Investigating the effect of social media fake news on consumer behavior: an empirical study with multiple moderations

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Abstract

The severity and prevalence of fake news on social media (SM) is growing, which leaves detrimental effects to businesses. Therefore, understanding consumer behavior when they are exposed to SM fake news is important. From the perspective of information asymmetry and signaling theory, this study derives that the negative effect of fake news on consumer trust is further reinforced in the presence of information asymmetry. Contrarily, vendors' signal credibility and consumers' perceived vendor reputation diminish the effect of fake news on consumer trust. Our research model is empirically validated via an online survey. The results support these three moderation effects. In addition, the results indicate that consumers' brand bias directly is a direct predictor of consumer purchase behavior. The findings suggests development of strategies for marketing managers and executives to mitigate the impact of SM fake news. Finally, the conclusion and future research opportunities are offered.

Keywords: fake news; consumer behavior; information asymmetry; consumer trust; signal credibility; brand bias

1. Introduction

During COVID-19 pandemic, people use social media (SM) often and for long period [1], which has increased their chance of exposure to fake news. SM fake news (hereafter "fake news") refers to all kinds of false contents and misleading information presented and circulated on SM with or without the aim of damaging the reputation of the subject [2]. The 'infodemic' exposed the audiences to abundance of fake news on COVID-19 and associated issues (e.g., product shortage), resulting user mistrust to the news SM propagates [1]. As the popularity of SM increases and so is the fake news [3], it has become a global concern [4] especially for businesses [5].

SM has become a popular tool to sellers for managing various business operations including marketing [6] and consumer relations [7]. Similarly, using SM, consumers receive product information, prior consumers' review, and more [8]. Despite the high potential of SM for enabling effective vendor-consumer dyads, the fake news it hosts leave deleterious effects to businesses [9]. Despite the serious significance of fake news on consumer behavior, the literature has devoted little attention to this critical phenomenon; this current research thus addresses three specific research gaps. *First*, according to *lemon market theory* [10], information asymmetries take place when vendor-consumer communication is poorly managed. Eventually, the good-quality sellers ('oranges') leave the marketplace for the bad ones ('lemons') [11]. In the current context, it is plausible that the perpetrators take advantage of information asymmetries, create fake news, and the SM users do the rest i.e., propagating it with negligible costs [12]. A major stream of research in marketing literature concerns the effect of fake news on consumer behavior [e.g., 13, 14]. However, scarcity of empirical research is evident explaining how fake news affects consumer behavior in the presence of information asymmetry. *Second*, we have little knowledge on how to eliminate the effects of fake news on businesses. To eliminate the effect of fake news, *signaling theory* [15] suggests using signal-cues from vendor. Given that information asymmetry is a qualifying condition for fake news, the application of signaling theory in the current context is sensible. *Third*, extant studies have either investigated the effect of fake news on consumer attitude e.g., trust [16], or on consumer behavior e.g., (re)purchase intention, loyalty, and word-of-mouth [4]. However, even though consumers' confirmation bias influences their actual behavior [e.g., 17], a complete picture integrating consumer attitude, confirmation bias, and behavior is limited.

Against the backdrop, this study aims to answer the following research questions

- *To what extent information asymmetries and vendors' signal-cues influence the relationship between social media fake news and consumer trust?*
- *How does confirmation bias affect consumer behavior in the presence of fake news?*

2. The Research Model and Hypotheses Development

The *signaling theory* [10] is a scaffold to understand how two parties (e.g., buyer and seller) deal with limited information in pre-contractual contexts [18]. Information asymmetry is the basic driver of *signaling theory* [19] where sellers have more information that is not widely known to the buyers. To convey information to the buyers, sellers can use extrinsic cues i.e., signals [18] such as pricing structures, firm reputation and brand announcement [20, 21]. Along with signals, signal credibility is also critical especially in the event of a crisis [22]. However, literature is scarce explaining how information asymmetry as well as the signaling cues affect the efficacy of SM fake news on consumers.

