Article:
Pal, Anjan orcid.org/0000-0001-7203-7126 and Banerjee, Snehasish orcid.org/0000-0001-6355-0470 (2021) Internet users beware, you follow online health rumors (more than counter-rumors) irrespective of risk propensity and prior endorsement. Information Technology and People. pp. 1721-1739. ISSN: 0959-3845

https://doi.org/10.1108/ITP-02-2019-0097

Internet users beware, you follow online health rumors (more than counter-rumors) irrespective of risk propensity and prior endorsement

Journal:	*Information Technology & People*
Manuscript ID	ITP-02-2019-0097.R3
Manuscript Type:	Article
Keywords:	Computer-mediated communication (CMC) < Technology, Human computer interaction (HCI) < Technology, Information sharing < Phenomenon, Social media < Technology, User generated content system < Technology, Information processing theory < Theory, Risk < Theoretical concept, Hypothesis testing < Methodology, Quantitative method < Method

Internet users beware, you follow online health rumors (more than counter-rumors) irrespective of risk propensity and prior endorsement

Purpose—The Internet is a breeding ground for rumors. A way to tackle the problem involves the use of counter-rumors—messages that refute rumors. This paper analyzes users' intention to follow rumors and counter-rumors as a function of two factors: individuals' risk propensity and messages' prior endorsement.

Design/methodology/approach—The paper conducted an online experiment. Complete responses from 134 participants were analyzed statistically.

Findings—Risk-seeking users were keener to follow counter-rumors compared with risk-averse ones. No difference was detected in terms of their intention to follow rumors. Users' intention to follow rumors always exceeded their intention to follow counter-rumors regardless of whether prior endorsement was low or high.

Research limitations/implications—This paper contributes to the scholarly understanding of people's behavioral responses when unbeknownstly exposed to rumors and counter-rumors on the Internet. Moreover, it dovetails the literature by examining how risk-averse and risk-seeking individuals differ in terms of intention to follow rumors and counter-rumors. It also shows how prior endorsement of such messages drives their likelihood to be followed.

Originality/value—The paper explores the hitherto elusive question: When users are unbeknownstly exposed to both a rumor and its counter-rumor, which entry is likely to be followed more than the other? It also takes into consideration the roles played by individuals' risk propensity and messages' prior endorsement.

Keywords: Rumor, Counter-rumor, Risk, Prior endorsement, Health Information, Intention to follow, Social media.

Paper type: Research paper

1. Introduction

Social media empowers society by allowing anyone with Internet access to submit user-generated content, which refers to anything produced by the general public rather than paid professionals for online dissemination (Bi et al., 2017; Daugherty et al., 2008). This positive development in facilitating unabated freedom of speech, however, comes with a downside stemming from the lack of editorial control. Since laypeople are able to create content without necessarily having either any domain expertise or any moral obligation to spread the truth, its veracity cannot be taken for granted (Starbird et al., 2018).

The absence of rigorous gatekeeping has converted the cyberspace into a breeding ground for fake news—unsubstantiated information disseminated using the online channel to appear as facts. The term 'fake news' was popularized by US President Donald Trump who allegedly used it to explain the negative press coverage of himself (Kim, 2019). Its emergence and subsequent proliferation have blurred the lines between lies and facts on the Internet—not only in a political context but also about health topics (Ozturk et al., 2015).

What is worrying is the statistic that about 75% of people who come across fake news end up believing it as accurate (Silverman and Singer-Vine, 2016). The stakes are even higher when a false piece of news becomes viral and spreads like a rumor (Pal et al., 2019). This paper defines rumors as false messages in circulation among members of the online community. When these messages spread, they sell falsehood to the populace as if it were the truth. After all, the saying, "repeat a lie often enough and it becomes the truth," is quite apt in the present digital era of alternative facts.

Particularly, health rumors have serious repercussions. For one, most people seek health information online as one of the first tasks after experiencing a health concern (Agree et al., 2015). Moreover, they often intend to follow online messages to make healthcare decisions (Mou et al., 2016). Intention to follow refers to users' decision to act as recommended by a message (Casaló et al., 2011). Health rumors mislead users, duping them into taking actions that one would unlikely take otherwise (World Health Organization, 2011; Zhang et al., 2015). For example, health rumors have previously caused public resistance to the administration of MMR vaccines. Rumors such as "the government is trying to limit the Black population by encouraging the use of condoms" have resulted in African Americans being significantly more prone to HIV/AIDS and unintended pregnancies than Hispanics and Whites in the US (Bird and Bogard, 2005). Clearly, when individuals' intention to follow rumors is high, it poses a serious threat to their health and well-being.

An emerging research strand suggests that individuals' intention to follow rumors could be lowered using counter-rumors, which refer to messages that refute rumors (Ozturk et al., 2015; Tanaka et al., 2013; Pal et al., 2017, 2019). In this strand, two research themes are particularly conspicuous. One focuses on the diffusion patterns of rumors and counter-rumors. Several models graphically depict their propagation. For example, a 'neighborhood model' envisages autonomy for each node to act against rumors by posting counter-rumors. In contrast, the 'delayed start model' assumes that counter-rumors are issued by centralized authorities after investigation, and hence are associated with a time lag (Habiba et al., 2010; Tripathy et al., 2013). The other research theme deals with factors that promote counter-rumoring. Counter-rumors can be posted for a variety of reasons. For example, users may post them from a sense of obligation triggered by social norms. They can also be galvanized toward counter-rumoring when they are aware of the adverse consequences of the rumors at stake (Fine, 2007).

These works notwithstanding, an intriguing question that has eluded scholarly attention is this: When users are unbeknownstly exposed to both a rumor and its counter-rumor, which entry is likely to be followed more than the other? This research gap is important to address because it will shed light on users' ability to differentiate between rumors and counter-rumors which are antithetical messages—the former usually affirmative and the latter generally negative—that do not always come with warning labels but both seemingly contain claims of the truth. Intention to follow rumors would reflect users' likelihood to be taken in by false messages while intention to follow counter-rumors would highlight their ability to discern the truth. Relatively higher intention to follow for counter-rumors vis-à-vis rumors would be a promising finding. It would suggest that users invest in seeking out the truth when exposed to online messages of dubious veracity. However, if users' intention to follow rumors exceeds that for counter-rumors, it would be a recipe for disaster. This in turn may call for behavioral changes among the online populace, more robust digital information literacy programs, and new policies to tackle online falsehood.

Furthermore, this paper conjectures that users' intention to follow online messages—either rumors or counter-rumors—will be shaped by two factors. The first is risk propensity, which refers to individuals' tendency to take risks (Branley and Covey, 2017; Benson et al., in press). It is heralded as a crucial trait in the context of online health information processing (Panzano and Roth, 2006; Meertens and Lion, 2008). Based on risk propensity, individuals can be categorized into two groups: risk-averse and risk-seeking. Compared with those who are risk-averse, risk-seeking individuals are more willing to take risks (Branley and Covey, 2017; Harrison et al., 2005). Users' motivation to evaluate the veracity of online health messages could partly stem from their risk propensity. Owing to their reluctance to take risks, risk-averse users might be more motivated to evaluate veracity of rumors and counter-rumors than risk-seeking users. Therefore, the former could be more careful than the latter while processing online messages, thereby being more likely to follow counter-rumors.

The second factor includes prior endorsement of messages. Prior endorsement reflects the number of times a message has already been shared by others. It highlights the consensus of others on a particular message, and is a measure of message virality (Burke and Develin, 2016; Johnson et al., 2015; Lee et al., 2016). If a message has been widely endorsed by others, individuals are more likely to join the bandwagon by further endorsing the entry (Fu and Sim, 2011). Consequently, messages that are endorsed widely are more likely to be followed by users than those that are seldom endorsed regardless of whether they contain rumors or counter-rumors. While the literature suggests that rumors tend to be endorsed more readily than counter-rumors (Chua and Banerjee, 2017b), it is still silent on how prior endorsement of the messages would shape individuals' intention to follow.

Therefore, the following two research questions (RQs) are formulated to guide the investigation:

RQ 1: How does users' risk propensity affect their intention to follow rumors and counter-rumors?

