Factors associated with belief or disbelief in false news: From the perspective of elaboration likelihood and moderating effect model

Chi-Ying Chen[1] and Shao-Liang Chang[2]

[1] Information Communication, Asia University, Taichung 41354, Taiwan
Pervasive Artificial Intelligence Research (PAIR) Lab, Taiwan
megcychen@asia.edu.tw
[2] Business Administration, Asia University, Taichung 41354, Taiwan

Abstract

Based on the elaboration likelihood model, this study examines the impact of central and peripheral cues to determine the relative influence of each cue on user's belief or disbelief in false news, and to investigate whether information literacy acts as a moderator to the cues. Results indicate that argument quality influences users to recognize the falsehood of messages delivered by either social media groups or news website groups. The impact of peripheral cues on social media tends to make users vulnerable to believing in false news (BFN), but not on news websites. Information literacy has no moderating effect on any cues, but has a direct effect on BFN from news website groups but not from social media groups.

Keywords: fake news, misinformation, information literacy, elaboration likelihood model

Background

Fake news is nothing new, in fact it has been with us since the development of the earliest writing systems (Marcus 1993); but this form of false information has become prominent recently due to its global implications. The widespread dissemination of false information can have negative consequences at both individual and societal levels; such as can be seen in stock price fluctuations (Rapoza, 2017), health emergencies and crises during an outbreak of Ebola (Oyeyemi et al., 2014), and political ramifications during the 2016 US presidential election (Allcott & Gentzkow, 2017).

Misinformation may also be understood in the context of fake news. Misinformation is defined as "cases in which people's beliefs about factual matters are not supported by clear evidence and expert opinion" (Nyhan & Reifler, 2010). Fake news is further defined with two key features; authenticity and misleading intent (Allcott & Gentzkow, 2017). That is, fake news contains false information created with some deceptive intention to mislead readers for ideological or financial gain (Lazer et al., 2018). Misinformation can instantly become viral when it is shared and re-shared by human behaviors or technologies. For example, studies have shown that social bots greatly misled online discussions during the 2016 U.S. presidential election (Bessi & Ferrara, 2016). In the week running up to election day around nineteen million bot accounts tweeted in support of a specific candidate, thus disturbing online communities and aggravating the public into an emotional response (Oxford Internet Institute, 2016). Furthermore, an artificial intelligence (AI) based technology 'Deepfake', that can combine and superimpose existing images and videos onto source images or videos, has been used to create convincing but inauthentic content. The fake videos created by Deepfake depict a person doing or saying something that never occurred in reality, but the actions are portrayed so vividly that it is no longer possible to differentiate genuine content from false (Meetup, 2018).

Executives of Facebook, Google, and Twitter have been asked by congressional committees to confirm their efforts to combat false stories due to social media being criticized as a potentially fertile ground for the dissemination of misinformation (Popken, 2018; Shaban et al., 2017). Mark Zuckerberg, the CEO of Facebook, told Congress that Facebook would use artificial intelligence to detect fakes. Today's AI operates at the "keyword" level, flagging text patterns and looking for statistical correlations among them and their sources, as Zuckerberg has acknowledged (Marcus & Davis, 2018). In addition to text features, Gfycat, a user-generated short-video hosting company, is being proactive in developing AI moderators to fight against Deepfakes (Cole, 2018). Other than content features of text and images, similar AI systems can evaluate how likely a story is to be false by identifying social context features, including major aspects of users, generated posts, and networks (Shu et al., 2018). The methodology of AI detection for fake news, as depicted in Figure 1, corresponds to the features (definitions) of fake news. However, using AI technology to fight against fake news has been criticized for putting technology into an arms race with itself, because abusers will not just stay where they are (Cole, 2018; Susarla, 2018). They often shift strategies with the intention of manipulating the fake content to make it appear more authentic and, moreover, find new ways to circumvent detection. Sooner or later, it perishes into technological cat-and-mouse games that play out on the internet all the time.