Confirmation bias refers to the tendency to process, interpret and accept information that is consistent with one's existing beliefs [23]. It explains why people sometimes process information in a biased manner [24]. In recent times, consumers receive enormous information that they cannot examine and validate accurately to form a rational conclusion. Consequently, they process or interpret information from their own viewpoint [24] and place a higher value on information that support their existing beliefs rather than those that contradict (confirmation bias) [25]. However, little research has explored how brand bias affects consumer attitude (e.g., trust) and behavior during uncertain situations.

To answer our research questions, we develop a research model (Figure 1). The model integrates concepts from *signaling theory* and *confirmation bias theory*, and is unique from two perspectives. First, it explains how information asymmetries increase and different signaling cues (signal credibility and brand reputation) decrease the negative impact of fake news on consumer trust. In this regard, the application of *signaling theory* is rational because asymmetry of information is a qualifying condition for the application of signaling theory to a SM fake news context [26]. Moreover, consumers recently encounter more fake news [3], creating a greater need for the sellers to communicate relevant signals that address public perceptions on fake news. Second, it investigates to what extent consumers' brand bias strengthens the impact of consumer attitude (i.e., trust) on consumers' (purchase) behavior.

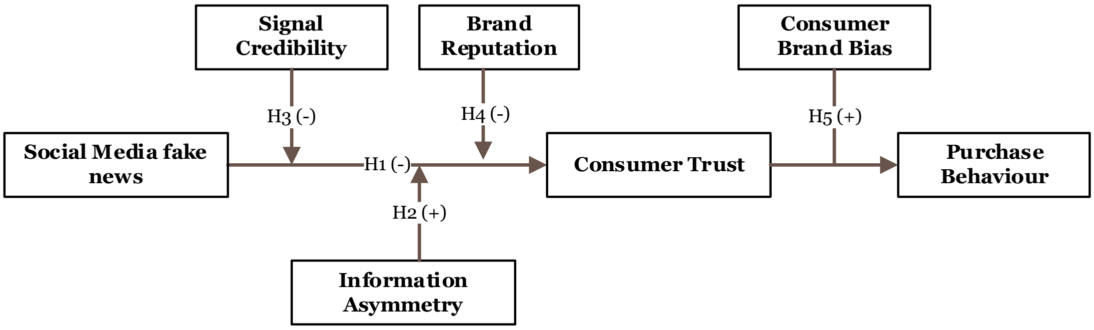

Figure 1. The Research Model

Consumer trust is defined as "consumers' affective experience with a specific brand" [27, p. 529]. Scholars discovered that trust, as a necessary precondition of the consumer-brand relationship, could help reduce uncertainty, facilitate positive attitudes, and build long-term commitment (e.g., loyalty and brand love) [28]. Prior studies suggest that SM fake news decreases consumer trust [16, 29, 30]. Building on this, we put forward that:

H1. SM fake news will decrease consumer trust.

Prior studies suggest information asymmetry predicts consumer behavior. For instance, Wells, Valacich [26] have demonstrated that the relationship between vendors' website quality and product quality is contingent upon information asymmetry. Similarly, Hossain, Rahman [31] have found that both the relation between consumers' purchase intention and vendor quality as well as perceived product quality are moderated by information asymmetry. Generally, consumers do not experience problems on a purchase when they know about the quality of a product or its seller [32]. However, when they are not sure about the product or the vendor, they try to minimize the risks by looking at associated information including product review [33]. In case of information asymmetry, they do not develop trust to the vendor. In the current context, when users on SM experience a potential fake news, they tend to understand its nature and minimize its consequences by looking at relevant information. When they have no or less accessible mechanisms to information, they tend to believe the contents, which can deteriorate consumer trust. Therefore, we suggest:

H2. Information asymmetries will positively moderate the impact of SM fake news on consumers' perceived trust; that is, the magnitude of the negative effect of SM fake news on consumer trust will be further increased when asymmetries of information are higher.