RQ 2: How does prior endorsement of rumors and counter-rumors shape a given user's intention to follow the messages?

The paper contributes in the following ways. First, through a review of related works, the paper justifies why it investigates Internet users' intention to follow online rumors and counter-rumors (cf. Section 2). This extends previous works that have mostly focused on constructs such as intentions to believe, share and trust but not follow (Chua and Banerjee, 2015, 2017b, 2018; Lee and Oh, 2017). Second, the paper develops a set of hypotheses to explain intention to follow rumors and counter-rumors while taking into account individuals' risk propensity in tandem with messages' prior endorsement. These have their theoretical roots in the elaboration likelihood model and the Matthew effect respectively, and together help deepen the extant scholarly understanding of human response to online falsehood as well as its rebuttals (cf. Section 3). Third, using an experimental design (cf. Section 4), the paper offers new insights into Internet users' intention to follow health-related rumors and counter-rumors on the Internet (cf. Section 5). The findings have implications for both research and practice (cf. Section 6).

2. Literature Review

2.1. Related Works on Rumors and Counter-Rumors

Given the Internet's ability to reach large audiences, it is widely used to seek and share health information (Chua and Banerjee, 2018; Deng et al., 2015; Li et al., 2018; Scanfeld et al. 2010). Consequently, numerous online health communities have now emerged. These include the likes of CrowdMed.com, HealthUnlocked.com and PatientsLikeMe.com. Almost 20% of all Internet users are reported to have engaged with online health communities, particularly when they have chronic conditions or serve as caregivers (Rupert et al. 2014).

However, user-generated content available in such online communities can be plagued by rumors offering inaccurate medical recommendations. Healthcare providers increasingly fear that patients may act on such online recommendations even before consulting doctors (Hou and Shim, 2010; van Uden-Kraan et al., 2010).

To aggravate the problem, rumors traditionally circulated via word-of-mouth not necessarily at an alarming pace (Allport and Postman, 1947). Nowadays however, they spread more easily, faster and wider—courtesy of applications such as Facebook, Twitter and Whatsapp (Avery, 2017; Ozturk et al., 2015). Health rumors often become viral because many users share online health-related messages supposedly to assist their peers without necessarily evaluating message veracity (Syed-Abdul et al., 2013; Wood, 2018). Previous studies have shown how rumors spread widely on social media during epidemic outbreaks such as H1N1 influenza and Zika virus (Shigemura et al., 2015; Sommariva et al., 2018; Wood, 2018; Zhang et al., 2015).

The use of online counter-rumors is a possible strategy to debunk rumors. Counter-rumors refer to messages that refute rumors on the Internet to confirm their dupery, often using negations (Ozturk et al., 2015; Tanaka et al., 2013). The presence of such messages promotes skepticism about the veracity of rumors (Bordia et al., 2005; Takayasu et al., 2015). Counter-rumors can even reduce users' belief in rumors (Bordia et al., 2005). Early exposure to counter-rumors might either prevent rumors from becoming viral, or curb the effects of rumors if they had already become viral.

Among the few studies on counter-rumors in the online setting, the results have often been inconsistent. On the one hand, some found counter-rumors effective to combat rumors (Bordia et al., 2005; Ozturk et al., 2015). On the other hand, some could not support the efficacy of counter-rumors (Kimmel and Audrain-Pontevia, 2010; Nyhan and Reifler, 2010). In fact, some works suggest the possibility of backfire effect such that counter-rumors could reinforce the influence of rumors (Lewandowsky et al., 2012; Nyhan and Reifler, 2010).

A possible reason for the inconsistent finding is the inherent difference in nature between a rumor and its counter-rumor. While the former tends to be sensational and hence has a wide appeal, the latter mostly contains negations that do not easily grab the eyeballs (Chua and Banerjee, 2018; Ozturk et al., 2015). This sets the stage to investigate differences in Internet users' behavioral response between rumors and counter-rumors.

In this regard, prior works have already examined constructs such as intention to believe, share and trust (Chua and Banerjee, 2015, 2017b, 2018; Lee and Oh, 2017). To extend the literature, this paper casts the spotlight on intention to follow—individuals' willingness to act as recommended by a message. This construct has been studied in other information processing contexts such as online travel information (Casaló et al., 2011), but not for online health information. Specifically, the motivation to investigate intention to follow health-related rumors and counter-rumors was rooted in the growing concern echoed in the literature that people may act on online recommendations even before consulting their doctors (Hou and Shim, 2010; van Uden-Kraan et al., 2010). Intention to follow rumors will misinform users' healthcare decision-making whereas intention to follow counter-rumors is desirable. However, the literature is currently silent on whether intention to follow differs between the two antithetical messages.

2.2. Related Works on Risk Propensity and Prior Endorsement

This paper investigates intention to follow health-related rumors and counter-rumors on the Internet based on two factors: user's risk propensity, and messages' prior endorsement. These were chosen because they have the potential to shape users' intention to follow a message while seeking health-related information on the Internet.

Risk propensity is defined as individuals' tendency to take risks (Branley and Covey, 2017; Benson et al., in press; Harrison et al., 2005). Individuals are known to vary drastically in terms of their inclination to take risks (Meertens & Lion, 2008), and this in turn affects their behavioral responses. For example, research suggests that individuals with high willingness to take risks are more likely to become victims of cybercrime on social media compared with those who avoid risks. This is because individuals who do not shy away from risks engage in rampant online behaviors, and often do not hesitate to reveal personal information or share hoaxes (Buchanan and Benson, 2019; Saridakis et al., 2016).

Risk has been a construct of much interest for health topics. Works such as Li et al. (2018) found perceived risk to be negatively associated with individuals' likelihood to seek and share health-related messages on social media. Risk propensity is a particularly pertinent individual trait in the context of online health information processing, which requires taking risks about individuals' well-being by following health-related online messages (Panzano and Roth, 2006; Meertens and Lion, 2008). Based on risk propensity in health information seeking behavior, individuals can be categorized as either risk-averse or risk-seeking. Risk-averse individuals refer to those who are reluctant to take risks. On the other hand, risk-seeking individuals are those who are willing to take risks (Chua et al., 2016; Harrison et al., 2005).

Prior endorsement refers to the number of times a message has been shared by others before a recipient receives it. It indicates the consensus of others on a particular message (Kelly, 1967). Highly endorsed messages indicate high level of acceptance. This in turn highlights the potential of the messages to become viral. Prior endorsement serves as a persuasive cue in affecting users' information selection, processing, decision making, and behavior (Alhabash et al., 2015; Fu and Sim, 2011). After all, individuals tend to assume that if many others think something is correct or good, it has to be so (Wan, 2015).

In the context of dubious online messages, research has widely studied endorsement, virality and propagation patterns (Aswani et al., 2017; Kim, 2018). Compared with counter-rumors, rumors have a tendency to attract endorsements faster, become viral quicker, and propagate wider (Guess et al., 2019; Li et al., 2018; Meng et al., 2018; Scanfeld et al. 2010). However, how prior endorsement in terms of number of shares influences users' intention to follow health-related rumors and counter-rumors has not been empirically analyzed.

3. Hypotheses Development

3.1 Role of Risk Propensity

The elaboration likelihood model (ELM) offers insights into how risk propensity could shape users' intention to follow rumors and counter-rumors. It suggests that when an issue increases in personal relevance (increase in elaboration likelihood), individuals' motivation to process related information rises depending upon their ability to do so. Their strategies to process information change from a peripheral route toward a more central route. Peripheral route refers to heuristic information processing whereas central route refers to effortful information processing (Petty et al., 1983; Yin et al., 2018).

In the context of health information seeking, risk propensity reflects personal relevance. After all, risk is deemed to be "an ingrained concept in health" (Hammer et al., 2019, p. 6). When individuals come across health-related information that possibly pertains to themselves or their family and friends, their sense of personal relevance is enhanced (Rotliman and Schwarz, 1998). Specifically, risk-averse individuals are expected to deem health-related messages extremely relevant. Given their high elaboration likelihood, they would make efforts to assess message veracity (Petty et al., 1983). Therefore, with the right information processing skills, they should be able to distinguish between a rumor and its counter-rumor. This leads to the following hypothesis:

H1(a): Among risk-averse individuals, intention to follow rumors will be lower than intention to follow counter-rumors.