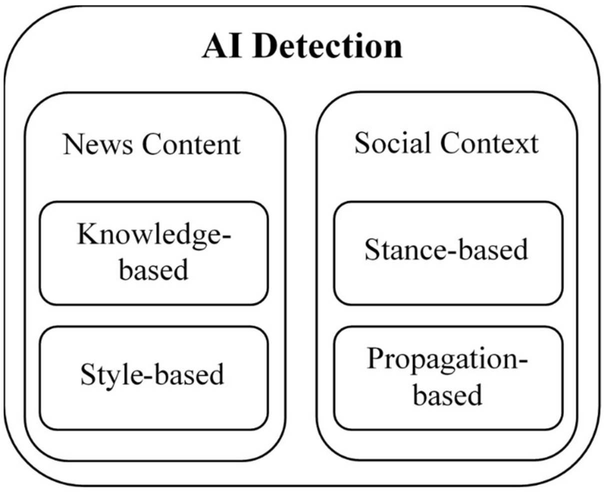

Figure 1. Approaches to fake news detection by AI
(Adapted from Shu et al., 2018)

A network of fact checking organizations has been established in many countries as concerns grow about the damage caused by false information. There are currently 161 active fact-checking organizations around the world, according to the Duke Reporters' Lab.[1] The process of fact-checking is intellectually demanding, time consuming, and heavily dependent on human effort to investigate and establish the veracity of data or documents. Consequently, the efficiency and scalability is limited. In addition, it has been found that online fake news disseminates much quicker and more broadly than real news (Vosoughi et al., 2018) and, by 2022, people in developed economies could be encountering more fake news than real information (Susarla, 2018). The contributions of fact checkers, hard-working though they are, would not be sufficient to meet an urgent demand, and thus much (perhaps most) false information will never get marked. An untagged false story may

[1] Available at: https://reporterslab.org/fact-checking/

actually increase the belief in its truthfulness due to the "implied truth effect", that is, the absence of a warning may be perceived as verification of the story (Pennycook et al., 2019)

Both solutions, AI algorithms and fact checking, are less than satisfactory. It is, therefore, argued that individuals should be at the center of efforts to deal with the threats of misinformation, given that humans, not robots, are more likely to spread misinformation (Khan & Idris, 2019; Vosoughi et al., 2018). A large-scale misinformation cascade can become viral within minutes when individuals share and retweet. To make things worse, it has been found that people often spread information without verification (Zubiaga & Ji, 2013) or even without reading the whole article (Gabielkov et al., 2016). From the perspective of information literacy, a literate individual is less likely to be misled because they are used to thinking critically and often try to distinguish false information from accurate information (Fallis & Whitcomb, 2009). Thus, information literacy is suggested as a major counterweight to the rising challenge of fake news.

Regardless of many discourses on how to combat the dissemination of false stories, we know little about what makes people susceptible to believing false news in an online context, and whether information literacy can leverage their vulnerability. To fill this knowledge gap, the current research explores and compares the impacts of factors associated with user's belief and recognition of misinformation and the moderating role of information literacy, based on the Elaboration Likelihood Model (ELM). The ELM, developed by Petty and Cacioppo (1984), is a dual process theory of attitude formation and change resulting in persuasion outcomes. This model has often been employed in IT persuasion research, such as consumer responses to online advertising (Cyr et al., 2018). The basic premise is that persuasion may be incurred through a central route based on the strength of arguments presented in a message, or a peripheral route based on cues such as attractiveness of the message source, image appeal, homophily, etc. The extent to which individuals scrutinize the information provided from each route depends on their state of "elaboration likelihood." Individuals in high elaboration likelihood states tend to engage in a cognitive processing of messages and be persuaded by argument quality. In contrast, those in low elaboration likelihood states are inclined to be motivated by peripheral cues. Both cues are analogous to the news content base and social context base of AI detection for fake news (refer to Figure 1). Therefore, the ELM model was chosen and the result is expected to offer some insights into AI detection development. Based on the foregoing discussion, we propose the research model illustrated in Figure 2, and outlined in the following hypotheses:

H1. Belief in False News (BFN) is associated with the intent to disseminate.

H2. Argument Quality influences BFN.

***H3*.** Topical Relevance is associated with BFN.

***H4*.** Image Appeal has an impact on BFN.

***H5*.** Source Trustworthiness is related with BFN.

***H6*.** Homophily influences BFN.

***H7*.** Information Literacy has an impact on BFN.

***H8*.** Information Literacy has a moderating effect on the relationships of Argument Quality (H8a), Topical Relevance (H8b), Image Appeal (H8c), Source Trustworthiness (H8d), and Homophily (H8e) with BFN.