Previous studies suggest signal credibility as an important driver that predicts consumer trust and subsequent behavior [34, 35]. Prior studies posit that higher signal credibility occurs when consumers believes that the vendor has made a significant investment in developing and communicating the signal [26]. Other studies (e.g., Chen, Chien [36] and Zimmer, Salonen

[37]) reiterate the importance of signal credibility of the seller through brand image, website investment and trusting behavior. In relation to perceiving messages i.e., processing fake news, extant research asserts that the perception and power of a message depends on the signal credibility [38]. In this notion, we argue:

H3. Signal credibility of seller will negatively moderate the impact of SM fake news on consumers' perceived trust; that is, the magnitude of the negative effect of SM fake news on consumer trust will be decreased when signal credibility is higher.

Extant studies put forward the significance of brand reputation on consumer trust (e.g., Rust, Rand [39], Ngo, Liu [40] and Afzal, Khan [41]). However, there is limited research that has investigated the role of brand reputation in the relationship between fake news and consumer trust. In the current context, it is plausible that the fake news has less effects on a business e.g., consumer trust when the businesses' reputation is high compared to when reputation less. In other words, SM users would believe a fake news more when there is a lack of reputation of the vendor and *vice versa*. Therefore, we posit:

H4. Perceived consumer brand reputation will negatively moderate the impact of SM fake news on consumers' perceived trust; that is, the magnitude of the negative effect of SM fake news on consumer trust will be decreased when perceived brand reputation is higher.

According to *confirmation bias theory*, people's 'belief polarization' increases when mixed or inconclusive findings are assimilated by opposite viewpoints [42]. In such instances, people have an unconscious propensity to interpret information in a way that confirms their previous beliefs and perceptions [43] while giving disproportionately less attention to alternative possibilities [42]. Such bias is potentially stronger for emotionally charged issues and deeply entrenched beliefs [23]. Consumers are likely to accept information to support their own beliefs regarding the brand [43]. Consumer brand bias – the extent to which a brand is regarded, understood, or interpreted by consumers [44] – can be assessed by evaluating favoritism [43] and loyalty [44]. The cognitive process of consumers whether or not to purchase a product is influenced on their familiarity and opinion about the brand [24]. If a consumer has a high level of bias regarding a brand, this will further strengthen their trust towards the brand [45], and they together can influence consumers' purchase behavior [17]. Therefore, we propose:

H5. Consumer brand bias will positively moderate the impact of consumer trust on purchase behavior; that is, the magnitude of the positive effect of consumer trust on purchase behavior will be further increased when consumer brand bias is higher.

3. Research Methodology

3.1 Measures

For consistency and robustness, we adopted the measures from existing scales. Specifically, *SM fake news* is measured with three items adapted from [46]. Participants have been asked to choose the extent to which they saw hoax, made-up, and exaggerated information on SM related to COVID-19. The measures for *information asymmetry* and *signal credibility* include four and three items, respectively, adopted from Wells, Valacich [26]. Similarly, *perceived brand reputation* is measured with four items from Fombrun and Gardberg [47], while *consumer trust* uses four items from [48]. Further, *consumers' brand bias* was measured by combining two items from Baloglu [49], two items from Bennett and Rundle-Thiele [50], and one newly developed item for the purpose of this research. Finally, *purchase behavior* was measured by three items adapted from [51] and Choo, Chung [52]. All items are reflective in nature and used a 5-point Likert-scale from 'strongly disagree' to 'strongly agree' (5).

3.2 Data collection

The survey design has followed a sequence of steps, including a pre-test (three PhD students researching on Marketing and four volunteers who regularly purchase from McDonald's), followed by a pilot test with 22 respondents. The feedback from both stages have assisted us to improve the survey. Then, the respondents for this study were recruited through Mechanical Turk (MTurk) platform [53]. Consumer behavior and marketing researchers have widely been collecting data from MTurk [54]. "MTurk samples are more representative than other convenience samples" [55, p. 46] that "allows researchers to reach a huge pool of potential respondents ..., which is virtually impossible using other data collection methods" [56, p. 588]. At the beginning of the survey, our prospective respondents were asked to indicate the social networking platform(s) they had visited most frequently during the last month and to report if they have made any purchase from McDonald's during the past three months. McDonald's has been chosen because food industry is one of the top targeted for fake news where SM accommodates numerous fake news against *McDonald's* e.g., serving human meats [57], and racist policies [58].