The opposite is anticipated for risk-seeking individuals, who might not deem health-related messages to be too personally relevant. Due to their relatively lower elaboration likelihood, they could be driven by the peripheral cue of message appearance (Petty et al., 1983). All else being equal, rumors with bold claims appear more sensational than counter-rumors containing negations (Chua and Banerjee, 2018; Ozturk et al., 2015). Therefore, the peripheral route of information processing could make risk-seeking individuals lean more toward rumors vis-à-vis counter-rumors. This leads to the following hypothesis:

H1(b): Among risk-seeking individuals, intention to follow rumors will be higher than intention to follow counter-rumors.

Furthermore, risk-averse individuals could be wary of all online health information if they have the slightest doubt about message veracity. Risk-seeking individuals, on the other hand, could be nonchalant about such messages. Their intention to follow either a rumor or a counter-rumor could be simply based on instincts (Harrison et al., 2005; Sitkin and Pablo, 1992). The contrasting attitude between the two groups of people could result in different behavioral responses. In this vein, Chua et al. (2016) found risk-averse users to be reluctant to either trust or share rumors, and risk-seeking users reluctant to trust but keen to share—especially when the rumors had a pessimistic flavor. However, it did not shed any light on the construct of intention to follow for either rumors or counter-rumors. Therefore, there is not enough literature to forecast the nature of the difference in behavioral responses between risk-averse and risk-seeking users. Hence, the following non-directional hypotheses are posited:

H1(c): Intention to follow rumors among risk-averse individuals will be different from that among risk-seeking individuals.

H1(d): Intention to follow counter-rumors among risk-averse individuals will be different from that among risk-seeking individuals.

3.2 Role of Prior Endorsement

The Matthew effect offers insights into how prior endorsement could shape users' intention to follow rumors and counter-rumors. Used to explain accumulated advantage, it refers to the phenomenon of the rich continually growing richer, and the poor getting poorer (Merton, 1968; Wan, 2015). Any advantage or fame accumulates disproportionately such that the advantaged receives increasing advantages over time while the disadvantaged receives increasing disadvantages. The Matthew effect has been used to explain many social phenomena including reward allocation among scientists (Merton, 1968; Rossiter, 1993) and helpfulness voting among online reviews (Chua and Banerjee, 2017a).

Due to the Matthew effect, highly endorsed messages would be viewed more favorably vis-a-vis those having low endorsement—regardless of whether they are rumors or counter-rumors (Fu and Sim, 2011). This is commonly attributed to individuals' tendency to join the bandwagon and converge to a widely endorsed viewpoint. In that case, three possibilities emerge. One, both rumors and counter-rumors under high endorsement would trigger intention to follow. Two, under low endorsement, rumors would still appear more sensational and appealing than counter-rumors. Three, individuals' intention to follow messages with high endorsement would exceed that under low endorsement. These lead to the following hypotheses:

H2(a): Under the condition of high endorsement, intention to follow rumors will not be different from intention to follow counter-rumors for the same individual.

H2(b): Under the condition of low endorsement, intention to follow rumors will be higher than intention to follow counter-rumors for the same individual.

H2(c): Intention to follow rumors under high endorsement will exceed that under low endorsement for the same individual.

H2(d): Intention to follow counter-rumors under high endorsement will exceed that under low endorsement for the same individual.

Table I summarizes the research questions and the hypotheses of the paper.

Insert Table I here.

4. Research Methods

A 2 (risk propensity: risk-averse, risk-seeking) x 2 (prior endorsement: high, low) mixed-experimental design was conducted online using Qualtrics. Risk propensity was a between-participants factor because an individual cannot be both risk-averse and risk-seeking. Prior endorsement was a within-participants factor because every individual was exposed to messages with both high and low prior endorsements.

4.1. Sampling and Experimental Procedure

Since random selection of participants from the entire online community worldwide is infeasible, purposive sampling was used based on two eligibility criteria. First, participants had to be between 21 to 40 years old and minimally undergraduate students in terms of their educational profile. This was necessary because young and educated individuals are known to widely seek health information on the Internet (Mou et al., 2016). Second, participants must have sought online health information in the last month. This meant that they were appropriate for the experimental task.

The invitation for voluntary participation was disseminated via university notice boards over a period of one month, with each participant requested to snowball. A total of 162 responses were collected. After removing incomplete responses, data from 148 participants were usable.

The recruited participants were given the experimental website URL. They were asked to imagine coming across a set of eight health-related messages on social media. These comprised four rumors coupled with their corresponding counter-rumors arranged in a random sequence. In other words, any message could appear at any of the eight positions. To minimize biases, participants were not explicitly told that the messages contained rumors and counter-rumors. After all, rumors and counter-rumors on the Internet seldom come with such labels.

The four rumors were selected from a list 50 health rumors drawn from the rumor-verification website Snopes.com, which has been widely used in prior studies (Chua and Banerjee, 2018; Liu et al., 2015). All the rumors were false, and of comparable length. They were also thematically similar, and highlighted consequences of drinking water—a very general topic. Guided by previous studies (Ozturk et al., 2015; Tanaka et al., 2013), counter-rumors were phrased as negations of the corresponding rumors.

Despite not being explicitly told about rumors and counter-rumors (Chua and Banerjee, 2018; Ozturk et al., 2015; Tanaka et al., 2013), the participants were informed that they were free to browse the Internet to check message veracity during the study participation. If any participant had searched for the messages in search engines such as Google, they would have retrieved the message veracity from Snopes.com. This in turn would have allowed them to make an informed decision about whether to follow rumors or counter-rumors. Such a way of looking at the messages would have been a manifestation of what is known as the central route of information processing according to the ELM. On the other hand, participants who would answer the questions heuristically would have followed what is referred as the peripheral route (Petty et al., 1983).

When participants were exposed to the eight messages (four rumors + four counter-rumors) as listed in Appendix 1, prior endorsement was induced by showing the number of times the messages had already been shared on social media platforms (Jin et al., 2015; Lee-Won et al., 2016). The first rumor and its counter-rumor (R1, CR1) as well as the third rumor and its counter-rumor (R3, CR3) represented the stimuli with high endorsement. The remaining four messages (R2, CR2, R4, CR4) bore annotations for low endorsement. Figure 1 shows sample labels of prior endorsement used in the experiment.

On the screen, participants could view only one of the eight messages at a time. Below each message, the questionnaire items for intention to follow were presented. Only after participants had confirmed their intention to follow for a given message, the next message would appear. This continued until participants were exposed to all the eight messages. Participants were allowed neither to visit a previously viewed Qualtrics-page nor to skip the current Qualtrics-page without answering the questionnaire items (cf. Section 4.2). Nonetheless, they had the option to open a new browser tab to look for information about the message they were reading.

As participants clicked ‘Next’ after answering questions about each message, the following page contained a manipulation check question. They were asked whether the message they read in the previous page was shared ‘many times’ or ‘few times’ on social media. Fourteen of the 148 participants responded incorrectly on at least one of the eight messages. Hence, they were removed from the sample for failing the manipulation check of prior endorsement. The remaining 134 participants (Gender: female = 43, male = 91; age: M = 26.27, SD = 1.89, Mdn = 26.17, Min = 22, Max = 38) were included for the final analysis.

Insert Figure 1 here.

4.2. Measures and Analysis

All questionnaire items (Table II) sought responses on a five-point rating scale with labels at extremes (1 = *strongly disagree*, 5 = *strongly agree*). Intention to follow was measured using three questionnaire items (Casaló et al., 2011; Zainal et al., 2017). Informed by the study of Merteens and Lion (2008) that examined individuals' tendency to take risks, risk propensity was measured using 10 questionnaire items. The reliability of the items was checked in terms of Cronbach's Alpha. Intention to follow met the recommended threshold. However, for risk propensity, the reliability was below 0.7. Hence, three of the weakest items were deleted to yield a final Cronbach's Alpha of 0.72.

Insert Table II here.

