating fake news, motivated us to find a way to focus on the users and how their media literacy needs can be detected. Motivated by our findings, we regard trust ratings and psychometric scales on interpersonal trust as one important way to address the problem of fake news. This aligns with Lazer et al.'s call to improve individual's evaluation of the quality of information sources through education [22]. Meanwhile, letting users rank the credibility of news on social media also introduces a variety of risk. Those who spread fake news could manipulate such ratings to seem more trustworthy. Users could also disagree on their trust ratings for controversial political and social issues. Trolling is another potential danger [38]. To address those risks, strategies for dealing with conflict and coordination could be adapted from collaborative knowledge building projects like Wikipedia [19]. Despite these limitations, trust ratings may be one important tool to measure and increase algorithmic awareness and to detect algorithmic bias [20, 9].

Configuring trust

Another important finding of our study concerns the outliers at both ends of the spectrum: Those prone to false distrust and those prone to false trust. The motivation to address those prone to false distrust connects to the investigation of fake news in the context of the 2016 U.S. presidential campaign. Guess et al. estimate that 60% of visits on Fake News websites came from the 10% of people with the most conservative online information diets. Socio-technical interventions to address these users and support their media literacy would have important societal consequences. User experience designers could e.g. use the mean trust ratings of users to give extra attention to those prone to false distrust and false trust. Prior work on spam filters showed that filter awareness and understanding do seriously impact the behaviors and attitudes toward spam filters [7]. Further research could investigate whether this is true for trust in news on social media as well.

Previous research showed that blind and visually impaired user trust automatically-generated captions, even when they are incorrect [26]. This implies that the platform that is serving such captions has a lot of influence on the trust of its users. To address people prone to distrusting, i.e. those who do not trust even though trusting would maximize utility by being better for them or their environment, a system could provide additional information that tries to increase trust. Researchers could use this to specifically target news items with a low ranking. Further research with a qualitative approach could focus on these items and elicit why these stories, in particular, were rated so negatively. Additional information and explanation could be provided to dispel potential doubts. Research on social media could further inquire the root of these doubts. Those who tend to overtrust by relying too much on online news could be predicted from their trust ratings by a machine learning system, which could provide them with additional information, e.g. an indication of the average trust placed in a specific news item or a certain source. However, practitioners need to be careful since research on the trust of blind participants in image captions also showed that tweets with high reported confidence were trusted significantly more even when they were erroneous [26]. Meanwhile, the vast majority of participants gave nuanced and fine-grained trust ratings. Overall, when participants are confronted with a task like rating trust in news, their trust ratings reflect the quality of a news source.

Social Navigation

Surprisingly, our results imply that social navigation features like Facebook likes, comments, and shares are not indicative of a trust rating. An aspect that possibly limits this finding is the lack of likes, comments, and shares from actual Facebook friends of a user. We removed the social navigation features from their original context. This is especially important since research showed that Facebook likes can be regarded as a form of virtual endorsement [24]. Research on the psychological, technological, and motivational factors for "liking" something showed that enjoyment and interpersonal relationships are the most salient motives [24]. The finding is nevertheless interesting as other sources imply that fake news is attracting more

likes than quality media [42]. The analysis by BuzzFeed suggests that the 20 top-performing fake news stories during the 2016 U.S. election outperformed the 20 top-performing quality media stories regarding shares, reactions, and comments on Facebook by 1.34 million interactions. In contrast to that, our results show that there is no significant relationship between the number of likes, shares, and comments, and ratings of trustworthiness. Neither a large number of Facebook likes, comments, and shares nor a small one is correlated with low or high trust ratings.

Predicting trust in less time

We showed that the mean trust rating of a participant can be predicted from his or her generalized beliefs on interpersonal trust and described how this can be used to cluster different news sources based on their trust ratings. For this, we considered 30 different statements of generalized trust from RITS (27 items) and STS (three items), which turned out to be a considerable time investment. Answering the 27 items of the RITS took a median time of 4:46 minutes. The three items of the STS required thirty seconds. On average, answering a single item takes 12 seconds ($SD=0:06$) on the RITS and 13 seconds ($SD=0:08$) on the STS. For practical applications in research and industry, the time it takes to apply the interpersonal trust scales could be reduced using an approach like recursive features elimination (RFE) [16]. RFE trains regression classifiers and recursively considers smaller subsets of items. This means that the least predictive items are removed. This could be applied to the 30 combined items of the RITS and STS to get a ranking of all available items based on their predictive power.

Stakeholders

The primary addressees of this research are those who design and develop systems that disseminate news through information systems, especially social media. We showed that faced with the task to rate their trust in news, participants can provide nuanced trust ratings on an 11-point rating scale that correspond to expert opinion. This would support Facebook's plans to let users rank the credibility of news [13]. Our research is also relevant to those who conduct research on these systems. They could build upon our trust operationalization and methodology to better understand trusting practices in a variety of contexts. The findings can further benefit those who use these systems. This will be most likely by proxy through the previous two groups. The benefit could also be more direct if the trust assessment via interpersonal trust scales is made available as a self-assessment tool that helps those who are prone to false distrust and false trust to learn about themselves and improve their media literacy.

LIMITATIONS

Our findings connect to Muir, who showed that operators can meaningfully rate their trust in a machine [30]. In the context of news on social media, we show that the young adults from Germany we had as participants can meaningfully rate their trust. However, we leave it open whether such ratings could be exactly replicated in the wild. The high accuracy of the trust ratings could be due to framing effects, which

are known to affect trust [26]. We conducted a controlled experiment preceded by a lecture on fake news. The setting could have made people read more slowly and more carefully. It could also have had a priming effect on the participants, e.g. by making them overly cautious and more alert. While this does not restrict our finding that participants are able to give meaningful trust ratings that distinguish quality media and fake news, it could have potentially influenced the scores assigned to different news items. It could also have influenced the rates of false positives and false negatives. Complementary research on trust *in vitro*, i.e. via specific tasks performed in the wild, could provide additional information on other factors that influence the trust rating, including, but not limited to, the usage situation (at home, at work, on the go), the emotional state of the user and his or her physical condition (e.g. fatigue or intoxication).

We had to weigh potential limitations regarding the generalisability of our findings against the necessity of having a homogeneous group of participants. Since a third of all young adults already use social media as their primary news source [32], we focused on high-school students, who are comparable in age and educational background. This limits biasing factors and controls for experience with online news and algorithmic news curation. Our experiment has a strong male bias, which could have biased the results. However, a representative German survey from 2017 shows the gender bias does not limit the generalisability of our findings. In this survey ($N=1,011$), age and gender have little influence on the experience with fake news, which is very similar for all people under 60, especially between 14-to-24-year-olds and 25-to-44-year-olds [21]. Finally, we conducted an external validation with independent media research experts (Table 1). The group of experts was heterogeneous in terms of age, gender (three male, six female), and background, and very different from the high school students in the experiment, which provides further evidence that our findings are generalizable.

CONCLUSION

We contribute an investigation of trust in news on social media that shows that young adults can rate their trust in online news. These ratings correspond to rankings of the sources by experts. We show that the mean trust rating of a participant can be predicted from his or her generalized beliefs on interpersonal trust and outline how this could be used to cluster different users as well as different news sources based on their trust ratings. Designers and developers can use our quantitative approach to better understand their users, to address false trust and false distrust (e.g. by supporting their media literacy), and to detect untrustworthy news sources.

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