In total, 309 valid responses were obtained. The majority of the respondents were noted in the age of 31 to 45 years old (48.5%), followed by 21 to 30 years (28.8%) and 46 to 60 years (23.3%). 83% of the respondents had visited McDonalds at least once in the last three months. In terms of gender, 57% were male and 43% were female respondents. More than 82.5% of the respondents were employed, and 65% had at least a bachelor's degree. Further to this, more than 90% of respondents were noted frequent SM users of platforms including Facebook, YouTube, Instagram, and Twitter.

4. Data Analysis and Results

4.1 Assessment of the measurement model

To operationalize the research objectives and to test the hypotheses in the research model, we use PLS-SEM, which is suitable for complex models [59] i.e., having multiple moderations [60, 61]. For data analysis, we used SmartPLS 3.2.7 [62].

We followed standard PLS-SEM procedure. Internal consistency was checked with composite reliability (CR); the *CR* values (*see* Table 1) were >=0.7 threshold and < 0.95 recommended value [60]. Next, for convergent validity, the outer loading of each item was >=0.6 [63] and the AVE value of each construct was >0.50 [60] (*see* Table 1). Finally, we relied on three measures of discriminant validity: cross-loading matrix (not supplied), the Fornell-Larcker criterion (Table 2), and the heterotrait-monotrait ration (HTMT) of the correlations; the HTMT value (parentheses values in Table 2) [64]. Lastly, we tested for common method bias (CMB). First, the Harman's one-factor showed that the first factor accounted for 17.48% of the variance and none stated the majority of the total variance. Second, following the marker variable (MV) technique, a MV ("I like blue cloths, I prefer blue to other colours"), which was theoretically unrelated to the nomological network, was included in the model. The result showed an insignificant effect of the MV on PB (β = -0.015, t = 0.434, p > 0.05). Third, in the correlation matrix, the correlation between MV and other variables were significantly below the 0.9 threshold. The collective results indicate that CMB is not likely to pose a problem for our study.

Table 1. The measures and their psychometric values

Items		Loading	CR	AVE
Fake News	On SM, I have seen ...		0.837	0.633
fkn_1	information related to McDonald's that I later found out as a hoax.	0.862		
fkn_2	content related to McDonald's that seem accurate at a time but later I found that it was made up.	0.696		

fkn_3	content related to McDonald's that was exaggerated but I was not aware if it was exaggerated at the time of seeing.	0.819		
Signal Credibility			0.873	0.698
sc_1	I believe McDonald's puts a significant effort in maintaining a high-quality brand.	0.914		
sc_2	I assume that McDonald's is investing a lot of time and money to design and maintain their brand image.	0.823		
sc_3	I see McDonald's makes a considerable financial investment to maintain their strong SM presence.	0.762		
Perceived Brand Reputation			0.869	0.571
pbr_1	I can see lot of advertising from McDonald's.	0.811		
pbr_2	In general, McDonald's has non-negative media coverage.	0.759		
pbr_3	People around me talk positively about McDonald's.	0.702		
pbr_4	People important to me discuss positively about McDonald's.	0.807		
Information Asymmetry			0.886	0.660
ia_1	I have a good idea of what products and services McDonald's offer.	0.792		
ia_2	I have sufficient information about McDonald's menu.	0.800		
ia_3	I possess adequate knowledge about McDonald's products.	0.835		
ia_4	If I need, I believe I can easily collect sufficient information about McDonald's raw materials.	0.823		
Consumer Trust			0.872	0.630
ct_1	I trust MacDonald's as my fast-food vendor.	0.822		
ct_2	I feel that I would trust MacDonald's for reliable products and services.	0.820		
ct_3	I feel that I would trust the commitments McDonald's make regarding its products and services.	0.798		
ct_4	I feel that I would trust that the products and services of McDonald's to meet my expectations.	0.732		
Consumer Brand Bias			0.941	0.761
cbb_1	I am emotionally attached to McDonald's.	0.909		
cbb_2	I have a sense of belonging to McDonald's.	0.869		
cbb_3	McDonald's is one of my favorite fast-food vendors.	0.885		
cbb_4	I find myself as a loyal customer of McDonald's.	0.858		
cbb_5	In general, I am bias towards McDonald's when it comes to fast-food.	0.839		
Purchase Behavior			0.913	0.778
pb_1	Number of times purchased from McDonald's in last three months: 0, 1-3, 4-6, 7-9, more than 9 times.	0.667		
pb_2	Approximate % of purchase from McDonald's when purchased on fast-food (in last three months): 0%, 1-20%, 21-40%, 41-60%, more than 60%.	0.662		
pb_3	Approximate spending in McDonald's in last three months: $0; $1-100; $101-200; $201-300; >$300.	0.719		