Participants' responses to the remaining seven items measuring risk propensity were averaged to create a composite index. A higher value in the index indicated greater tendency toward being risk-averse. The index was negatively correlated with intention to follow across all the messages ($r = -0.44$, $p < 0.001$). To categorize the participants as either risk-averse or risk-seeking, the technique of median-split was employed (Kim et al., 2015; Stein et al., 2016). The median of the risk propensity composite index was calculated. Thereafter, participants with a composite index score more than the median were labelled as risk-averse while the rest were labelled as risk-seeking (Chua et al., 2016).

To test the hypotheses and answer the research questions, a series of t-tests was employed. With respect to RQ 1, H1(a) was tested using a paired-samples t-test among risk-averse participants. The two pairs of observations included: (1) a composite index created by adding responses to the intention to follow questionnaire items for the four rumors, and (2) a composite index created by adding responses to the intention to follow questionnaire items for the four counter-rumors.

To test H1(b), a similar approach was followed. Only the sample was changed to risk-seeking participants.

H1(c) was tested using an independent samples t-test. Risk-averse participants and risk-seeking participants were the two samples. The dependent variable was a composite index created by adding participants' responses to the intention to follow questionnaire items for the four rumors.

To test H1(d), a similar approach was followed. Only the dependent variable was changed to a composite index created by adding participants' responses to the intention to follow questionnaire items for the four counter-rumors.

Furthermore, paired-samples t-tests were used to test all the hypotheses related to RQ 2 that focused on the same individual. For H2(a), the two pairs of observations included: (1) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two rumors with high endorsement, and (2) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two counter-rumors with high endorsement.

For H2(b), the two pairs of observations included: (1) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two rumors with low endorsement, and (2) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two counter-rumors with low endorsement.

For H2(c), the two pairs of observations included: (1) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two rumors with high endorsement, and (2) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two rumors with low endorsement.

For H2(d), the two pairs of observations included: (1) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two counter-rumors with high endorsement, and (2) a composite index created by adding participants' responses to the intention to follow questionnaire items for the two counter-rumors with low endorsement. The comparisons made in the hypotheses are depicted in Figure 2.

Insert Figure 2 here.

Finally, as a post-hoc investigation, a mixed-design analysis of variance (ANOVA) was used to check for any potential interaction between risk propensity (a between-participants variable), and prior endorsement (a within-participants variable). The analysis was repeated twice with intention to follow rumors and intention to follow counter-rumors as the two dependent variables. Given that the within-participants variable had only two levels, violation of sphericity was not an issue.

5. Results

RQ 1 was addressed as follows: With respect to H1(a), a paired samples t-test was conducted among risk-averse participants to compare their intention to follow rumors ($M = 43.23$, $SD = 5.12$) and counter-rumors ($M = 35.76$, $SD = 6.40$). A statistically significant difference was detected; $t(52) = 7.14$, $p < 0.001$. Risk-averse participants unfortunately intended to follow rumors more than counter-rumors. Hence, H1(a) was not supported.

With respect to H1(b), another paired samples t-test was conducted among risk-seeking participants to compare their intention to follow rumors ($M = 43.90$, $SD = 4.62$) and counter-rumors ($M = 40.80$, $SD = 7.53$). The result emerged statistically significant; $t(80) = 5.70$, $p < 0.001$. Risk-seeking participants also intended to follow rumors more than counter-rumors. Hence, H1(b) was supported.

With respect to H1(c), an independent-samples t-test was conducted to compare intention to follow rumors among risk-averse ($M = 43.23$, $SD = 5.12$) and risk-seeking ($M = 43.90$, $SD = 4.62$) participants. No statistically significant difference could be found; $t(132) = -0.79$, $p = 0.43$. Hence, H1(c) was not supported.

With respect to H1(d), another independent-samples t-test was conducted to compare intention to follow counter-rumors among risk-averse ($M = 35.76$, $SD = 6.40$) and risk-seeking ($M = 40.80$, $SD = 7.53$) participants. There was a statistically significant difference; $t(132) = -4.03$, $p < 0.001$. Risk-seeking participants were keener to follow counter-rumors compared with risk-averse individuals. Hence, H1(d) was supported.

RQ 2 was addressed as follows: With respect to H2(a), a paired-samples t-test was conducted to compare participants' intention to follow rumors ($M = 22.23$, $SD = 2.85$) and counter-rumors ($M = 18.82$, $SD = 4.12$) under high endorsement. There was a statistically significant difference; $t(133) = 8.66$, $p < 0.001$. When both rumors and counter-rumors came with high endorsements, the former was more likely to be followed than the latter. Hence, H2(a) was not supported.

With respect to H2(b), a paired-samples t-test was conducted to compare participants' intention to follow rumors (*M* = 21.40, *SD* = 3.34) and counter-rumors (*M* = 19.99, *SD* = 3.95) under low endorsement. A statistically significant difference emerged; t(133) = 4.66, $p < 0.001$. When both rumors and counter-rumors had low endorsements, the former was more likely to be followed than the latter. Hence, H2(b) was supported.

With respect to H2(c), a paired samples t-test was conducted to compare participants' intention to follow rumors under high endorsement (*M* = 22.23, *SD* = 2.85) and that under low endorsement (*M* = 21.40, *SD* = 3.34). A statistically significant difference arose; t(133) = 2.44, p = 0.02. Rumors with high endorsement were followed more than those with relatively low endorsement, thereby lending support to the Matthew effect. Hence, H2(c) was supported.

With respect to H2(d), a paired samples t-test was conducted to compare participants' intention to follow counter-rumors under high endorsement (*M* = 18.82, *SD* = 4.12) and that under low endorsement (*M* = 19.99, *SD* = 3.95). The result was statistically significant; t(133) = -4.53, $p < 0.001$. Counter-rumors with low endorsement were followed more than those with relatively high endorsement, thereby contradicting the Matthew effect. Hence, H2(d) was not supported. The results are summarized in Table III.

Furthermore, the mixed-design ANOVA failed to identify any statistically significant interaction effect between risk propensity and prior endorsement on intention to follow rumors. The interaction effect on intention to follow counter-rumors was non-significant.

Insert Table III here.

6. Discussion and Conclusion

6.1. Key Findings

This paper gleans three key findings. First, on a pessimistic note, rumors tend to attract more favorable behavioral responses compared with counter-rumors. Specifically, intention to follow was higher for rumors vis-à-vis counter-rumors among both risk-averse and risk-seeking participants. The same trend was identified in the high endorsement as well as the low endorsement conditions. This qualifies previous research that has found rumors to become viral more easily than counter-rumors (Starbird et al., 2014, 2018; Zubiaga et al., 2016). Such a finding could be attributed to the relatively more sensational nature of rumors vis-à-vis counter-rumors (Chua and Banerjee, 2018; Dubois et al., 2011; Ozturk et al., 2015). Thus, having a counter-rumor with high prior endorsement does not necessarily guarantee its ability to refute rumors. Moreover, the paper demonstrates that rumors are not only shared more but also followed more—a perfect recipe for disaster.

Second, contrary to expectation, risk-seeking individuals followed counter-rumors more than risk-averse individuals did. According to the ELM, the latter was expected to exhibit higher elaboration likelihood, higher propensity to evaluate message veracity, and hence higher intention to follow counter-rumors (Petty et al., 1983). A possible explanation of the counter-intuitive finding is this: Since risk-seeking individuals are more likely to follow online health-related rumors without evaluating their veracity, they might also be willing to follow counter-rumors easily (Harrison et al., 2005; Meertens and Lion, 2008; Panzano and Roth, 2006). In other words, they never seem to be taking online health information with a pinch of salt. In contrast, risk-averse individuals could lack the information literacy skills to discern the truth on the Internet, and therefore fail to separate rumors from counter-rumors. More research is needed to verify these possibilities.

Third, the Matthew effect makes its presence felt for rumors but not for counter-rumors. Given that rumors become viral easily and quickly when they first set in on social media (Starbird et al., 2014; Zubiaga et al., 2016), they continue to grow with endorsement from the online community. Given their increasing social proof, they trigger a domino effect, thereby getting endorsed repeatedly. This echo chamber effect lends support to the Matthew effect in the context of online rumors (Chua and Banerjee, 2017a; Wan, 2015).