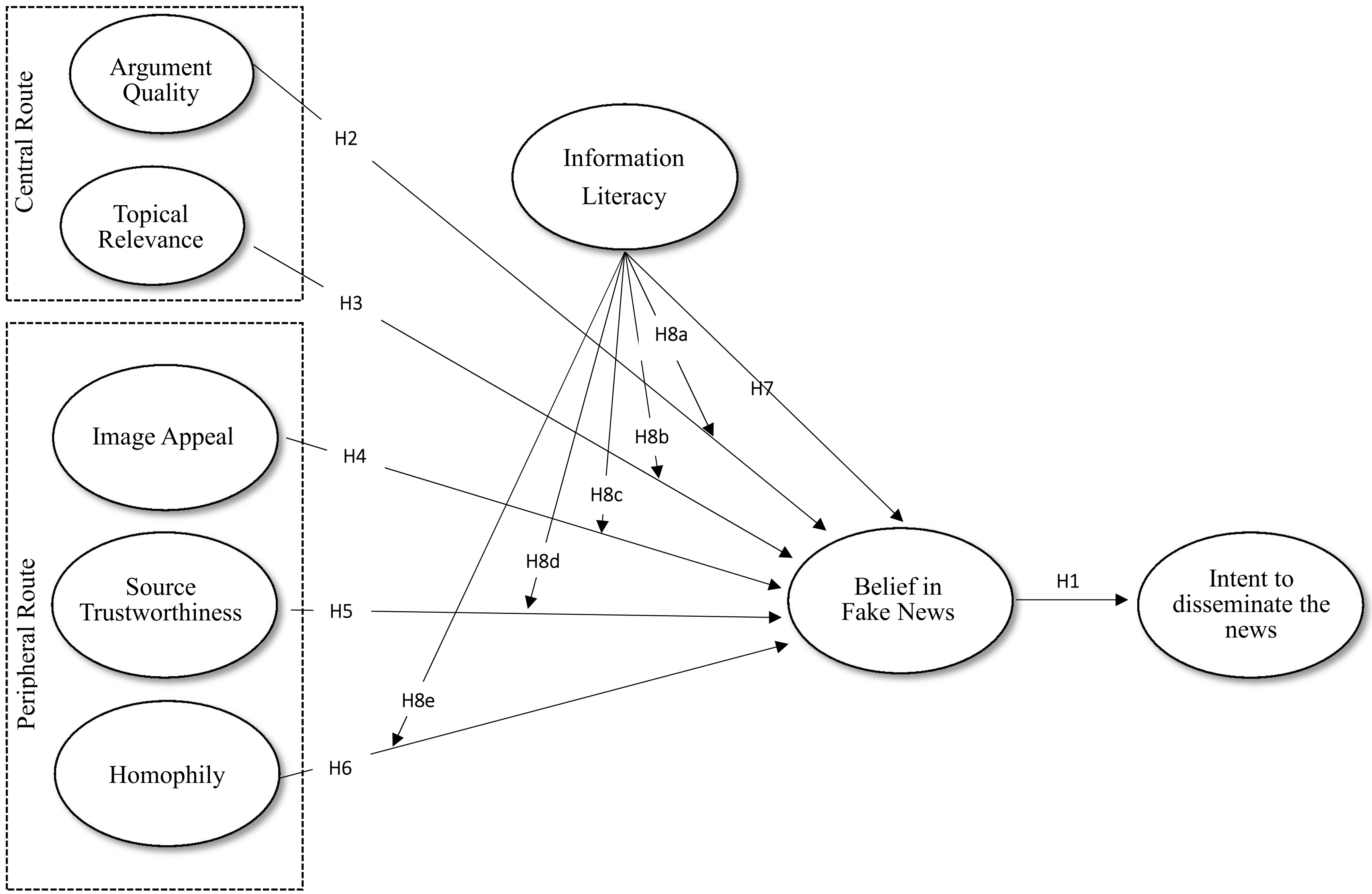

Figure 2. Research model

Method

Participants and Procedure

Participants were recruited from students from Asia University, with a sample age around the 20s, and students from Taichung community colleges, with a sample age above 30. Participants encountered a false news message in an online context, and then completed an online measurement. We reviewed over 100 fact-checking reports by Taiwan Fact-Check Center and selected four news messages judged false; two of them were from social media (Facebook and LINE) and the other two were from news websites. Participants from randomly selected classes in Asia University and in Taichung community colleges were presented with one of the four false news items and then asked to complete an on-line survey. In study A, 227 participants were asked to read a policy-related false news from Facebook; in study B, 237 participants were presented with life-related misinformation from LINE; in study C, 221 participants were asked to read a policy-related false message from a news website, and in study D, 248 participants were presented with a life-related false news item from another news website. Data from studies A and B were combined to analyze the modeling structure of believing in false news on social media, while data from studies C and D were combined to analyze the modelling structure of believing in false news on news websites.