Table 2. The discriminant validity tests

	CBB	*FkN*	*IA*	*PB*	*PBR*	*SC*	*CT*
CBB	**.87**						
FkN	-0.15(.20)	**0.80**					
IA	0.46(.53)	-0.30(0.4)	**0.81**				
PB	0.77(.87)	-0.19(0.26)	0.41(0.48)	**0.88**			
PBR	0.327(.4)	-0.6(0.78)	0.47(0.59)	0.37(0.47)	**0.76**		
SC	0.73(.87)	-0.25(0.35)	0.42(0.52)	0.67(0.83)	0.41(0.51)	**0.81**	
CT	-0.05(.09)	-0.63(0.79)	0.27(0.33)	0.04(0.08)	0.44(0.5)	0.11(0.12)	**0.794**

4.2 Assessment of the structural model

To evaluate the structural model, we checked the R^2 value of the endogenous variables. The R^2 values of TST and PB were found to be 0.47 and 0.61 respectively, representing that the model has a good prediction accuracy. Then, to measure the model's predictive relevance, we estimated the Stone-Geisser Q^2 value by using the blindfolding method [65, 66]. We further assessed our model's predictive relevance by presenting 'out-of-sample' predictions. For this, we used *PLSpredict*, which checks a model's accuracy when predicting the outcome value of new cases [67]. We used *PLSpredict* with 10 folds and 10 repetitions to mimic how the PLS model could be used to predict a new observation. First, we found that the indicators of PB outperform the most naïve benchmark (i.e., the training sample's indicator means), as all the indicators yield Q^2 predict values above 0 (i.e., 0.405, 0.403, and 0.433). Then, comparing the RMSE values from the PLS model (0.942, 0.976, 0.940) with the linear model (LM) (0.976, 1.006, 1.012), we found that the PLS model produced lower prediction errors for all the indicators of PB. Similar results were observed for MAE and MAPE values. Finally, the *Q^2_predict* values for PLS model (0.445, 0.438, 0.512) were higher than that of the LM (0.405, 0.403, 0.433). The results show that our model has higher predictive accuracy [68].

To check the hypotheses, we evaluated the structural model with the path coefficient, *t* values, and *p* values, obtained from bootstrapping. For the moderation tests, we used SmartPLS's 'moderating effect' option by selecting two-staged calculation method, standardized product term generation, and automatic weighing mode. The results in Table 3 show that, FkN has a significant negative impact on CT; hence, our H1 is accepted. As a post-hoc test, the indirect effect of FkN on PB (β = -0.058, p < 0.05) suggests that fake news decreases consumer purchase. Next, the interaction effect of FkN and IA is significant. It means IA strengthen the negative relationship between FkN and CT; hence, our H2 is accepted, which is further substantiated by the slope analysis (Appendix A1). Further, SC negatively moderates the relationship between FkN and CT (i.e., SC weakens the negative effect of FkN on CT, see Appendix A2). Hence, H3 is supported. Next, PBR significantly weakens the negative relationship between FkN and CT (Appendix A3); hence, H4 is supported. Then, CT affects PB (β = 0.093, p < 0.05). Finally, though CBB has a direct and strong influence on PB (β = 0.797, p < 0.001), its moderating effect between CT and PB is insignificant. Therefore, H5 is rejected. Table 3 summarizes the hypotheses testing in this study.