Interestingly, the Matthew effect did not hold good for counter-rumors. Counter-rumors with low endorsement were followed more than those with relatively high endorsement. This contradictory finding could reflect some other issues involved in the process of rumor refutation. One issue could be the backfire effect, which refers to the reinforcement of rumor belief (Lewandowsky et al., 2012; Nyhan and Reifler, 2010). Prior works suggest that an inappropriate attempt of refutation can reinforce misconception about the rumor *per se* (Lewandowsky et al., 2012*)*. Another issue is that counter-rumors that simply refute rumors using negations might not be convincing (Pal et al., 2019). They should incorporate reasonable explanations as to why the rumor is false.

6.2. Theoretical and Practical Implications

The findings of this paper have several theoretical and practical implications. On the theoretical front, the implications are three-fold. First, while previous studies have often considered the possibility of tackling false rumors with counter-rumors (Ozturk et al., 2015; Tanaka et al., 2013), this paper contributes to the scholarly understanding of people's behavioral responses when they are unbeknownstly exposed to both rumors and counter-rumors on the Internet. This represents a shift in the extant academic discourse.

Second, this paper presents a research framework to investigate intention to follow rumors and counter-rumors by considering individuals' risk propensity and messages' prior endorsement. These were rooted in the ELM and the Matthew effect respectively (Bi et al., 2017; Petty et al., 1983; Merton, 1968). The paper dovetails the literature by examining how risk-averse and risk-seeking individuals differ in terms of intention to follow rumors and counter-rumors. It also shows how prior endorsement of such messages drives users' likelihood to follow them.

Third, the paper unearths several new and unexpected findings. For example, contrary to H1(a), risk-averse users showed higher intention to follow for rumors vis-à-vis counter-rumors. This might be attributed to the lack of adequate online information processing skills. Users probably need to cultivate robust Internet-related epistemic beliefs, which refers to perceptions about the nature of knowledge and the process of knowing from online sources (Chua and Banerjee, 2017b). Future research could examine the interplay between risk propensity and epistemic beliefs. Next, contrary to H1(c), risk-averse and risk-seeking individuals did not differ in their intention to follow rumors. While prior research found both to fare similarly in terms of intention to trust rumors (Chua et al., 2016), this paper dovetails the literature by demonstrating both to be similar with respect to intention to follow. Moreover, contrary to H2(a), rumors were followed more than counter-rumors under high endorsement. This is perhaps vestige of the relatively more sensational nature of rumors vis-à-vis counter-rumors (Dubois et al., 2011). Finally, contrary to H2(d), counter-rumors with low endorsement were followed more than those with relatively high endorsement. This can perhaps be explained in light of the less-is-better effect (Hsee, 1998). When counter-rumors did not have high prior endorsement, curious participants might have checked the veracity of the entries using Google searches. This in turn could have caused a high intention to follow. Future research in this area could explore methods such as screencast videography (Kawaf, 2019) to better understand users' real-time behavioral responses in the digital space. Overall, these twists in the findings open up uncharted avenues for further inquiry.

On the practical front, the implications are three-fold. First, the paper demonstrates that counter-rumors that simply refute rumors using negations are not potent enough to combat online falsehood. Therefore, crafting persuasive counter-rumors seems to be the need of the hour. The messages could explicitly justify why a rumor is false to fill the coherence gap left behind by the refutation.

Second, moderators of online health communities such as CrowdMed.com, HealthUnlocked.com and PatientsLikeMe.com should take proactive steps to restrict the flow of rumors. They could liaise with health educators to keep up the quality and accuracy of the information archives. They should also encourage individual users to evaluate the veracity of all messages as much as possible prior to sharing. This can prevent well-meaning online peers from being inadvertently tricked into disseminating dubious messages.

Third, this paper encourages all Internet users to take online health-related messages with a pinch of salt. When in doubt, they are recommended to directly seek advice from medics before relying on online health-related messages. Policymakers could consider introducing more robust digital information literacy programs. A greater ability to curb the instinct to follow online messages will make users' Internet browsing more productive and less harmful. This in turn will attenuate the capacity of rumors to distort public opinion about healthcare decision-making.

6.3. Limitations and Further Research Directions

The paper has three limitations. First, it only considered health rumors related to drinking water. Hence, it advocates caution in generalizing its findings. Second, the rumors had an affirmative tone while the counter-rumors were phrased negatively. Interested scholars could replicate the current study by using other forms of counter-rumors. Additional factors such as perceived sensationalism of rumors and perceived persuasiveness of counter-rumors could also be studied. Lastly, the research did not capture participants' elaboration while reading the online messages. Future research could measure elaboration using proxy variables such as number of Google searches, or time spent on Google searches. Screencast videography could also be employed (Kawaf, 2019).

The paper also identifies several other directions for future research. For one, interested scholars could investigate the extent to which users' intention to follow counter-rumors could be enhanced by boosting the messages' argument strength. Another direction could involve investigating if risk-averse users differ from risk-seeking users in their intention to follow such persuasive counter-rumors. The role played by other individual traits such as digital information literacy and epistemic beliefs could also be investigated. Yet another direction of research could focus on the impact of online rumors and counter-rumors on demographic slices such as the elderly, or those suffering from specific diseases and hence could be predisposed to believing a certain kind of information. Such works would enrich the current understanding of the impact of health-related falsehood on the online populace.

References

Avery, E. (2017), "Public information officers' social media monitoring during the Zika virus crisis, a global health threat surrounded by public uncertainty", *Public Relations Review*, Vol. 43 No. 3, pp. 468-476.

Agree, E., King, A., Castro, C., Wiley, A. and Borzekowski, D. L. (2015), "It's Got to Be on This Page: Age and cognitive style in a study of online health information seeking", *Journal of Medical Internet Research*, Vol. 17 No. 3, e79.

Alhabash, S., McAlister, A., Quilliam, E., Richards, J. and Lou, C. (2015), "Alcohol's getting a bit more social: When alcohol marketing messages on Facebook increase young adults' intentions to imbibe", *Mass Communication and Society*, Vol. 18 No. 3, pp. 350-375.

Allport, G. and Postman, L. (1947), *The psychology of rumor*, Oxford, England, Henry Holt.

Aswani, R., Kar, A., Aggarwal, S. and Ilavarsan, P. (2017), "Exploring content virality in Facebook: A semantic based approach", *Proceedings of the Conference on e-Business, e-Services and e-Society* (pp. 209-220). Springer, Cham.

Buchanan, T. and Benson, V. (2019). "Spreading disinformation on Facebook: Do trust in message source, risk propensity, or personality affect the organic reach of "Fake News"?", *Social Media+ Society*, Vol. 5 No. 4, pp. 1-9.

Benson, V., Ezingeard, J. and Hand, C. (in press), "An empirical study of purchase behaviour on social platforms: The role of risk, beliefs and characteristics", *Information Technology & People*, Available at dx.doi.org/10.1108/ITP-08-2017-0267

Bi, S., Liu, Z. and Usman, K. (2017), "The influence of online information on investing decisions of reward-based crowdfunding", *Journal of Business Research*, Vol. 71, pp. 10-18.

Bird, S. and Bogard, L. (2005), "Conspiracy beliefs about HIV/AIDS and birth control among African Americans: Implications for the prevention of HIV, other STIs, and unintended pregnancy", *Journal of Social Issues*, Vol. 61 No. 1, pp 109–126.

Bordia, P., DiFonzo, N., Haines, R. and Chaseling, E. (2005), "Rumors denials as persuasive messages: Effects of personal relevance, source, and message characteristics," *Journal of Applied Social Psychology*, Vol. 35 No. 6, pp. 1301-1331.

Branley, D. and Covey, J. (2017), "Is exposure to online content depicting risky behavior related to viewers' own risky behavior offline?", *Computers in Human Behavior*, Vol. 75, pp. 283-287.

Burke, M. and Develin, M. (2016), "Once more with feeling: Supportive responses to social sharing on Facebook", *Proceedings of the ACM Conference on Computer-Supported Cooperative Work & Social Computing, ACM,* pp. 1462-1474.

Camargo Jr, K. and Grant, R. (2015), "Public health, science, and policy debate: Being right is not enough", *American Journal of Public Health*, Vol. 105 No. 2, pp. 232-235.