Measurement

For the purpose of this research an online survey, adapted from previously validated constructs in the literature, was developed with measurements of: central cues (argument quality and topical relevance), peripheral cues (image appeal, source trustworthiness, and homophily), information literacy, belief in fake news, and the intent to disseminate. Except for belief in fake news, all items in the survey were constructed as 'highly disagree–highly agree' statements on a five-point Likert scale.

Participants were asked to rate the accuracy of the news messages to which they were exposed based on the degree to which they believed them to be true, based on a five-point scale (1 = Not at all accurate, 5 = Very accurate).

Analysis

Structural Equation Modeling (SEM) was conducted to test the hypotheses by using SmartPLS. Partial least squares (PLS) path modeling method is an appropriate technique for testing models/theories in the early stage of development (Urbach, & Ahlemann, 2010). In the absence of research concerning a user's information processing model in facing false messages, as well as the interaction effect of information literacy, we deem PLS to be a good analyzing method. A positive association value between a central/peripheral cue and BFN implies the specific cue influences users to be susceptible to believing false news. Alternatively, if the association is negative, the implication is that the cue foster user's recognition of misinformation.

Results

Confirmatory factor analysis (CFA) was utilized to assess discriminant validity. It is recommended that the factorial loadings of measurement items on their respective latent constructs should be larger than their loadings on other constructs (Gefen & Straub, 2005). Further assessment of interconstruct correlations were also examined. It is advocated that the reliability should be higher than 0.5, and ideally, higher than 0.7 (Chin, 2010). The criterion measurements for both data sets (social media group and news website group) were satisfied.

SEM for Social Media Group

Figure 3 depicts the model of the social media group (n=464). The R^2 value for BFN is 0.318, and the R^2 value for disseminating intent is 0.525. Based on the results in Figure 3, Hypotheses H1, H2, H3, and H5 are supported, while H4, H6, and H7 are not supported. BFN is highly associated with Disseminating Intent. In addition, Argument Quality negatively influences BFN, while Topical Relevance, and Source Trustworthiness influence in a positive way. Information Literacy is not related with BFN and neither moderates any of the central and peripheral cues.

SEM for News Website Group

Figure 4 depicts the analytical results of the model for news website group (n=469). The R^2 value for BFN is 0.192, and the R^2 value for disseminating intent is 0.495. Based on the results in Figure 4, Hypotheses H1, H2, H5, H6 and H7 are supported, while H3 and H4 are not supported. BFN is also highly associated with disseminating intent. In addition, Argument Quality, Source trustworthiness, Homophily, and Information Literacy all negatively influence BFN. Information Literacy moderates none of the central and peripheral cues.