Table 3. Evaluation of the hypotheses

	Paths	***β* values**	***t* values**	***p* values**	**Results**
H1	FkN to CT	-0.623	8.579	0.000	Supported
H2	FkN*IA to CT	0.196	3.696	0.000	Supported
H3	FkN*SC to CT	-0.206	3.124	0.002	Supported
H4	FkN*PBR to CT	-0.094	2.029	0.043	Supported
H5	CT*CBB to PB	-0.05	1.179	0.239	Rejected

Note: FkN, fake news; CT, consumer trust; IA, information asymmetry; SC, signal credibility; PBR, perceived brand reputation; CBB, consumer brand bias; PB, purchase behavior

In order to enrich our PLS-SEM analysis, particularly to identify the antecedents that have a relatively high importance to our dependent construct i.e., PB, we applied the importance-performance map analysis (IPMA). IPMA considers the average value of the latent variables and their indicators (i.e., performance) instead of only analysing the path coefficients (i.e., importance) [69]. By following the steps of [69], we developed the importance-performance map as a chart (Figure 2). According to Ringle and Sarstedt [69], analysing the map, "constructs in the lower right area (i.e. above average importance and below average performance) are of highest interest to achieve improvement, followed by the higher right, lower left and, finally, the higher left areas" (page 1873). We found that CBB has a high importance (0.67) for PB; a one-point increase in CBB's performance (from 55.9 to 56.9) increases the performance of PB by 0.67, ceteris paribus, i.e., from 59.5 to 60.17. Since the performance of CBB is relatively low (but has the highest importance), there is substantial room for improvement. Hence, when managers aim at increasing the performance of PB, their first priority should be to improve the performance of aspects captured by CBB.

Furthermore, we have conducted an IPMA on the indicator level to identify relevant and even more specific areas of improvement. We have found that, indicator *cbb1_1* ("I am emotionally attached to McDonald's") has the highest priority for improvement. A one-unit point increase in *cbb1_1*'s performance increases the performance of PB by 0.162 (ceteris paribus). Indicators *cbb1_5*, *cbb1_3*, and *cbb1_4* follow with second to fourth priority. The other indicators are less relevant for improving PB's performance.