Casaló, L., Flavián, C. and Guinalíu, M. (2011), "Understanding the intention to follow the advice obtained in an online travel community," *Computers in Human Behavior*, Vol. 27 No. 2, pp. 622-633.

Chua, A. and Banerjee, S. (2015), "Analyzing users' trust for online health rumors", *Proceedings of the International Conference on Asian Digital Libraries, Springer, Cham*, pp. 33-38.

Chua, A. and Banerjee, S. (2017a), "Analyzing review efficacy on Amazon.com: Does the rich grow richer?", *Computers in Human Behavior*, Vol. 75, pp. 501-509.

Chua, A. and Banerjee, S. (2017b), "To share or not to share: The role of epistemic belief in online health rumors", *International Journal of Medical Informatics*, Vol. 108, pp. 36-41.

Chua, A. and Banerjee, S. (2018), "Intentions to trust and share online health rumors: An experiment with medical professionals," *Computers in Human Behavior*, Vol. 87, pp. 1-9.

Chua, A., Banerjee, S., Guan, A., Xian, L.J. and Peng, P. (2016), "Intention to trust and share health-related online rumors: Studying the role of risk propensity." *Proceedings of the Science and Information Computing Conference* (pp. 1136-1139), IEEE.

Daugherty, T., Eastin, M. and Bright, L. (2008), "Exploring consumer motivations for creating user-generated content", *Journal of Interactive Advertising*, Vol. 8 No. 2, pp. 16-25.

Deng, Z., Liu, S. and Hinz, O. (2015), "The health information seeking and usage behavior intention of Chinese consumers through mobile phones", *Information Technology & People*, Vol. 28 No. 2, pp. 405-423.

Dubois, D., Rucker, D. and Tormala, Z. (2011), "From rumors to facts, and facts to rumors: The role of certainty decay in consumer communications", *Journal of Marketing Research*, Vol. 48 No. 6, pp. 1020-1032.

Fine, G. (2007), "Rumor, trust and civil society: Collective memory and cultures of judgment", *Diogenes*, Vol. 54 No. 1, pp. 5-8.

Fu, W. and Sim, C. (2011), "Aggregate bandwagon effect on online videos' viewership: Value uncertainty, popularity cues, and heuristics", *Journal of the American Society for Information Science and Technology*, Vol. 62 No. 12, pp. 2382-2395.

Guess, A., Nagler, J. and Tucker, J. (2019), "Less than you think: Prevalence and predictors of fake news dissemination on Facebook", *Science Advances*, Vol. 5 No. 1, Article eaau4586.

Habiba, Y., Berger-Wolf, T. and Saia J. (2010), "Finding spread blockers in dynamic networks", in Giles, L., Smith, M., Yen, J. and Zhang, H. (Eds.), Lecture Notes in Computer Science: Vol. 5498, *Advances in Social Network Mining and Analysis*, Springer, Germany, Berlin, pp. 55-76.

Hammer, C. C., Brainard, J., Innes, A. and Hunter, P. R. (2019), "(Re-) conceptualising vulnerability as a part of risk in global health emergency response: Updating the pressure and release model for global health emergencies", *Emerging Themes in Epidemiology*, Vol. 16, Article 2, pp. 1-8.

Harrison, J., Young, J., Butow, P., Salkeld, G. and Solomon, M. (2005), “Is it worth the risk? A systematic review of instruments that measure risk propensity for use in the health setting”, *Social Science & Medicine*, Vol. 60 No. 6, pp. 1385-1396.

Hou, J. and Shim, M. (2010), “The role of provider–patient communication and trust in online sources in Internet use for health-related activities”, *Journal of Health Communication*, Vol. 15 No. sup3, pp. 186-199.

Hsee, C.K. (1998), “Less is better: When low-value options are valued more highly than high-value options”, *Journal of Behavioral Decision Making*, Vol. 11, pp. 107-121.

Jin, S., Phua, J. and Lee, K. (2015), “Telling stories about breastfeeding through Facebook: The impact of user-generated content (UGC) on pro-breastfeeding attitudes”, *Computers in Human Behavior*, Vol. 46, pp. 6-17.

Kawaf, F. (2019), “Capturing digital experience: The method of screencast videography”, *International Journal of Research in Marketing*, Vol. 36 No. 2, pp.169-184.

Kim, J. (2018), “They liked and shared: Effects of social media virality metrics on perceptions of message influence and behavioral intentions”, *Computers in Human Behavior*, Vol. 84, pp. 153-161.

Kim, J., Park, J. and Im, J. S. (2015), “Relationship maintenance strategies on the Facebook pages of current US Senators”, *Journal of Communication Management*, Vol. 19 No. 3, pp. 224-238.

Kim, S. (June 30, 2019), “‘It’s only fake news’: Even on a historic day, Trump complains about media coverage”, The Washington Post. Available at https://www.washingtonpost.com/politics/its-only-fake-news-even-on-a-historic-day-trump-complains-about-media-coverage/2019/06/30/b8ed865a-9b5b-11e9-85d6-5211733f92c7_story.html

Kimmel, A. and Audrain-Pontevia, A. F. (2010), “Analysis of commercial rumors from the perspective of marketing managers: Rumor prevalence, effects, and control tactics”, *Journal of Marketing Communications*, Vol. 16 No. 4, pp. 239-253.

Lee, H. and Oh, H. J. (2017), “Normative mechanism of rumor dissemination on Twitter”, *Cyberpsychology, Behavior, and Social Networking*, Vol. 20 No. 3, pp. 164-171.

Lee, S., Hansen, S. and Lee, J. (2016), “What makes us click ‘like’ on Facebook? Examining psychological, technological, and motivational factors on virtual endorsement”, *Computer Communications*, Vol. 73, pp. 332-341.

Lee-Won, R., Abo, M., Na, K. and White, T. N. (2016), “More than numbers: Effects of social media virality metrics on intention to help unknown others in the context of bone marrow donation”, *Cyberpsychology, Behavior, and Social Networking*, Vol. 19 No. 6, pp. 404-411.

Lewandowsky, S., Ecker, U. K., Seifert, C. M., Schwarz, N. and Cook, J. (2012), “Misinformation and its correction continued influence and successful debiasing”, *Psychological Science in the Public Interest*, Vol. 13 No. 3, pp. 106-131.

Li, Y., Wang, X., Lin, X. and Hajli, M. (2018), “Seeking and sharing health information on social media: A net valence model and cross-cultural comparison”, *Technological Forecasting and Social Change*, Vol. 126, pp. 28-40.

Liu, X., Nourbakhsh, A., Li, Q., Fang, R. and Shah, S. (2015), "Real-time Rumor Debunking on Twitter", *Proceedings of the International Conference on Information and Knowledge Management, ACM*, pp. 1867-1870.

Marett, K. and Joshi, K. (2009), "The decision to share information and rumors: Examining the role of motivation in an online discussion forum", *Communications of the Association for Information Systems*, Vol. 24 No. 1, pp. 47-68.

Meertens, R. and Lion, R. (2008), "Measuring an individual's tendency to take risks: The risk propensity scale1", *Journal of Applied Social Psychology*, Vol. 38 No. 6, pp. 1506-1520.

Meng, J., Peng, W., Tan, P. N., Liu, W., Cheng, Y. and Bae, A. (2018). "Diffusion size and structural virality: The effects of message and network features on spreading health information on twitter", *Computers in Human Behavior*, Vol. 89, pp. 111-120.

Merton, R. (1968), "The Matthew effect in science", *Science*, Vol. 159 No. 3810, pp. 56-63.

Mou, J., Shin, D. H. and Cohen, J. (2016), "Health beliefs and the valence framework in health information seeking behaviors", *Information Technology & People*, Vol. 29 No. 4, pp. 876-900.

Nyhan, B. and Reifler, J. (2010), "When corrections fail: The persistence of political misperceptions", *Political Behavior*, Vol. 32 No. 2, pp. 303-330.

Ozturk, P., Li, H. and Sakamoto, Y. (2015), "Combating rumor spread on social media: The effectiveness of refutation and warning", *Proceedings of the Hawaii International Conference on System Sciences, IEEE*, pp. 2406-2414.