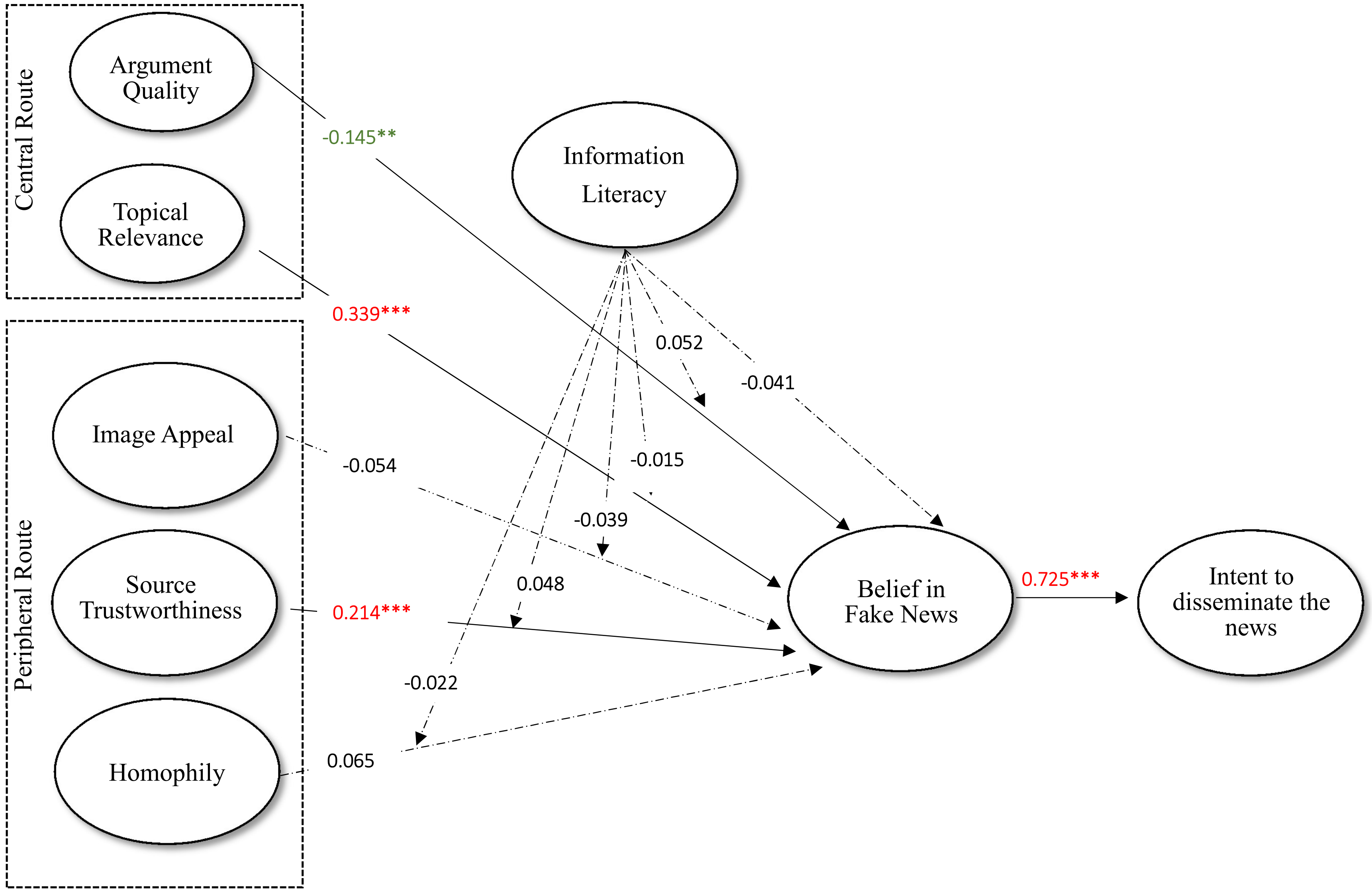

Figure 3. Results from Structural Model Analysis of Social Media Group

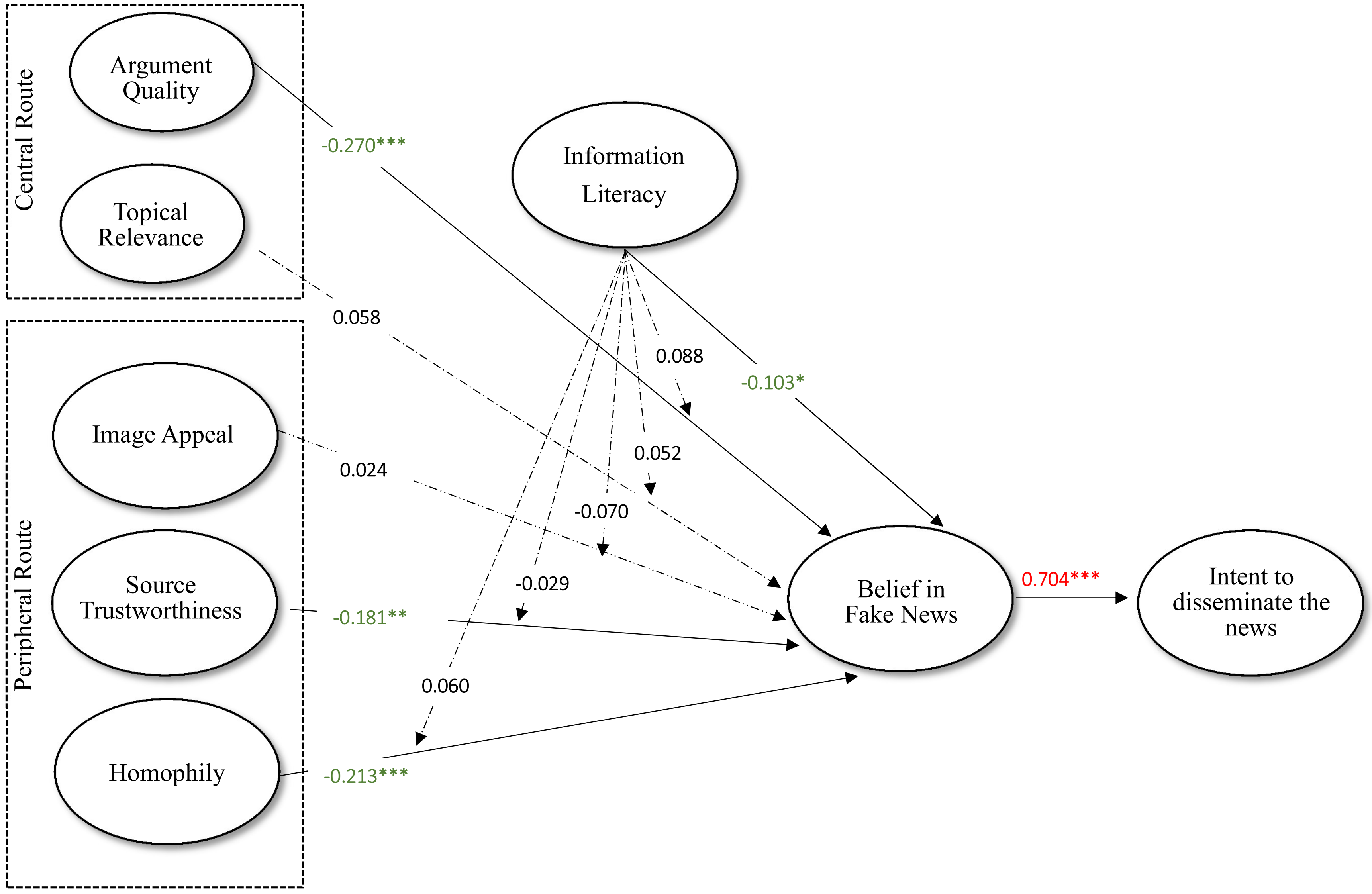

Figure 4. Results from Structural Model Analysis of News Website Group

Discussion

This study examines the impact of central cues (argument quality and topical relevance) compared with multiple peripheral cues (image appeal, source trustworthiness, and homophily) to determine the relative impact of each cue on a user's belief in, or disbelief of, false information, and to investigate whether information literacy acts as a moderator to both type of cues. The literature in this regard is rare. The example stimuli of false news were either taken from social media or news websites so that the results reveal the differences in a user's information processing model while they consume misinformation from both platforms. According to the analytical results, several insights are derived from this work:

1. Both type of models indicate that user's news disseminating intent is highly associated with their belief in the message. It is somewhat contradictory to the finding that the majority of Tweets were shared by users without even reading the contents (Gabielkov et al., 2016).

2. The Argument Quality of the central route plays an important role for the information processing of false news. The negative relationship between Argument Quality and BFN in both models indicates that users depend on the argument quality to recognize the falsehood of the information from either social media or news websites. On the other hand, Topical Relevance contributes positively to BFN for social media groups.

3. Source Trustworthiness of the peripheral route is associated with the perception of false news. The relationship is positive in the model of the social media group. It demonstrates that users tend to believe in false news if they read the messages from their trusted social media. Alternatively, the relationship between Source Trustworthiness and BFN is negative in the model of the news website group, and Homophily is also negatively related. Therefore, the impact of peripheral cues on social media tends to make users vulnerable to believing in false news, but not on news websites. Thus, social context of AI detection methodology is necessary as a complementary tool to leverage the damage of false stories on social media.

4. Information Literacy does not moderate the relationship between central/peripheral cues and BFN for both platforms. However, it has a direct effect on BFN for news websites but not for social media. Since the role of individuals as media gatekeepers for social media information is essential, information literacy in this regard is urgent.

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Author Biographies

Chi-Ying Chen is an associate professor of information communication, Asia University. Her research covers the use of digital media and its psychosocial and cultural implications.
Shao-Liang Chang is a professor of Business Management, Asia University. He is interested in information and technologies management.