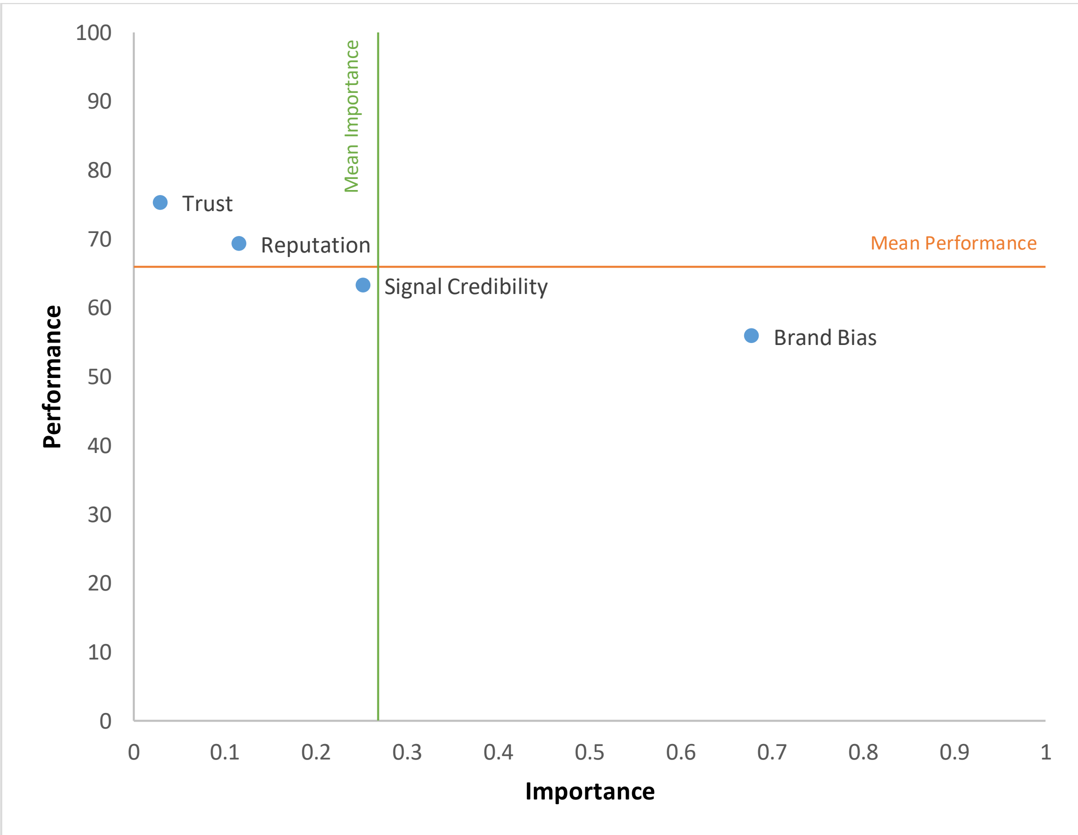

Figure 2. The importance-performance map of the target construct purchase behaviour

5. Discussion

5.1 Implications for research

This research has several implications for research. *First*, the concept of signaling theory has been studied in marketing [21] to understand the impact of certain signals on firm-level outcomes e.g., pricing structures, brand messages. Our study investigates the novel application of *signaling theory* and extends its generalizability by investigating the impact of fake news on consumer behavior. Hence, it provides an insightful lens for future research on marketing in general, and SM and consumer behavior in particular.

Second, this study contributes to the strategic marketing literature by investigating the effects of a critical yet substantially neglected factor, i.e., signaling cues. While signaling cues are prevalent on SM and other e-commerce marketing channels [26], to offset the impact of fake news on consumer behavior, our study has identified two possible interplays of signaling cues such as reducing information asymmetry and developing strong reputation and credible signals. Understanding this has open room for wider theoretical extension in the field of digital marketing.

Third, while previous research attempted to explain how SM can bias users' beliefs and perceptions, thereby influencing individual behavior [42], the nuanced non-static relationship between consumer trust and purchase behavior in the context of fake news has not identified completely. Our study suggests that consumer trust and brand bias together do not influence consumers' purchase decision. However, each of them individually does. The *t*-values of 2.16 and 26.8 for trust and CBB respectively suggest that CBB shapes a customer's purchase decision more strongly than consumer trust and guides to buy from a particular brand instead of another. In other words, in uncertain conditions with numerous potential fake news, consumers rank brand biasness over trust. This is plausible [70, 71]. CBB is their mental judgement that may has been created from their own subjective reality, prior experience and/or the information they receive. From a theoretical perspective, CBB is a mental or emotional evaluation that helps consumers to reach purchasing decisions with relative speed and minimal mental effort. However, the eventual decision (i.e., purchase) might not always positive or rational.

5.2 Implications for practice

By examining the effect of fake news on consumer behavior, this study offers three practical implications, which in combination suggests a shared role of marketing administrators, SM administrators, and consumers to lessen the effects of fake news. *First*, fake news reduces consumer trust, which is consistent with previous studies [e.g., 16]. It recommends sellers and SM administrators to apply contemporary technologies e.g., machine learning, artificial intelligence [72] to detect fake news automatically as soon as possible and act on it. We also empirically derive that information asymmetry itself does not affect consumer trust but enhances the negative effects of fake news on trust, supported by extant studies [26]. It means information asymmetry itself does not harm a business until there are uncertainties e.g., fake news exist [31]. In other words, in the presence of information asymmetry, fake news has more severe impact on consumer trust. This finding makes the marketing managers' job even harder and suggests them to devise appropriate marketing and communication strategies to minimize information asymmetry about their products. For example, 'push pop-up messages' in the form of updates and more visual clickable contents may help to overcome information scarcity. Also, fast-food sellers should provide information to consumers regarding their sourcing of raw materials, product manufacturing processes, and waste disposal mechanisms to install trust [31].

Secondly, on reducing the effect of fake news, this study provides pragmatic suggestions. It is plausible that, to eliminate the effect of fake news, consumers tend to rely on assessing relevant signals. In such uncertain conditions, the extrinsic cues (e.g., signal credibility) tend to compensate for a lack of intrinsic cues (e.g., fake news, information asymmetry) [26].