Pal, A., Chua, A. and Goh, D. (2017), "Does KFC sell rat? Analysis of tweets in the wake of a rumor outbreak", *Aslib Journal of Information Management*, Vol. 69 No. 6, pp. 660-673.

Pal, A., Chua, A. and Goh, D. (2019), "Debunking rumors on social media: The use of denials", *Computers in Human Behavior*, Vol. 96, pp. 110-122.

Panzano, P. and Roth, D. (2006), "The decision to adopt evidence-based and other innovative mental health practices: Risky business?" *Psychiatric Services*, Vol. 57 No. 8, pp. 1153-1161.

Petty, R. E., Cacioppo, J. and Schumann, D. (1983), "Central and peripheral routes to advertising effectiveness: The moderating role of involvement", *Journal of Consumer Research*, Vol. 10 No. 2, pp. 135-146.

Rossiter, M. W. (1993). "The Matthew Matilda effect in science", Social Studies of Science, Vol. 23 No. 2, pp. 325-341.

Rotliman, A.J. and Schwarz, N. (1998), "Constructing perceptions of vulnerability: Personal relevance and the use of experiential information in health judgments," Personality and Social Psychology Bulletin, Vol. 24 No. 10, pp.1053-1064.

Rupert, D., Moultrie, R., Read, J. G., Amoozegar, J. B., Bornkessel, A. S., O'Donoghue, A. C. and Sullivan, H. W. (2014), "Perceived healthcare provider reactions to patient and caregiver use of online health communities", *Patient Education and Counseling*, Vol. 96 No. 3, pp. 320-326.

Saridakis, G., Benson, V., Ezingeard, J. N. and Tennakoon, H. (2016). “Individual information security, user behaviour and cyber victimisation: An empirical study of social networking users”, *Technological Forecasting and Social Change*, Vol. 102, pp. 320-330.

Scanfeld, D., Scanfeld, V. and Larson, E. L. (2010), “*Dissemination of health information through social networks: Twitter and antibiotics*”, *American Journal of Infection Control*, Vol. 38 No. 3, pp. 182-188.

Shigemura, J., Harada, N., Tanichi, M., Nagamine, M., Shimizu, K., Katsuda, Y., ... and Yoshino, A. (2015), “Rumor-related and exclusive behavior coverage in Internet news reports following the 2009 H1N1 influenza outbreak in Japan”, *Disaster Medicine and Public Health Preparedness*, Vol. 9 No. 4, pp. 459-463.

Silverman, C. and Singer-Vine, J. (2016), “Most Americans who see fake news believe it, new survey says.” Available at https://www.buzzfeednews.com/article/craigsilverman/fake-news-survey

Sitkin, S. B. and Pablo, A. L. (1992), “Reconceptualizing the determinants of risk behavior”, *Academy of Management Review*, Vol. 17 No. 9, pp. 9–38.

Sommariva, S., Vamos, C., Mantzarlis, A., Đào, L. U. L. and Martinez Tyson, D. (2018), “Spreading the (fake) news: Exploring health messages on social media and the implications for health professionals using a case study”, *American Journal of Health Education*, Vol. 49 No. 4, pp. 246-255.

Starbird, K., Maddock, J., Orand, M., Achterman, P. and Mason, R. (2014), “Rumors, false flags, and digital vigilantes: Misinformation on Twitter after the 2013 Boston Marathon Bombing”, *Proceedings of the iConference,* pp. 654 - 662.

Starbird, C., Arif, A., and Wilson, T. (2018). Understanding the structure and dynamics of disinformation in the online information ecosystem. University of Washington Seattle. Available at https://apps.dtic.mil/dtic/tr/fulltext/u2/1058867.pdf

Stein, A. T., Greathouse, L. J. and Otto, M. W. (2016), “Eating in response to exercise cues: Role of self-control fatigue, exercise habits, and eating restraint”, *Appetite*, Vol. 96, pp. 56-61.

Syed-Abdul, S., Fernandez-Luque, L., Jian, W. S., Li, Y. C., Crain, S., Hsu, M. H., ... and Liou, D. M. (2013), “Misleading health-related information promoted through video-based social media: anorexia on YouTube”, *Journal of Medical Internet Research*, Vol. 15 No. 2.

Takayasu, M., Sato, K., Sano, Y., Yamada, K., Miura, W., and Takayasu, H. (2015), “Rumor diffusion and convergence during the 3.11 earthquake: A Twitter case study”, *PLoS One*, Vol. 10 No. 4. Available at http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0121443

Tanaka, Y., Sakamoto, Y. and Matsuka, T. (2013), “Toward a social-technological system that inactivates false rumors through the critical thinking of crowds”, *Proceedings of the Hawaii International Conference on System Sciences, IEEE*, pp. 649-658.

Tan, A. S., Lee, C. J. and Chae, J. (2015), “Exposure to Health (Mis) Information: Lagged Effects on Young Adults’ Health Behaviors and Potential Pathways,” *Journal of Communication*, Vol. 65 No. 4, pp. 674-698.

Tripathy, R., Bagchi, A. and Mehta, S. (2013), "Towards combating rumors in social networks: Models and metrics", *Intelligent Data Analysis*, Vol. 17 No .1, pp. 149-175.

van Uden-Kraan, C. F., Drossaert, C. H., Taal, E., Smit, W. M., Seydel, E. R. and van de Laar, M. A. (2010), "Experiences and attitudes of Dutch rheumatologists and oncologists with regard to their patients' health-related Internet use", *Clinical Rheumatology*, Vol. 29 No. 11, pp. 1229-1236.

Wan, Y. (2015), "The Matthew effect in social commerce", *Electronic Markets*, Vol. 25 No. 4, pp. 313-324.

Wood, M. (2018), "Propagating and Debunking Conspiracy Theories on Twitter During the 2015–2016 Zika Virus Outbreak", *Cyberpsychology, Behavior, and Social Networking*, Vol. 21 No. 8, pp. 485-490.

World Health Organization. (September 12, 2016), "Dispelling Rumours Around Zika and Complications", WHO. Available at http://www.who.int/emergencies/zika-virus/articles/rumours/en/

Yin, C., Sun, Y., Fang, Y. and Lim, K. (2018), "Exploring the dual-role of cognitive heuristics and the moderating effect of gender in microblog information credibility evaluation", *Information Technology & People*, Vol. 31 No. 3, pp. 741-769.

Zainal, N. T. A., Harun, A. and Lily, J. (2017), "Examining the mediating effect of attitude towards electronic words-of mouth (eWOM) on the relation between the trust in eWOM source and intention to follow eWOM among Malaysian travelers", *Asia Pacific Management Review*, Vol. 22 No. 1, pp. 35-44.

Zhang, Z., Zhang, Z. and Li, H. (2015), "Predictors of the authenticity of Internet health rumours", *Health Information & Libraries Journal*, Vol. 32 No. 3, pp. 195-205.

Zubiaga, A., Liakata, M., Procter, R., Hoi, G. W. S. and Tolmie, P. (2016), "Analysing how people orient to and spread rumours in social media by looking at conversational threads", *PloS One*, Vol. 11 No. 3, e0150989.