Hence, businesses should manage the cues effectively. For instance, consumer trust is not directly influenced by *signal credibility*; however, the detrimental effects of fake news on consumer trust can be mitigated if the signals from vendor are perceived as credible. This is consistent with previous research [73]. Hence, businesses should invest on SM marketing and make sure their investments are visible to the consumers. In addition, they can communicate quality assurance information to contribute to signal credibility. Similar to signal credibility, while *perceived brand reputation* and *consumer trust* are directly unrelated, the former reduces the effect of fake news on the latter. It is plausible that consumers' trust on a seller will be less affected by fake news when the sellers' brand reputation is high, compared to when the reputation is low. Hence, we emphasize the importance of communicating detailed information about the brand, its products, and its functional processes through SM platforms, which may contribute to brand reputation [31].

Thirdly, this study suggests the significance to foster brand biasness in manipulating purchase decision when fake news are prevalent. Based on our IPMA, when managers aim at increasing consumer purchase, their first priority should be to improve the performance of aspects captured by consumer brand bias. After increasing consumer brand bias, managers then can focus on trust, reputation, and signal credibility respectively. Marketing executives can reinforce the brand image into their consumers to enhance confirmation bias by tailoring marketing campaigns that resonate with consumers' perceptions [25].

5.3 Limitations and future research directions

Despite its significant implications, our study has two main limitations that advise future research directions. *First,* this research has collected data from a cross-sectional survey. As fake news and its related impacts are dynamic in nature, future research can adopt a longitudinal design. In this regard, we can compare the effects of fake news during COVID-19 with the post pandemic setting assuming that consumers may not react to fake news on a constant fashion over periods, and thus would have lesser impacts on consumer behaviour. *Second,* we did not differentiate the results between the consumers from developing and developed countries, whereas prior studies suggest that the consumers of a developing country may behave differently from that of developed countries for various demographic, economic, and cultural differences [e.g., 74]. For instance, consumers in Iraq have not changed their buying habits because of fake news [75], which is quite opposite in Australia and New Zealand [76]. Future studies applying multi-group analysis and comparing the responses to fake news consumers from between developing and developed countries would be interesting.

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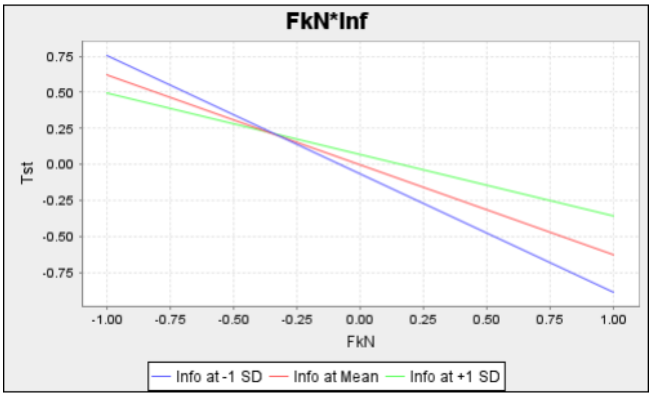
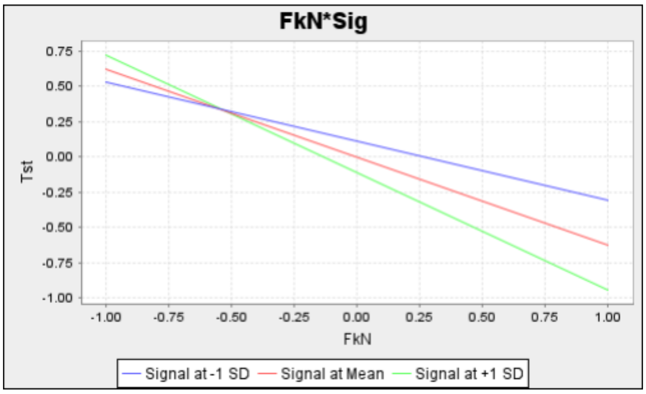
Appendix A. Slope analysis of the significant moderators

Appendix A1. The Interaction of information asymmetry between SM fake news and consumer trust



Appendix A2. The interaction of signal credibility between SM fake news and consumer trust



Appendix B3. The Interaction of perceived brand reputation between SM fake news and consumer trust