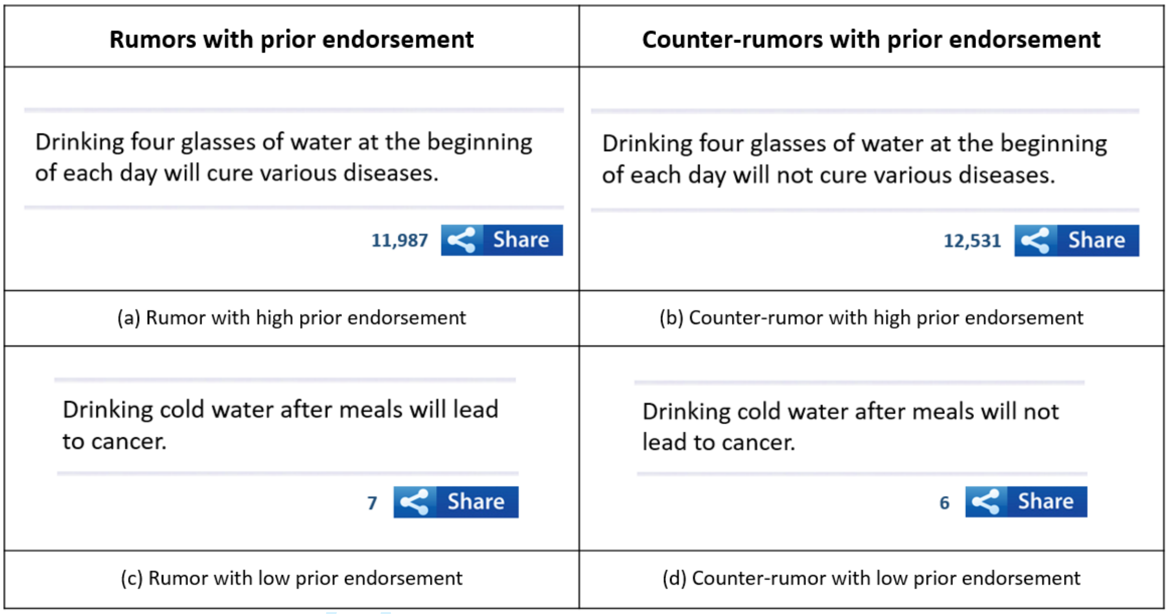

Figure 1. Examples of the experimental stimuli.

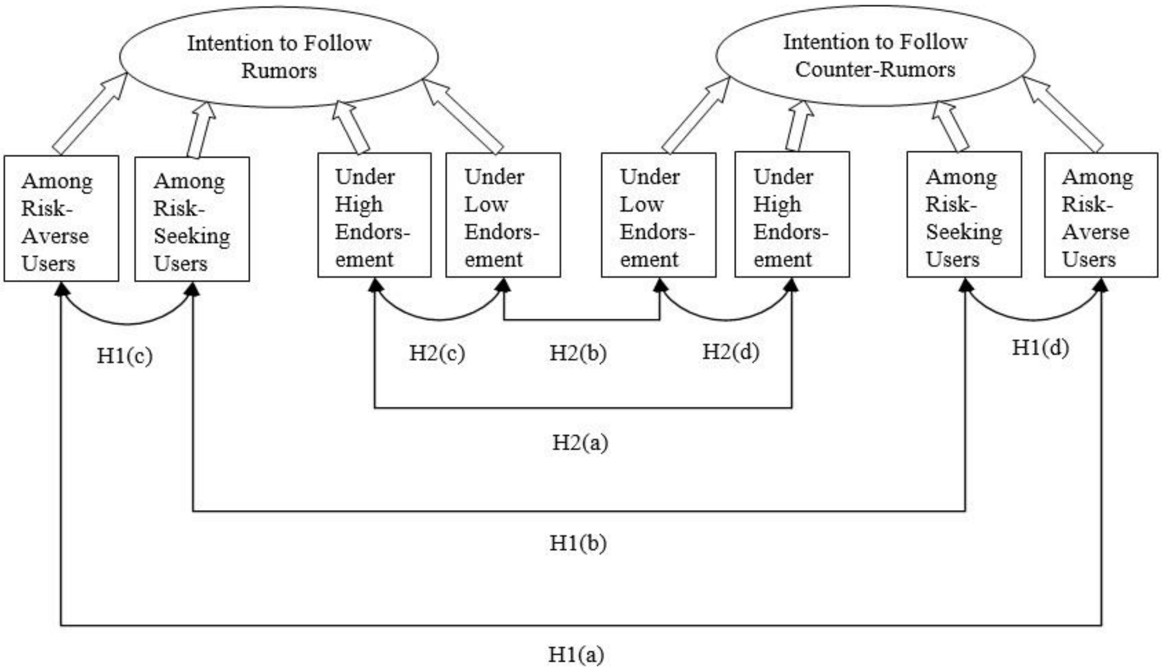

Figure 2. Depiction of comparisons made in the hypotheses.

Table I

Research questions and hypotheses

Research Questions	Related hypotheses
RQ 1: How does users' risk propensity affect their intention to follow rumors and counter-rumors?	H1(a): Among risk-averse individuals, intention to follow rumors will be lower than intention to follow counter-rumors.
	H1(b): Among risk-seeking individuals, intention to follow rumors will be higher than intention to follow counter-rumors.
	H1(c): Intention to follow rumors among risk-averse individuals will be different from that among risk-seeking individuals.
	H1(d): Intention to follow counter-rumors among risk-averse individuals will be different from that among risk-seeking individuals.
RQ 2: How does prior endorsement of rumors and counter-rumors shape a given user's intention to follow the messages?	H2(a): Under the condition of high endorsement, intention to follow rumors will not be different from intention to follow counter-rumors for the same individual.
	H2(b): Under the condition of low endorsement, intention to follow rumors will be higher than intention to follow counter-rumors for the same individual.
	H2(c): Intention to follow rumors under high endorsement will exceed that under low endorsement for the same individual.
	H2(d): Intention to follow counter-rumors under high endorsement will exceed that under low endorsement for the same individual.

Table II

Measures in the questionnaire

Variables	Measures
Intention to follow (Casaló et al. 2011; Zainal et al., 2017)	Indicate your degree of agreement with the following statements: (a) I feel comfortable to trust this message. (b) I am confident to rely on this message. (c) I will feel secure to follow the suggestion in this message.
Risk propensity (Merteens and Lion, 2008)	Indicate your degree of agreement with the following statements: (a) I do not take risk with my health. (b) I prefer to avoid risks related to my health. # (c) I view myself as a risk-avoider in terms of health-related issues. # (d) I take risks about my health. (R) (e) I take risks on health issues if there is no known harmful effect. (R) (f) I prefer to avoid risks related to chronic diseases (e.g., diabetes). (g) I take risks about my health if the harmful effect if any is minimal (e.g., herbal cures). (R) (h) Taking risks about my health is not challenging to me. (R) (i) I take risks about my health if the harmful effect if any is significantly large (e.g., smoking). (R) (j) I avoid risks about my health if the immediate benefit is huge (e.g., give pleasure). #

Note.

R indicates the reverse coded items.

# indicates questionnaire items that were dropped from the final analysis in order to make Cronbach's Alpha greater than 0.7

Table III

Summary of the results

Research Questions	Related hypotheses	t-Stat	Outcome
RQ 1: How does users' risk propensity affect their intention to follow rumors and counter-rumors?	H1(a): Among risk-averse individuals, intention to follow rumors will be lower than intention to follow counter-rumors.	7.14***	Not supported
	H1(b): Among risk-seeking individuals, intention to follow rumors will be higher than intention to follow counter-rumors.	5.70***	Supported
	H1(c): Intention to follow rumors among risk-averse individuals will be different from that among risk-seeking individuals.	-0.79	Not supported
	H1(d): Intention to follow counter-rumors among risk-averse individuals will be different from that among risk-seeking individuals.	-4.03***	Supported
RQ 2: How does prior endorsement of rumors and counter-rumors shape a given user's intention to follow the messages?	H2(a): Under the condition of high endorsement, intention to follow rumors will not be different from intention to follow counter-rumors for the same individual.	8.66***	Not supported
	H2(b): Under the condition of low endorsement, intention to follow rumors will be higher than intention to follow counter-rumors for the same individual.	4.66***	Supported
	H2(c): Intention to follow rumors under high endorsement will exceed that under low endorsement for the same individual.	2.44*	Supported
	H2(d): Intention to follow counter-rumors under high endorsement will exceed that under low endorsement for the same individual.	-4.53***	Not supported

*** $p < 0.001$, * $p < 0.05$

Appendix 1

Rumor and Counter-rumor messages

Rumors	Counter-rumors
R1: Drinking four glasses of water at the beginning of each day will cure various diseases.	**CR1:** Drinking four glasses of water at the beginning of each day will not cure various diseases.
R2: Drinking cold water after meals will lead to cancer.	**CR2:** Drinking cold water after meals will not lead to cancer.
R3: Drinking water in which okra has been soaked overnight will eliminate diabetes.	**CR3:** Drinking water in which okra has been soaked overnight will not eliminate diabetes.
R4: Drinking eight glasses of water per day helps to avoid being chronically dehydrated.	**CR4:** Drinking eight glasses of water per day does not help to avoid being chronically dehydrated.